An Empirical Analysis of the Adaptive Market Hypothesis and Investor Sentiment in Extreme Circumstances

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Abstract

The Efficient Market Hypothesis (EMH) has been widely studied in the literature, however there remains no consensus among academics whether markets are efficient or not. Although it was initially thought to hold, the recent explosion of studies that find that markets are not efficient has cast serious doubt on the validity of the EMH. Furthermore, the vast majority of the literature examines the EMH over some predetermined sample period, disregarding the fact that the level of efficiency may change over time and a large sample period may not be efficient or not for the whole period. A new theory that tries to accommodate both these facets is the Adaptive Market Hypothesis (AMH), proposed by Andrew Lo (2004). This theory enables market efficiency and market inefficiencies to co-exist together and market efficiency to evolve over time.

The main objective of this thesis is to examine the AMH and stock return behaviour in major stock markets using very long data and determine whether it is a more appropriate model for describing stock market behaviour than the EMH. A five-type classification is proposed to distinguish the differing behaviour of stock returns over time. Daily data is spilt into five-yearly subsamples and investigated in respect of linear and nonlinear time-series tests, three calendar anomalies and the moving average technical rule. The results suggest that the AMH provides a better description of the behaviour of stock returns than the classic EMH. Linked to the AMH is the fact that investors are not rational and investor psychology plays a real role in investor's decision making. With that in mind, this thesis also examines the level of investor sentiment in stock returns during World War Two in Britain. This is a time period that has not been studied in great detail and provides an opportunity to examine investor sentiment in extreme circumstances. The empirical results show that there was strong negative investor sentiment from major negative events and a strong level of local bias during the period known as the Blitz.

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Chapter 1: Introduction

1.1. Motivation for Study

The ‘Efficient Market Hypothesis’ (hereafter EMH), coined and formalized in the seminal paper of Fama (1970), has gained continual attention from researchers in the field of finance. The EMH refers to a market in which new information is quickly and correctly reflected in its current price. To this end, no investor can consistently gain returns greater than the market as prices react instantaneously and appropriately to new information. This means that stock market returns must be independent and unpredictable. Although Fama (1970) introduced three forms of the EMH which are distinguished by their differing information sets, the weak-form EMH has been the most widely studied and will be the primary focus of this thesis. The weak-form asserts that market prices fully reflect all information contained in the price history of the market. Thus the weak-form states that trend analysis is futile.

Hundreds of published articles spanning over 40 years have examined the EMH in great detail through a variety of testing procedures. However, as Lo (2008) notes, there is still no consensus among economists on whether financial markets are efficient or not. Many studies in the 1960s and 1970s found the EMH to hold, while from the 1980s to the present day, there has been an explosion in the number of studies that find markets are not efficient. This is due to the voluminous number of papers that have found stock returns not to be independent and to the discovery of stock market anomalies that generate significant abnormal returns. Further, some of these inefficiencies have been persistent and of a large magnitude.

If a market is weakly efficient, stock returns must be independent of each other. If returns are not independent, investors could use this information to make abnormal returns[1]. Testing for the independence of stock returns is the traditional way of examining market efficiency and there are many testing procedures used. The traditional and most often used test is the autocorrelation test but many other tests have been formulated to examine linear independence such as the runs test, variance-ratio test and numerous unit root tests. More recently, there has been explosion in tests examining the nonlinear dependence of returns

[1] Abnormal returns refers to difference between the actual return and the expected return.

(since the traditional tests only examined linear dependence) such as the BDS test, Engle LM test and McLeod-Li test.

However, the tests for independence may fail to pick up some predictability in the market. Predictability refers to anomalies or trading rules that produce abnormal returns. One popular group of anomalies are related to the time of the year and are called calendar anomalies. These anomalies find stock returns are systematically higher or lower depending on the day of the week, day of the month, or month of the year. Three of the most popular and well-studied calendar anomalies are the Monday effect, January effect and turn-of-the-month effect. The Monday effect finds that returns that are generated on Mondays are significantly negative and lower than other days of the week. The January effect finds returns in the first half of January are significantly greater than the rest of the year, while the turn-of-the-month effect finds that returns around the turn-of-the-month are significantly higher than the rest of the month. Another group of market anomalies are related to technical analysis. Technical analysis involves forecasting future prices through the identification and exploitation of recurring patterns in past prices. Thus it aims to identify irregular patterns forced by the economic, monetary, political or psychological attitudes of investors. Many technical rules have been found but one of the most popular is the simple moving average rule. A moving average is an average of observations of the level of the index or stock over several consecutive time periods, with the objective of smoothing out seasonal variations (volatility) in the data. The standard moving average rule, which utilizes the price line and the moving average of price, generates buy/sell signals on which the investor trades. This strategy is expressed as buying (or selling) when the short-period moving average rises above (or falls below) the long-period moving average.

Overall there appears to be a conflict between the EMH and the recent literature which finds returns are not independent and market anomalies do exist. Another issue is that the EMH has traditionally been examined in the academic literature over some predetermined sample period and the study reports whether that sample period is efficient over not. However, the level of efficiency of a market may change over time, and it is naïve to assert that a large sample period is either efficient or not for the whole period. Thus market efficiency may not be an all-or-nothing condition and may change over time depending on a number of factors.

Andrew Lo (2004) noted these two facts about market efficiency and proposes a new model that enables market efficiency and market anomalies to co-exist and allows market efficiency to evolve over time. This model is called the 'Adaptive Market Hypothesis' (hereafter AMH) which asserts that market efficiency is an ever-changing phenomenon which depends on the market conditions and market participants. It states that market efficiency is not a guaranteed outcome and that profit opportunities are available from time to time. This new theory has received some attention in the literature since its formulation and will be a focus of this thesis.

Thus this thesis investigates whether the AMH is a more appropriate model to explain stock return behaviour over long time periods than the traditional EMH. This is done through the examination of tests for independence as well as examining well known calendar anomalies and technical rules in three long standing stock markets. Further, a five-type classification of the behaviour of stock returns is proposed which depends on the behaviour of stock returns over time. Linked to the AMH is the fact that investors are not rational and investor psychology plays a real role in investor's decision making. With that in mind, this thesis also examines a period of time that has not been examined in great detail Britain in World War Two, and whether investor sentiment was present. This time period gives the opportunity to study investor sentiment in extreme circumstances and is examined through event studies and regression analysis.

1.2. Objective of Study

The main objective of this thesis is to examine the behaviour of three long-standing stock markets and whether the AMH is a better model of explaining their behaviour than the traditional EMH model. More specially, this thesis focuses on the behaviour of the US, UK and Japanese stock markets over time utilising; (1) time-series analysis, (2) technical analysis and (3) calendar effects. Thus this thesis provides a detailed examination of behaviour of stock markets over long sample periods, adding to the expanding literature in this area. Furthermore, this thesis examines the British stock market during WW2 to contribute to the literature on investor sentiment and psychology.

1.3. Contributions of Study

The main contributions of this study are;

1. An examination of the newly formulated AMH through time-series analysis (including nonlinear tests), calendar anomalies and technical analysis to determine whether it is a more appropriate model in describing stock market behaviour than the traditional EMH.

2. A proposed classification of stock returns behaviour to enable a comparison of returns from differing trading strategies over time.

3. To further the knowledge of the behaviour of calendar anomalies and technical rules since the publication of the seminal papers in these areas as well as an examination of the profitability of these anomalies.

4. To propose two modified versions of the moving average rule that outperform the original moving average rule and the buy-and-hold strategy.

5. To further the literature on investor sentiment in extreme circumstances and during a period of time which has not been examined in great detail.

1.4. Chapter Outline

Chapter 2 provides a synopsis of the EMH, thereby laying the foundation for this thesis. A brief review of the history and the theory of the EMH are provided, as is an introduction to various anomalies that are contrary to the EMH. Also included is a brief account of the various testing procedures used in the literature to examine the EMH and the major criticisms they have faced recently. It is followed by a detailed explanation of the AMH and its implications for stock market returns and their behaviour. Also explained is the stock return classification proposed in this thesis. This chapter also examines the three stock markets examined in this study and explains the differences between them.

Chapter 3 studies the independence of stock returns over time in the three markets through linear and nonlinear tests. The primary purpose of this chapter is to examine whether the AMH can explain the behaviour of stock returns through tests for independence. The linear tests utilised are the autocorrelation test, runs test, variance ratio test and unit root tests for stationarity. The returns are then whitened (through an AR and AR-GARCH pre-whitening method) to remove all linear correlation and the residuals of this model are then subjected to the McLeod Li test, Engle LM test and BDS test. The behaviour of the returns is analysed through five-yearly subsamples since they provide enough observations to accurately evaluate the independence of returns while at the same time providing enough results to deem how the market has behaved over time. Also, the behaviour of returns in each case are categorized into one of five types previously described.

Chapter 4 investigates the behaviour of stock returns over time through an examination of well-known calendar effects. The purpose of this chapter is to study whether the AMH can explain the behaviour of stock returns through calendar anomaly analysis. The calendar anomalies studied are the Monday effect, the January effect and the turn-of-the-week effect. The anomalies are studied through regression analysis, break analysis as well as dividing them into five-yearly subsamples. Again, the behaviour of returns of each market is categorized into one of the five types previously prescribed and the profitability of these calendar effects over time are examined through two simple trading strategies.

Chapter 5 examines the behaviour of stock returns over time through an examination of one of the most well-known technical analysis rules. Thus the purpose of this chapter is to study whether the AMH can explain the behaviour of stock returns through the moving average rule. The moving average rule is examined for data after the Brock et al (1992) data to determine whether the rule is still successful. Again a five-yearly subsample analysis is conducted and each market is categorized into one of the five types for each of the variations of the moving average rule. Also two modified versions of the moving average are examined, namely the perfectly and an imperfectly anticipated moving average rules to study whether investors have been predicting the following days signal. Similar to chapter 4, the profitability of the technical rules is examined through two simple trading strategies.

Chapter 6 studies the British stock market during World War Two. The purpose of this chapter is to study a period of time that has not been examined in great detail and which also presents an opportunity to examine investor sentiment in extreme situations. Major positive and negative events, major naval disasters as well as the Blitz period are examined through abnormal and cumulative abnormal returns as well as event studies.

Finally, Chapter 7 summarises the findings of this thesis and indicates areas where future research may be fruitful.

Chapter 2: Literature Review

2.1. Introduction

The idea of stock market efficiency is central to finance since a well-functioning stock market is an essential component in a competitive economy. Market efficiency was first used to describe a market of which relevant information is fully incorporated into the price of financial assets. Fama (1970) explains this, '*the idea is a market in which prices provide accurate signals for resource allocation: that is, a market in which firms can make production-investment decisions, and investors can choose among the securities that represent ownership of firms' activities under the assumption that security prices at any time fully reflect all available information'* (p383). Consequently, prices play a key role as allocation decisions depend on the prices of traded stocks.

Louis Bachelier laid the theoretical groundwork for the Efficient Market Hypothesis (EMH) and Random Walk Theory. In his PhD Dissertation 'The Theory of Speculation' (1900), he began studying market prices assuming that the time series would exhibit evident patterns. However he soon began to notice that the price changes were actually random. Bachelier stated that '*part, present and even discounted future events are reflected in market price, but often show no apparent relation to price changes*', thus concluding that '*the mathematical expectation of the speculator is zero'*(p9). Cowles (1933) also found that there was no evidence of any ability to predict the market.

Nonetheless, this idea was mostly overlooked until Maurice Kendall (1953) re-examined this proposition. Kendall examined 22 UK stock and commodity price series and the results surprised him. He found that '*in series of prices which are observed at fairly close intervals the random changes from one term to the next are so large as to swamp any systematic effect which may be present*'(p11). The near-zero serial correlation of price changes was an observation that appeared inconsistent with the views of economists at the time[2]. Initially economists believed this confirmed the irrationality of the market, however it soon became apparent that it was evidence of the random walk model. If prices wander randomly, then market analysts cannot predict the future behaviour of security prices. Roberts (1959) also

[2] Also, Kendall (1953) was the first to note the time dependence of the empirical variance (nonstationarity).

demonstrated that a time series generated from a sequence of random numbers was indistinguishable from a record of US stock prices. Furthermore, Osborne (1959) analysed US stock price data and showed that common stock prices have properties analogous to the movement of molecules.

Despite evidence on the randomness of stock price changes, there were occasional instances where certain series appeared to follow predictable paths. In 1960 there was a realisation that autocorrelation could be induced into returns series as a result of using time-averaged security prices. However Working (1960) and Alexander (1961) found that once return series are based on end-of-period prices, returns appear to fluctuate randomly. The problem of time-averaging, identified by Working (1960), was the first work on thin trading and a precursor to studies of market microstructure.

The mid-1960s proved to be a turning point in the research on the random character of stock prices. In 1964, Cootner published his collection of papers while Fama (1965) reproduced his doctoral dissertation where he concluded '*it seems to be safe that this paper has presented strong and voluminous evidence in favour of the random walk hypothesis'* (p98). Since then, the EMH has been examined extensively in the literature, with many studies finding conflicting results. In the next section the EMH is explained in more detail as is the random walk model.

2.2. The Efficient Market Hypothesis

The origins of the EMH can be traced back to Samuelson (1965), whose contribution is summarized in his article '*Proof that Properly Anticipated Prices Fluctuate Randomly'*. According to his hypothesis, in an informationally efficient market, price changes must be unforecastable if they fully reflect the expectations and information of all market participants. Since news is announced randomly, prices must fluctuate randomly. Consequently, it states that it is not possible to exploit any information set to predict future price changes (Campbell et al. 1997).

Harry Roberts (1967) coined the term the '*Efficient Markets Hypothesis*' and made the distinction between weak and strong form tests, which became the classic taxonomy in Fama (1970). Building on Samuelson's and Roberts' work, Fama (1970) published the definitive paper on the EMH, which was the first of three review papers. He reviewed the theory and evidence of market efficiency to that date and defined an efficient market as '*a market in which prices always fully reflect available information is called efficient*' (p383). By definition, available information must appear unpredictably and stock price change in response to new information must also be unpredictable. Consequently, the market fails to provide any abnormal profits.

The expected return model, according to Fama (1970) can be stated as;

$$E\left(p_{i,t+1}|\varphi_t\right) = p_{i,t}\left[1 + E\left(r_{i,t+1}|\varphi_t\right)\right] \tag{2.1}$$

Where, $E(\ )$ is the expected value, $p_{i,t}$ is the price of security i at time t, $r_{i,t+1}$ is the rate of returns for security i at time period 1 and φ_t is the set of information that is fully reflected in the price of asset i at period t. The left hand side of equation 2.1 is the expected price of security i tomorrow, given all the available information today (φ_t). This set of information includes past and current events of anything that will impact on the price of security i, such as earnings, state of economy and all relevant economic factors. It also includes anything that is known about the relationships amongst the variables (Fama 1970). Thus the expected price of security i tomorrow is a function of the price of security i today and the expected return of security i. However, expected return theory implies that the price tomorrow minus the expected price today is zero[3] as seen by;

$$X_{i,t+1} = P_{i,t+1} - E\left(p_{i,t+1}|\varphi_t\right) \tag{2.2}$$

Thus;

$$E\left(X_{i,t+1}|\varphi_t\right) = 0 \tag{2.3}$$

An important assumption is that investors are certain about the best models to use in forecasting future returns. However when this assumption is relaxed and investors are not assumed to know the true forecasting model, then the use of the mathematical expectation operator in market efficiency becomes not very attractive, and it becomes meaningful to

[3] However expected stock returns are positive since prices are expected to rise over time.

define markets as being efficient locally in time with respect to the information set available at the time (Timmermann and Granger 2004). This approach is useful as a there is a growing consensus in the literature that forecasting models may work for some time, and that time-varying regularity may exist in asset returns, as will be demonstrated later.

2.2.1. Assumptions of Market Efficiency

The theoretical foundations for the EMH rest on the following assumptions (Shleifer 2000);

1. Investor rationality. Investors are assumed to be rational which means that they value securities logically and correctly update their beliefs when new information is available.
2. Arbitrage. To the extent that some investors are not rational, rational investors use arbitrage to remove these trades, without affecting prices.
3. Collective rationality. The random errors of investors are cancelled out in the market. Some investors may not be rational but since they trade randomly, they cancel each other out without affecting the prices.
4. Costless information and trades. Information is free and readily available to every investor in the market and there are no transaction costs.

These conditions ensure that investors that have access to available information cannot earn above-competitive returns. However, a violation of any of the conditions does not immediately imply inefficiency since abnormal returns may still be absent. The irony of efficient markets is that if every investor assumed that markets were efficient, then the market would be inefficient as no one would analyse stocks or trade because no profits could be made (Grossman and Stiglitz 1980). Hence the efficiency of a market depends on market participants who believe that the market is inefficient and it is worthwhile trading stocks in order to gain substantial profits (Shleifer 2000).

If the EMH is valid in a stock market, it will then reflect that the market prices of stocks are reasonable estimates of the underlying worth of the stocks[4]. This does not mean that the errors in prices don not happen, or that they are wrong but it means that the errors in prices are randomly disturbed about the true values. Prices may be high in certain times and low in

[4] However, as Shiller (1984) later points out, prices are not reasonable estimates of the underlying value of stocks.

others, but it is not possible to detect a trend. Thus we have a well-functioning stock market. If the EMH does not hold, then profitable investment rules may be devised to earn above-average risk-adjusted returns. Such a condition may be detrimental to the future development of the market while it will also have the effect of moving the market towards efficiency. Therefore, market 'inefficiencies' suggest that there is a transfer of wealth from naive investors to sophisticated and well-informed investors.

2.2.2. Forms of Market Efficiency

Fama[5] (1970) distinguished three forms of the efficient market hypothesis which each use different information sets to determine the stock price;

1. Weak-form efficiency asserts that stock prices already reflect all information that can be derived by examining market trading data such as history of past prices, training volume, or short interest. This version of the hypothesis implies that trend and technical analysis is futile. Past stock price data are publicly available and virtually costless to obtain. If such data ever conveyed reliable signs about future performance, all investors would have already learned to exploit the signals. Ultimately, the signals lose their value as they become widely known because a buy signal, for instance, would result in an immediate price increase.
2. Semi-strong-form efficiency states that all publicly available information regarding the prospects of a firm are reflected in the stock price, and therefore one cannot use fundamental analysis to determine whether a stock is undervalued or overvalued. Such information includes, in addition to past prices, fundamental data on the firm's product line, quality of management, balance sheet composition, patents held, earning forecasts, and accounting practices. The semi-strong-form supports the notion that there is no learning lag in the distribution of public information.
3. Strong-form efficiency goes beyond the semi-strong-form to state that stock prices reflect all information relevant to the firm, even including information available only to company insiders. This version implies that insiders who are privy to information before it becomes known to the rest of the market also cannot earn any excess profits, i.e. insider information is of no use. This form is near impossible to test as insider information is impossible to gauge.

[5] Fama (1970) acknowledged that Roberts (1959) originally introduced levels of market efficiency.

Semi-strong efficiency implies weak-form efficiency while strong-form efficiency implies semi-strong and weak efficiency. If weak-form efficiency can be rejected, then also the semi-strong and strong-form efficiency can be rejected.

In an efficient market the current price of a security fully reflects all available information. These conditions ensure that investors possessing available information cannot earn above-normal returns. A lot of theoretical work in finance has been conducted to understand the behaviour of security prices and the efficiency of the market. An efficient market usually means that stock prices and returns are determined as the outcome of the supply and demand in a competitive market with rational traders. Rational traders instantaneously adjust the security prices to any relative piece of information. Thus traders cannot systematically generate profits greater than the market through the acquisition of new information once risk and transactions costs have been accounted for (Jensen 1978). There have been a number of concepts developed on the way to creating the EMH, namely the Martingale Model and the Random Walk models.

2.3. Development of the Martingale and Random Walk

2.3.1. Martingale Model

The oldest and most important theory about asset pricing is the Martingale Model, which was established by Bachelier (1900) and Samuelson (1965). This theory postulates that the changes in the prices of assets cannot be systematically forecasted. In other words, the returns of any asset are supposed to be a random, independent and identically distributed process (*i.i.d.*). According to this model, any attempts to predict the future prices of an asset will not have a statistically significant explanatory power and are worthless.

Let $P_{i,t}$ represent an asset's price at time *t*, and φ_t a set of information available at data *t*, where φ_t consists of all the past prices of the asset ($\varphi_t = \{ P_{i,t}, P_{i,t-1}, P_{i,t-2} .....\}$). The martingale hypothesis denotes that tomorrow's price is expected to be equal to today's price, given the asset's price history. That is, if $P_{i,t}$ is considered as a stochastic variable then $P_{i,t}$ is said to be a martingale when it satisfies the following condition:

$$E\left[P_{i,t+1}|\varphi_t\right] = P_t \quad (2.4)$$

The crucial features of φ_t are that is contains only things that are known at time t and that it contains the current and all past prices of the asset. Hence:

$$E\left[P_{i,t+1} - P_t|\varphi_t\right] = 0 \quad (2.5)$$

This is known as the fair game, which was established by Bachelier, where the expected return is zero given the asset's price history. Investors must have access to the information set (φ_t) and believe that holding the asset is just like playing a fair game. Also, non-overlapping price changes are uncorrelated at all leads and lags, so all linear forecasting for the future price changes based on historical prices has no predictive power.

So in an efficient market, the current prices reflect all historical prices and it should not be possible to make profit by expectation of future prices from price history. Hence, the market is efficient when price changes are random and unpredictable. However in finance, there is a trade-off between risk and return, and the martingale hypothesis does not involve risk considerations in any way. Some financial models (eg CAPM) determine the equilibrium return of the asset according to the risk of the asset, so there is a trade-off between risk and expected returns. But the martingale hypothesis puts a restriction on expected return and does not take risk into consideration, which means the martingale property is not a sufficient condition for rationally determined asset prices.

Nonetheless, the martingale assumption has become a powerful tool in modern theories of asset price (Campbell et al 1997). Theoretically, once asset returns are properly adjusted for risk then the martingale property does hold. For instance, an asset's risk may imply that it must offer some level of positive return to the investor. Thus the asset's price change is expected to be positive but the actual returns are still unforecastable. This leads to a random walk model of the asset price where one can show that if returns are properly adjusted for risk, then the martingale property holds for the adjusted returns.

2.3.2. Random Walk

The random walk hypothesis is associated with the weak-form of market efficiency, which asserts that price movements will not follow any patterns or trends and that the past history of stock prices has no memory and thus cannot be used to make meaningful predictions concerning the future price of the stock. Malkiel (2003) explains the logic of the random walk model by arguing that '*if the flow of information is unimpeded and information is immediately reflected in stock prices, then tomorrow's price changes will reflect only tomorrow's news and will be independent of the price changes today. But news is by definition unpredictable, and, thus, resulting price changes must be unpredictable and random*'(p59). Randomly evolving stock prices would be the necessary consequence of intelligent, rational investors competing to discover relevant information on which to buy or sell stocks before the rest of the market becomes aware of the information. Therefore, a random walk would be the natural result of prices that reflect all current knowledge. If stock price movements were predictable, it would be evidence of stock market inefficiency, because the ability to predict prices would indicate that all available information was not already reflected in stock prices. If the random walk hypothesis holds, the weak-form of market efficiency must hold, and vice versa. Thus the random walk model is;

$$P_{i,t+1} = \mu + P_{i,t} + \varepsilon_t \qquad (2.6)$$

This model shows that the asset price at time $t+1$ is given by the price at the immediately previous moment, a term of expected change known as drift plus an unpredictable error component. The drift coefficient μ reflects how prices change on average to provide the expected rate of returns from holding the asset over time. The random walk model can be obtained through the martingale process by restrictions on the error term ε_t. The behaviour of the error term ε_t is extremely important, and restrictions on the behaviour of this term produces three versions of the Random Walk Model, as stated by Campbell et al (1997).

The strongest version of the random walk model is the one in which increments at price P_t given by error term ε_t, belong to the same distribution (identically distributed) and are independent. In addition the original distribution can be used, in which the most common cases is the same as assuming that ε_t belongs to a normal distribution with zero mean and constant variance σ^2. Random Walk I (RW1) is even more restrictive than the Martingale Model, since in the latter model the increments are nonlinearly uncorrelated and any nonlinear combination of increments should also be uncorrelated. The runs test can be used to test the RW1.

The RW1 model is extremely restrictive, therefore it should not be used in real financial series as it rules out the possibility of structural changes in the data generating process, such as parameter changes, of which the most relevant are changes in volatility. A more appropriate version, the Random walk 2 (RW2) only requires the increments to be independent, but not necessarily to originate from the same distribution. This maintains the characteristic of linear unpredictability and allows for changes in unconditional volatility. Filter rules can be used to test the RW2.

The most general form of the random walk model requires only that ε_t be uncorrelated over time and is called the Random Walk 3 model (RW3). However, the squared increments are correlated thus this process is not independent as such. This version rules out the use of linear forecasting techniques such as regression analysis (Campbell et al, 1997). RW3 is the most widely tested form of the random walk, and autocorrelation tests are usually used to test it. Lo and MacKinlay (1988) proposed to limit the generality of RW3 in order to realize the dependency feature in RW3. They allowed for certain types of heteroskedasticity in the noise process, which can be achieved through a mixing process. Thus they used the heteroskedasticity method of White and Domowitz (1984) and it became useful in expressing the type of heterogeneity and the amount of dependency in the noise process.

2.4. Tests for Market Efficiency

Throughout the last 50 years, the EMH has been tested extensively in a wide range of markets. From its beginnings to the early 1970s, the EMH was deemed to be an accepted model as empirical evidence against it was extremely rare. However from the late 1970s to the present day, evidence against the EMH has become a lot more common, as Jensen (1978) puts it, '*I believe there is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Market Hypothesis. . . . Yet, in a manner remarkably similar to that described by Thomas Kuhn in his book, The Structure of Scientific Revolutions, we seem to be entering a stage where widely scattered and as yet in cohesive* *evidence is arising which seems to be inconsistent with the theory. . . . it is evidence which we will not be able to ignore'* (p95). In the following section, the main methods for testing the validity of EMH are introduced[6] as well as the main evidence against the EMH.

2.4.1. Linear Tests

Linear serial correlation tests were the original tools employed to investigate the weak-form EMH in the literature. This statistical process only requires the price changes to be uncorrelated hence it is the least restrictive version of the random walk hypothesis, namely the Random Walk 3 model. However, since the seminal work of Lo and MacKinlay (1988), the variance-ratio test has been the preferred choice for examining the serially correlation of stock returns. The variance ratio test examines whether stock prices follow a random walk by comparing the variance of the *k*-period return to the one period return. Since its formulation, the variance-ratio test has been subjected to numerous developments to improve its power[7]. The popular runs test has also be used to a great extent to test for serial correlation in stock returns. The runs test has the advantage of being non-parametric, meaning that the normality assumption of distribution can be ignored. The test compares the actual number of runs of a series to the expected number of runs, where a run is defined as '*a succession of identical symbols which are followed or preceded by different symbols*' (p15, Siegel, 1956). The unit root test is another type of statistical test favoured by researchers in the weak-form EMH literature which examines whether the return series is stationary. Early studies employed a conventional unit root tests, particularly the Augmented Dickey-Fuller (ADF) test. However more sophisticated unit root tests have now been manufactured such as the Phillips and Perron (PP) test and the KPSS test. Although each test has weaknesses, the general assumption is that if all of the tests come to same conclusion, the conclusion is accurate.

2.4.2. Non-Linear

The development of new statistical tools capable of uncovering hidden nonlinear structures in time series data has led to a huge literature reporting the existence of nonlinear serial dependencies across international stock markets. Early studies used the previously mentioned tests which are unable to capture nonlinear dependence in stock returns. This was

[6] Each following chapters have their own extensive literature review.
[7] For a survey on the developments, Charles and Darné (2009).

highlighted by Hinich and Patterson (1985) who stated that many early examinations implicitly assumed the observed time is generated from a Gaussian process and thus ignored the possible nonlinear correlations. Furthermore, Amini et al (2010) show that even when no linear dependency can be found, a series can still exhibit strong nonlinear correlations. `

Many statistical tools have been developed to examine the nonlinear nature of stock returns (see McLeod and Li 1983; Hinich and Patterson 1985; Tsay 1989; De Gooijer 1989; Scheinkman and LeBaron 1989; Brock et al 1996[8]). The most popular test is the non-parametric BDS test (Brock et al 1996), which examines the nonlinear structure in returns on the residuals of an ARMA model that account for the linear correlation in returns. It is very popular due to its availability[9] and that it has highest power compared to other nonlinear tests when performed under different conditions (Patterson and Ashley 2000). However, the BDS test gives no information as to which data generating mechanism would be appropriate to model the data, thus other tests are usually also conducted.

2.5. Anomalies

Tests for market efficiency are plentiful and the previous section only provided a short introduction to them, which will be added to in the following chapters. However, they are not the only method of detecting inefficiencies in stock markets. Anomalies are empirical results that seem to conflict the traditional theories of asset pricing behaviour. They indicate that profit opportunities are available (indicating market inefficiency) or that the asset-pricing model is not an accurate reflection of how prices behave. If profit opportunities are available, they should be arbitraged away by the market according to the EMH. However, evidence has shown that many of these anomalies produce profit opportunities for long periods and are discussed below.

One strand of market anomalies finds that stock returns are systematically higher or lower depending on the day the week, the day of the month, or month of the year. A persistent finding within the literature is the tendency for asset returns to be negative on Mondays, which was first documented by market practitioners and then academics. Maberly (1995) shows that financial practitioners were aware of the Monday effect as early as the late 1920s,

[8] For a more comprehensive survey see Lim and Brooks (2011).
[9] Available in Eviews and the Patterson Ashley (2000) toolkit.

with the first documented finding by Kelly (1930), who found Monday to be the worse day to buy stocks from a three-year statistical study. The first academic study was conducted by Cross (1973), who studied the S&P 500 from 1953 to 1970 and reported that the proportion of increases on Friday is significantly higher than the proportion of increases on Mondays. Another anomaly found in the literature is that returns in January appear to have higher returns than other months of the year. This anomaly is known as the January effect and was first documented by Rozeff and Kinney (1976). Rozeff and Kinney (1976) used the NYSE for the period 1904 to 1974 and found that the average return for the average return for the month of January was 3.48% compared to only 0.42% for the other months. A relatively recent but very strong anomaly is the turn-of-the-month effect, where returns are found to be statistically greater on the last day first three days of the month than any other days of the month. It was first proposed by Ariel (1987) in the US stock market and found that mean daily stock returns are positive at the beginning of the month and continuing through the first half of the month. However, returns after this point are predominantly negative. Lakonishok and Smidt (1988) investigated the DJIA from 1897 to 1986 and discovered that the rate of return is especially high for the last trading day of the month and the first three trading days of the next month. More specifically, they find that returns during the turn-of-the-month are 0.475% compared to 0.061% for non-turn-of-the-month days. An interesting facet is that the DJIA increased by 56% during this sample period, an average increase of 0.349% per month, indicating that without the turn-of-the-month returns, the DJIA would have actually fallen during this period. Further, McConnell and Xu (2008) extend Lakonishok and Smidt's (1988) study to include data up to 2005 for the DJIA and find that the turn-of-the-month effect is still evident. Even when they extend their sample from 1897 to 2005, they find significance evidence of the effect, with all of the positive return to equities occurring during the turn-of-the-month interval.

Not only are calendar anomalies found in the literature but other anomalies have been documented. One of the most well-known anomalies is the value effect, where portfolios constructed from value stocks appear to produce superior investment returns over long horizon. Value stocks are ones which have high earnings, assets or cash flows relative to the share price. It was first noted by Basu (1977) who noted that firms with high earnings to price ratios earned positive abnormal returns relative to CAPM. Another popular anomaly documented by Banz (1981) is the size effect, which finds that small stocks tend to have higher average returns than larger firms. Since small firms include a disproportionate number of companies in financial stress, the higher expected returns may be compensation for exposure to the risks associated with these firms. A large area of research has examined the momentum and contrarian effects. Momentum is the phenomenon documented by Jegadeesh and Titman (1993) that portfolios with high returns in the recent past continue to produce above-average returns over a 3-12 month horizon and thus past winners (portfolios formed due to their high returns) out-perform recent past losers. However, DeBondt and Thaler (1985) find a contrarian effect, where past losers (stocks that have low returns in the past 3-5 years) have higher average returns than past winners (stocks that have high returns in the past 3-5 years). It is possible that markets take a few weeks to react to new information, but having reacted then continue to overshoot until an ultimate correction occurs some years down the line. Thus investors initially underreact and then overreact to new information (Barberis et al 1998). Further, Fama and French (1996), with their three factor model, suggest that three specific factors; the excess return on the market portfolio, the size of the anomaly, and the book-to-market anomaly, to a large extent explain empirical return patterns. Many other anomalies are found in the literature` but only the most celebrated and examined ones are reported.

2.6. Technical Analysis

Technical analysis has a long history of widespread use by participants in speculative markets. Park and Irwin (2007) note that its origins date back to the 18th century when the Japanese developed a form of technical analysis known as candlestick charting, that was not introduced to the West until the 1970s. Technical analysis involves forecasting future prices through the identification and exploration of recurring patterns in past prices. Thus it aims to identify irregular patterns in prices.

The moving average rule is one of the most popular amongst practitioners and has been extensively studied in the academic literature. Moving average systems take different forms according to the method used to average past prices in the moving average calculations. For example, the simple moving average rule uses equal weighting on each past price, while the exponential moving average rule gives more weight to recent prices than not so recent prices. A moving average is an average of observations of the level of the index over several consecutive time periods. The objective is to smooth out seasonal variations (volatility) in the data. The standard moving average rule, which utilizes the price line and the moving average of price, generates buy/sell signals on which the investor trades. This strategy is expressed as buying (or selling) when the short-period moving average rises above (or falls below) the long-period moving average.

Another popular strand of technical rules are the filter rules, which aim to 'filter' out smaller price movements by constructing trailing stops for price movements above or beneath the current trend. The trailing stops have various forms such as some predetermined amount of past extreme prices (Alexander's Filter Rule) or particular weighted averages of past prices (the Parabolic Time/Price system). The Alexander Filter Rule generates buy (sell) signals when today's price rises (falls) by *x*% above (below) its recent low (high). The Parabolic Time/Price system uses the trailing stop that works as function of both the direction of the price movement and the time over which the movement takes place.

There are many other technical rules documented in the literature and examining all of them is not the aim of this thesis. The moving average rule is examined in this thesis and is studied in more detail in Chapter 5 with a detailed review of the literature.

2.7. Problems with Conventional Tests

The traditional tests for the EMH fall into 3 main categories;

1. Tests that investigate the significance of autocorrelations of returns of current returns on past returns to test market efficiency.

2. Tests that examine the random walk of security returns through the runs test, variance ratio test, unit root tests etc.

3. Tests that examine the predictability of the security returns, such as calendar anomalies or technical analysis rules.

Although the previous literature review is not exhaustive, it does demonstrate that these testing procedures have one major shortcoming. That is, that they use statistical tests to evaluate whether a market is efficient over some predefined period. Antoniou et al (1997) argued in favour of examining the evolution of the stock market, rather than simply taking a snapshot of the market at a particular point in time. This is because standard testing procedures ensures market efficiency is measured as a steady state over some predefined period. In other words, these tests lead to the inference that a market either is or is not weak-form efficient for the sample period as a whole meaning examining different subsamples with large overlapping sections may produce very different results.

Gu and Finnerty (2002) argue that efficiency should evolve over time since the weak-form EMH is based on the random arrival of information, more frequent and accurate information would make their “shocks” more random, smaller and less heavy. Advances in information technology (larger quantity, better quality, higher frequency and speed of information at a lower cost) would help to increase market efficiency and reduce the arbitrage opportunities in the market. Also, investors’ growing ability to use relevant information in forming their trading strategies may also play an important role in the evolution of market efficiency. If investors believe that stock prices follow some random pattern, they would trade based on that pattern, so the pattern would disappear or be strengthened. If they simply buy-and-hold, or follow a trend, the market would not be efficient. As investors become capable of promptly and rationally using relevant information for their investments, their trading decisions would tend to reflect the random nature of information and the market would tend to move towards being efficient.

As conventional tests for market efficiency have failed to take the evolving nature of markets into consideration, a number of methodologies to test this have been explored in recent time. One such methodology is the Kalman Filter framework which allows for time-varying parameters and a GARCH structure for the residuals. The time-varying autoregressive coefficients are used to determine the changing degree of predictability for the stock market. If the market does become more efficient over time, the smoothed time varying estimates of the autocorrelation coefficient would gradually converge towards zero. The first study using the Kalman Filter framework was by Emerson et al (1997). Contrary to their hypothesis, they found times of efficiency and times of inefficiency, and there are no real movement towards efficiency over time. This framework was formalized by Zalewska-Mitura and Hall (1999) as a ‘Test for Evolving Efficiency’ (TEE). The TEE has been used to test evolving efficiency in emerging stock markets from the former communist bloc (Zalewska-Mitura and Hall

(2000), Rockinger and Urga (2000, 2001). It has also been used in China (Li, 2003a, b) and Africa (Jefferies and Smith 2005).

Another test is the fixed-length moving sub-sample windows approach to test the evolution of market efficiency. This rolling windows approach computes the relevant test statistic that is capable of detecting serial dependence for the first window of a specified length, and then rolls the sample one point forward eliminating the first observation and including the next one for re-examination. For instance, in a fixed-length rolling windows of 30 observations, the first window starts from day 1 and ends on day 30, the second window comprises observations running from day 2 through day 31 and so on. Tabak (2003) examined the random walk hypothesis using rolling variance tests with a fixed window of 1024 days, and concluded that the Brazilian stock market has become increasingly more efficient.

Cajueiro and Tabak (2004) formally proposed the calculation of Hurst exponent over time for stock returns using the rolling sample approach as a statistical tool to test the assertion that emerging stock markets are becoming more efficient. The authors argue that stock markets have presented different levels of efficiency over time mainly due to the variation of the effects of speed of information, capital flows and non-synchronous trading. Using 40-year time windows and stock data from 11 emerging markets (and the US and Japan), the Hurst exponent is found to be time-varying reflecting the evolution of market efficiency over time in each market under study. Thus the existence of both short-term and long term-term linear dependencies provides evidence against the weak-form market efficiency. Lim et al (2006) used fixed-length sub-samples to detect nonlinear dependences to detect how market efficiency has evolved over time. They found that market efficiency follows an evolutionary path, with is consistent with the findings on autocorrelation coefficients and Hurst exponents.

Classical EMH cannot explain why markets go through periods of efficiency and then periods of inefficiency. The EMH states that there are no profit opportunities in the market using trend analysis, and that if there are, rational traders trade these profits away quickly. However, Lim et al (2006) for example, find Asian stock markets do not present a clear trend towards efficiency. Furthermore, calendar anomalies and technical analysis have shown through subsample analysis that profit opportunities vary over time. A new hypothesis that aims to bridge the gap between the classic EMH and market inefficiencies, is the Adaptive Markets Hypothesis proposed by Andrew Lo (2004).

2.8. The Adaptive Markets Hypothesis

To accommodate the changing degree of market efficiency over time, Lo (2004) proposes a new version of the EMH derived from evolutionary principles. Lo argues that valuable insights can be derived from the biological perspective and calls for an evolutionary alternative to market efficiency. Thus Lo proposes a new paradigm in which EMH can co-exist alongside behavioural finance in an intellectually consistent manner. This paradigm is called the Adaptive Market Hypothesis (AMH hereafter), which is an evolutionary idea that has been followed up by Farmer and Lo (1999), Lo (2002) and Farmer (2002), before it was formalized by Lo in 2004.

Lo (2004) argues that many of the behavioural biases in finance are in fact consistent with an evolutionary model of individuals learning and adapting to a changing environment. It is the impact of these evolutionary forces on financial institutions and market participants that determines the efficiency of markets, and the performance of investments, businesses and industries. The principles outlining AMH are explained in Lo (2005) as;

1. Individuals act in their own self-interest
2. Individuals make mistakes
3. Individuals learn and adapt
4. Competition drives adaptation and innovation
5. Natural selection shapes market ecology
6. Evolution determines market dynamics

Thus these principles imply a number of practical implications within finance. Firstly, the risk premium varies over time due to the stock market environment and demographics of investors in that environment. For example until recently, US markets were populated with investors who had never experienced a genuine bear market, which no doubt has shaped their aggregated risk preference. Thus irrespective of whether prices fully reflect all available information, the particular path that market prices have taken over the past few years influences their current aggregate risk preferences. The second implication that is contrary to the EMH is that arbitrage opportunities do exist from time to time in the market. Lo (2004) cites Grossman and Stiglitz (1980) who observe that without such profit opportunities, there would be no incentive to gather information, and the price discovery aspect of financial markets would collapse. Thus from an evolutionary viewpoint, active liquid financial markets imply that profit opportunities must exist. However as they are exploited, they do disappear. But new opportunities are continually being created as certain species die out and rather than move towards a higher efficiency, the AMH implies that complex market dynamics such as trend, panics, bubbles and crashes are continually witnessed in natural market ecologies. The third implication is that investment strategies are successful and unsuccessful, depending on certain market environment. Contrary to the EMH, the AMH implies that such strategies may decline for a time, and then return to profitability when environmental conditions become more conducive to such trades. An example of this was presented in Lo (2005) when he computed the rolling first-order autocorrelation of month returns of the S&P Composite Index from January 1871 to April 2003. Lo found that the degree of efficiency varies through time in a cyclical fashion, and there are periods in the 1950's when the market was more efficient than in the early 1990s. Although such cycles are not ruled out by the EMH in theory, in practice none of its existing empirical implementations have incorporated these dynamics, assuming instead a world in which markets move to efficiency. The final implication of the AMH is that characteristics such as value and growth may behave like 'risk factors' from time to time, that is, stocks with these characteristics may yield higher expected returns during periods when those attributes are in favour. For example during the US technology bubble of the late 1990's, growth stocks garnered higher expected returns than value stocks, only to reverse when the bubble burst. Although such nonstationarities causes problems for the EMH, the AMH places no restrictions on what can be a risk factor. A consequence of this implication is that market efficiency is not an all-or-nothing condition, but is a characteristic that varies continuously over time and across markets. Lo (2005) argues that convergence to equilibrium is neither guaranteed nor likely to occur, and that it is incorrect to assume that the market must move towards some ideal state of efficiency. Instead, the AMH relies on more complex market dynamics, such as cycles, trends, crashes and bubbles that occur in financial markets.

The AMH has gained increasing attention in the recent academic literature. Neely et al (2007) investigate the AMH, however they investigate how the returns on trading rules have declined over time, and examine the rate which they decline. They implicitly state that if the returns decline at a slow enough rate, it shows evidence of AMH. However, Lo (2005) states that in an adaptive market '*strategies may decline for a time, and then return to profitability* *when environmental conditions become more conducive to such trades'* (Lo 2005 p25). Thus trading rules not only decline, but come back again to produce profits when the market conditions are right. Thus although Neely et al (2007) show the decline of certain trading rules, they do not show evidence of an adaptive market as defined by Lo (2005). Lim and Brooks (2006) examine the evolving efficiency of developed and developing stock markets through the portmanteau bicorrelation test statistic. Using a rolling sample approach, they find that the degree of market efficiency varies through time in a cyclical fashion. Todea et al (2009) study the profitability of the moving average strategy over windows using linear and nonlinear tests from 1997-2008. They report that returns are not constant over time, but rather episodic show when sub-periods of linear and non-linear correlation appear. Thus they conclude by stating that the degree of market efficiency varies in a cyclical fashion over time like postulated by the AMH. Ito and Sugiyama (2009) examine the time-varying autocorrelation of monthly S&P500 returns. They show that the degree of market efficiency varies over time, with the market being most inefficient during the late 1980s and most efficient around the year 2000. Further, Kim et al (2011) investigate the AMH using the return predictability of the daily and weekly DJIA from 1900 to 2009. They use two autocorrelation tests (variance ratio and portmanteau) and a generalised spectral test to obtain monthly measures of the degree of stock return predictability by applying a moving-subsample window. They find strong evidence that return predictability fluctuates over time in a similar way to that described by Lo and that the US market has become more efficient after 1980. They also utilise regression analysis to determine how the return predictability over time is related to changing market and economic conditions. They find that there is no return predictability during market crashes, while economic and political crises are associated with a high degree of return predictability. Smith (2011) investigates the adaptive nature of fifteen European emerging stock markets, along with the developed markets of Greece, Portugal and the UK. Utilising rolling window variance ratio tests for the period February 2000 to December 2009 they find that the most efficient markets were the Turkish, UK Hungarian and Polish markets, while the least efficient were the Ukrainian, Maltese and Estonian. Each of the eighteen markets provides evidence of the time-varying nature of return predictability which is consistent with the adaptive markets hypothesis. Lim et al (2013) examine the return predictability of the three major US stock indices using two data-driven tests, the automatic portmanteau Box-Pierce test and the wild bootstrapped automatic variance ratio test. By using a rolling window from 1969 to 2008, they show patterns in the time variation of return predictability that is consistent with the AMH while most periods with significant return autocorrelations can be associated with major exogenous events.

2.9. Classification of the Behaviour of Stock Returns

This thesis aims to examine the behaviour of stock market returns over time to determine whether the AMH provides a better description of the behaviour of stock returns than the classic EMH. Five-yearly subsamples are chosen to enable an observation of the behaviour of returns over time since this method provides enough observations to gain a clear picture of how the market has behaved over time while at the same time providing each test with enough observations to generate reliable results. To make the analysis more straightforward, a categorization of market behaviour is suggested depending on the independence/predictability of each of the subsamples over time. For example, if an autocorrelation test is employed to examine the independence of the stock returns over time, it is very unlikely that the result will be stable over time. The market is likely to go through periods of independence and periods of dependence. In analysing the behaviour over time, a polynomial trendline is chosen since it will provide a clear smoothing of the behaviour of returns over time. Polynomial trendlines of order 3 are employed in each chapter and the trendline is used to distinguish which of the five-types is chosen. When presenting a graph of results and plotting a trendline is not appropriate, analysis of the results is sufficient to determine which behaviour type the returns behave in. The five-types are;

1) Efficient market. The market has never been inefficient and the market is perfectly efficient throughout the sample. This means that there is no level of predictability or dependence in returns. This is seen in Figure 1.1 as being on the x-axis throughout the sample i.e. at the point where there is no market inefficiency and thus market efficiency.

2) Move towards efficiency. The market has been inefficient, but over time market forces have forced the market to become efficient. This can be seen in Figure 1.1. as above the x-axis indicating market inefficiency but then a convergence and permanent resting point at zero.

3) Switch to inefficiency. The market has been efficient but over time the market has become inefficient. This can be seen in Figure 1.1. as being on the x-axis (market efficiency) and then a move above the x-axis to indicate a level of inefficiency in the market.

4) Adaptive Market Hypothesis. The market has gone through at least three different stages of efficiency. That is, the market has either been efficient, inefficient and then efficient again, or inefficient, efficient and inefficient again. This can be seen in Figure 1.1 with the market going from and to the x-axis at least three times. If the market moves between the two states just two times, this indicates either type 2 or type 3.

5) Market inefficiency. The market been inefficient throughout the sample and has never been efficient. In this circumstance the market has a level of predictability or dependence throughout the sample and indicates market inefficiency throughout. This is seen in Figure 1.1. as being continuously above the x-axis and never going to market efficiency.

Figure 1.1. Classification of the behaviour of stock market returns over time with regards to the polynomial trendline.

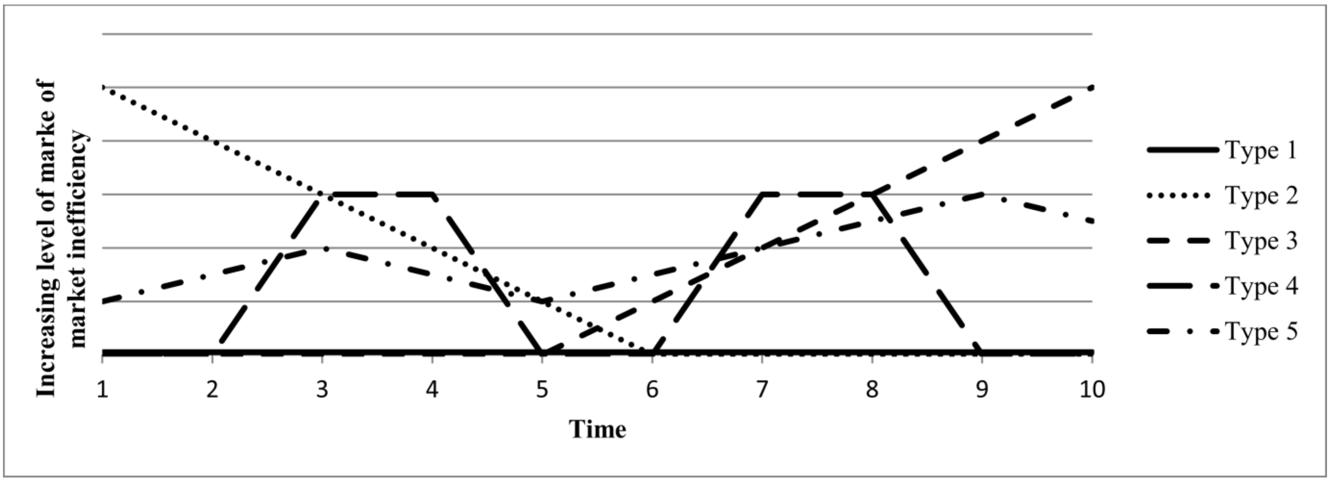


Figure 1.1 documents the types of market behaviour graphically over time. The y-axis is characterised as the level of market inefficiency and the x-axis as time. Thus the further you go up the y-axis the more market inefficiency is found and the x-axis itself is zero market inefficiency, thus supporting market efficiency. A market inefficiency level of zero indicates market efficiency and this is classified as type 1. Type 2 is where the market had a level of inefficiency but has moved to market efficiency over time, so according to figure 1.1., the level of inefficiency was at zero but is now positive. Type 3 indicates a switch from efficiency to inefficiency, while type 4 documents the adaptive nature of returns. In this type

the market has changed between being efficient and inefficient (or vice versa) at least three times. Finally type 5 documents market inefficiency, so the market has been inefficient throughout the sample and is above the x-axis.

Market efficiency is evident with types 1 and 2 while market inefficiency is characterized by types 3, 4 and 5. As you go down the scale from 1 to 5, efficiency decreases, while inefficiency increases. In the classic EMH theory, type 1 is optimal, with type 2 still conforming to the EMH as predictability/independence diminish to zero quickly. One important note is that type 3 could be early stage type 4. Type 3 is a switch in the predictability/dependence of returns. But type 4 requires the market to go through at least three different stages of predictability/independence, so type 3 may just be two-thirds on the way to being type 4 and being an adaptive market. Type 5 characterises market inefficiency since this is when the market has constant predictability/dependence in returns.

This thesis uses this classification in the time-series, calendar anomalies and technical analysis chapters to put the behaviour of the stock markets studied into groups. The behaviour of the anomalies must lie within one of these groups and it will enable a comparison of the behaviour of the stock returns when subjected to various tests. Chapter 3 examines the independence of stock returns over time through a battery of tests. Thus this chapter uses the independence of returns to categorize the behaviour of stock returns over time. Chapter 4 examines the excess returns of various calendar effects over time. Thus in this instance the calendar anomalies are documented regarding their excess return behaviour over time. Chapter 5 studies the moving average rule over time and thus uses the buy-sell differences to document how the technical rule behaves over time.

2.10. Markets Examined in this Study

Three long standing stock indices are examined in this thesis to enable a detailed examination of the behaviour of these indices over time. The DJIA is one of the longest standing market in the US, as is the FT30 in the UK. These two markets are both made up of 30 companies; however their composition makeup’s are quite different. The TOPIX is the longest stock market index in Japan and will enable a comparison between two well developed economies and one developing economy over long sample periods.

2.10.1. Dow Jones Industrial Average

The DJIA Industrial Average (DJIA hereafter) was created by Wall Street Journal editor and Dow Jones & Company co-founder Charles Dow and one of his business associates, Edward Jones. It was first calculated on May 26th 1896 and is the second oldest U.S. index after the Dow Jones Transportation Average. The DJIA is made up 30 large, publically owned companies based in the U.S. The average is price-weighted, and to compensate for the effects of stock splits and other adjustments, it is currently a scaled average. The value of the DJIA is not the actual average of the prices, but rather the sum of the component prices divided by a *divisor,* which changes whenever one of the stocks has a stock split or stock dividend, so as to generate a consistent value for the index. The current divisor, after many adjustments, is less than one indicating that the index is larger than the sum of the prices of the components. Thus;

$$DJIA = \frac{\sum p}{d} \tag{2.7}$$

Where *p* are the prices of the component stocks and *d* it the Dow Divisor. When the DJIA was first calculated in 1896, it represented the average of 12 stocks from leading American industries; with only General Electric currently still part of the index. However, the DJIA has been subject to criticism. Some critics argue that is not representation of the overall market performance of the U.S. due to the small number of stocks it includes and the way it is calculated. They prefer to cite float-adjusted market-value weights indices such as the S&P 500 or the Wilshire 5000 as better indicators of the U.S. stock market. Although the DJIA has received criticism, it is still the most cited and most widely recognized of the stock indices.[10]

2.10.2. Financial Times 30

The Financial Times 30 (FT30 hereafter) was devised by Maurice Green and Otto Clarke from the Financial News in 1935 and was called the Financial News 30 until the paper merged with the Financial Times in 1945. The index was first calculated on the 1st June 1935 and is the oldest index in the UK.

[10] http://www.djaverages.com/

The FT30 is based on the share prices of 30 British companies from a wide range of industries. It's method of calculation has been essentially unchanged since its inception and is quite different to most other indices in the UK. The companies listed in the index are made up of those in the Industrial and Commercial sectors and exclude financial sector and government stocks. The price is the equal weighting of the 30 constituents, and the constituents only change when a company needs to be removed for some reason, such as a merger or failure. Thus the FT30 is more stable than all FTSE indices, which decide their constituents based on market capitalisation and change quarterly. The index is calculated by;

$$FT30_{today} = FT30_{yesterday} \times \sum_{i=30}^{t} \left(\frac{Price_{i,today}}{Price_{i,yesterday}} \right) \qquad (2.8)$$

Where $FT30_{today}$ is the price of the FT30 today, $FT30_{yesterday}$ is the price of the FT30 yesterday, $Price_{i,\ today}$ is the price of security i today, and $Price_{i,\ yesterday}$ is the price of security i yesterday.

When a company is removed from the index, a new company is selected based on a number of considerations. Firstly, the constituent reflects the breadth of the UK economy. Secondly, that the shares are actively traded and are not in the hands of a small number a holders. Thirdly, that the company is a leader in its field and are UK-based or have UK origins. Finally, the shares trade without any undue influence on the price from overseas, although this consideration is less relevant today. Company size is not of paramount, although all recent additions have been in the FTSE 100 at time of entering the index. Only two original constituents remain in the index from 1935, namely GKN (Guest Keen & Nettlefolds) and Tate & Lyle.[11]

2.10.3. Tokyo Stock Price Index

The Tokyo Stock Price Index (TOPIX hereafter) is a composite index of all common stocks listed on the First Section of the Tokyo Stock Exchange (TSE) which was established after World War II in 1949. The TOPIX is a measure of the changes in aggregate market value of

[11] http://www.ft.com/cms/s/0/a218a81e-078b-11db-9067-0000779e2340.html#axzz1XGDFqTFc

the TSE common stocks and was first measured on 4th January 1951. The base for the index (100 points) is the aggregate market value of its component stocks as of the close on 4th January 1968. The aggregate market value is calculated by multiplying the number of listed shares of each component stock by its price and totalling the products derived there from. In computing the index, the base market value is used as the denominator of a fraction whose numerator represents the current aggregate market value. The fraction is multiplied by 100 (the index value on the base date) and is reduced to a decimal figure to the nearest one-hundredth[12]. Thus;

$$TOPIX = \frac{Current\ Market\ Value}{Base\ Market\ Value} \times Basepoint \qquad (2.9)$$

The TOPIX is the longest-standing stock market in Japan and although calculated quite differently to the DJIA and FT30, its availability of long-standing data makes it an obvious choice.

2.11. Summary

The concept of the EMH asserts that asset returns are unforecastable, and can be traced back to the pioneering theoretical contribution of Bachelier (1900) and the empirical work of Cowles (1933). It became a dominate paradigm in financial economics during the mid-1960s since the seminal work of Fama (1965; 1970). The empirical examination of the EMH is huge, and not surprisingly there is no agreed consensus on its validity. Early research supported the EMH, although recently a number of important studies have found predictability in stock returns. Numerous stock market anomalies have been found in the data, not all of which are discussed in this thesis. However, Fama (1997) argues that these anomalies are indicative of a need to continue the search for better models of asset pricing and that the EMH is still valid. Also, the importance of the EMH is further demonstrated by the fact that profit opportunities found are still referred to as anomalies and that the EMH is still a major topic in any text book on financial theory.

The growing strength of anomalies which counter the classic EMH have asked the question '*is there a more appropriate model to describe the behaviour of stock prices*?' One model

[12] http://www.tse.or.jp/english/rules/derivatives/topixf/index.html

that initially appears to unify the EMH and stock market anomalies is the AMH. Although the AMH is in its infancy, it has been supported by some strong evidence in the literature and only a further examination of it will deem whether it is an appropriate model in describing stock market return behaviour. Thus this is the aim of this thesis by using tests for independence, calendar effects and technical analysis. Linked to the AMH is the fact that investors are not rational and investor's psychology plays a real role in investor decision making. With that in mind, this thesis examines investor sentiment during World War Two in Britain to determine the level of investor sentiment in the most extreme of circumstances.

Chapter 3: An Examination of the Independent Behaviour of Stock Returns

3.1. Introduction

An efficient market is a market where available information fails to provide abnormal profit to investors. Thus market efficiency yields a number of testable predictions about the behaviour of assets and their returns. The main two that are examined in this thesis are that prices move in an independent manner and that there is no predictability in stock returns. The subsequent chapters study the predictability of stock returns while this chapter investigates the independence of the stock returns over time. Since this chapter only examines the independence of stock returns, if a market has no dependence between its returns, it is deemed efficient.

A number of tests for independence are examined in order to fully determine how stock returns have behave over time. The serial correlation test is the most traditional test to investigate the correlation between two price changes. The serial correlation coefficient measures the relationship between values of a random variable at time *t* and its value in the previous period. If the series behaves like a random walk, its price changes are expected to have zero autocorrelation coefficients at different lags. The runs test, which also examines the serial correlation in a series, is also utilised due to its non-parametric property. Unlike the serial correlation test, it does not require returns to be normally distributed (Poshakwale 1996). These two tests are the traditional tests for market efficient but more tests have been developed and will be used to enhance the power of the results.

The variance ratio test which was first documented by Lo and MacKinlay (1988) is also examined. This test investigates whether stock returns are serially uncorrelated, like the serial correlation and runs test. However, the major benefit of this test is that the test statistic includes a correction for the heteroskedasticity property of stock price returns. This is an important feature since a common characteristic of stock market returns are that they are heteroskedastic, which is ignored by the serial correlation. In section 3.3 the data of the three indices is examined and each return series appears heteroskedastic indicating the appropriateness of this test statistic given the data examined.. The stationarity of the returns series is also tested to determine the randomness of returns. If a series displays a unit root (non-stationary), it implies that the series has no tendency to return to its mean value. That is, its behaviour is not mean-reverting and independent. The presence of a unit root (non-stationarity) in stock prices is only a necessary, but not a sufficient condition for the random-walk process.

The tests introduced so far examine the linear dependency of returns when nonlinear dependency could be present and not captured by the linear tests. Thus in order to examine the nonlinear dependence in returns, a pre-whitening procedure is conducted to eliminate any linear dependence from the returns through an AR(p) model. These filtered returns will then be tested for nonlinearity through the McLeod Li (1983) and the Engle LM (1982) test. Furthermore, the BDS test (Brock, Dechert and Scheinkman 1996) is also utilized to examine the nonlinearity of returns. It is a nonparametric test for serial dependence in time series analysis, where the series must be stationary, with a null hypothesis that the data generating processes are independent and identically distributed. However, the BDS test gives no information about the type of nonlinearity found. Also, the AR(p) filter does not account for the heteroskedasticity in returns. Thus an AR-GARCH filter is also used and the BDS test is conducted on the filtered returns.

Similar to the rest of this thesis, data is divided into five-yearly subsamples to show how the stock returns have behaved over time. The results for each period will provide an idea of how the markets have behaved during five-yearly periods and over time throughout the full sample. The behaviour of each market under each test is also categorised through the suggested classification of markets in the previous chapter.

3.2. Literature Review

Early papers found a low degree of serial correlation (for example Working 1934; Kendall 1943, 1953; Cootner 1962; Osborne 1962; Samuelson 1965; Fama 1965), although Kendall (1953) found that stock returns were serially uncorrelated in the case of the Chicago wheat weekly series. It was also found that weekly share index prices were serially correlated for the British Industrial Index and that New York monthly cotton prices seemed to follow a Markov process. However, this was dismissed by claiming that '*such serial correlations as is present in these series is so weak as to dispose at once of any possibility of being able to use them for prediction*' (Kendall 1953 in Cootner 1964, p92). Moore (1962) supported this for the lags of the S&P 500 stock index claiming that the autocorrelations coefficients were '*uniformly small'* and '*quite insignificant'*. Cowles and Jones (1937) found significant serial correlation in averages time series indices of stock prices. However Alexander (1961) stated that these serial correlations are the result of 'spurious correlation'. He showed that Cowles and Jones (1937) results were the result of spurious correlation, which is a direct result of using the average of a month as the value for that month. Therefore, Cowles (1960) revisited his previous work but this time used weekly prices based on Wednesday closing prices. However, serial correlations were still present. Cootner (1962) also presented evidence against the random walk hypothesis by demonstrating that a specific decision rule outperforms randomly bought stocks. Alexander (1964) answered the critics of his 1961 paper and concluded that the S&P Industrials does not follow a random walk.

Although all of these results seem to conform to the EMH, an early rejection of the EMH was documented by Niederhoffer and Osborne (1966) on the DJIA during the month October 1964. The results displayed four non-random properties; (1) a general tendency for price reversal between trades, (2) reversals are relatively more concentrated at integers where stable slow-moving participants offer to buy and sell, (3) quick moving competitors aware of these barriers can take positions at nearby prices, thus making profits and (4) after two changes in the same direction, the changes of continuation in that direction are greater than after changes in the opposite directions. These results conclusively concluded that the random walk hypothesis was rejected for the DJIA and this was the first official rejection of the random walk hypothesis. Scholes (1969) indicated that the officers of corporations sometimes have monopolistic access to information about their firms, meaning they can take advantage of information other investors are not privy to, and so make abnormal profits.

Testing the EMH using serial correlation is still utilised in the literature today, for example Laurence et al (1997) who investigated the assumption that emerging markets are not efficient, but should become more efficient over time. They tested the four stock markets in China from 1993 to 1996 and find that the markets are not efficient, but become more efficient throughout the sample period. Similarly, Kavussanos and Dockery (2001) used a cross section of prices of the Athens Stock Exchange in order to test the predictability of its prices. They find that prices are not stationary but returns are stationary, but they are unable to confirm that the market is efficient due possibly to the low liquidity and limited transparency in the market. Also, Borges (2010) examines six major European stock markets for weak-form efficiency through a number of tests, including the serial correlation test. They find that monthly data suggests efficiency for all markets but only four of the six meet most of the criteria for a random walk in daily data, probably due to the non-normal nature of the daily data.

The early studies examining market efficiency also applied the runs test, with the majority of them supporting efficiency. Fama (1965) studied the DJIA over the period 1957-1962 and found little evidence of dependence. Cooper (1982) studied world stock markets using monthly, weekly and daily data for 36 countries and found that the USA and UK supported the random walk hypothesis and thus market efficiency. Worthington and Higgs (2004) investigated market efficiency in developed and developing European markets through the serial correlation test, runs test and three unit root tests. They find that only Germany, Ireland, Portugal, Sweden and the UK comply with the most stringent criteria for market efficiency. Recent papers have also utilised the runs test, notably Dezelan (2000), Kompa and Matuszewska-Janica (2009), Borges (2009; 2010). Thus although the runs test, along with the serial correlation test, are traditional tests for testing market efficiency, they are still utilised today.

Since the seminal paper by Lo and MacKinlay (1988), the variance ratio (VR hereafter) test has become the standard tool for investigating if stock returns are serially correlated. The VR tests the random walk hypothesis against stationary alternatives, by exploiting the fact that the variance of random walk increments is linear in all sampling intervals. It is usual to examine various holding periods, with the estimated variance ratio statistics compared to unity to determine if the series is non-random. Lovatt, Boswell and Noor (2007) tested the predictability of UK stock returns for the sample period 1st January 1992 to 20th March 1998 using the autocorrelation test at various lags and the variance ratio test. They used company data from the FTSE All-Share and randomly allocated them into 10 portfolios of size and both equally and value-weighted returns were calculated for all portfolios and for the full sample. Both the autocorrelation test and the variance ratio test reject the random hypothesis for all portfolios and the full sample, hence providing evidence of predictability in daily UK stock returns. Hung, Lee and Pai (2009) use parametric and nonparametric VR tests to examine the weak form of EMH for the large- and small-capitalization stock indices of the TOPIX and FTSE. They use the Lo MacKinlay (1988) and Wright (2000) VR tests for the sample period 1st January 1993 to 17th October 2005 for the TOPIX and 1st January 1986 to 17th October 2005. To enhance the resting power of the nonparametric VR test, the multiple

VR test of Chow and Denning (1993) is first extended to Wright's rank-based and sign-based VR tests and the critical values are obtained through the Belaire-French and Contreras (2004) method. They find that the weak-form EMH is supported for large-cap stock indices, but rejected for small-cap indices, suggesting that small-cap indices might contain exploitable essences of developing profitable trading strategies, predicting the volatility or option prices.

The early studies in market efficiency also generally employ conventional univariate unit root tests, in particular the popular augmented Dickey-Fuller (ADF) test, Phillip and Perron (PP) test and the KPSS test. These tests concluded that stock prices can generally be characterized by a random walk process. Al-Loughani and Chappell (1997) test the validity of the weak form of the EMH for the FT30, covering the period 30th June 1983 to 16th November 1989. They conducted the study during this time period because government economic policy towards the financial markets was relatively unchanging, suggesting random walk behaviour should be present. However, using the Dickey-Fuller, Augmented Dickey-Fuller, and serial-correlation tests, the results found evidence of significant heteroskedasticity (differing variances). The random walk hypothesis was rejected and the series was explained by a GARCH M(1,1) model. This study is an example that even in a period of constant economic policy, the random walk hypothesis does not always hold. Choudhry (1997) demonstrated that six Latin American countries, using the ADF test, were conforming to EMH, while Kawakatsu and Morey (1999) showed that 16 emerging markets are random using the DF-GLS and KPSS tests. Also Chadhuri and Wu (2003) found that 17 emerging markets are random using the ADF and PP tests. Due to the lower power of the ADF unit root test in identifying stationarity when the underlying data generating process is characterized by a nonlinear process, Caner and Hansen (2001) propose a unit root test built on an unrestricted two-regime threshold autoregressive model. This newly developed threshold unit root test has been adopted by Narayan (2006). The consensus is that stock price indices exhibit threshold nonlinearity, with Narayan (2006) reporting unit roots in both regimes. Koustas et al (2008) re-examine the US stock market using a statistical framework in which the null hypothesis of a unit root is tested against the alternative of a globally stationary three-regime self-exciting threshold autoregressive (SETAR) process. Their results show the inner regime is characterized by a unit root while the two outer regimes are well captured by a stationary autoregressive process. Despite all the methodological advances, Rahman and Saadi (2008) state that a unit root is a necessary pre-requisite for the random walk hypothesis but not a sufficient condition, thus the presence of a unit root does not imply a random walk since the return series must also be serially uncorrelated or serially independent.

The previous four tests examine the linear nature of returns but as Amini et al (2010) show, there may still be some nonlinear dependence in returns not picked up by the linear tests. Due to this fact, the number of tests for nonlinearity in stock markets has exploded in recent times and a complete review was conducted by Tsay (2005). The tests can be divided into two broad categories. The first category contains nonlinear tests which do not provide a specific nonlinear alternative such as the Brock-Dechert-Scheinkman (BDS) test (Brock et al, 1996), the bispectrum test (Hinich, 1982), Tsay's test (Tsay, 1989), the neural network test (Lee et al, 1993) and the bicorrelation test (Hinich, 1996). Although these tests have been used substantially in the literature, they fail to provide any information about the type of nonlinear dynamics if the null hypothesis is rejected. The second category involves testing linearity of a time series against a well-specified nonlinear model and employing the likelihood ratio, LM or Wald test. Such tests are the SETAR-type nonlinearity (Tsay, 1989), smooth transition autoregressive type nonlinearity (Luukkonen et al, 1988) and ARCH processes (Engle, 1982). The majority of the papers that use such tests have found overwhelming evidence of nonlinear dependence in stock markets, suggesting that nonlinearity is a real phenomenon in international stock markets that has been largely ignored until the 1990s.

The first major paper investigating nonlinearity in time series was by Hinich and Patterson (1985). The paper involved estimating the bispectrum of the observed time series. If the process generating rates of return is linear with independent innovations, then the skewness of the bispectrum will be constant. The results show that the daily returns of 15 common stocks in the US are not generated by a linear process, but by a nonlinear process. De Gooijer (1989) applied two nonlinear tests on daily data of 27 stock returns traded on five world stock exchanges. He used a diagnostic test and a linear autoregressive time series model against a bilinear model as the alternative. Although most returns appeared to be generated by white noise when linear techniques were used, De Gooijer found significant nonlinear dependences. Peters (1989) also found results that showed the presence of nonlinearities in the monthly returns of the S&P 500 Index. Furthermore, Peters (1991) was successful in discovering a chaotic attractor for the S&P 500 returns. This finding provided significant evidence that the S&P 500 stock returns were driven by deterministic chaos. Scheinkman and LeBaron (1989) analysed weekly returns of the CRSP and concluded that these returns appeared to be driven by a nonlinear deterministic influence and were unpredictable. Brock et al (1991) examined both the S&P 500 and the CRSP values weighted indices' weekly returns. They concluded that although there was extensive evidence of nonlinearity in the returns which was largely due to the lack of stationarity in the series, the source of such nonlinearities could not be confirmed as being chaotic determinism.

Abhyankar et al (1995) tested for the presence of nonlinear dependence and chaos on real-time returns on the FTSE 100 index using a six month sample. They used the Hinich and Patterson (1985) bispectrum and BDS test and found nonlinear dependence at all frequencies. Opong et al (1999) examined the behaviour of the FTSE100, FTSE250, FTSE350 and FTSE All-Share equity indices and covered the period of inception of each index to September 1997. In order to test the null hypothesis that the indices are random, independent and an identically distributed process, they used the R/S analysis and the BDS test. They found that each series they examined to not be identically distributed and conclude that the FTSE indices were not truly random due to some cycle or pattern that showed up more frequently than would have been expected in a true random series. Omran (1997) investigated the nonlinear behaviour of the FTSE All-Share for the sample period 4th January 1988 to 28th February 1994. They chose this data set as it included the 1987 stock market crash. They first conducted the BDS test and found that the null hypothesis of i.i.d. stock returns should be rejected and that the series has nonlinear dependence. These findings are similar to the results of de Lima (1995) who found nonlinear dependence in stock returns of US data after the 1987 stock market crash.

Ashley and Patterson (2001) introduced a 'nonlinearity' toolkit which uses a selection of the best tools for detecting nonlinearity in a time series. The tests included in the toolkit are the Engle LM test, Hinich test, Tsay's test, Hinich bicorrelation test and the BDS test. Panagiotidis (2005, 2009) used this toolkit to investigate the weak-form efficiency of the Athens Stock Exchange and found strong evidence of nonlinear dependence in both case. Alagidede and Panagiotidis (2009) and Lim and Brooks (2009) consistently show that nonlinearity is a stylized fact of stock returns. Further, Hiremath and Kamaiah (2010), Alagidede (2011), Caraiani (2012) and Lim and Hooy (2012) all detect nonlinear behaviour in stock returns through a variety of testing procedures. From the explosion in testing nonlinearity in stock returns, it is obvious that nonlinearity is an important issue and any testing procedure should include at least one nonlinear detecting test.

3.3. Data

The data used in this study are daily prices of three long-standing stock market indices. The sample period for the DJIA is from 2nd January 1897 to 31st December 2009, the FT30 sample begins from 1st July 1935 to 31st December 2009 and the TOPIX sample begins from 4th January 1951 to 31st December 2009[13]. The starting dates are set by the availability of data for these specific stock market indices. Summary statistics for the three stock indices for the full sample and subsamples are presented in Table 3.1. The daily return for each index is calculated by;

$$r_t = In(p_t) - In(P_{t-1}) \tag{3.1}$$

where $In(p_t)$ is the natural logarithm of the index at time t. Dividends are omitted from returns based on these series' because dividends will effectively be small and constant due to the short-term nature of the predictions.

[13] The DJIA data was obtained from Global Financial Data and Datastream, the FT30 data was obtained from the Financial Times and Datastream and the TOPIX data was obtained from Datastream.

Table 3.1. Descriptive Statistics of Daily Returns. Significance tests are only applied to the skewness, kurtosis and Jarque-Bera statistics. ***, **, * indicate significance at 1%, 5% and 10% respectively.

Sample Period		Obs	Mean	S.D.	Max	Min	Skewness	Kurtosis	JB
Panel A: DJIA									
Full Sample		30868	0.00019	0.01091	0.14272	-0.25632	-0.54189	24.23***	581356.6***
1897	**1899**	895	0.00054	0.01182	0.05498	-0.09129	-0.52850	8.81***	1302.42***
1900	**1904**	1489	0.00004	0.01078	0.06172	-0.06247	-0.40721	7.01***	1041.10***
1905	**1909**	1503	0.00024	0.00988	0.06476	-0.08653	-0.49050	9.10***	2392.61***
1910	**1914**	1385	-0.00021	0.00785	0.04303	-0.07159	-0.77277	11.77***	4572.70***
1915	**1919**	1491	0.00045	0.01141	0.05324	-0.07516	-0.55783	6.27***	740.91***
1920	**1924**	1499	0.00008	0.00915	0.04128	-0.04313	-0.32735	4.81***	232.05***
1925	**1929**	1499	0.00052	0.01283	0.11640	-0.13720	-1.63780***	28.60***	41614.83***
1930	**1934**	1499	-0.00052	0.02274	0.14273	-0.08778	0.53568	6.57***	866.37***
1935	**1939**	1502	0.00025	0.01252	0.07012	-0.08072	-0.33341	7.50***	1296.28***
1940	**1944**	1503	9.15e-6	0.00742	0.04625	-0.07043	-1.57745***	19.58***	17842.86***
1945	**1949**	1503	0.00022	0.00735	0.03517	-0.05716	-1.01232	9.83***	3177.47***
1950	**1954**	1503	0.00057	0.00586	0.02128	-0.04765	-0.94556	8.50***	2121.72***
1955	**1959**	1503	0.00055	0.00682	0.04048	-0.06766	-0.84828	11.11***	4299.66***
1960	**1964**	1503	0.00038	0.00656	0.04579	-0.05882	-0.12630	11.66***	4700.55***
1965	**1969**	1503	0.00014	0.00604	0.02543	-0.02023	0.00522	3.78***	38.44***
1970	**1974**	1503	0.00002	0.00946	0.04952	-0.03567	0.27173	5.37***	371.35***
1975	**1979**	1503	0.00040	0.00787	0.03833	-0.03038	0.12700	3.76***	40.15***
1980	**1984**	1503	0.00044	0.00905	0.04781	-0.03586	0.37410	4.67***	213.04***
1985	**1989**	1503	0.00075	0.01229	0.09666	-0.25632	-6.29782***	135.54***	1110043.0***
1990	**1994**	1503	0.00042	0.00749	0.04467	-0.04006	-0.10218	6.04***	579.92***
1995	**1999**	1503	0.00093	0.00925	0.04861	-0.07454	-0.61348	9.51***	2749.62***
2000	**2004**	1503	0.00017	0.01150	0.06155	-0.07396	-0.07260	6.66***	837.91***
2005	**2009**	1503	0.00017	0.01288	0.10508	-0.08201	0.01782	15.04***	9075.15***
Panel B: FT30									
Full Sample		19155	0.00015	0.01058	0.10781	-0.12400	-0.19629	12.69***	75169.29***
1935	**1939**	1142	-0.00025	0.00827	0.08077	-0.05553	0.16549	16.90***	9195.70***
1940	**1944**	1283	0.00032	0.00512	0.03969	-0.04841	-1.30036***	25.30***	26936.71***
1945	**1949**	1268	-0.00005	0.00568	0.04193	-0.04051	-0.90933	12.34***	4783.23***
1950	**1954**	1274	0.00043	0.00472	0.02410	-0.03523	-0.66272	8.82***	1891.69***
1955	**1959**	1277	0.00048	0.00805	0.05821	-0.04632	-0.16042	8.58***	1664.35***
1960	**1964**	1274	-7.39e-6	0.00793	0.05690	-0.06662	-0.40098	9.81***	2496.28***
1965	**1969**	1269	0.00015	0.00977	0.07981	-0.08750	-0.18110	16.00***	8941.25***
1970	**1974**	1272	-0.00073	0.01447	0.10781	-0.10255	-0.05320	8.62***	1675.30***
1975	**1979**	1274	0.00074	0.01662	0.09619	-0.06926	0.34802	5.99***	500.19***
1980	**1984**	1303	0.00064	0.01146	0.07058	-0.07940	-0.06962	6.07***	512.28***
1985	**1989**	1301	0.00054	0.01133	0.09119	-0.12400	-1.78312***	25.70***	28619.23***
1990	**1994**	1304	0.00016	0.00905	0.05940	-0.04032	0.41396	5.63***	716.10***
1995	**1999**	1305	0.00043	0.00882	0.04021	-0.03853	-0.09253	5.39***	311.86***
2000	**2004**	1305	-0.00057	0.01308	0.06215	-0.06447	-0.24797	5.65***	395.10***
2005	**2009**	1304	-0.00002	0.01496	0.08589	-0.09136	-0.26207	8.76***	1814.80***
Panel C: TOPIX									
Full Sample		15390	0.00028	0.01024	0.12864	-0.15810	-0.48570	16.00***	109082.1***
1951	**1954**	1041	0.00092	0.01102	0.06196	-0.09159	-0.69953	11.92***	3539.39***
1955	**1959**	1304	0.00075	0.00667	0.02999	-0.05899	-0.94250	10.99***	3659.71***
1960	**1964**	1305	0.00010	0.00867	0.03868	-0.04429	-0.12324	5.24***	276.99***
1965	**1969**	1304	0.00052	0.00702	0.03553	-0.04130	-0.46381	6.85***	852.87***
1970	**1974**	1304	0.00035	0.00929	0.04078	-0.07762	-1.62075***	14.41***	7645.81***
1975	**1979**	1304	0.00038	0.00498	0.02424	-0.02078	0.07372	5.09***	238.57***
1980	**1984**	1305	0.00053	0.00599	0.03369	-0.04448	-0.15591	7.84***	1277.75***
1985	**1989**	1304	0.00088	0.01015	0.08978	-0.15810	-2.46289***	56.06***	154305.4***
1990	**1994**	1305	-0.00047	0.01301	0.09116	-0.07365	0.38753	8.97***	1973.35***
1995	**1999**	1305	0.00008	0.01169	0.06599	-0.05248	0.15823	5.90***	463.24***
2000	**2004**	1305	-0.00031	0.01293	0.06127	-0.06574	-0.22637	4.84***	195.05***
2005	**2009**	1304	-0.00018	0.01573	0.12865	-0.10007	-0.25222	10.83***	3341.92***

Of the three indices full samples, the TOPIX has the highest mean return of 0.000283, while the FT30 has the lowest daily average return of 0.000154. In the case of the standard deviation of stock returns, all three indices have very similar fluctuations, suggesting that there may be some relationship between the volatility of these three stock returns. When subsamples are considered, it can be seen that the DJIA mean generally increases over time, albeit a huge drop in the 1930-1934 period and during the 2000s (possibly due to recessions). However, the standard deviation tends to stay relative similar over time except the 1930-1934 period, again where the standard deviation is exceptionally high. There is also quite high standard deviation during the 2000s, possibly due to the dot com crash and the recession. These results for the 1930-1934 period are probably the result of the early 1930s crash and subsequent recession. Subsample analysis for the FT30 shows that the mean varies considerably over time, while the standard deviation tends to increase over time. However, the TOPIX shows that the mean decreases consistently over time, while the standard deviation increases over time, with both measures moving in opposite direction.

Kurtosis is a measure of whether the data is flat or peaked, relative to a normal distribution. Series with a low kurtosis tend to have a flat top near the mean, rather than a sharp peak, while a series with a high kurtosis have a distinct peak near the mean and have heavy tails. The kurtosis is calculated by;

$$K = \frac{\frac{1}{T}\sum_{t=1}^{T}(y_t - \bar{y})^4}{\sigma^4} \tag{3.2}$$

Where $\bar{y}$ is the mean, σ is the standard deviation, and T is the number of observations. A normal distribution has a kurtosis of 3, with a positive kurtosis indicating a peaked distribution, while a negative kurtosis indicating a flat distribution. If the distribution has thicker tails than does the normal distribution, its kurtosis will be greater than three. The kurtosis coefficient of all three indices exceeds 3, indicating a leptokurtic distribution, with the DJIA return series having the greatest leptokurtic distribution and the FT30 the smallest.

Skewness is a measure of symmetry within the return series, that is, if it looks the same to the left as it does to the right of the centre point. The formula for the skewness is;

$$S = \frac{\frac{1}{T}\sum_{t=1}^{T}(y_t - \bar{y})^3}{\sigma^3} \tag{3.3}$$

Where $\bar{y}$ is the mean, σ is the standard deviation, and T is the number of observations. Positive values for skewness indicate data that is skewed right, while negative values signify data skewed to the left. Thus a positive skewed data set will have a right tail that is heavier than the left tail, and vice-versa. The skewness coefficient for all is negative, which is common to what is found in most data (for example Premaratne and Bera, 2001; Jasic and Wood, 2004). Thus, the skewness and kurtosis values for the three indices deviate from the normal distribution, indicating that the distributions of indices return series' are not normal.

To investigate the extent of the non-normality in the distributions of the indices return series, the Jarque-Bera statistic is used to test whether each series is normally distributed. The test statistic measures the difference of the skewness and kurtosis of the series with those from a normal distribution. The Jarque-Bera statistic should be distributed as X^2 with 2 degrees of freedom under the null hypothesis of a normal distribution. The reported probability is the probability that the statistic exceeds the observed value under the null hypothesis, where a small probability value leads to the rejection of the null hypothesis of a normal distribution. The formula for the Jarque-Bera is;

$$JB = \frac{T-k}{6}\left[S^2 \frac{1}{4}(K-3)^2\right] \tag{3.4}$$

Where T is the number of observations, k is zero for an ordinary series and the number of regressors when examining residuals to regression equation, S is skewness and K is kurtosis (Bera, 1981). As shown by Table 3.1, all indices have a probability associated the JB test of less than 0.0001, which is statistically significant at 1% level and confirms that the distribution of the daily returns of the three markets are not normal.

Although the basic assumption of the random walk model is that the distribution of the return series should be normal, it can be seen from Table 3.1 that the frequency distribution of the returns for each index is not normal, as a normal distribution has a kurtosis of 3 and a skewness coefficient of zero. However, most (if not all) financial series' tend to be non-normal in nature and although it isn't of great surprise, it is worth noting.

3.4. Linear Methodology

The linear tests that are initially conducted are the autocorrelation test, the runs test, the variance ratio test and three unit root tests.

3.4.1. Autocorrelation

The autocorrelation test is a reliable tool for investigating the independence of random variable in a series. If autocorrelations are found, returns are not independent. However if autocorrelations are not found, it does not necessarily imply independence of the series. It only implies that there are no linear autocorrelation dependences in the series. There could be nonlinear dependences in the series which are not picked up[14], as discussed by Amini et al (2010). Autocorrelations occur when the covariances and correlations between different disturbances are not all non-zero (i.e. $Cov(\varepsilon_i, \varepsilon_j) = \sigma_{ij}$ for all $i \neq j$, where ε_t is the value of the disturbance in the i^{th} observation).

$$\rho_k = \frac{\gamma_k}{\gamma_0} \qquad (3.5)$$

Where γ_1 is the covariance at lag k and γ_0 is the variance. The first order autoregressive process contains values of ε_t lagged by just one period, indicating that the disturbance in period t is influenced by the disturbance in the previous period, ε_{t-1}. A second order process contains values of ε_t lagged two periods, indicating that the disturbance in period t is influenced by the disturbance in the past two periods, i.e. $\varepsilon_{t-1}, \varepsilon_{t-2}.$

Three cases can be distinguished concerning parameter ρ:

1) **Positive autocorrelation.** In this case ρ>0, which means that positive values of ε_{t-1} tend to be followed by positive values of ε_t, and negative values of ε_{t-1} tend to be followed by negative values of ε_t. There is a tendency for random disturbances to spill over from one time period to the next.
2) **Negative autocorrelation.** In this case ρ<0, which means that positive values of ε_{t-1} tend to be followed by negative values of ε_t, and negative values of ε_{t-1} tend to be

[14] This is discussed in more detail later.

followed by positive values of ε_t. There is a tendency for successive disturbances to alternate sign over time, a contrarian effect.

3) **No autocorrelation.** In this case ρ=0, which means that $\varepsilon_t = u_t$. There is no relationship between ε_t and ε_{t-1} and successive disturbances have no relationship at all.

The autocorrelation test examines whether the correlation coefficients are significantly difference from zero. The null hypothesis is that ρ=0 and this would imply a random walk process. The autocorrelation coefficient is significant if its t-statistic is outside a [$\pm 1.64/\sqrt{T}$], [$\pm 1.96/\sqrt{T}$] or [$\pm 2.58/\sqrt{T}$] band for 10%, 5% and 1% significance respectively, where T is the total number of observations. Since market efficiency states that returns must be independent, this study focuses on the first order autocorrelations even though up to 7 lags are reported.

3.3.2. Runs Test

The runs test is a non-parametric test which also investigates the randomness of the series in share price movements. However unlike the autocorrelation test it does not require returns to be normally distributed (Poshakwale 1996). The test examines whether the value of one observation influences the values taken by later observations. If there is no influence, the sequence is considered random.

The runs test makes no assumptions of the magnitude of share price changes so ignores huge price falls such as the crash in October 1987. If an uninterrupted series of data is random in the runs test, the actual number of runs in the series should be close to the expected number of runs, irrespective of signs. A run can be defined as '*a succession of identical symbols which are followed or preceded by different symbols or by no symbols at all*' (Siegel, 1956), so a run is a sequencing of the same value or category of a variable. There are three possible types of stock price change: increase, decrease or no change, and therefore three possible types of run. If stock returns increase sequentially five times (+ + + + +) it counts as one run. A new run count begins when this sequence is broken with a decrease or no change. Therefore, the runs test can reveal the cutting point (mean or median), the number of runs below the mean/median, the number of runs above or equal to the mean/median (Poshakwale, 1996).

The number of positive runs is denoted by P, while the number of negative runs is denoted by N. The formula to calculate the expected number of runs is;

$$E(u) = \frac{2PN(P+N)}{(P+N)} + 1 \tag{3.6}$$

The variance of runs is calculated by;

$$\sigma^2 = \frac{2PN(2PN - P - N)}{(P+N)^2(P+N-1)} \tag{3.7}$$

If the *z*-value is greater than the critical values, we reject the null hypothesis of independence of the series. Otherwise, we conclude that the returns are independent. Furthermore, the sample will not be independent if it consists of too many or too few runs. Hence, the independence of returns can be assessed by analysing the distribution of the duration of specific runs. If the actual number of runs exceeds (falls below) expected runs, a positive (negative) *z*-value is obtained. A positive (negative) *z*-value indicates negative (positive) serial correlation in the return series. Thus the *z*-statistic is calculated by;

$$z = \frac{R - \hat{R}}{standard\ error} \tag{3.8}$$

Where R is the observed number of runs, $\hat{R}$ is the expected number of runs and SR is the standard deviation of the total number of runs.

3.4.2. Variance-Ratio Test

Since the seminal work of Lo and MacKinlay (1988), the variance ratio test emerged as a primary tool in examining whether stock returns are serially uncorrelated, with Hoque et al (2007) stating that it has become the most commonly used econometric tool for testing the random walk hypothesis. However the variance ratio test has been subjected to a number of developments in recent years[15].

The variance ratio test is based on the statistical property that if the stock price follows a random walk, then the variance of the *k*-period return is equal to *k* times the variance of the one period return. That is, the variance of its 10-day returns is equal to 10 times the variance of its daily return. Lo and MacKinlay (1988) provide a single test for this hypothesis using the single variance ratio, denoted by VR(k). Let r_t denote an asset return at time t, where t = 1,2,3….T. Then the variance ratio for r_t, with holding period k is;

$$VR(k) = \sigma_k^2 / k\sigma^2 \tag{3.9}$$

Where σ_k^2 = $Variance(r_t + r_{t-1} + \dots + r_{t-k+1})$ is the variance of k-period return. It can be rewritten as;

$$VR(k) = 1 + 2\sum_{j=1}^{k-1}\left(1 - \frac{j}{k}\right)\rho(j) \tag{3.10}$$

Where $\rho(j)$is the autocorrelation of r_t of order j. That is, the variance ratio is one plus t a weighted sum of autocorrelation coefficients for the asset returns with positive and declining weights. The VR tests the null hypothesis that the variance ratio equals 1 for all k's since returns are serially uncorrelated with $\rho(j)$ = 0. Alternatively, values for VR(k) greater than 1 imply positive serial correlations while values less than 1 imply negative serial correlations or mean reversions.

Lo and MacKinlay (1988) proposed the asymptotic distribution of VR(x; k) by assuming that k is fixed when $T \rightarrow \infty$. They showed that if x_t is *i.i.d.*, i.e. under the assumption of homoskedasticity, then under the null hypothesis that V(k) = 1, the test statistic $M_1(k)$ is given by;

$$M_1(k) = \frac{VR(x;k) - 1}{\Phi(k)^{1/2}} \tag{3.11}$$

[15] For a survey on the developments of the variance ratio test look at Charles and Darné (2009).

which follows the standard normal distribution asymptotically. The asymptotic variance, $\Phi(k)$, is given by;

$$\Phi(k) = \frac{2(2k-1)(k-1)}{3k} \tag{3.12}$$

To accommodate the returns exhibiting conditional heteroskedasticity, Lo and MacKinlay (1988) proposed the heteroskedasticity robust test statistic $M_2(k)$;

$$M_2 k = \frac{VR(x;k)-1}{\Phi^*(k)^{1/2}} \tag{3.13}$$

which follows the standard normal distribution asymptotically under the null hypothesis that $V(k) = 1$, where;

$$\Phi^*(k) = \sum_{j=1}^{k-1}\left[\frac{2(k-j)}{k}\right]^2 \delta(j) \tag{3.14}$$

$$\delta(j) = \left\{\sum_{t=j+1}^{T}(x_t-\hat{\mu})^2\left(x_{t-j}-\hat{\mu}\right)^2\right\} \Big/ \left\{\left[\sum_{t=1}^{T}(x_t-\hat{\mu})^2\right]^2\right\} \tag{3.15}$$

The $M_2(k)$ test is applicable to returns of a price series and the usual decision rule for the standard normal distribution is applied. This study utilises $M_2(k)$ due to the heteroskedastic property of the returns series' studied, as revealed in Table 3.1. In estimating VR(k), a choice must be made for the value of the holding periods k. In the literature a popular choice for daily returns is 2, 4, 8 and 16. Even though these are arbitrary and made with little or no justification, we shall use these as they are the standard values used[16].

The variance ratio test allows for the use of overlapping stock returns and thus increases the number of observations used to construct the test statistic. The methodology also includes a

[16] An alternative automatic method for choosing k is suggested by Choi (1999).

correction for the test statistic to allow for the heteroskedasticity property of stock returns. These features increase the efficiency and the power of the test compared to standard serial correlation tests[17]. However, if a stock return is purely random, thus neither positively nor negatively correlations, the variance test looks at individual variance ratios for a specific aggregation interval, which requires VRs of all intervals to equal 1, which is an obvious flaw of the variance ratio test (Buguk and Brorsen 2003). Since the stock returns exhibit conditional heteroskedasticity, we do not consider the Lo MacKinlay $M_1(k)$, and only apply the Lo MacKinlay $M_2(k)$ test. The holding periods (k) considered are (2, 4, 8, 16) which is consistent with the majority of the previous literature.

3.4.4. Unit Roots

One strand of tests for efficiency is to determine whether the series is stationary or non-stationary. A series is stationary if its mean and variance are constant over time and the value of the covariance between the two time periods depended only on the distance or gap or lag between the two time periods and not the actual time at which the covariance is computed (Gujarati 2009). If Y_t is a stochastic time series with the following properties, it is a stationary process with;

$$\begin{aligned} Mean&: \quad E(Y_t) = \mu \\ Variance&: \quad var(Y_t) = E(Y_t - \mu)^2 = \sigma^2 \\ Covcariance&: \quad \gamma_k = E[(Y_t - \mu)(Y_{t+k} - \mu)] \end{aligned} \tag{3.16}$$

Where γ_k, the covariance at lag k is the covariance between the values of Y_t and Y_{t+k}. Thus in a stationary process no matter at what point we measure them, its mean, variance and autocovariance remain the same, i.e. they are time invariant. A nonstationary process however, has a time-varying mean and/or a time-varying variance. Stationarity is important since if the series is nonstationary, we can only study its behaviour for the time period under consideration. Thus we cannot generalize it to other time periods and forecasting such nonstationary time series may be of little practical value.

[17] Lo and MacKinlay (1989) show that the variance-ratio test is more powerful that either the Box-Pierce or the Dickey Fuller test for several common time-series process such as an AR(1) process.

The classic nonstationary example is the random walk model (RWM).We can distinguish between three types of random walk models: (1) pure random walk model, (2) the random walk model with drift, (3) the random walk model with drift and a deterministic trend.

Pure Random Walk Model

Suppose u_t is a white noise error term with mean 0 and variance σ^2. Then the series is said to be random walk if;

$$Y_t = Y_{t-1} + u_t \qquad (3.17)$$

Where Y_t is the value of stock at time *t*, which depends on the prior period's value plus a stochastic error term. This implies that the price today is the best indicator of the price tomorrow, i.e. tomorrow's price is today's price plus a random error. Hence no abnormal gains can be made and the series is nonstationary. But if we take the first difference of the equation (i.e. take Y_{t-1} from each side), it becomes stationary;

$$\Delta Y_t = (Y_t - Y_{t-1}) = u_t \qquad (3.18)$$

This equation is the pure random walk model differenced stationary.

Random Walk Model with Drift

In this model, a drift term is introduced to equation (3.16) to form;

$$Y_t = \delta + Y_{t-1} + u_t \qquad (3.19)$$

Where δ is the drift term and equation (3.18) is a random walk model with drift, which is nonstationary. If we take the first difference of equation (3.18), we produce;

$$\Delta Y_t = (Y_t - Y_{t-1}) = \delta + u_t \qquad (3.20)$$

Which shows that as Y_t drifts upwards or downwards, depending on δ being positive or negative. Such a trend is called a stochastic trend. Equation (3.19) is a difference stationary process because the nonstationarity in Y_t can be eliminated by taking first differences of the time series.

Random Walk Model with Drift and Deterministic Trend

In this model, a deterministic trend is added to equation (3.18) to form;

$$Y_t = \beta t + \delta + Y_{t-1} + u_t \tag{3.21}$$

Where βt is a deterministic trend and equation (3.20) is a random walk model with drift and deterministic trend, which is nonstationary. It is also called a trend stationary process. Although the mean of Y_t is $\beta t + \delta$, which is not constant. Once the values of $\beta t + \delta$ are known, the mean can be forecast perfectly. Therefore if we subtract the mean of Y_t from Y_t, the resulting series will be stationary, hence the name trend stationary. If we take the first difference of equation (3.20) we form;

$$\Delta Y_t = \beta t + \delta + u_t \tag{3.22}$$

Which means that Y_t is nonstationary. To test for stationarity, the widely used test in the literature has been the unit root test. Below I will first explain what a unit root is, then I will describe the various tests that can be used to find one and finally I will discuss the limitations of the tests.

The pure random walk model can be written as;

$$Y_t = \rho Y_{t-1} + u_t \tag{3.23}$$

If $\rho = 1$, we face the unit root problem, which is the situation of nonstationarity. If however, $|\rho| \leq 1$, then it can be shown that the time series Y_t is stationary. Thus in order to determine the stationarity of a series, we can test whether it possesses a unit root. If we manipulate equation (3.22) by subtracting Y_{t-1} from both sides we obtain;

$$\begin{aligned} Y_t - Y_{t-1} &= \rho Y_{t-1} - Y_{t-1} + u_t \\ &= (\rho - 1) Y_{t-1} + u_t \end{aligned} \tag{3.24}$$

Which can be alternatively written as;

$$\Delta Y_t = \delta Y_{t-1} + u_t \tag{3.25}$$

Where δ = (ρ – 1) and Δ is the first difference operator. Thus in practice, we estimate equation (3.24) and test the null hypothesis that $\delta = 0$. If $\delta = 0$, then $\rho = 1$, that is, we have a unit root, meaning the time series under consideration is nonstationary. Therefore, the null hypothesis is that $\delta = 0$ (which means $\varphi = 1$ and the series is nonstationary) and the alternative hypothesis being $\delta < 0$ (the series being stationary). Dickey and Fuller (1979) showed that under the null hypothesis, the estimated t-values of δ follow the τ statistic of Monte Carlo Simulation. This has been known as the Dickey-Fuller (DF hereafter) test. To calculate the DF, estimate the random walk model with and without trend by OLS, divide the estimated coefficient of Y_{t-1} in each case by its standard error to compute the τ statistic, which is then referred to the DF tables. If the computed τ statistic exceeds the absolute DF statistic, we reject the null hypothesis that δ = 0, in which case the time series is stationary. On the other hand, if the computed τ statistic does not exceed the absolute critical value, we do not reject the null hypothesis, in which case the time series is nonstationary. However, the DF test assumes that the white noise term was uncorrelated. However, a more sophisticated version of this test, called the Augmented Dickey-Fuller test, was proposed by Said and Dickey (1984), and this test will be conducted instead of the original DF test.

Under the former DF test, the error term was assumed to be uncorrelated. However, it is possibly the case that the error term is correlated. This test accounts for this and is conducted by adding the lagged values of the dependent variable ΔY_t. The pure random walk becomes:

$$\Delta Y_t = \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \, \Delta Y_{t-i} + u_t \tag{3.26}$$

Where u_{t} is a pure white noise error term and where $\Delta Y_t = (Y_{t-1} - Y_{t-2})$. The number of lagged difference terms to include is often determined empirically, with the idea being to include enough terms so that the error term is serially uncorrelated. In our testing this will be determined by the Akaike Information Criterion (*AIC*). The *AIC* imposes a penalty for adding regressors to the model. It is written as;

$$In\,AIC = {}^{2k}/_{n} + In\,({}^{RSS}/_{n}) \tag{3.27}$$

Where *InAIC* is the natural log of *AIC* and *2k/n* is the penalty factor. The lag length with the lowest AIC is preferred and this test has the advantage of being useful for in-sample as well as out-of-sample forecasting. The ADF test follows the same asymptotic distribution as the DF test, so the same critical values can be used. Hence the two hypotheses are;

H_0: $\delta = 0$ (i.e. there is a unit root and the time series is nonstationary)

H_1: $\delta < 0$ (i.e. the time series is stationary)

Again, the null hypothesis is rejected if the τ statistic is larger than the critical value, and the null cannot be rejected if the τ statistic is less than the critical value.

The Phillips and Perron (1988) proposed an alternative non-parametric approach to test for unit roots. The PP test differs from the ADF test mainly in how they deal with serial correlation and heteroskedasticity in the errors. Where the ADF test uses a parametric autoregressive to approximate the structure of the errors in the test regression, the PP test ignores any serial correlation in the test regression. The test regression for the PP test is;

$$\Delta Y_t = \beta_1 t + \delta Y_{t-1} + u_t \tag{3.28}$$

Where u_t is I(0) and may be heteroskedastic. The PP test corrects for any serial correlation and heteroskedasticity in the errors of u_t of the test regression by directly modifying the test statistics. This gives the PP test the advantage over the ADF test in that it is robust in general forms of heteroskedasticity in the error term, u_t. Another advantage is that you do not have to specify a lag length for the test regression, which is helpful as different lag criteria tests often provide different recommended lags. Under the PP test, the null hypothesis is the same as with the ADF test, and the critical values are the same ones used by the ADF test. Hence, a test statistic larger than the critical value rejects the null hypothesis, and the series is deemed to be nonstationary.

There have been a number of criticisms of both the ADF and PP unit root tests. One such criticism is that it they have low power, which means they tend to accept the null of a unit root more frequently than is warranted, i.e. these tests may find a unit root even when none exists. Another criticism is that they have poor size properties, meaning that there is a good probability of the tests committing a Type I error, which means they may reject the null hypothesis when in fact, it is true. Also, with these type tests, the underlying data generating process has large negative moving average components. This is of great concern to modellers because many macroeconomic time series contain moving average terms (Gujarati and Porter 2009). The power of the ADF test is also reduced by too large a number of lagged differences. On the other hand, too small a number of lags has the effect that the test is no longer correctly applicable due to the autocorrelation of the estimated residuals. To avoid the problem of overly rejecting the null hypothesis, the KPSS test will also be used.

The KPSS test was developed by Kwiatkowski et al (1992) and is an alternative unit root test to the ADF and PP tests. While the ADF and PP tests have the null hypothesis that a series is nonstationary, the KPSS test has the null hypothesis that the series is stationary. This is beneficial to our testing as one of the main faults of the ADF and PP test is that they overly reject the null hypothesis when it is true. The test is derived from the model;

$$\begin{gathered} Y_t = \beta_1 t + u_t \\ u_t = u_{t-1} + \varepsilon_t \quad \varepsilon_t \sim (0, \sigma^2) \end{gathered} \tag{3.29}$$

Where $\beta_1 t$ contains deterministic components, u_t is I(0) and may be heteroskedastic. Also, the u_t is a pure random walk with variance. The null hypothesis that Y_t is I(0) is formulated as H_0: $\sigma^2 = 0$, which implies that u_t is constant. This null hypothesis implies a unit root is present in the series, stating the series is nonstationary. The critical values for the test statistic are available from Kwiatkowski et al (1992 Table 1, p166). Kwiatkowski et al (1992) state that the ADF test and the way it is carried out ensures the null is accepted unless there is strong evidence to the contrary, emphasizing that it is not powerful against relative alternatives. The ADF test concentrates on the null hypothesis of being non-stationary, and if this is rejected, it assumes the series is stationary, even when there is no evidence of the series being stationary (Kwiatkowski et al, 1992).

So far, the tests for independence have been linear as they only detect linear relationships in the returns. However, returns may exhibit nonlinear properties which are ignored by these tests. Thus we examine each series using a battery of nonlinear tests.

3.5. Nonlinear Methodology

The previous section outlined the linear testing procedure that is conducted. However, there may also be nonlinear dependence in returns and as Amini et al (2010) show, the absence of linear dependency does not necessarily mean there is no nonlinear dependency in the returns. Nonlinear dependence in stock returns has gained much attention in recent times as it indicates possible dependence when linear tests indicate independence (Alagidede 2011; Caraiani 2012; Lim and Hooy 2012). The early studies which examined the EMH largely used conventional tests such as autocorrelation, variance ratio, and the runs test which are not capable of capturing nonlinear patterns in returns series. The use of linear models in such conditions may give the wrong inference about the unpredictability of returns, as the presence of nonlinearity in stock returns contradicts the EMH.

Many statistical tests for non-linear dependence have been proposed in the literature in recent times. Instead of only using a single statistical test, a battery of nonlinear tests are employed to examine the nonlinear structure in stock returns that will enable a deeper and more detailed insight into the series while minimising the probability of missing something and thus drawing the wrong conclusions. For example, the BDS test is deemed the most sophisticated in the literature, however it gives no information about which data generating mechanism would be appropriate to model the data. If the battery of tests display a unanimous consensus in favour of a specific result, this result will be deemed correct.

The linear structure in the returns is removed from the data through a pre-whitening model. An AR(p) model is fitted to the data with the optimal length determined when the standardised residuals are no longer correlated through the Ljung-Box Q-statistic up to 20 lags[18]. The AR(p) model in which the Q-statistic at 20 lags is not significant at the 10% level of significance will be chosen. The serially uncorrelated residuals of this model are then tested for nonlinear independence using each of the tests below. Other specifications such as the ARMA or GARCH could have been utilised as an alternative pre-whitening model, but the GARCH model cannot be used unless the linearity assumption has been rejected (Panagiotidis 2002).

The Ljung-Box Q-statistic for serial correlation is given by;

$$Q_{LB} = n(n+2)\sum_{j=1}^{m}\left(\rho_j^2/(n-j)\right) \tag{3.30}$$

Where ρ_j is the j^{th} autocorrelation and n is the number of observations. For a large sample, the Ljung-Box statistic follows a chi-square distribution with m degrees of freedom. The Ljung-Box statistic can be used to test the hypothesis that all the autocorrelations are zero, and thus the series is white noise (Box and Pierce, 1970). Thus the Q-statistic on the residuals will reveal any linear dependencies still evident in the data. The Q-statistics are documented in Table 3.8 and are consistent with the previous autocorrelation results. The residuals of the pre-whitening model will be tested through a battery of nonlinear tests, namely the McLeod and Li test (1983), Engle LM test (1982) and BDS (1996) test.

3.5.1. McLeod Li Test

The McLeod and Li test (McLeod and Li 1983) is a portmanteau test of nonlinearity. To test for nonlinear effects in the time series, they propose the following statistic;

$$Q(m) = \frac{n(n+2)}{n-k}\sum_{k=1}^{m} r_a^2(k) \tag{3.31}$$

$$r_a^2(k) = \frac{\sum_{t=k+1}^{n} e_t^2 e_{t-k}^2}{\sum_{t=1}^{n} e_t^2} \quad k = 0, 1, \dots., n-1 \tag{3.32}$$

[18] Similar to Hsieh (1989) approach except this study looks at up to 20 lags to ensure that the linear autocorrelation has been removed.

Where r_a the autocorrelations of the squared residuals, e_t^2, obtained from fitting a model to the data. If the series e_t is independently and identically distributed then the asymptotic distribution of $Q(m)$ is χ^2 with m degrees of freedom. The null hypothesis is independence of returns. If the null hypothesis is rejected, it indicates the presence of ARCH/GARCH effects in the data and nonlinear dependence.

3.5.2. Engle LM Test

The Engle LM test is also utilised, which was suggested by Engle (1982) to detect ARCH disturbances. The residuals of the AR(p) model are tested for heteroskedasticity. The Engle LM statistic is computed from an auxiliary test regression, which is;

$$\hat{e}_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \hat{e}_{t-i}^2 + v_t \qquad (3.33)$$

Where e is the residual from the pre-whitening AR(p) model. The test statistic is the usual F-statistic for the regression on the squared residuals, such that;

$$F\ statistic = \frac{RRSS - URSS}{URSS} \times \frac{T-k}{m} \qquad (3.34)$$

Where $URSS$ is the residual some of squares from the unrestricted regression, $RRSS$ is the residual sum of squares from the restricted regression, m is the number of restrictions, T is the number of observations and k is the number of repressors in the unrestricted regression. Under the null hypothesis of a linear generating mechanism for e_t, NR^2 for this regression is asymptotically $\chi^2(p)$. If the null hypothesis is rejected, there is evidence of ARCH/GARCH effects in the data.

3.5.3. BDS Test

The BDS test is a powerful and frequently used (Chen and Yeh 2002) non-parametric test for serial dependence (or alternatively a nonlinear structure) in time series analysis, which was set out by Brock, Dechert and Scheinkman (1987) although the version used here is based on Brock et al (1996). Patterson and Ashley (2000) conducted a simulation study of the powers of various nonlinear dependency tests and found the BDS test performed better under different conditions. However, the BDS test gives no information to which data generating mechanism would be appropriate to model the data, thus the previous tests were also conducted.

The null hypothesis is that the data generating processes are independent and identically distributed (*i.i.d.*), while the alternative hypothesis is '*an indication that the model is misspecified*' (Brock et al 1996). The failure to accept the null hypothesis dismisses the idea of market efficiency as the test is a measure of nonlinear predictability of the sample (once the linear dependence of returns have been filtered out). One of the main benefits of this test is that it does not require returns to be normal distributed (nearly all returns are non-normal), as the BDS test does not require higher moments to exist.

The correlation integral is the probability that any two points are within a certain length '*e*' apart in phase space. As we increase '*e*', the probability scales according to the fractional dimension of the phase space. The correlation integrals are calculated according to;

$$C_m(e) = (1/N^2) \times \sum_{i,j=1}^{T} Z\big(e - |X_i - X_j|\big), i \neq j \tag{3.35}$$

Where $Z(e) = 1$ if $[e - |X_i\text{-}X_j| > 0]$, 0 otherwise; T = the number of observations, e = distance, C_m = correlation integral for dimension m, X = the index series.

The m dimension is a point in m-dimensional space where m is the embedding dimension given by;

$$M_1 \colon x_t^1 = x_{t,} \tag{3.36}$$

$$M_2 \colon x_t^2 = (x_t, x_{t+1}) \tag{3.37}$$

$$M_m \colon x_t^m = \big(x_t \ \ldots \ x_{t+(m-1)}\big) \tag{3.38}$$

The function z counts the number of points within a distance e of one another. The correlation integral calculates the probability that two points that are part of two trajectories in phase space are 'e' units apart. Brock et al. demonstrated that;

$$|C_n(e,T) - C_1(e,T)^N| \times \sqrt{T} \qquad (3.39)$$

Is normally distributed with a mean of 0. The BDS statistic, W, that follows is normally distributed and given by;

$$W_N(e,T) = |C_n(e,T) - C_1(e,T)^N| \times \sqrt{\frac{T}{S_N(e,T)}} \qquad (3.40)$$

Where $S_N(e, T)$ = the standard deviation of the correlation integrals.

Brock et al. demonstrate that the BDS statistic, W, has a limiting normal distribution under the null hypothesis of *i.i.d.* when the data series consists of more than five hundred observations. Hsieh (1991) points out that, structural changes in the data series can cause a rejection of the null hypothesis of IID on the basis of the BDS test. Thus there is a rational of breaking up the sample period and examining subsamples separately. A problem with the BDS test is the choice of 'e' which represents the maximum distance for the pair (X_i, X_j). A large value of 'e' will retain all pairs, and the value of the correlation integral will equal unity where a small value will lead to no retention of any pair, and will result in a value of zero for the correlation integral. Brock et al. (1991), Hsieh (1991) and Sewell et al. (1993) use 'e' equal to 0.5σ, 1σ, 1.5σ and 2σ. The value of σ represents the standard deviation of the data. As for the choice of the relevant embedding dimension m, Hsieh (1989) suggests consideration of a broad range of values form 2 to 10 for this parameter. Under the null hypothesis that the index series under study is random, the null hypothesis can be rejected with 95% confidence when W exceeds 2.0. Also the null can be rejected with 99% confidence when W exceeds 3.0.

The test is two sided and the null hypothesis is that the residuals are *i.i.d.* In small samples the distribution of the test statistic is not normal, however with a sample over 250 observations it is not seen as a problem. Thus the normal distribution is assumed with critical values of 2.57 for 1%, 1.96 for 5% and 1.64 for 10%. There is a consensus in the literature that the BDS test is a powerful one, however Brooks and Henry (2000) reveal that the BDS test can sometimes confuse different types of nonlinear structure (such as threshold autoregressive and GARCH models) and has small power in detecting neglected asymmetries in conditional variance models. Nevertheless, both problems are present when a GARCH filter is used thus it and an AR model are utilised.

Nevertheless, if nonlinearity is detected and it can be accounted fully by conditional heteroskedasticity, it does not imply a violation of the EMH. As highlighted by Hong and Lee (2005), the EMH has implications on and only on the conditional mean, but it does not impose a restriction on the dynamics in conditional variance and other higher-order conditional moments. To address this, AR-generalized autoregressive conditional heteroskedasticity (GARCH)-filtered returns are examined. A rejection of the null hypothesis implies that the detected nonlinearity most likely entered the series through the mean of the return generating process, and hence contrary to the EMH.

It is generally postulated that most of the nonlinear dependence in financial time series occurs due to neglected conditional heteroskedasticity that could be captured through ARCH/GARCH models. This is not surprising since the BDS test has high power against ARCH/GARCH models where nonlinearity has entered through the conditional variance. The approach suggested is to fit an AR-GARCH model to the returns and its standardized residuals are then tested for *i.i.d.* using the BDS test (Hsieh 1989, 1991; Opong et al 1999; Poshakwale 2002; Saadi et al 2006). A further rejection of i.i.d. would suggest that the conditional heteroskedasticity is not the main source of nonlinearity. Instead the nonlinear dependence is of an unknown form in the data after volatility clustering is removed.

Unlike the case of linear models, the Monte Carlo simulations presented by Brock et al (1991) find that the nuisance parameter-free result does not hold when the BDS test is applied to the standardized residuals of ARCH and GARCH models. They suggest bootstrapping the null distribution to obtain the critical values for the BDS statistic when applying the test to standardized residuals from these nonlinear models. However, de Lima (1998) later establishes that the asymptotic distribution of the BDS is still normal when the test is applied to the natural logarithm of the squared standardized residuals from ARCH/GARCH models.

Thus to determine whether there still exists any remaining nonlinear predictability after accounting for volatility clustering, we filter the original returns with an AR(p)-GARCH(1,1) model such as;

$$r_t = \beta_0 + \sum_{i=1}^{p} \beta_i r_{t-i} + \varepsilon_t \qquad (3.41)$$

$$\varepsilon_t \sim N(0, h_t)$$

$$h_t = \alpha_0 + \alpha_1 h_{t-1} + \alpha_2 \varepsilon_{t-1}^2 \qquad (3.42)$$

Where r_t is the returns series, ε_t is the residual of the mean equation and h_t is the conditional variance of the residual. The natural logarithm of the squared standardized residuals, $In(\zeta_t^2)$ where $\zeta_t = \varepsilon_t / \sqrt{h_t}$ are then subjected to the BDS[19] test. A GARCH(1,1) model is used since it is the model that has best described stock returns in the literature.

3.6. Empirical Results

3.6.1. Linear Empirical Results

The results for the linear and nonlinear tests explained above are presented and discussed in this section. Table 3.2 reports the autocorrelation coefficients for the DJIA, FT30 and TOPIX. The full sample of all three indices possess a first order autocorrelation that is significant and positive, indicating that stock returns are indeed to an extent predictable on the basis of the past price history. Table 3.2 also documents the autocorrelation coefficient for the subsamples in the DJIA. The results show that during the first five subsamples there is very little or no significant autocorrelation in any of the lags. However, the 1920-1924 and 1925-1929 subsamples have significant first order autocorrelation, with the 1925-1929 subsample possessing many lags that are significant. Nevertheless, the next two subsamples possess no significant autocorrelation, indicating that during the 1930s the stock market was

[19] The McLeod-Li Test and Engle LM Test are not conducted on the AR-GARCH residuals since the BDS should capture all of the nonlinearity if present.

independent[20]. The subsamples for the 1940s, 1950s, 1960s and 1970s all possess first order significant autocorrelations, with many of the other lags being significant too. Thus during these years, the stock market appears to be predictable. However the next five subsamples, covering the 1980s, 1990s and first half of the 2000s, shows little or no autocorrelations suggesting independence in the stock market returns. Finally the last subsample (2004-2009) shows that the first 2 lags of the autocorrelation coefficient to be significant and negative, with the third coefficient being positive and significant, indicating that DJIA returns had some predictive power during the late 2000s. These results suggest that DJIA returns have gone through periods of being independent and through periods being dependent. Thus the behaviour of returns appear to follow the AMH and can be categorized by type 4. The FT30s autocorrelation results show that the first six subsamples are not independent, with a significant first lag autocorrelation coefficient in each case. However, the next two subsamples (1965-1969 and 1970-1974) have no significant autocorrelation coefficient in the first six lags, suggesting that returns during this period were independent. Again the first order autocorrelation coefficient is positive and significant for the 1975-1979 period, but again there is no significance in the coefficient for the 1980-1984 period. The next three subsamples (1985-1989, 1990-1994 and 1995-1999) possess first order significant autocorrelation in returns, indicating the returns were predictable during these sample periods. However, the two sample periods in the 2000s possess very little significant autocorrelation suggesting that returns were independent during these periods. These results suggest that FT30 returns have fluctuated during periods of dependence and independence indicating the AMH and type 4 behaviour. TOPIX subsample analysis of the autocorrelation coefficient show that most of the subsamples contain at least a significant first order correlation coefficient, with only the 1965-1969, 1995-1999 and 2005-2009 subsamples providing independence. Again this indicates that the independence of returns in this market fluctuate over time, confirming the AMH and categorized by type 4.

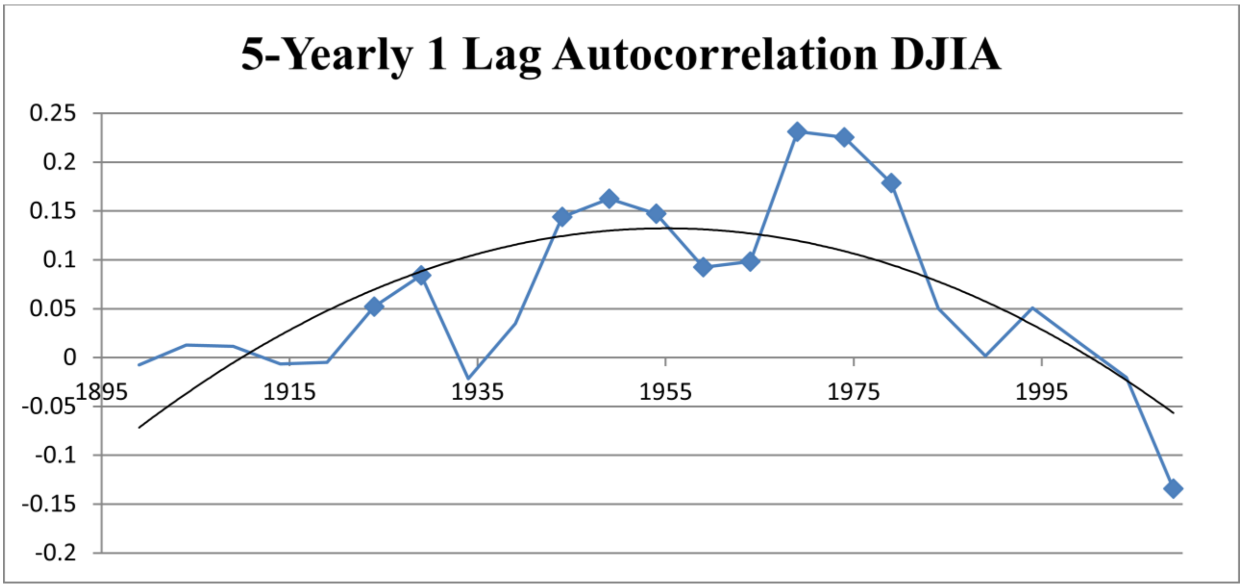
Figure 3.1 depicts the first order autocorrelation coefficient of each market plotted over time. The blotted points are autocorrelation coefficients that are statistically significant at 5%. It is clear from all three graphs that each markets independence fluctuates over time, with the market going through periods of independence and dependence supporting the AMH and type 4 of the previously described classification.

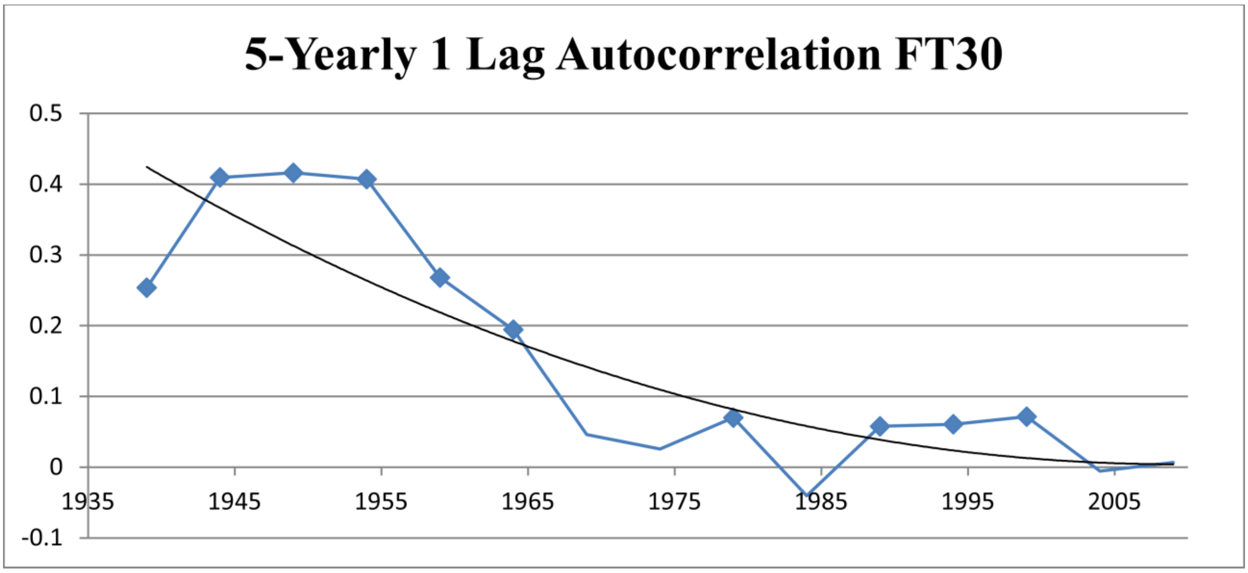
[20] Possibly due to the 1930s stock market crash.

Table 3.2. Test results for 5-yearly autocorrelation test. ***, **, * indicate significance at 1%, 5% and 10%.

Sub Periods		Autocorrelation - Lags						
Start Year	**End Year**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Panel A: DJIA								
Full Sample		0.0268***	-0.0358***	0.0118***	0.0327***	0.0182***	-0.0181***	-0.0269***
1897	**1899**	-0.0075	0.0068	0.0439	0.1327***	-0.0127	-0.0305	0.0177
1900	**1904**	0.0128	-0.0573**	0.0508**	0.0425*	0.0730***	-0.0344	-0.0822
1905	**1909**	0.0114	-0.0110	0.0435*	0.1035***	0.0697***	-0.0101	-0.1105***
1910	**1914**	-0.0064	-0.0181	0.0334	-0.0024	0.0263	-0.0189	-0.0387
1915	**1919**	-0.0047	0.0045	-0.0162	-0.0042	0.0593	0.0068	-0.0374
1920	**1924**	0.0522**	-0.0166	0.0395	0.0178	-0.0001	0.0760***	-0.0075
1925	**1929**	0.0842***	-0.2124***	-0.0188	0.2198***	0.0956***	-0.0935***	-0.0664**
1930	**1934**	-0.0215	0.0131	-0.0112	0.0270	-0.0036	-0.0191	-0.0171
1935	**1939**	0.0348	-0.0142	0.0415	0.0294	0.0500*	-0.0632**	-0.0401
1940	**1944**	0.1440***	-0.0147	0.1214***	0.0211	-0.0402	0.0910***	-0.0008
1945	**1949**	0.1626***	-0.1086***	-0.0297	0.0428	0.0222	-0.0703	0.0275
1950	**1954**	0.1473***	-0.0783***	0.0093	-0.0089	-0.0115	-0.0132	0.0039
1955	**1959**	0.0926***	-0.0986***	-0.0146	0.0577**	0.0493*	-0.0095	-0.0385
1960	**1964**	0.0983***	-0.0111	0.0573**	0.0370	-0.0019	-0.0320	0.0260
1965	**1969**	0.2312***	0.0355	0.0240	0.0630**	0.0447	0.0174	0.0149
1970	**1974**	0.2255***	-0.0244	-0.0257	-0.0144	-0.0559**	-0.0380	0.0119
1975	**1979**	0.1787***	-0.0408	0.0159	-0.0123	-0.0212	-0.0558**	-0.0194
1980	**1984**	0.0503*	0.0436	-0.0275	-0.0449	0.0035	0.0098	-0.0222
1985	**1989**	0.0016	-0.1064	-0.0109	-0.0547*	0.0808***	0.0065	0.0259
1990	**1994**	0.0507*	0.0015	-0.0321	-0.0071	0.0054	-0.0582**	-0.0686**
1995	**1999**	0.0152	-0.0324	-0.0588**	-0.0132	-0.0290	0.0276	-0.0354
2000	**2004**	-0.0204	-0.0320	0.0091	0.0323	-0.0417	-0.0137	-0.0286
2005	**2009**	-0.1341***	-0.0937***	0.0911***	-0.0167	-0.0172	-0.0170	-0.0468*
Panel B: FT30								
Full Sample		0.0737***	0.0016	-0.0058	0.0328	-0.0020	-0.0217***	-0.0050
1935	**1939**	0.2537***	0.0625**	-0.0371	-0.0577*	-0.0320	0.0075	-0.0110
1940	**1944**	0.4096***	0.3836***	0.1541***	0.1206***	0.1179***	0.0468*	0.0179
1945	**1949**	0.4161***	0.2491***	0.1125***	-0.0201	-0.0341	-0.0581**	-0.0362
1950	**1954**	0.4072***	0.2111***	0.0651**	-0.0093	-0.0224	0.0011	0.0049
1955	**1959**	0.2680***	0.0488*	-0.0398	-0.0182	0.0076	0.0164	0.0093
1960	**1964**	0.1944***	-0.0349	-0.1057***	-0.0625**	-0.0290	-0.0220	0.0098
1965	**1969**	0.0459	-0.0283	0.0094	-0.0111	-0.0517*	-0.0370	-0.0220
1970	**1974**	0.0259	-0.0344	0.0040	-0.0222	0.0275	-0.0009	-0.0570**
1975	**1979**	0.0700**	-0.0335	0.0314	0.0457	0.0198	-0.0697	0.0156
1980	**1984**	-0.0403	0.0397	0.0201	-0.0272	0.0417	0.0245	-0.0690
1985	**1989**	0.0577**	0.0022	0.0136	0.0901***	0.0023	0.0240	0.0512*
1990	**1994**	0.0607**	0.0308	0.0183	0.0734***	-0.0198	-0.0094	-0.0905***
1995	**1999**	0.0714***	-0.0340	-0.0514*	0.0177	0.0153	-0.0538*	-0.0320
2000	**2004**	-0.0055	0.0049	-0.0632**	0.0612**	-0.0344	-0.0284	0.0265
2005	**2009**	0.0069	-0.0600**	-0.0475	0.1111***	-0.0520*	-0.0570**	0.0347
Panel C:TOPIX								
Full Sample		0.0849***	-0.0187**	0.0011	0.0288***	-0.0001	-0.0344***	0.0007
1951	**1954**	0.1976***	0.0128	0.0239	0.0618**	0.0392	-0.0445	0.0246
1955	**1959**	0.0763***	0.0871***	0.0660**	0.0050	0.0305	-0.0022	0.0484*
1960	**1964**	0.1700***	0.0516*	0.0277	0.0650**	0.0407	0.0121	-0.0181
1965	**1969**	0.0512*	0.0267	0.0596**	0.0094	-0.0097	0.0089	0.0056
1970	**1974**	0.1336***	0.0994***	0.0791***	0.0544**	0.0201	-0.0126	-0.0091
1975	**1979**	0.1772***	0.0926***	0.0176	-0.0444	-0.0338	-0.0596**	-0.0077
1980	**1984**	0.1310***	0.0000	0.0308	0.0038	-0.0339	0.0011	-0.0130
1985	**1989**	0.0540**	-0.0623***	0.0168	0.0508*	-0.0216	-0.0498*	0.0059
1990	**1994**	0.1436***	-0.0784***	-0.0106	0.0542**	-0.0161	-0.0163	-0.0117
1995	**1999**	0.0303	-0.0374	-0.0123	-0.0079	-0.0401	-0.0650**	0.0086
2000	**2004**	0.0608**	-0.0167	-0.0413	-0.0307	-0.0181	-0.0475*	0.0256
2005	**2009**	0.0010	-0.0764***	-0.0436	0.0415	0.0157	-0.0556**	-0.0293

Figure 3.1: The five-yearly first lag autocorrelations plotted for the three markets. The end year of the subsample is on the x-axis and the autocorrelation coefficient is on the y-axis. The blotted points are the autocorrelation coefficients that are statistically significant at 5%.





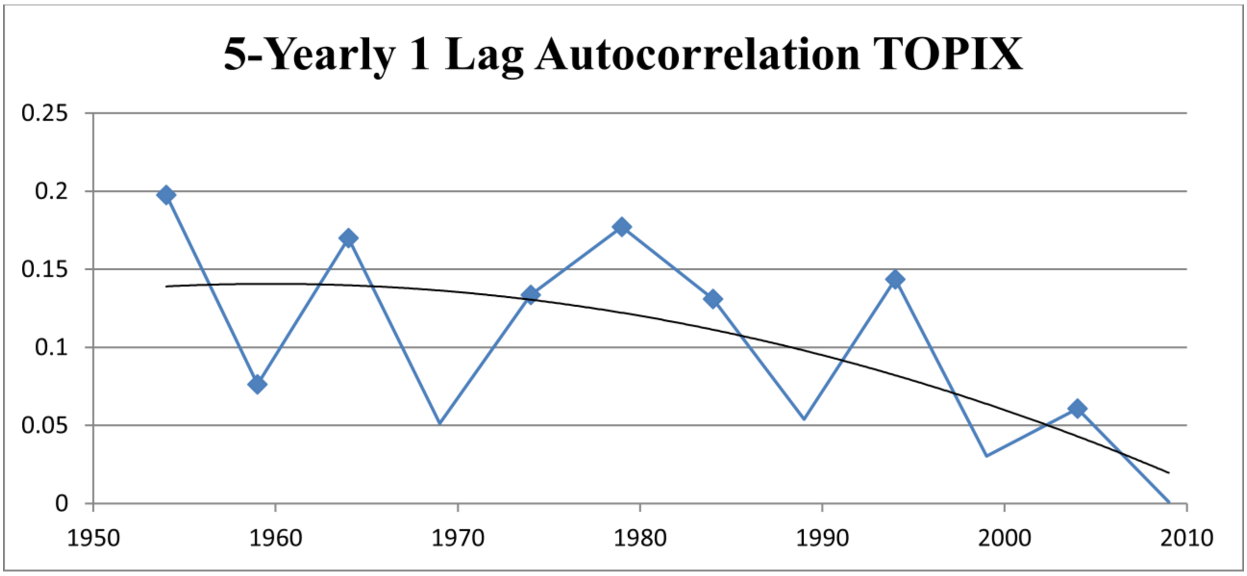


Table 3.3 presents the runs test results for the DJIA, FT30 and TOPIX. Panel A reports that the full sample for the DJIA, along with the sample periods 1900-1904 and 1920-1929 are all significant at 5%, indicating that these subsamples are not independent. Also, from the subsample period 1940-1944 to 1970-1974, they are all negative and significant, indicating that the observed number of runs is significantly fewer than the expected number of runs. Therefore for all of these sample periods, the null hypothesis that the return series follows a random walk can be rejected. However, from the subsample period 1975-1979 to 1995-1999, the returns are independent as the z-values are insignificant. Nevertheless, the series returns becomes dependent again for the last two subsample periods, indicating that the DJIA returns have fluctuated between being dependent and independent, suggesting type 4 behaviour and the AMH. The FT30 results from Table 3.3 report that returns were dependent at the beginning of the sample until the 1975-1979 subsample period, with each z-value being negative and significant. However from this point to the end of the sample, the z-value are mostly negative and insignificant, indicating that the returns are now independent, although the actual number of runs is fewer than the expected number of runs. Thus the runs test for the FT30 suggests that returns have reversed from being dependent to being independent around the early 1970s mark and can be categorized by type 3. The TOPIX results from Table 3.3 suggest that the TOPIX is generally dependent. Only three subsample periods are not negative and significant (1965-1969, 1995-1999 and 2005-2009), suggesting that the TOPIX is generally dependent and the observed number of runs is significantly fewer than the expected number of runs. Therefore the TOPIX conforms to the AMH and type 4 behaviour.

Although the empirical results for the runs test give an insight into the behaviour of stock price returns, the test is not considered a sophisticated method for identifying movements, since the termination of the movement is simply predicted when the price level has temporarily changed direction, regardless of the size of the price change that caused the change in sign. However, it is robust as it does not make any assumptions about the nature of the underlying returns. The results are generally consistent with the serial correlation test in the previous section.

Table 3.3: Test results for 5-yearly runs test. The first two columns are the sample periods chosen, the third column indicating the number of observations examined, the fourth column documenting the median, while the fifth and sixth columns indicate the number of observations greater than and less than the median. The seventh column shows that expected number of runs, with column eight showing the actual number of runs found, while the ninth and tenth columns indicate the z-statistic and the p-value respectively. ***, **, * indicate significance at 1%, 5% and 10%.

Sample Periods		Runs Test							
Start Year	**End Year**	**Cases**	**Mean**	**Cases < Mean**	**Cases > Mean**	**Expected Number of runs**	**Actual Number of Runs**	**z-Statistic**	**p-value**
Panel A: DJIA									
Full Sample		30868	0.000190	15000	15868	15422.80	14733	-7.86***	0.00
1897	**1899**	895	0.000540	435	460	448.15	426	-1.48	0.07
1900	**1904**	1488	0.000014	723	765	744.41	691	-2.77***	0.00
1905	**1909**	1502	0.000227	723	779	750.96	737	-0.72	0.24
1910	**1914**	1384	-0.000201	664	720	691.87	696	0.22	0.59
1915	**1919**	1490	0.000453	729	761	745.66	725	-1.07	0.14
1920	**1924**	1498	0.000068	710	788	747.97	691	-2.95***	0.00
1925	**1929**	1486	0.000483	666	820	736.02	695	-2.15**	0.02
1930	**1934**	1485	-0.000575	745	740	743.49	767	1.22	0.89
1935	**1939**	1501	0.000242	727	774	750.76	767	0.84	0.80
1940	**1944**	1502	0.000004	703	799	748.93	677	-3.73***	0.00
1945	**1949**	1414	0.000192	685	729	707.32	624	-4.44***	0.00
1950	**1954**	1337	0.000531	643	694	668.53	581	-4.80***	0.00
1955	**1959**	1259	0.000403	599	660	629.02	554	-4.24***	0.00
1960	**1964**	1257	0.000201	614	643	629.17	555	-4.19***	0.00
1965	**1969**	1230	-0.000068	604	626	615.80	515	-5.57***	0.00
1970	**1974**	1262	-0.000216	642	620	631.81	519	-6.36***	0.00
1975	**1979**	1262	0.000224	635	627	631.97	600	-1.80*	0.04
1980	**1984**	1264	0.000304	648	616	632.59	608	-1.39	0.08
1985	**1989**	1263	0.000658	616	647	632.12	656	1.35	0.91
1990	**1994**	1264	0.000246	625	639	632.92	654	1.19	0.88
1995	**1999**	1263	0.000869	627	636	632.47	621	-0.65	0.26
2000	**2004**	1256	0.000041	618	638	628.84	667	2.15**	0.98
2005	**2009**	1286	0.000022	591	695	639.79	681	2.31**	0.99
Panel B: FT30									
Full Sample		19155	0.000154	9635	9520	9578.15	8284	-18.70***	0.00
1935	**1939**	1142	-0.000248	523	619	567.96	418	-8.94***	0.00
1940	**1944**	1284	0.000312	650	634	642.90	461	-10.16***	0.00
1945	**1949**	1367	-0.000047	4686	781	600.16	373	-13.50***	0.00
1950	**1954**	1275	0.000460	627	648	638.33	446	-10.78***	0.00
1955	**1959**	1278	0.000477	603	675	637.97	458	-10.10***	0.00
1960	**1964**	1273	-0.000009	604	669	635.84	500	-7.64***	0.00
1965	**1969**	1267	0.000159	622	645	634.29	517	-6.60***	0.00
1970	**1974**	1271	-0.000737	642	629	636.43	575	-3.45***	0.00
1975	**1979**	1273	0.000795	681	592	634.39	605	-1.66*	0.05
1980	**1984**	1302	0.000639	667	635	651.61	638	-0.75	0.23
1985	**1989**	1300	0.000548	624	676	649.96	621	-1.61	0.05
1990	**1994**	1303	0.000160	682	621	651.07	655	0.22	0.59
1995	**1999**	1304	0.000434	650	654	652.99	631	-1.22	0.11
2000	**2004**	1304	-0.000570	591	713	647.29	636	-0.63	0.26
2005	**2009**	1303	-0.000028	590	713	646.69	650	0.18	0.57
Panel C: TOPIX									
Full Sample		15390	0.000283	7482	7908	7690.10	6912	-12.55***	0.00
1951	**1954**	1041	0.000923	551	490	519.71	400	-7.45***	0.00
1955	**1959**	1303	0.000746	664	639	652.26	526	-7.00***	0.00
1960	**1964**	1305	0.000096	673	632	652.86	562	-5.04***	0.00
1965	**1969**	1304	0.000517	669	635	652.56	642	-0.59	0.28
1970	**1974**	1305	0.000345	621	684	651.98	560	-5.11***	0.00
1975	**1979**	1303	0.000384	666	637	652.18	601	-2.84***	0.00
1980	**1984**	1304	0.000527	693	611	650.42	579	-3.97***	0.00
1985	**1989**	1303	0.000882	676	627	651.58	576	-4.20***	0.00
1990	**1994**	1304	-0.000471	626	678	651.96	589	-3.49***	0.00
1995	**1999**	1304	0.000076	704	600	648.85	619	-1.66*	0.05
2000	**2004**	1304	-0.000310	622	682	651.62	592	-3.31***	0.00
2005	**2009**	1304	-0.000181	586	718	646.32	632	-0.80	0.21

The results of the variance ratio test for the three stock markets are documented in Table 3.4. The DJIA results for the full sample show that there is negative correlation between returns for all four tested *k*'s, which are statistically significant at 1%. The results for the subsample analysis show that only the period 1940-1944 has significant positive correlation for all four *k*'s tested. However, some subsamples have certain *k*'s which provide significant negative autocorrelation, namely the 1950-1954, 1955-1959, 1970-1974, 1975-1979 and 1980-1984 subsamples. All other subsamples do not have any *k*'s that are significant, indicating that returns may have some correlation, but they are not statistically significant. Some of the subsamples have test statistics that are equal to unity, which indicates independence, but due to the lack of significance associated with the results, independence of returns is not accepted. Thus the DJIA variance ratio test results indicate that returns do conform to the AMH and type 4 behaviour.

In contrast to the DJIA full sample results, FT30 full sample results are positively serially correlated, also significant at 1% confidence. From 1935 to 1959 every subsample's *k* produces a test statistic that is significant which provides strong evidence of positive serial correlation. The subsamples 1960-1964, 1985-1989, 1990-1994 and 1995-1999 all have at least one *k* that is greater than one and at least 5% statistically significant. All but eleven of the test statistics are greater than one, suggesting that the FT30 has more positive serial correlation than negative serial correlation. Also, of the last two subsamples, 6 out of the 8 test statistics are less than one, suggesting that the FT30 is moving towards negative correlation from positive (although none of them are statistically significant). Thus, the FT30 results suggest that returns independence vary over time, indicating type 4 behaviour.

The TOPIX full sample results show that at each *k*, the test statistic is greater than one and significant at 1% confidence, indicating positive serial correlation, similar to the FT30. For the subsample analysis, all test statistics are greater than one from 1950-1984, with only two *k*'s being not statistically significant at at least 10%. Similar to the FT30, towards the end of the sample the test statistics gradually fall in value with a number of them being less than one, suggesting that the correlation in returns has shifted from being positive to negative, although none of the negative correlations are statistically significant. Hence TOPIX returns have followed a random walk since 1995, but before that returns were non-random, suggesting a switch in the market and type 3 behaviour.

Table 3.4. Test results for the 5-yearly Lo MacKinlay Variance Ratio test. The columns show variance ratios for number *k* of heteroskedastic test statistics. The p-values based on the empirical distribution are in parentheses. A p-value less than 0.05 means that the null hypothesis that an equity price index follows a random walk can be rejected at the 5% level, in favour of the alternative hypothesis that the returns are positively serially correlated. ***, **, * indicate significance at 1%, 5% and 10%.

		DJIA				**FT30**				**TOPIX**			
		$M_2(k)$				**$M_2(k)$**				**$M_2(k)$**			
Sample Period		**k = 2**	**k = 4**	**k= 8**	**k = 16**	**k = 2**	**k = 4**	**k= 8**	**k = 16**	**k = 2**	**k = 4**	**k= 8**	**k = 16**
Full Sample		0.684589*** (0.00)	0.673678*** (0.00)	0.692712*** (0.00)	0.716636*** (0.00)	1.073792*** (0.00)	1.109575*** (0.00)	1.144081*** (0.00)	1.243455*** (0.00)	1.084973*** (0.00)	1.108995*** (0.00)	1.133461*** (0.01)	1.168451*** (0.02)
1897	**1899**	0.994230 (0.92)	1.021715 (0.83)	1.147899 (0.34)	1.254912 (0.24)	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
1900	**1904**	1.016626 (0.69)	0.993955 (0.94)	1.072156 (0.52)	1.099786 (0.52)	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
1905	**1909**	1.012951 (0.82)	1.032401 (0.73)	1.192731 (0.14)	1.273946 (0.12)	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
1910	**1914**	0.995024 (0.95)	0.991873 (0.94)	0.992468 (0.96)	0.964140 (0.85)	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
1915	**1919**	0.995379 (0.90)	0.991604 (0.90)	1.016143 (0.88)	1.077825 (0.60)	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
1920	**1924**	1.050363 (0.09)	1.083919 (0.14)	1.176911 (0.05)	1.275510 (0.04)	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
1925	**1929**	0.991605 (0.84)	0.911414 (0.21)	0.920090 (0.42)	0.818240 (0.19)	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
1930	**1934**	0.674493 (0.30)	0.523346 (0.32)	0.446612 (0.32)	0.421558 (0.33)	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
1935	**1939**	1.036021 (0.28)	1.062555 (0.34)	1.126747 (0.24)	1.118624 (0.45)	1.255541*** (0.00)	1.431245*** (0.00)	1.425801** (0.02)	1.477059** (0.04)	n/a	n/a	n/a	n/a
1940	**1944**	1.144205*** (0.01)	1.263774 (0.01)	1.428811*** (0.01)	1.554797 (0.01)	1.410043*** (0.00)	2.078909*** (0.00)	2.746558*** (0.00)	3.019325*** (0.00)	n/a	n/a	n/a	n/a
1945	**1949**	1.059450*** (0.00)	1.024481 (0.53)	0.994057 (0.92)	1.010260 (0.91)	1.418311*** (0.00)	1.938310*** (0.00)	2.180219*** (0.00)	2.504156*** (0.00)	n/a	n/a	n/a	n/a
1950	**1954**	0.993791 (0.60)	0.974151 (0.19)	0.948745* (0.09)	0.923526* (0.07)	1.409275*** (0.00)	1.860840*** (0.00)	2.099350*** (0.00)	2.350732*** (0.00)	1.199467*** (0.00)	1.321500*** (0.00)	1.473516*** (0.00)	1.705784*** (0.00)
1955	**1959**	0.989097 (0.27)	0.965735** (0.04)	0.944478** (0.02)	0.913959 (0.01)	1.269764*** (0.00)	1.435966*** (0.00)	1.485091*** (0.00)	1.675342*** (0.00)	1.076937* (0.10)	1.234167 (0.00)	1.377949*** (0.00)	1.528571*** (0.00)
1960	**1964**	0.986831 (0.19)	1.096526 (0.45)	1.135281 (0.48)	1.125105 (0.58)	1.194617*** (0.00)	1.206016 (0.04)	1.066675 (0.62)	1.201328 (0.24)	1.171532*** (0.00)	1.325455*** (0.00)	1.514718*** (0.00)	1.676319*** (0.00)
1965	**1969**	0.990912 (0.36)	1.102208 (0.42)	1.141692 (0.46)	1.131125 (0.56)	1.047208 (0.53)	1.049410 (0.68)	0.980449 (0.90)	1.030725 (0.87)	1.052563 (0.12)	1.127648** (0.05)	1.189105* (0.07)	1.218258 (0.14)
1970	**1974**	0.984562 (0.95)	0.985388 (0.53)	0.944569* (0.10)	0.893321** (0.02)	1.026836 (0.62)	1.010505 (0.91)	0.992595 (0.95)	1.068224 (0.69)	1.135292*** (0.01)	1.342320*** (0.00)	1.556449*** (0.00)	1.654739*** (0.00)
1975	**1979**	0.999720 (0.97)	0.988161 (0.37)	0.964114 (0.08)	0.933269 (0.02)	1.072206 (0.12)	1.090415 (0.28)	1.158771 (0.22)	1.308131 (0.10)	1.179027*** (0.00)	1.369131*** (0.00)	1.364329*** (0.00)	1.449376*** (0.00)
1980	**1984**	0.997251 (0.67)	0.988297 (0.31)	0.969207 (0.08)	0.937803 (0.03)	0.959975 (0.37)	0.990864 (0.90)	1.019782 (0.86)	0.980367 (0.90)	1.132762*** (0.00)	1.216885*** (0.00)	1.253216** (0.04)	1.289979* (0.08)
1985	**1989**	1.314322 (0.32)	1.453087 (0.34)	1.507450 (0.36)	1.540973 (0.36)	1.057573 (0.58)	1.099132 (0.57)	1.248095 (0.30)	1.519403* (0.08)	1.055624 (0.63)	1.031912 (0.86)	1.043641 (0.86)	1.029188 (0.92)
1990	**1994**	1.000944 (0.69)	0.997748 (0.68)	0.985324 (0.14)	0.971119 (0.06)	1.061952* (0.10)	1.133186 (0.05)	1.216885** (0.04)	1.317986** (0.03)	1.145287*** (0.00)	1.136779* (0.07)	1.162416 (0.18)	1.209481 (0.23)
1995	**1999**	1.000092 (0.97)	1.333250 (0.32)	1.492277 (0.33)	1.567792 (0.33)	1.073062** (0.04)	1.050262 (0.47)	1.012018 (0.91)	1.036337 (0.83)	1.031930 (0.37)	1.006300 (0.93)	0.918095 (0.44)	0.969532 (0.84)
2000	**2004**	0.998531 (0.54)	1.327317 (0.33)	1.481169 (0.34)	1.534799 (0.36)	0.994142 (0.88)	0.965178 (0.64)	0.952392 (0.69)	1.038857 (0.82)	1.062423 (0.02)	1.051508 (0.35)	0.966719 (0.71)	0.847924 (0.26)
2005	**2009**	0.997784 (0.57)	0.994511 (0.39)	0.993143 (0.42)	0.984551 (0.24)	1.008282 (0.85)	0.930749 (0.41)	0.924512 (0.59)	0.922240 (0.71)	1.002568 (0.96)	0.907377 (0.36)	0.859886 (0.40)	0.808715 (0.44)

These results differ somewhat from the autocorrelation results for each market. For example, the DJIA found significant positive serial correlation from 1920-1929, 1940-1979 and from 2005-2009, whereas the variance ratio test found significant positive serial correlation from 1940-1959 and only very rarely in any other subsample. However, the results of the FT30 and TOPIX for the variance ratio test are quite similar to their results for the autocorrelation test. This may suggest that the serial correlation results are affected more by the heteroskedastic property of their returns in the DJIA market than the FT30 and TOPIX markets. To investigate the series further, we conduct three of the most common unit root tests to overcome the potential problems associated with each one.

Tables 3.5, 3.6 and 3.7 document the results for the ADF, PP and KPSS tests for the DJIA, FT30 and TOPIX respectively. The ADF and PP test have nonstationarity as their null hypothesis, with the alternative hypothesis being stationarity. To avoid an over rejection of the null hypothesis, the KPSS test was also conducted, which has stationarity as its null hypothesis and nonstationarity as its alternative hypothesis. The results for each tests full sample show that the price level for the DJIA is nonstationary, but when the first difference is taken (returns), the series becomes stationary at 1% significance. In each case the pure random walk, the random with drift and the random walk with drift and deterministic trend are all significant at 1%, indicating that the DJIA returns are trend stationary with a drift. The subsample analysis for the DJIA shows that all samples price level are nonstationary except the random walk with drift of the 1910-1914 subsample, which rejects the null at 5% significance indicating stationarity. All of the returns reject the null hypothesis at 1%, suggesting that returns are stationary at 1% significance. These results for the ADF test are supported by the PP test, which deliver very similar results. Again the only price level that does not accept the null hypothesis is the random walk with drift 1910-1914 subsample, which is stationary with 5% significance. As with the ADF test, all returns for the PP test reject the null hypothesis of nonstationary at 1%, indicating stationarity of returns. The KPSS test results show that each subsample for the price level reject the null hypothesis of stationarity at 5% significance, except the 1945-1949 subsample of random walk with drift. However, the same subsamples random walk with drift and deterministic trend rejects the null hypothesis at 1%, indicating that that subsample price level, and all subsamples, are nonstationary with drift and deterministic trend. The returns show that the 1900-1904, 1905-1909, 1915-1919, 1975-1979 and 2005-2009 subsamples are only stationary with drift and stay nonstationary when a deterministic trend is included. The 1960-1964 subsample is only stationary with a drift and deterministic trend, while the remaining subsample are stationary with a drift, and with a drift and deterministic trend. The results show that in some subsamples, we may have over rejected the null in the ADF and PP test. These results show that the price level of the DJIA appear to be nonstationary in every subsample for all three tests for the random walk with drift and deterministic trend, and for the majority of subsamples tested for the pure random walk and random walk with drift. Thus, since nonstationarity suggests the randomness of a series, we can conclude that the DJIA appears to be random and generally integrated at order one and type 1 behaviour.

Table 3.6 indicates those results for the ADF, PP and KPSS test for the FT30 for the full sample 1935-2009 and 5 yearly subsamples. The results for the full sample show that each form the random walk is nonstationary in the price series, and stationary at returns. This indicates that the FT30 is integrated of order one and is trend stationary with drift in returns. However, the subsample analysis reveals that the subsample 1975-1979 is stationary at the price level for a random walk with drift, while the subsample 2000-2004 is stationary for a pure random walk. This indicates that these forms of the random walk model are not appropriate for the FT30 price series. However, within these subsamples and all other subsamples, the other forms the random walk model are nonstationary, indicating the randomness of these prices. The results for the returns are all stationary at 1% significance, indicating that returns are non random. However, the result for the KPSS test indicates that each subsample price series is nonstationary, indicating randomness in the price series. The returns are all stationary in some form of the random walk model except the 1955-1959 and 1970-1974 subsamples, in which both forms of the random walk model are nonstationary. Thus the FT30 can be categorized as type 1 behaviour.

Table 3.7 shows the results for the unit roots on the TOPIX price level and returns series. The results for the full sample show that the price level is nonstationary for all three unit root tests, while the returns are stationary in all forms of the random walk model for the ADF and PP test, but only for the random walk with drift and deterministic trend for the KPSS test. The results for the subsample analysis indicate that the price level is nonstationary in some form of the random walk model for all subsamples. However, the pure random walk model and random walk with drift are both stationary for the subsample 1990-1994, suggesting that the drift parameter is key to this subsample. All returns for the subsample are significant at 1%, thus rejecting the null hypothesis of nonstationarity, indicating stationarity in the returns series. The Phillips-Perron test results are similar to the ADF test results example the subsample 1975-1979 is stationary at the price level for the random walk with drift and deterministic trend. The KPSS test results show that price level of all subsamples reject the null hypothesis at either random walk model, indicating the nonstationary property of the TOPIX price series. Also, all subsamples accept the null hypothesis at either random walk model for returns, indicating the stationarity of returns. Thus the TOPIX can be categorized as type 1 behaviour.

Table 3.5. Test results for the 5-yearly three unit roots for the DJIA. ***, **, * indicate significance at 1%, 5% and 10%.

Augmented Dickey-Fuller		Price Level: Pure RW	Price Level: RW with drift	Price Level: RW with drift and deterministic trend	Returns: Pure RW	Returns: RW with drift	Returns: RW with drift and deterministic trend
Panel A: Augmented Dickey-Fuller Test							
Full Sample		1.888828*	1.183362	-0.420786	-61.40087***	-61.47964***	-61.48303***
1897	**1899**	0.757129	-1.250840	-2.513381	-12.39789***	-12.45324***	-12.45283***
1900	**1904**	0.017754	-1.463485	-1.243179	-14.80109***	-14.79695***	-14.82058***
1905	**1909**	0.714676	-1.316827	-1.330840	-14.49493***	-14.51716***	-14.51244***
1910	**1914**	-1.171000*	-2.990866**	-3.052543	-37.41312***	-37.42416***	-37.41348***
1915	**1919**	0.953188	-1.979496	-1.967810	-10.59890***	-10.69248***	-10.72007***
1920	**1924**	0.295896	-0.827012	-2.249046	-14.06855***	-14.06700***	-14.22521***
1925	**1929**	-0.271953	-1.357811	-0.244870	-8.287003***	-8.431824***	-8.443545***
1930	**1934**	-1.931172*	-1.913718	-0.785701	-39.48365***	-39.49081***	-39.54951***
1935	**1939**	0.317006	-2.003444	-1.917154	-15.50673***	-15.51923***	-15.54182***
1940	**1944**	-0.009768	-1.469074	-2.063017	-7.800954***	-7.798851***	-7.968146***
1945	**1949**	-0.238139	-2.651305	-2.789411	-8.887249***	-8.932844***	-8.929751***
1950	**1954**	-0.584301	-2.050699	-1.817720	-27.82957***	-28.17176***	-28.20823***
1955	**1959**	-0.795122	-0.804316	-1.150814	-28.60468***	-28.85701***	-28.91403***
1960	**1964**	-1.021617	-0.735645	-1.194260	-34.48288***	-34.57686***	-34.71189***
1965	**1969**	-1.099789	-0.155007	-1.386617	-30.46090***	-30.46559***	-30.47845***
1970	**1974**	-1.159246	0.677285	-0.655086	-26.06512***	-26.05650***	-26.04795***
1975	**1979**	-0.762349	0.012646	-1.770965	-26.73131***	-26.80228***	-26.79922***
1980	**1984**	-0.866030	-0.595659	-1.090702	-36.45770***	-36.53195***	-36.53579***
1985	**1989**	-0.800086	-1.023154	-1.320096	-30.15568***	-30.32872***	-30.31862***
1990	**1994**	-0.963533	-0.725877	-1.248424	-36.33351***	-36.42013***	-36.44956***
1995	**1999**	-0.868935	-1.226452	-1.282364	-37.45529***	-37.80773***	-37.79571***
2000	**2004**	-1.220223	-1.090068	-2.160921	-39.22190***	-39.21840***	-39.28983***
2005	**2009**	-1.037844	-0.429282	-1.642883	-32.46945***	-32.47066***	-32.47569***
Panel B: Phillips-Perron Test							
Full Sample		1.525504	0.862592	-0.657531	-171.1806***	-171.1841***	-171.1721***
1897	**1899**	0.846614	-1.209000	-2.176155	-30.18914***	-30.22128***	-30.21342***
1900	**1904**	-0.139995	-1.517013	-1.147607	-38.19024***	-38.17769***	-38.19187***
1905	**1909**	0.703253	-1.277678	-1.295205	-38.29643***	-38.30507***	-38.29251***
1910	**1914**	-1.161448	-2.983614**	-3.045337	-37.41290***	-37.42344***	-37.41282***
1915	**1919**	1.040096	-2.124418	-2.069566	-38.68309***	-38.73120***	-38.74263***
1920	**1924**	0.225591	-0.864301	-2.327379	-36.87555***	-36.86515***	-36.90406***
1925	**1929**	-0.410023	-1.279714	0.123488	-35.34284***	-35.37686***	-35.36794***
1930	**1934**	-1.803337*	-1.840559	-1.083545	-39.47748***	-39.48376***	-39.54337***
1935	**1939**	0.327492	-2.000521	-1.907560	-37.44457***	-37.44407***	-37.44210***
1940	**1944**	-0.151741	-1.532639	-2.132456	-33.93756***	-33.92713***	-33.92010***
1945	**1949**	-0.218601	-2.734483*	-2.860751	-32.55505***	-32.56043***	-32.54870***
1950	**1954**	-0.578112	-2.047983	-1.804358	-32.96047***	-33.17512***	-33.18732***
1955	**1959**	-0.794262	-0.804316	-1.127349	-34.70304***	-34.76574***	-34.81379***
1960	**1964**	-1.025062	-0.463283	-0.955769	-34.61723***	-34.65327***	-34.74442***
1965	**1969**	-1.109876	0.116292	-1.195480	-30.77268***	-30.70015***	-30.70154***
1970	**1974**	-1.144304	0.650708	-0.662742	-30.21489***	-30.20351***	-30.19189***
1975	**1979**	-0.762240	0.002934	-1.762520	-31.91106***	-31.94510***	-31.93903***
1980	**1984**	-0.866065	-0.597960	-1.090053	-36.45778***	-36.54556***	-36.51751***
1985	**1989**	-0.810348	-1.046572	-1.327671	-38.38256***	-38.57213***	-38.55812***
1990	**1994**	-0.963409	-0.729047	-1.248248	-36.28471***	-36.35689***	-36.38711***
1995	**1999**	-0.868955	-1.227626	-1.271167	-37.44165***	-37.92171***	-37.90877***
2000	**2004**	-1.246377	-0.762479	-1.785409	-39.26664***	-39.26540***	-39.36683***
2005	**2009**	-1.037183	-0.383662	-1.606787	-44.35994***	-44.37062***	-44.39134***
Panel C: KPSS Test							
Full Sample		n/a	11.52930***	3.580821***	n/a	0.095310	0.035739
1897	**1899**	n/a	3.221466***	0.309500***	n/a	0.082853	0.069613
1900	**1904**	n/a	1.725739***	0.449456***	n/a	0.187107	0.152068**
1905	**1909**	n/a	0.534384**	0.567147***	n/a	0.198162	0.196765**
1910	**1914**	n/a	0.818568***	0.263598***	n/a	0.088202	0.081091
1915	**1919**	n/a	0.986386***	0.489070***	n/a	0.263886	0.185508**
1920	**1924**	n/a	1.778395***	0.441549***	n/a	0.448126*	0.100507
1925	**1929**	n/a	3.821838***	0.462245***	n/a	0.084670	0.080382
1930	**1934**	n/a	2.973070***	1.115141***	n/a	0.421042*	0.085806
1935	**1939**	n/a	0.658274**	0.667894***	n/a	0.190189	0.097391
1940	**1944**	n/a	1.295774***	0.888829***	n/a	0.339982	0.050612
1945	**1949**	n/a	0.368754*	0.282760***	n/a	0.113880	0.113512
1950	**1954**	n/a	0.747601***	0.391852***	n/a	0.313011	0.144324*
1955	**1959**	n/a	0.629757**	0.530588***	n/a	0.390934*	0.128828*
1960	**1964**	n/a	0.950429***	0.604035***	n/a	0.583236**	0.054595
1965	**1969**	n/a	2.264755***	0.775720***	n/a	0.151878	0.073382
1970	**1974**	n/a	2.217979***	1.060092***	n/a	0.106196	0.097203
1975	**1979**	n/a	2.315612***	0.752140***	n/a	0.311778	0.294715***
1980	**1984**	n/a	0.928141***	0.702866***	n/a	0.140334	0.058993
1985	**1989**	n/a	0.833299***	0.748173***	n/a	0.079913	0.079946
1990	**1994**	n/a	1.130751***	0.759803***	n/a	0.162166	0.038234
1995	**1999**	n/a	0.718301**	0.731104***	n/a	0.038754	0.036090
2000	**2004**	n/a	2.288977***	0.541512***	n/a	0.411900*	0.032345
2005	**2009**	n/a	2.503277***	0.914885***	n/a	0.229374	0.193117**

Table 3.6. Test results for the 50yearly three unit roots for the FT30. ***, **, * indicate significance at 1%, 5% and 10%.

Augmented Dickey-Fuller		Price Level			Returns		
		Pure RW	RW with drift	RW with drift and deterministic trend	Pure RW	RW with drift	RW with drift and deterministic trend
Panel A: Augmented Dickey-Fuller Test							
Full Sample		-0.199795	-1.011472	-1.946400	-128.5212***	-128.5432***	-128.5402***
1935	**1939**	-0.822753	-0.525238	-2.310060	-26.02075***	-26.02743***	-26.04819***
1940	**1944**	1.358081	-0.031280	-3.320783*	-15.02071***	-15.06257***	-15.09280***
1945	**1949**	-0.336526	-2.221749	-2.539891	-17.52021***	-17.51448***	-17.52458***
1950	**1954**	2.408924	1.320414	0.052184	-23.00862***	-23.13576***	-23.19367***
1955	**1959**	2.362030	2.674910*	1.411499	-27.05596***	-27.11993***	-27.24773***
1960	**1964**	-0.104567	-1.789117	-2.056188	-21.94188***	-21.93311***	-21.94007***
1965	**1969**	0.341775	-1.218256	-1.383360	-33.97388***	-33.96905***	-33.95695***
1970	**1974**	-1.208843	0.488109	-0.049079	-34.64228***	-34.71636***	-34.87196***
1975	**1979**	0.562057	-3.512188***	-2.929558	-33.40985***	-33.46900***	-33.66500***
1980	**1984**	2.011152	-0.011683	-2.538514	-37.42870***	-37.53543***	-37.52379***
1985	**1989**	1.273801	-1.133449	-2.092576	-33.94805***	-34.01019***	-33.99965***
1990	**1994**	0.544275	-0.999326	-2.685833	-33.94609***	-33.94305***	-33.93355***
1995	**1999**	1.404390	-0.777032	-3.064158	-33.52926***	-33.59207***	-33.57930***
2000	**2004**	-2.564457**	-2.200776	-1.126301	-36.22793***	-36.28321***	-36.33033***
2005	**2009**	-0.288744	-1.087193	-1.672565	-17.16047***	-17.15403***	-17.17673***
Panel B: Phillips-Perron Test							
Full Sample		-0.252218	-1.053472	-2.022467	-129.8838***	-129.8325***	-129.8291***
1935	**1939**	-0.884167	-0.388169	-2.198731	-25.70709***	-25.70380***	-25.70558***
1940	**1944**	1.526249	-0.017957	-2.953604	-24.67473***	-24.65303***	-24.63438***
1945	**1949**	-0.322714	-1.851104	-2.192184	-23.21089***	-23.20137***	-23.18811***
1950	**1954**	2.741506	1.769603	0.396928	-23.12826***	-23.15527***	-23.15940***
1955	**1959**	2.537800	3.198641	1.841775	-27.05596***	-27.12888***	-26.97154***
1960	**1964**	-0.194850	-1.968061	-2.265235	-28.83970***	-28.82698***	-28.81968***
1965	**1969**	0.336993	-1.232572	-1.414470	-33.94146***	-33.93551***	-33.92273***
1970	**1974**	-1.231443	0.578317	0.020267	-34.63176***	-34.70451***	-34.86576***
1975	**1979**	0.550993	-3.506863***	-2.949894	-33.43732***	-33.46829***	-33.66760***
1980	**1984**	2.098317	0.045571	-2.536736	-37.42870***	-37.51017***	-37.49881***
1985	**1989**	1.001148	-1.304239	-2.473518	-34.62084***	-34.62051***	-34.60935***
1990	**1994**	0.472039	-1.124721	-2.894165	-34.05719***	-34.05120***	-34.04047***
1995	**1999**	1.514396	-0.703448	-2.895597	-33.45566***	-33.51092***	-33.49749***
2000	**2004**	-2.583975***	-2.208165	-1.110686	-36.22776***	-36.28692***	-36.33902***
2005	**2009**	-0.274621	-0.998787	-1.611873	-35.86139***	-35.84711***	-35.86512***
Panel C: KPSS Test							
Full Sample		n/a	14.07482***	2.276614***	n/a	0.077827	0.075991
1935	**1939**	n/a	3.266916***	0.705774***	n/a	0.223610	0.078220
1940	**1944**	n/a	4.039336***	0.357038***	n/a	0.143140	0.083932
1945	**1949**	n/a	1.017553***	0.663613***	n/a	0.112544	0.030531
1950	**1954**	n/a	2.121500***	0.654171***	n/a	0.416310*	0.184495**
1955	**1959**	n/a	1.619971***	0.724566***	n/a	0.670881**	0.146034**
1960	**1964**	n/a	1.004949***	0.736382***	n/a	0.108889	0.047919
1965	**1969**	n/a	2.487326***	0.395123***	n/a	0.125870	0.123383*
1970	**1974**	n/a	1.128031***	0.948967***	n/a	0.886872***	0.194677**
1975	**1979**	n/a	3.126845***	0.354881***	n/a	0.628478**	0.110845
1980	**1984**	n/a	4.108682***	0.726596***	n/a	0.032020	0.019758
1985	**1989**	n/a	3.157311***	0.315526***	n/a	0.053736	0.045947
1990	**1994**	n/a	3.496829***	0.236431***	n/a	0.070387	0.059586
1995	**1999**	n/a	3.886727***	0.136511*	n/a	0.029087	0.028769
2000	**2004**	n/a	3.740270***	0.812946***	n/a	0.320683	0.095354
2005	**2009**	n/a	1.526930***	0.904140***	n/a	0.261958	0.129586*

Table 3.7. Test results for the 5-yearly three unit roots for the TOPIX. ***, **, * indicate significance at 1%, 5% and 10%.

Augmented Dickey-Fuller		Price Level			Returns		
		Pure RW	RW with drift	RW with drift and deterministic trend	Pure RW	RW with drift	RW with drift and deterministic trend
Panel A:Augmented Dickey-Fuller Test							
Full Sample		-0.473954	-1.341092	-1.327914	-86.06534***	-86.14092***	-86.24064***
1951	1954	0.873096	-1.634896	-1.063586	-26.24696***	-26.38350***	-26.49948***
1955	1959	3.592861	0.577303	-0.922387	-22.25197***	-22.58978***	-22.58181***
1960	1964	0.070864	-2.376163	-2.641035	30.40048***	-30.39200***	-30.45803***
1965	1969	3.126206	1.710080	-0.144446	-34.10496***	-34.26729***	-34.30299***
1970	1974	0.596059	-1.008078	-0.345710	-21.79966***	-21.82752***	-21.84046***
1975	1979	2.125458	-1.284012	-3.242004*	-30.01444***	-30.15427***	-30.16206***
1980	1984	2.914465	1.114934	-1.035117	-31.42558***	-31.62773***	-31.65356***
1985	1989	2.720033	-0.078113	-2.494436	-33.93954***	-34.16882***	-34.15969***
1990	1994	-2.264240**	-3.668070***	-2.967096	-26.07695***	-26.11249***	-26.18530***
1995	1999	0.141094	-1.1281264	-0.734404	-35.01634***	-35.00435***	-35.04338***
2000	2004	-1.405522	-2.351487	-1.695192	-33.94672***	-33.95206***	-34.00515***
2005	2009	-0.518679	-0.712071	-1.846270	-27.50367***	-27.49898***	-27.55113***
Panel B:Phillips-Perron Test							
Full Sample		-0.512777	-1.374546	-1.417186	-114.3118***	-114.2376***	-114.2194***
1951	1954	0.915923	-1.654613	-1.016178	-26.20044***	-26.38350***	-26.45519***
1955	1959	2.905748	0.286469	-1.203663	-34.18511***	-34.07062***	-34.06410***
1960	1964	0.024259	-2.456287	-2.679230	-30.75334***	-30.74432***	-30.75091***
1965	1969	2.8652352	1.489869	-0.357172	-34.31130***	-34.40335***	-34.42509***
1970	1974	0.519579	-1.034308	-0.487708	-32.12525***	-32.13102***	-32.13059***
1975	1979	2.221472	-1.269143	-3.157363***	-30.09244***	-30.18346***	-30.19080***
1980	1984	3.040723	1.214912	-0.955551	-31.42558***	-31.61591***	-31.63429***
1985	1989	2.655340	-0.101630	-2.543604	-33.93954***	-34.12793***	-34.11822***
1990	1994	-2.221639**	-3.618126***	-2.928534	-31.01211***	-31.02045***	-31.06505***
1995	1999	0.138095	-1.193975	-0.744944	-35.00089***	-34.98854***	-35.02771***
2000	2004	-1.625455*	-2.383526	-1.425126	-33.92046***	-33.94822***	-34.06429***
2005	2009	-0.522101	-0.617543	-1.798371	-36.24422***	-36.23919***	-36.33694***
	Panel C: KPSS Test						
Full Sample		n/a	11.50985***	1.199753***	n/a	0.967950***	0.064139
1951	1954	n/a	2.989382***	0.767879***	n/a	0.558945**	0.079800
1955	1959	n/a	3.402697***	0.570546***	n/a	0.123993	0.122495*
1960	1964	n/a	0.426555*	0.303027***	n/a	0.281121	0.071285
1965	1969	n/a	3.394122***	0.616349***	n/a	0.238148	0.095447
1970	1974	n/a	3.258121***	0.583725***	n/a	0.358987*	0.275312***
1975	1979	n/a	4.126023***	0.136623*	n/a	0.091789	0.039138
1980	1984	n/a	3.680787***	0.767629***	n/a	0.223310	0.062599
1985	1989	n/a	4.124859***	0.256217***	n/a	0.080172	0.055043
1990	1994	n/a	2.294063***	0.762936***	n/a	0.328445	0.052732
1995	1999	n/a	1.049832***	0.420969***	n/a	0.280670	0.139635*
2000	2004	n/a	2.536764***	0.987941***	n/a	0.374551*	0.040517
2005	2009	n/a	2.063366***	0.888522***	n/a	0.399697*	0.110272

3.6.2. Nonlinear Empirical Results

The nonlinear empirical results are documented below, but first the linear dependence in returns has to be removed. Table 3.8 documents the Ljung-Box statistics for the returns of the three indices studied. If the stock returns are autocorrelated, nonlinearities cannot be detected reliably by testing the original data. Significant autocorrelation structures of returns are found in all subsamples except the 1910-1914, 1930-1934, 1980-1984 and 2000-2004 subsamples for the DJIA, and 1965-1969 subsample for the TOPIX. Thus on the basis of the Ljung-Box portmanteau test we can conclude that the stock returns are characterized by temporal linear relationships. Therefore to examine the nonlinear dependence in returns, the removal of linear dependence must be conducted.

Table 3.8. Ljung-Box statistics for the daily returns. ***, **, * indicate significance at 1%, 5% and 10%.

		Ljung-Box Test Statistics			
		Qrr(5)	**Qrr(10)**	**Qrr(15)**	**Qrr(20)**
Panel A: DJIA					
Full Sample		109.40***	162.38***	170.73***	178.37***
1897	**1899**	17.85***	25.97***	34.98***	37.69***
1900	**1904**	19.67***	33.23***	37.90***	47.52***
1905	**1909**	26.74***	51.19***	54.27***	58.94***
1910	**1914**	3.04	7.57	12.43	15.10
1915	**1919**	5.75	19.99**	28.50**	34.60**
1920	**1924**	7.33	17.09**	25.49**	34.49**
1925	**1929**	164.15***	218.72***	233.46***	245.92***
1930	**1934**	2.23	6.85	11.60	19.91
1935	**1939**	8.90*	20.76**	25.55**	31.62**
1940	**1944**	56.87***	75.04***	75.93***	93.94***
1945	**1949**	58.77***	80.64***	101.13***	110.91***
1950	**1954**	37.72***	49.25***	54.64***	58.12***
1955	**1959**	30.66***	38.73***	40.97***	55.69***
1960	**1964**	18.22***	23.45***	29.78**	54.96***
1965	**1969**	75.65***	82.50***	92.05***	98.46***
1970	**1974**	70.22***	82.31***	86.43***	89.92***
1975	**1979**	43.62***	53.94***	60.33***	62.32***
1980	**1984**	9.16	10.28	12.90	16.11
1985	**1989**	26.59***	58.45***	32.75***	41.42***
1990	**1994**	4.67	17.41*	28.62**	35.79**
1995	**1999**	7.29	19.24**	29.24**	45.32***
2000	**2004**	5.44	8.53	17.50	28.31
2005	**2009**	45.99***	59.62***	73.00***	94.36***
Panel B:FT30					
Full Sample		125.32***	190.79***	215.44***	224.97***
1935	**1939**	84.74***	88.50***	95.99***	99.95***
1940	**1944**	472.31***	509.85***	547.20***	659.32***
1945	**1949**	317.12***	339.79***	352.64***	372.41***
1950	**1954**	274.85***	282.63***	288.21***	288.67***
1955	**1959**	97.50***	103.80***	115.08***	118.50***
1960	**1964**	70.16***	94.91***	107.67***	116.22***
1965	**1969**	7.37	15.77	20.29	33.29**
1970	**1974**	3.98	14.81	28.63**	31.87**
1975	**1979**	12.12**	44.43***	61.70***	29.22***
1980	**1984**	7.96	16.16*	17.69	24.00
1985	**1989**	15.21***	27.44***	41.80***	44.16***
1990	**1994**	14.06**	30.32***	38.881***	44.32***
1995	**1999**	12.36**	23.16***	30.74***	3.48**
2000	**2004**	11.77**	27.55***	34.71***	46.10***
2005	**2009**	27.45***	35.34***	40.86***	49.53***
Panel C: TOPIX					
Full Sample		128.99***	150.68***	167.96***	192.36***
1951	**1954**	47.14***	56.58***	69.02***	77.69***
1955	**1959**	24.48***	32.36***	37.73***	41.45***
1960	**1964**	49.99***	50.90***	59.37***	65.90***
1965	**1969**	9.25	11.69	17.77	23.93
1970	**1974**	48.84***	52.23***	63.00***	81.72***
1975	**1979**	46.76***	74.62***	76.55***	84.33***
1980	**1984**	25.23***	27.31***	34.18***	37.39***
1985	**1989**	13.25**	22.79**	330.06**	43.40***
1990	**1994**	39.35***	44.69***	47.25***	53.51***
1995	**1999**	5.42	20.92**	25.69**	33.76**
2000	**2004**	9.10	14.47	16.90	20.32
2005	**2009**	12.71**	20.06**	29.11**	34.55**

The pre-whitening AR model enabled the examination of the existence of nonlinear structures in the stock market returns. The AR models serve as a filter for removing any linear relationships, enabling an examination of just the nonlinear returns. The AR models identified and estimated are presented in Table 3.9, with the model diagnostics showing that the elimination of a linear structure has succeeded. However, the lack of significant autocorrelations in the AR residuals does not imply that they behave purely randomly. Three tests for nonlinearity are conducted on the residuals. The McLeod-Li statistics ($Q_{rr}(k)$) of the squared AR residuals reveal that all subsamples of the three indices are highly significant, which indicates a high level of nonlinear dependence in the returns. Table 3.9 also reveals the Engle LM test statistics, which also examines the nonlinear dependence in the filtered returns. For up to lags 2, 4 and 6 there is nonlinear dependence in each subsample at 5% significance. To enhance the power of our testing, the BDS test statistics are also calculated. Table 3.10 shows significant values of the BDS test statistics for nearly all of the dimensions for the subsamples. Every subsample has the majority of different dimensions indicating nonlinear dependence in the returns. Since linear dependence has been eliminated in advance, the BDS test brings forth clear evidence of the existence of nonlinear dependence in the stock returns.

The results from Table 3.9 and Table 3.10 indicate significant nonlinear dependence in stock market returns even when linear dependence has been filtered out through an AR(p) model. Unlike the linear dependence which was found to fluctuate over time, the nonlinear dependence appears to be consistent throughout the sample periods. Thus the nonlinear dependence of each return series is strong and can be categorized by type 5.

Table 3.9. Test results for the nonlinear dependence on the AR filtered stock returns. Qss(k) is McLeod-Li statistic which tests the null hypothesis that the increments are iid. The Tsay statistics tests that all coefficients are zero and are calculated at lags 4 and 6. The Engle LM statistics are calculated up to lags 2, 4 and 6. ***, **, * indicate significance at 1%, 5% and 10%.

			Ljung-Box Test Statistics				McLeod-Li Test Statistics				Engle LM Test Statistics		
		AR	**Qr(5)**	**Qr(10)**	**Qr(15)**	**Qr(20)**	**Qrr(5)**	**Qrr(10)**	**Qrr(15)**	**Qrr(20)**	**Lag 2**	**Lag 4**	**Lag 6**
							Panel A: DJIA						
Full Sample		11	0.0058	0.0235	5.68	11.55	4424.4***	6429.2***	7576.5***	8420.8***	2122.18***	2361.35***	2814.80***
1897	**1899**	4	0.0969	4.96	12.81	15.02	138.30***	193.57***	204.30***	207.90***	59.83***	98.85***	102.61***
1900	**1904**	7	0.0916	0.7982	5.08	11.76	211.05***	240.67***	249.10***	269.02***	121.74***	149.24***	155.80***
1905	**1909**	7	0.0675	2.94	8.96	14.02	355.53***	479.96***	505.74***	508.30***	297.15***	300.87***	307.84***
1910	**1914**	0	3.04	7.57	12.43	15.10	286.30***	293.05***	295.27***	296.02***	186.44***	195.75***	196.72***
1915	**1919**	13	0.0419	0.0944	1.22	9.58	134.56***	178.43***	195.49***	202.34***	81.18***	84.09***	103.19***
1920	**1924**	9	0.0631	1.02	10.22	20.02	59.94***	113.27***	131.86***	152.96***	36.67***	38.60***	54.20***
1925	**1929**	15	0.0769	0.1694	0.8072	5.91	722.62***	1012.0***	1135.2***	1195.8***	395.47***	139.65***	449.17***
1930	**1934**	0	2.23	6.85	11.60	19.91	94.11***	155.34***	192.16***	210.18***	56.00***	60.99***	83.27***
1935	**1939**	6	0.0550	5.34	10.08	15.85	203.13***	420.19***	562.18***	652.88***	59.98***	109.92***	169.73***
1940	**1944**	6	0.1297	5.85	7.78	24.98	274.03***	424.32***	434.06***	506.19***	143.08***	223.10***	283.18***
1945	**1949**	15	0.0228	0.1265	0.2683	2.95	165.62***	183.41***	214.84***	233.74***	58.70***	118.99***	119.06***
1950	**1954**	2	2.80	10.43	16.73	20.60	155.50***	190.05***	261.53***	270.87***	10.52***	134.82***	145.19***
1955	**1959**	10	0.0348	0.1917	3.06	14.59	35.39***	46.54***	47.31***	50.98***	24.54***	24.97***	34.23***
1960	**1964**	18	0.1170	0.5050	1.17	5.98	258.78***	303.45***	349.81***	386.24***	193.21***	220.76***	221.34***
1965	**1969**	8	0.0666	1.18	8.34	13.24	77.82***	124.98***	144.25***	158.51***	34.37***	47.55***	52.93***
1970	**1974**	9	0.0065	0.2339	2.80	7.34	229.58***	401.32***	564.56***	721.86***	86.84***	127.80***	150.17***
1975	**1979**	8	0.0999	2.71	7.62	11.11	29.02***	50.18***	76.76***	118.80***	8.14**	21.95***	23.71***
1980	**1984**	0	9.16	10.28	12.90	16.11	48.61***	74.45***	115.79***	151.72***	6.32**	29.76***	40.68***
1985	**1989**	5	0.1207	3.69	10.17	19.52	22.35***	26.36***	26.76***	27.07***	13.21***	15.15***	19.25***
1990	**1994**	7	0.0931	2.34	10.93	16.52	42.53***	68.27***	101.80***	120.70***	15.36***	24.15***	36.36***
1995	**1999**	14	0.1329	0.2892	0.4926	13.02	137.77***	174.58***	184.13***	214.67***	81.70***	82.18***	103.59***
2000	**2004**	0	5.44	8.53	17.50	28.31	202.27***	305.62***	364.92***	403.26***	45.44***	138.42***	146.76***
2005	**2009**	17	0.0962	0.2722	0.3695	4.85	670.33***	1235.9***	1817.0***	2242.4***	262.17***	289.15***	392.90***
							Panel B: FT30						
Full Sample		19	0.0108	0.0577	0.0919	0.5531	5798.6***	8221.5***	10290***	11873***	2768.4***	3167.8***	3305.0***
1935	**1939**	18	0.0612	0.2460	0.3065	1.50	150.81***	171.72***	178.76***	179.75***	54.43***	115.17***	118.19***
1940	**1944**	20	0.4645	0.6530	1.16	1.86	708.85***	1395.6***	1786.4***	2150.5***	212.67***	297.28***	373.24***
1945	**1949**	19	0.0534	0.1444	0.2908	3.63	197.90***	145.39***	158.23***	160.41***	87.94***	95.04***	95.52***
1950	**1954**	2	5.16	9.93	12.73	15.64	59.77***	61.64***	63.00***	63.89***	33.65***	36.35***	48.70***
1955	**1959**	15	0.0223	0.0829	0.4064	5.07	100.06***	108.41***	109.28***	111.25***	82.15***	84.56***	84.58***
1960	**1964**	12	0.1898	0.2632	2.20	4.48	308.04***	310.48***	311.93***	319.21***	323.46***	326.82***	329.04***
1965	**1969**	5	0.0244	7.56	11.41	22.56	244.61***	245.51***	246.24***	246.74***	287.15***	205.36***	308.71***
1970	**1974**	13	0.0339	0.1861	4.63	6.68	197.17***	214.29***	222.91***	237.65***	175.49***	181.74***	184.58***
1975	**1979**	20	0.5665	3.43	6.14	7.46	296.56***	490.29***	637.79***	765.37***	101.50***	150.98***	173.12***
1980	**1984**	1	5.62	13.29	14.85	20.60	152.06***	163.36***	166.41***	170.29***	128.51***	133.26***	134.97***
1985	**1989**	11	0.1457	0.3821	5.42	8.88	545.29***	568.82***	571.03***	576.12***	421.25***	423.67***	423.10***
1990	**1994**	10	0.0497	0.0852	7.76	12.04	63.88***	87.68***	144.38***	150.53***	43.49***	48.11***	48.54***
1995	**1999**	2	3.67	12.58	20.73	25.77	282.77***	565.53***	845.38***	1082.4***	73.98***	119.36***	179.28***
2000	**2004**	10	0.0219	0.1152	7.30	16.39	338.91***	617.60***	784.04***	873.09***	127.15***	177.91***	198.25***
2005	**2009**	5	0.1339	6.35	12.24	22.20	430.70***	741.24***	1058.1***	1299.5***	76.08***	202.32***	258.81***
							Panel C: TOPIX						
Full Sample		18	0.0115	0.0376	0.0554	2.37	3177.5***	4835.8***	5738.9***	6670.4***	1533.5***	1820.0***	1937.3***
1951	**1954**	10	0.0643	0.2602	10.23	18.85	121.40***	132.86***	197.78***	378.16***	116.18***	117.76***	117.75***
1955	**1959**	2	4.86	14.04	19.55	23.40	117.32***	131.06***	133.33***	134.06***	76.28***	84.46***	94.92***
1960	**1964**	1	6.04	7.00	13.43	25.09	131.00***	226.41***	259.01***	292.02***	53.91***	82.26***	95.87***
1965	**1969**	0	9.25	11.69	17.77	23.93	68.23***	84.36***	87.75***	93.56***	37.00***	55.06***	56.57***
1970	**1974**	3	1.09	4.66	14.07	23.27	167.46***	170.63***	172.53***	175.77***	109.63***	110.48***	113.52***
1975	**1979**	10	0.0763	0.2240	2.84	14.36	69.92***	98.21***	102.00***	125.74***	36.34***	50.02***	54.93***
1980	**1984**	1	3.60	6.66	13.08	16.53	192.43***	199.74***	230.11***	240.67***	129.00***	131.48***	138.33***
1985	**1989**	8	0.0642	1.26	8.22	18.75	158.09***	160.79***	164.61***	175.39***	156.37***	168.75***	168.53***
1990	**1994**	2	4.62	8.24	10.03	17.72	147.57***	192.36***	202.80***	212.58***	48.38***	75.91***	95.72***
1995	**1999**	9	0.0408	0.1012	5.28	12.23	104.98***	166.24***	199.91***	269.79***	58.95***	76.89***	99.66***
2000	**2004**	1	3.60	9.02	11.10	14.82	44.64***	82.46***	89.06***	95.25***	11.70***	37.92***	49.80***
2005	**2009**	4	0.1184	7.56	15.77	21.19	738.65***	1394.8***	1685.2***	1892.2***	344.08***	422.61***	440.02***

Table 3.10. Test results for the BDS test on the AR filtered stock returns. The first row reports the dimension while the second row documents the embedding dimension by values of the standard deviation of the sample. ***, **, * indicate significance at 1%, 5% and 10% significantly.

Dimension			2				6				10			
Embedding Dimension		AR model	0.5σ	1σ	1.5σ	2σ	0.5σ	1σ	1.5σ	2σ	0.5σ	1σ	1.5σ	2σ
							Panel A: DJIA							
Full Sample		11	0.011341***	0.022363***	0.020713***	0.014555***	0.003761***	0.052932***	0.105876***	0.106638***	0.000425***	0.032963***	0.126685***	0.172350***
1897	1899	4	0.009313***	0.021436***	0.021148***	0.014260***	0.000993***	0.023239***	0.069076***	0.078347***	3e-5***	0.007537***	0.063583***	0.113733***
1900	1904	7	0.006527***	0.014273***	0.014139***	0.010459***	0.001637***	0.026440***	0.063911***	0.071392***	0.000113***	0.013497***	0.069534***	0.111681***
1905	1909	7	0.005627***	0.013923***	0.014408***	0.011539***	0.000983***	0.021837***	0.058593***	0.073724***	7e-5***	0.008676***	0.054794***	0.105371***
1910	1914	0	0.002272*	0.004487*	0.006268***	0.007528***	0.001054***	0.020184***	0.050790***	0.061215***	3e-5***	0.008783***	0.053374***	0.095219***
1915	1919	13	0.004629***	0.011931***	0.014519***	0.011149***	0.000710***	0.018094***	0.056699***	0.071558***	3e-5***	0.006770***	0.051260***	0.098073***
1920	1924	9	0.002796***	0.008027***	0.008764***	0.005863***	0.000318***	0.010960***	0.038804***	0.047602***	2e-5***	0.003517***	0.036100***	0.073260***
1925	1929	15	0.012074***	0.022730***	0.020302***	0.013440***	0.003262***	0.051485***	0.100915***	0.094222***	0.000286***	0.030281***	0.121511***	0.151102***
1930	1934	0	0.005259***	0.011114***	0.010663***	0.006933***	0.002609***	0.035112***	0.070434***	0.065186***	0.000371***	0.023066***	0.088118***	0.113684***
1935	1939	6	0.008503***	0.017749***	0.014963***	0.008939***	0.002002***	0.037574***	0.084162***	0.082490***	0.000146***	0.017370***	0.091941***	0.137942***
1940	1944	6	0.008068***	0.014639***	0.014963***	0.011141***	0.001539***	0.026298***	0.061553***	0.067083***	8e-5***	0.014318***	0.074436***	0.110391***
1945	1949	15	0.007163***	0.015708***	0.016527***	0.012627***	0.000933***	0.017878***	0.047314***	0.061481***	5e-5***	0.007901***	0.044083***	0.081389***
1950	1954	2	0.004596***	0.011280***	0.012073***	0.008181***	0.000450***	0.012118***	0.033199***	0.037890***	3e-5***	0.004701***	0.032191***	0.061264***
1955	1959	10	0.003956***	0.010477***	0.011084***	0.008378***	0.000539***	0.014147***	0.041590***	0.050519***	4e-6***	0.004673***	0.037038***	0.072731***
1960	1964	18	0.009266***	0.020807***	0.019427***	0.013251***	0.001533***	0.032089***	0.079252***	0.085526***	8e-5***	0.012783***	0.076763***	0.129337***
1965	1969	8	0.002774***	0.007270***	0.008394***	0.006216***	0.000381***	0.010366***	0.033892***	0.041772***	5e-6***	0.002987***	0.027310***	0.056149***
1970	1974	9	0.006786***	0.015161***	0.013200***	0.006744***	0.001052***	0.026674***	0.077771***	0.083571***	4e-5***	0.011878***	0.085152***	0.141519***
1975	1979	8	0.001034	0.002759	0.003428*	0.002649**	0.000112***	0.003806***	0.015060***	0.023403***	4e-6***	0.001256***	0.013580***	0.036663***
1980	1984	0	0.000125	0.000668	0.002475	0.003185**	7e-5	0.001991	0.013156***	0.025616***	-2e-6**	0.000564**	0.010591***	0.035165***
1985	1989	5	0.004550**	0.011938***	0.012650***	0.009415***	0.001811***	0.033659***	0.068725***	0.068136***	0.000214***	0.022752***	0.093653***	0.125464***
1990	1994	7	0.002563**	0.006923***	0.007338***	0.005344***	0.000507***	0.013097***	0.037534***	0.046599***	8e-6***	0.005170***	0.035511***	0.069154***
1995	1999	14	0.003209***	0.007847***	0.009729***	0.008459***	0.000772***	0.016086***	0.042996***	0.050212***	5e-5***	0.008306***	0.049657***	0.079879***
2000	2004	0	0.003700***	0.010344***	0.011709***	0.008287***	0.001015***	0.024204***	0.069543***	0.081229***	6e-5***	0.011837***	0.074096***	0.127121***
2005	2009	17	0.016633***	0.029796***	0.025036***	0.018571***	0.010047***	0.093948***	0.146221***	0.134258***	0.001728***	0.071699***	0.187616***	0.221311***
							Panel B: FT30							
Full Sample		19	0.023688***	0.032843***	0.026017***	0.017239***	0.015853***	0.086188***	0.130196***	0.119307***	0.005986***	0.065117***	0.157846***	0.188625***
1935	1939	18	0.018738***	0.034131***	0.027992***	0.019447***	0.005890***	0.066835***	0.115812***	0.116303***	0.000502***	0.036834***	0.119660***	0.1660880***
1940	1944	20	0.028285***	0.044571***	0.039270***	0.028065***	0.017061***	0.113684***	0.170017***	0.158044***	0.004049***	0.088937***	0.204032***	0.238344***
1945	1949	19	0.025265***	0.041716***	0.033991***	0.022275***	0.011720***	0.093437***	0.139665***	0.122296***	0.002386***	0.066866***	0.157418***	0.173312***
1950	1954	2	0.010993***	0.021609***	0.019293***	0.011976***	0.002552***	0.038999***	0.080707***	0.074821***	0.000181***	0.018952***	0.076345***	0.097000***
1955	1959	15	0.014287***	0.027426***	0.024839***	0.016812***	0.002561***	0.039037***	0.077000***	0.076786***	0.000146***	0.018704***	0.080664***	0.109492***
1960	1964	12	0.012618***	0.025549***	0.022805***	0.014510***	0.002139***	0.036684***	0.078405***	0.076073***	0.000204***	0.017724***	0.082194***	0.114418***
1965	1969	5	0.008756***	0.018686***	0.016711***	0.011030***	0.002066***	0.031707***	0.063022***	0.055962***	0.000120***	0.014938***	0.063606***	0.082145***
1970	1974	13	0.006889***	0.017905***	0.019587***	0.013754***	0.001524***	0.033112***	0.086306***	0.094828***	8e-5***	0.013717***	0.088288***	0.145024***
1975	1979	20	0.004638***	0.013331***	0.017230***	0.015349***	0.000569***	0.018379***	0.064115***	0.091622***	2e-5***	0.006494***	0.060132***	0.134745***
1980	1984	7	0.003509***	0.007311***	0.007124***	0.005464***	0.000341***	0.008914***	0.028408***	0.037029***	8e-6***	0.002718***	0.024556***	0.054388***
1985	1989	11	0.004755***	0.010554***	0.010587***	0.008202***	0.000910***	0.018861***	0.051706***	0.058558***	5e-5***	0.007979***	0.053844***	0.090902***
1990	1994	10	0.000841	0.002546	0.003804**	0.004322***	0.000273***	0.006921***	0.023405***	0.034460***	1e-5***	0.002401***	0.022529***	0.053086***
1995	1999	2	0.006469***	0.016360***	0.017718***	0.011686***	0.000764***	0.022047***	0.069835***	0.084012***	3e-5***	0.007681***	0.066723***	0.126092***
2000	2004	10	0.010648***	0.021963***	0.019744***	0.012991***	0.002451***	0.040957***	0.095763***	0.103858***	0.000230***	0.019788**	0.100604***	0.160400***
2005	2009	5	0.020899***	0.029864***	0.021330***	0.012104***	0.013647***	0.105562***	0.139713***	0.120541***	0.002572***	0.087416***	0.179419***	0.200589***
							Panel C:TOPIX							
Full Sample		18	0.014543***	0.025267***	0.021256***	0.014170***	0.006122***	0.065629***	0.111738***	0.101775***	0.000928***	0.043295***	0.134499***	0.165379***
1951	1954	10	0.006601***	0.013867***	0.014111***	0.012172***	0.001154***	0.021017***	0.046883***	0.052479***	8e-5***	0.009049***	0.047113***	0.077780***
1955	1959	2	0.005944***	0.012702***	0.012530***	0.008606***	0.001150***	0.023344***	0.056688***	0.057071***	5e-5***	0.008279***	0.047922***	0.069761***
1960	1964	1	0.004806***	0.010810***	0.010026***	0.006601***	0.000860***	0.020437***	0.059652***	0.068275***	5e-5***	0.007706***	0.055460***	0.100073***
1965	1969	0	0.008269***	0.016693***	0.014582***	0.007788***	0.001123***	0.023129***	0.058400***	0.059990***	4e-5***	0.008645***	0.053410***	0.085792***
1970	1974	3	0.016038***	0.030174***	0.025780***	0.016964***	0.003985***	0.061978***	0.118828***	0.113429***	0.000289***	0.032001***	0.130293***	0.166118***
1975	1979	10	0.004516***	0.008530***	0.008585***	0.005570***	0.000736***	0.015047***	0.035696***	0.037482***	3e-5***	0.006153***	0.033375***	0.054838***
1980	1984	1	0.008061***	0.013983***	0.012440***	0.009095***	0.002939	0.033790***	0.064802***	0.071362***	0.000274***	0.017372***	0.063917***	0.098577***
1985	1989	8	0.011029***	0.020736***	0.017002***	0.010720***	0.005345***	0.069031***	0.109926***	0.086340***	0.000614***	0.047956***	0.145561***	0.145533***
1990	1994	2	0.012726***	0.026729***	0.024640***	0.014986***	0.003383	0.052359***	0.104531***	0.096386***	0.000257***	0.026911***	0.116600***	0.150592***
1995	1999	9	0.002026*	0.007832***	0.01121***	0.009896***	0.000302***	0.011633***	0.041839***	0.058630***	1e-5***	0.004567***	0.038276***	0.086633***
2000	2004	1	0.000798	0.000984	0.001204	0.001113	0.000235***	0.006214***	0.023045***	0.030155***	4e-6***	0.001954***	0.023851***	0.052417***
2005	2009	4	0.010858***	0.021301***	0.020367***	0.014103***	0.004876***	0.054811***	0.103934***	0.106862***	0.000713***	0.035824***	0.123898***	0.170582***

Table 3.11. Test results for the BDS test on the AR-GARCH filtered stock returns. The first row reports the dimension while the second row documents the embedding dimension by values of the standard deviation of the sample. ***, **, * indicate significance at 1%, 5% and 10% significantly.

Dimension			**2**				**6**				**10**			
Embedding Dimension		**AR-GARCH model**	**0.5σ**	**1σ**	**1.5σ**	**2σ**	**0.5σ**	**1σ**	**1.5σ**	**2σ**	**0.5σ**	**1σ**	**1.5σ**	**2σ**
Panel A: DJIA														
Full Sample		11	-0.000277	-0.000544	-0.000304	5.68e-5	-1.00e-5	-0.000272	-0.000212	0.000796	-2.78e-7	-0.000107	-0.000415	0.000878
1897	**1899**	4	-0.001384	-0.003467	-0.003776	-0.002495	5.17e-5	0.000334	-0.003856	-0.006199	-2.78e-6	0.000266	-0.001649	-0.005304
1900	**1904**	7	-0.001404	-0.002356	-0.001626	-0.000317	7.61e-5	0.001041	0.003155	0.004924	7.05e-7	9.15e-5	0.001845	0.005867
1905	**1909**	7	-0.000442	4.24e-5	0.001067	0.001342	-3.36e-5	0.001649	0.005049	0.004513	-8.23e-8	0.000119	0.001600	0.001146
1910	**1914**	0	0.000493	0.000915	0.001026	0.000872	-6.80e-5	-0.000101	0.003005	0.007573	-6.08-6	-0.000313	0.000305	0.005866
1915	**1919**	13	-0.000337	-0.000626	8.94e-5	0.000275	4.11e-5	-0.000141	0.000190	0.000230	-3.73e-6	-0.000504	-0.002702	-0.004920
1920	**1924**	9	-0.000646	-0.001159	-0.001014	8.60e-6	-9.74e-5*	-0.001519	-0.001628	0.001856	-4.97e-6***	-0.000410	-0.002039	0.000623
1925	**1929**	15	-0.002285**	-0.005650***	-0.004799**	-0.002401	-0.000184**	-0.004698***	-0.013259***	-0.011423*	-3.17e-6	-0.000863*	-0.007417*	-0.009351
1930	**1934**	0	2.91e-6	0.000289	-0.000471	-0.000813	5.51e-5	0.000505	0.000676	0.001130	1.13e-5***	0.000248	0.001268	0.002811
1935	**1939**	6	-0.001444*	-0.002677	-0.001881	-0.000616	-0.000158**	-0.001731	-0.005607	-0.006263	3.16e-7	-0.000454	-0.003837	-0.005844
1940	**1944**	6	-0.000170	0.000385	0.000576	0.000449	8.80e-6	0.000245	0.001459	0.004737	-3.98e-6***	0.000129	0.000381	0.005629
1945	**1949**	15	-0.002149**	-0.004144**	-0.003154	-0.002016	-0.000108	-0.003981**	-0.009188*	-0.009745	-2.20e-6	-0.000672	-0.004080	-0.005683
1950	**1954**	2	0.002126*	0.004301*	0.003729*	0.002535	2.22e-5	0.002793	0.003939	0.002623	-2.41e-6	0.001215*	0.003980	0.000214
1955	**1959**	10	0.000187	-0.000831	-0.000484	0.000125	0.000156	0.002688	0.008707	0.011824*	3.74e-6	0.000788	0.008118**	0.018402**
1960	**1964**	18	0.000412	0.000194	-0.001058	-0.001764	-5.49e-6	0.001088	0.001450	-0.004091	-6.11e-6	0.000751	0.002146	-0.009141
1965	**1969**	8	0.002291*	0.001924	0.000941	0.000848	0.000290**	0.001025	3.88e-6	0.001211	2.15e-5***	0.000867	0.002155	0.005691
1970	**1974**	9	5.69e-5	5.33e-5	-0.000521	-0.001086	-0.000128	-0.001207	-0.001662	-0.001124	-6.45e-6***	-0.000352	-0.002133	-0.004407
1975	**1979**	8	-0.001143	-0.001374	-0.002079	-0.002325	-6.48e-5	-0.002208	-0.004170	-0.002760	-1.99e-6	-0.000495	-0.002339	-0.001828
1980	**1984**	0	-0.001690*	-0.003692*	-0.003064	-0.0011394	-6.38e-5	-0.001794	-0.007338	-0.007381	-5.11e-6***	-0.000373	-0.00595*	-0.012165
1985	**1989**	5	0.001333*	0.003297*	0.003233	0.002322	4.58e-5	0.000483	0.001962	0.003225	1.57e-7	0.000120	0.001171	0.003214
1990	**1994**	7	-0.000738	-0.002449	-0.002373	-0.001183	-3.95e-5	-0.001630	-0.002610	-0.000281	-4.24e-6	-0.000611	-0.002921	-0.002674
1995	**1999**	14	0.000600	-0.000810	-0.001281	-0.000714	5.94e-5	-0.000798	-0.001726	-0.002650	7.25e-6**	-0.000247	-0.002907	-0.005793
2000	**2004**	0	0.000560	0.001075	0.001829	0.001356	-9.09e-5	-0.000742	0.001593	0.004344	-9.24e-6***	-0.000313	0.001282	0.006942
2005	**2009**	17	0.00134	-0.000739	-0.001082	-0.000781	-5.05e-5	-0.000652	-0.002805	-0.002226	5.90e-6***	-0.000369	-0.003384	-0.004652
Panel B: FT30														
Full Sample		19	0.000692***	0.001480***	0.001104**	0.000531	2.77e-5	0.000654	0.001253	0.000620	9.32e-7	0.000174	0.000739	0.000127
1935	**1939**	18	-0.001570	-0.003299	-0.002522	-0.001806	-7.41e-5	-0.000997	0.001953	0.004372	-1.79e-7	-0.000301	0.002219	0.008132
1940	**1944**	20	-0.000710	-0.001147	-6.65e-5	0.000436	-0.000141	-0.002832	-0.004956	-0.003879	-9.06e-6***	-0.000487	-0.001923	-0.003220
1945	**1949**	19	-0.000374	-0.000718	-0.001460	-0.001201	0.000118	0.001383	0.002555	0.001019	-5.42e-6***	0.000152	0.000872	0.002334
1950	**1954**	2	0.000351	0.000182	-0.001586	-0.001952	0.000228**	0.00228	-0.001188	-0.005898	-5.21e-6	0.000623	-0.001109	-0.007955
1955	**1959**	15	0.001157	0.002747	0.002053	0.000964	8.97e-5	0.003393	0.004460	-0.001330	-5.22e-6	0.000979	0.002641	0.000448
1960	**1964**	12	-1.83e-7	-0.000802	-0.002090	-0.002578	0.000151	0.001497	-0.000442	-0.005411	4.19e-6*	0.000519	1.49e-5	-0.004141
1965	**1969**	5	-0.001437	-0.003044	-0.002513	-0.001536	-8.41e-5	0.000137	0.000767	0.000963	-6.75e-7	-4.31e-5	0.000333	-0.000439
1970	**1974**	13	-0.002743**	-0.004902**	-0.004588*	-0.002013	-0.000176	-0.004063	-0.007762	-0.001698	5.40e-6	-0.001038	-0.005142	-0.000769
1975	**1979**	20	0.000494	0.001863	0.002729	0.002196	-7.07e-5	-0.000301	0.003158	0.006689	-1.38e*5***	-0.000491	0.000152	0.006692
1980	**1984**	7	0.001511	0.004320**	0.003653*	0.001778	-6.97e-5	0.000482	0.000555	-0.002449	1.10e-5	0.000535	0.000124	-0.003216
1985	**1989**	11	0.001018	0.002100	0.001326	-0.000238	-2.24e-5	0.000479	0.000772	-0.001171	5.34e-6	0.000889	0.002211	-7.05e-5
1990	**1994**	10	0.001587	0.002920	0.001634	-0.001096	0.000186	0.006082**	0.013477**	0.008068	-5.65e-6	0.001888**	0.013252***	0.019506**
1995	**1999**	2	0.002267**	0.005960***	0.005480***	0.002775*	-0.000148	-0.001774	-0.003043	-0.002011	-9.04e-6***	-0.000754	-0.004498	-0.005383
2000	**2004**	10	-0.000137	0.000922	0.001157	-0.000458	-4.55e-5	0.001027	0.002836	-0.003427	-8.51e-6***	-0.000212	-0.001767	-0.008825
2005	**2009**	5	-0.000586	0.000748	0.002058	0.001116	-0.000185	-0.000338	0.002613	0.004774	-7.38e-6**	0.000245	0.003403	0.008073
Panel C:TOPIX														
Full Sample		18	0.001191***	0.003190***	0.003303***	0.001851***	0.000128***	0.003201***	0.009468***	0.009568***	3.11e-6***	0.000793***	0.006512***	0.011353***
1951	**1954**	10	-0.000802	-0.001003	-0.000795	-0.000335	-0.000159	-0.002458	-0.004505	-0.004431	-6.81e-6*	-0.000854	-0.006218	-0.013936
1955	**1959**	2	-0.001353	-0.001996	-0.002429	-0.001811	-6.84e-5	-0.002877	-0.005276	-0.001709	-3.67e-6	-0.000941*	-0.004736	-0.001326
1960	**1964**	1	-1.55e-5	0.002190	0.003697	0.002269	8.10e-5	0.001743	0.005695	0.006667	-6.68e-6*	0.000241	0.001318	0.003283
1965	**1969**	0	0.000127	0.001404	0.001956	0.001149	0.000172*	0.004399**	0.009050*	0.006447	1.52e-6	0.000874*	0.004649	0.005581
1970	**1974**	3	-0.000658	-0.002716	-0.002869	-0.001529	-5.61e-5	-0.002155	-0.006409	-0.008156	-2.56e-7	-0.000490	-0.002997	-0.008060
1975	**1979**	10	0.002910***	0.007167***	0.006734***	0.004029**	0.000178**	0.004952***	0.014437***	0.015684**	-4.42e-6**	0.000841*	0.007222*	0.013634*
1980	**1984**	1	0.001369	0.002169	0.001692	0.000170	0.000229***	0.002289	0.002281	-0.003501	-1.00e-6	0.000113	-0.000561	-0.008512
1985	**1989**	8	-0.001305	-0.004502**	-0.005450***	-0.003869***	0.000208**	0.002865	0.007515	0.007482	7.93e-6***	0.001202**	0.008596*	0.013596
1990	**1994**	2	0.003193***	0.005597**	0.005967***	0.005629***	6.80e-7	0.000283	0.004238	0.009317	-1.10e-5**	-0.000342	-0.000579	0.002362
1995	**1999**	9	8.77e-5	0.001939	0.003096	0.001901	0.000150	0.003925	0.016609***	0.0199277***	-2.70e-6	0.001013	0.015003***	0.031567***
2000	**2004**	1	0.002774**	0.008645***	0.012179***	0.010326***	0.000287**	0.005546***	0.020467***	0.026649***	3.86e-6	0.001557**	0.014658***	0.030353***
2005	**2009**	4	0.002180*	0.008045***	0.009845***	0.005551***	1.89e-5	0.003438*	0.015055***	0.014780**	6.47e-7	0.001034*	0.010161***	0.016735**

Table 3.11 reports the BDS statistics for the AR-GARCH filtered returns over the full sample period and the subsample periods. It is obvious that the pre-filtering procedure has reduced the magnitude of the BDS statistics substantially. However, there are still periods in which the null of i.i.d. is rejected indicating that there remains nonlinear dependence in the returns even when heteroskedasticity is removed. Nevertheless, the majority of subsamples cannot reject the null of i.i.d. indicating that conditional heteroskedasticity is the main source of nonlinear dependence in the three series. As Hong and Lee (2005) state, the EMH has only implications on the conditional mean, indicating that the nonlinear predictability detected previously in Table 3.10 that disappears after the AR-GARCH filtering in Table 3.11 does not imply violation of the EMH. Thus Table 3.11 shows that each series has done through periods of dependence and independence indicating evidence of the AMH.

3.7. Conclusion

Market efficiency was well accepted in the finance literature up to the mid-1970s as the majority of empirical studies supported the proposition. However since then, a number of studies have found significant inefficiencies in many different stock markets. This chapter has examined tests for independence of stock returns since the independence of returns is a prerequisite for an efficient market. The contribution to the literature of this chapter is the examination of how the independence of stock returns have behaved over time through a battery of linear and nonlinear tests, as well as classifying the behaviour of each into the classification suggested in chapter two. Table 3.12 provides a summary of the results reported, where the key conclusion are;

(i) The linear autocorrelation, runs and variance ratio tests suggest that the DJIA is an adaptive market, while the FT30 is an adaptive market according to the autocorrelation and variance ratio tests. Further, the autocorrelation and runs test both suggest the TOPIX is an adaptive market, indicating that the AMH is a more appropriate model in describing how stock returns have behaved over time.

(ii) The three unit root tests suggest that all three markets are efficient over time due to the constant stationarity found in each sub-sample.

(iii) Once the returns were filtered through an AR model to remove all linear correlations, all three markets provide evidence of significant dependence in stock returns through the nonlinear McLeod-Li, Engle LM and BDS tests.

(iv) Since the AR-filter can ignore heteroskedasticity in stock returns, an AR-GARCH filter is also used and the filtered returns are subjected to the same nonlinear tests. The results show that each market has gone through periods of independence and dependence indicating the adaptive nature of returns.

The AMH is found to best describe the behaviour of stock returns over time through the linear tests since the majority of results suggest an adaptive nature of behaviour. Some could argue that this is expected since five-yearly subsamples were taken and the chance of each of the subsamples producing thethe same results is very small, making the AMH the likely outcome. However, the EMH states that there should be no dependence in stock returns and if there are, they should disappear quickly as investors take advantage of them. This is clearly not found in any of the markets under any of the linear tests as each market goes through periods of dependence and independence. The fact that the three unit roots tests suggest that returns are stationary in each subsample is not surprising since the majority of all stock market returns are found to be stationary. The fact that this suggests that the markets are efficient should not be taken with much credibility and will not be relied on for the analysis.

To examine the nonlinear dependence in stock returns, an AR-filter was applied to the stock returns to eliminate all linear correlation in returns. The residuals of this AR model are then subjected to the Mc-Leod Li, Engle LM and BDS test to examine the nonlinear dependence of the returns. The results for each subsample indicate strong dependence for all three tests indicating strong evidence of market inefficiency. However as Lim and Hooy (2012) note, the AR filter may have eliminated to linear dependence but there may still be heteroskedasticity in the returns. Thus an AR-GARCH model is chosen to eliminate the heteroskedasticity in returns and finds that these filtered returns each go through periods of dependence and independence according to the BDS test, indicating the adaptive nature of the market. In summary, the evidence in this chapter seems to be very supportive of the AMH but tests for predictability in stock returns need to be assessed before coming to a complete conclusion about each market's returns behaviour over time.

Table 3.12: Summary and classification of test results. I stands for the independence of returns while D stands for the dependence of returns.

				AR				AR-GARCH
Sample Period		**Autocorrelation**	**Runs**	**Variance Ratio**	**McLeod Li**	**LM Engle**	**BDS Test**	**BDS Test**
				Panel A: DJIA				
Full Sample		D	D	D	D	D	D	I
1897	**1899**	I	I	I	D	D	D	I
1900	**1904**	I	D	I	D	D	D	I
1905	**1909**	I	I	I	D	D	D	I
1910	**1914**	I	I	I	D	D	D	I
1915	**1919**	I	I	I	D	D	D	I
1920	**1924**	D	D	I	D	D	D	I
1925	**1929**	D	D	I	D	D	D	D
1930	**1934**	I	I	I	D	D	D	I
1935	**1939**	I	I	I	D	D	D	I
1940	**1944**	D	D	D	D	D	D	I
1945	**1949**	D	D	I	D	D	D	D
1950	**1954**	D	D	I	D	D	D	I
1955	**1959**	D	D	D	D	D	D	D
1960	**1964**	D	D	I	D	D	D	I
1965	**1969**	D	D	I	D	D	D	D
1970	**1974**	D	D	I	D	D	D	I
1975	**1979**	D	I	I	D	D	D	I
1980	**1984**	I	I	I	D	D	D	I
1985	**1989**	I	I	I	D	D	D	I
1990	**1994**	I	I	I	D	D	D	I
1995	**1999**	I	I	I	D	D	D	I
2000	**2004**	I	D	I	D	D	D	I
2005	**2009**	D	D	I	D	D	D	I
Classification		AMH	AMH	AMH	Inefficient	Inefficient	Inefficient	AMH
				Panel B: FT30				
Full Sample		D	D	D	D	D	D	D
1935	**1939**	D	D	D	D	D	D	I
1940	**1944**	D	D	D	D	D	D	I
1945	**1949**	D	D	D	D	D	D	I
1950	**1954**	D	D	D	D	D	D	I
1955	**1959**	D	D	D	D	D	D	I
1960	**1964**	D	D	I	D	D	D	I
1965	**1969**	I	D	I	D	D	D	I
1970	**1974**	I	D	I	D	D	D	D
1975	**1979**	D	D	I	D	D	D	I
1980	**1984**	I	I	I	D	D	D	I
1985	**1989**	D	I	I	D	D	D	I
1990	**1994**	D	I	D	D	D	D	D
1995	**1999**	D	I	I	D	D	D	D
2000	**2004**	I	I	I	D	D	D	I
2005	**2009**	I	I	I	D	D	D	I
Classification		AMH	Switch to Efficiency	AMH	Inefficient	Inefficient	Inefficient	AMH
				Panel C: TOPIX				
Full Sample		D	D	D	D	D	D	D
1950	**1954**	D	D	D	D	D	D	I
1955	**1959**	D	D	I	D	D	D	I
1960	**1964**	D	D	D	D	D	D	I
1965	**1969**	I	I	I	D	D	D	I
1970	**1974**	D	D	D	D	D	D	I
1975	**1979**	D	D	D	D	D	D	D
1980	**1984**	D	D	D	D	D	D	I
1985	**1989**	D	D	I	D	D	D	D
1990	**1994**	D	D	I	D	D	D	D
1995	**1999**	I	I	I	D	D	D	D
2000	**2004**	D	D	I	D	D	D	D
2005	**2009**	I	I	I	D	D	D	D
Classification		AMH	AMH	AMH	Inefficient	Inefficient	Inefficient	AMH

Chapter 4 – The Behaviour of Calendar Effects

4.1. Introduction

Market efficiency states that stock market returns must be independent and unpredictable. However, a number of market anomalies have been found to have significant predictive ability. One strand of market anomalies finds that stock returns are systematically higher or lower depending on the day of the week, the day of the month, or month of the year. These anomalies are called calendar anomalies and will be the focus of this chapter.

The three calendar anomalies examined in this chapter are the day-of-the-week effect, month-of-the-year effect and the turn-of-the-month effect. The day-of-the-week effect is where average returns are significantly higher on some days of the week than others. This chapter focuses on the most popular and accepted day-of-of-the-week anomaly, the Monday effect. The Monday effect states that returns on Mondays are significantly less than other days of the week. The Monday effect can be traced back to Kelly (1930) in his book on investing, who found Monday to be the worse day to buy stocks from a three-year statistical study. The first academic paper to document the effect was Cross (1973), who found that from 1953 to 1970, the S&P500 advanced only 39.5% of the time on Mondays while the mean was -0.18%. The month-of-the-year anomaly is also examined in this chapter. This anomaly states that stock returns are higher in the month of January, especially during the first half of the month, than other trading months. This anomaly was first documented by Rozeff and Kinney (1976) for the NYSE where they studied the period 1904 to 1974 and found the average return in January to be 3.48% compared to only 0.42% in other months. The third and final calendar anomaly examined in this chapter is the relatively newly found turn-of-the-month effect. This anomaly states that stock returns are significantly higher during the last trading day and the first three trading days of a month compared to the rest of the month. It was first documented by Ariel (1987) in the NYSE from 1963 to 1981 where it was found that returns during the turn-of-the-month period was 0.47%, whereas the average returns during any other four day period was of 0.061%.

Nevertheless, calendar anomalies have failed to yield consistent returns over and above a simple buy-and-hold strategy. Mills and Coutts (1995), Draper and Paudyal (1997) and

Brooks and Persand (2001) argue that these anomalies are not profitable after taking account of transaction and illiquidity costs. It has also been argued that even if no calendar anomalies exist, an extensive search for anomalies in any data set will provide some anomaly in the data (Burton 2003). Thus anomalies may be the result of data mining. All of the anomalies studied in this chapter have however, been documented in many markets and over long time periods and therefore are unlikely to be due to data mining. Also, transaction costs can be small for large investment firms who invest millions of dollars so the effect of them may be small[21]. Hence the calendar effects studied in this chapter are of great interest to academics and practitioners alike.

This chapter is organised in the following manner. Section 4.2 describes the literature while Section 4.3 outlines the methodology. Section 4.4 presents the data while section 4.5 reports the empirical results. Section 4.6 analyses and concludes the chapter.

4.2. Literature Review

4.2.1. Monday effect

An extensive literature documents that weekday returns vary with the day of the week (day-of-the-week-effect). A persistent finding within the literature is the tendency for asset returns to be negative on Mondays which was first documented by market practitioners and then academics. Maberly (1995) shows that financial practitioners were aware of the Monday effect as early as the late 1920s, with the first documented finding by Kelly (1930) who found Monday to be the worse day to buy stocks from a three-year statistical study. Also Merrill (1966) examined the period 1952 to 1965 for the DJIA and found that prices only increased on 43% of Mondays, compared to 50% for non-Mondays. The first academic to document the Monday effect was Cross (1973), who studied the S&P 500 from 1953 to 1970. Over this period, the index advanced on 62% of the Fridays and had a mean on Friday of 0.12%. On Mondays however, the index advanced only 39.5% of the time, and the mean was -0.18%. Cross also found that the performance on Monday was dependent on the pervious Friday's performance. French (1980) studied the S&P 500 from 1953 to 1977 and found day-of-the-week evidence in US stocks, including negative and statistically significant Monday returns.

[21] In addition although returns net of trading costs may be small, anomalies are often used for timing trades to maximise returns.

Gibbons and Hess (1981) also documented similar results when studying the S&P 500 and CRSP value- and equally-weighted indexes from NYSE and AMEX securities from 1962-1978, as did Keim (1987) for US indexes from 1963 to 1985. Lakonishok and Smidt (1988) extend the sample size by conducting a ninety-year study on weekday returns for the DIJA. They report negative Monday returns for the entire sample (1897-1986) and for each of their selected subsamples, with average Monday returns being significantly less than zero for all but two of the subsample periods. Furthermore, Schwert (1990) documented the weekend effect in the US from 1802 to 1987 and Siegel (1998) furthered these findings by examined the Monday effect over the period 1885 to 1997. He concludes that if Monday returns had been equal to the average of non-Mondays over this entire sample period, the DJIA would be almost twice its level it was at the end of 1997.

The evidence of the weekday effect has also been found in the UK and Japan. Theobald and Price (1984) document a negative return on Monday from 1975 to 1981 for the FT30 and FTSE All-Share, while Jaffe and Westerfield (1985) find negative Monday returns for the FT30 from 1950 to 1983. Mills and Coutts (1995) find significant negative returns on Mondays for the FTSE250 and 350 indices and negative but not significant returns for the FTSE100. Dubois and Louvet (1996) find low Monday returns in the FTSE All-Share and Arsad and Coutts (1997) document a negative Monday effect in the FT30 from 1935 to 1994. Tong (2000) also find pervasive weekday effects in the US, UK and Japan, with the US and UK exhibiting a significant Monday effect at 5% significance. He also finds that in the UK and Japan's bad Fridays are responsible for 70% of the Monday effect. Doyle and Chen (2009) show that the FTSE100 and NSADAQ Monday returns are negative and do not diminish over time during the period 1993 to 2007. They also indicate that the weekday effect is not conditional on the average returns in the previous week.

The Monday effect was one of the first calendar anomalies to be discovered and the previous evidence suggests that it has been quite strong. However a number of studies have found that it has diminished and in some cases even reversed over time. Connolly (1989) finds that Monday returns were significantly different from non-Monday returns before 1974, but were not significantly different after 1974, although they remained negative. These results were confirmed by Chang et al (1993). Kamara (1997) reports that the Monday effect has diminished significantly since the introduction of the S&P500 futures contract in 1982.

Marquering et al (2006) studied the DJIA from 1960-2003 and found that the Monday effect has declined in recent years.

While some studies find the weekend effect diminishing, a number have seen a complete reversal in returns. Brusa and Pu (2000) discover that Monday returns for large US stocks were positive and the largest of any day of the week during the 1990s. Mehdian and Perry (2001) confirm this 'reversal' in returns for large US stocks from November 1987 to August 1998, although they did find a persistent negative Monday return for small stocks. Brusa and Liu (2004) document that this reversal in returns is concentrated on positive returns in the first and third weeks of each month, while Brusa et al (2005) find that the positive weekend returns are correlated with the previous Friday's return, suggesting that the positive Monday returns are likely to be observed after a positive Friday return. Boudreaux et al (2010) study the Monday effect in the DJIA, S&P500 and the NASDAQ during the sample 1976-2002. By breaking their samples in bear and non-bear market periods, they find evidence of a weekend effect with weekend returns being greater than non-weekend returns only in non-bear markets. They attribute this finding to a wealth effect where as stock prices rise, investors gain confidence and are more likely to act upon broker recommendations during the week.

4.2.2. January Effect

The January effect is one of the most accepted and tested seasonal anomalies in finance. This anomaly states that returns in January appear to be higher than in other months of the year. It was first documented by Rozeff and Kinney (1976) and has gained much attention from academics and practitioners. Rozeff and Kinney (1976) study the NYSE for the period 1904 to 1974 and find that the average return for the month of January was 3.48% compared to only 0.42% for the other months. Keim (1983) also employ the NYSE from 1963 to 1979 and found that nearly 50% of the average magnitude of the risk-adjusted premium of small firms relative to large firms is due to January abnormal returns. He also found that 50% of the January premium is due to abnormal returns during the first week of trading in the year. Roll (1983) and Reinganum (1983) support these findings for small firms, and particularly for small firms with low share prices (Branch and Chang 1990). However, if this given this result, one reasonable suggestion would be that the January effect should be weaker for larger firms. Kohers and Kohli (1991) however, provide evidence that the January effect is not related to the small firm effect. Nevertheless, high returns are not found in an index that is composed of only large firms, like the DJIA. Lakonishok and Smidt (1988) find no evidence of the January effect in the DJIA for the whole of January, and only find mild support for rates of return being larger in the first half of the month than in the last half.

Gultekin and Gultekin (1983) use data from some 17 countries including the UK and Japan for the sample period 1959 to 1970 using the Capital International Perspective (CIP). This is an index that provides monthly stock market returns based on 1,110 share prices and counts for approximately 60% of the total value of all shares traded in the countries examined. They find that returns in January and April are significantly high for the UK but just in January in Japan. The January effect is evident for all countries and they attribute the abnormal returns to be due to the turn of the tax year. Kato and Shallheim (1985) examined excess returns in January for the Tokyo Stock Exchange. They find excess returns in January and a strong relationship between return and size, with the smallest firms returning 8% and the largest 7%. Also Mills and Coutts (1995) study the January effect for the FTSE100, Mid 250 and 350 Indices from January 1986 to October 1992. They find evidence supporting the January effect, with daily returns being positive and significant for January and February in the FTSE100 and for January in the Mid250.

Although there has been strong empirical evidence in favour of the January effect, recent research has argued that the magnitude of the anomaly has declined. Riepe (1998) states that during the 1980s and 1990s there was an increase in general knowledge about the January effect and the emergence of futures contracts. This has resulted in a low-cost alternative for investors to profit from the effect. Consistent with this, Mehdian and Perry (2002) suggest that the January effect has disappeared in the US. They study the DJIA, NYSE and S&P500 and find that from 1964 to 1987 January returns are positive and significant for all three stock markets. However after 1987, January returns are positive but not significant, thus indicating that the anomaly has disappeared. Also, Gu (2003) uses a power ratio of the mean returns in January compared to the mean return of the year. The results show that both large and small firm stock indices have declined since 1988 and it has disappeared for the Russell indices. The declining trend is also evident in the Dow 30 since 1930. However, these two studies use monthly returns while using daily returns may give a more accurate picture of the evolution of stock prices. Marquering et al (2006) also find that since the January effect was discovered in 1976, it has diminished and seems to have disappeared at the start of the 21st

century. Moller and Zilca (2008) examine daily data of the NYSE, AMEX and NASDAQ from 1927 to 2004 and conclude that the magnitude of the January effect has not declined. However, they do find higher abnormal returns in the first part of January and lower abnormal returns in the second part of January in the subsample 1995 to 2004. These returns offset each other, thus the overall magnitude of the January effect appears similar to its magnitude in the previous 1965-1994 period.

4.2.3. Turn-of-the-month Effect

The turn-of-the-month effect on stock returns was first found by Ariel (1987) in the US stock market. Ariel used equally-weighted and value-weighted daily stocks from the NYSE during the period 1963 to 1981. The study finds that mean daily stock returns are positive at the beginning of the month and continuing through the first half of the month. However, returns after this point are predominantly negative. Ariel defines a trading month as the last day of the previous month to the last trading day of the following trading month. The first half of the month consist of nine trading days, and the rest of the month are considered the second half of the month. He reports that the mean daily return on the first half of the trading month is significantly higher than the mean daily return from the last half for both indices. This intra-month effect is also present in all four five-year subperiods that Ariel investigates. This phenomenon has been called the turn-of-the-month effect. Lakonishok and Smidt (1988) investigate the DJIA from 1897 to 1986 and discovered that the rate of return is especially high for the last trading day of the month and the first three trading days of the next month. More specifically, they find that returns during the turn-of-the-month are 0.475% compared to 0.061% for non-turn-of-the-month days. An interesting facet is that the DJIA increased by 56% during this sample period, an average increase of 0.349% per month, indicating that without the turn-of-the-month returns, the DJIA would have actually fallen during this period. McConnell and Xu (2008) extend Lakonishok and Smidt's (1988) study to include data up to 2005 for the DJIA and find that the turn-of-the-month effect is still evident. Even when they extend their sample from 1897 to 2005, they find significance evidence of the effect, with all of the positive return to equities occurring during the turn-of-the-month interval. Thus on average, during the other trading days of the month, investors received no reward for the risk they took. They find that it is not due to the concentration of buying shares at the turn-of-the-month, or just confined to the US. Thus their results suggest no explanation for this profitable calendar effect. They also report that the turn-of-the-month effect is evident in 31 of the 35 countries examined.

The turn-of-the-month anomaly has also been examined in the UK and Japanese markes with Ziemba (1991) finding the turn-of-the-month effect using days -5 to +2 for each month using data for the NSA and TOPIX indices in Japan for the period 1949-1988. These results were supported by Cadsby and Ratner (1992) who used days -1 to +3, and find excess significant returns in the Financial Times 500 Share Index using data from 1983 to 1988. However, they find no evidence of the effect in Japan using data from 1979-1988 in the Nikkei. Hensel et al (1994) test the S&P500 and value-line small-cap indices for the period May 1982 to April 1992 and find that two-thirds of a month's gains occur on trading days -1 to +4 and rest of the gains occur during trading days +5 to +9, suggesting that returns in the second half of the month were, at best, noise. Agrawal and Tandon (1994) use turn-of-the-month days -1 to +3 to test the effect in 18 countries from 1970 to 1987. They find evidence of the effect in 14 of these countries, including the USA (DJIA), the UK (FT30) and Japan (Nikkei). Hensel and Ziemba (1996) examined investing in the S&P 500 Index on turn-of-the-month days and in t-bills over the other days. They report that the turn-of-the-month strategy outperformed a baseline strategy by 0.63% per year over the period 1928-1993. Kunkel et al (2003) tested the turn-of-the-month effect in 19 countries and found the effect present in 15 of them, including the US (S&P500), the UK (FTSE100) and Japan (Nikkei225) for the period 1988 to 2000. He also documents that in the 15 countries where the effect is present, it accounts for 87% of the monthly returns.

Even though the turn-of-the-month effect is a relatively new anomaly, it has also been examined to determine if it is as strong as it once was. Marquering et al (2006) find that the turn-of-the-month effect is slightly weaker than pre-1987 data for the DJIA, with the linear trendline downward sloping. However, the results do not suggest the anomaly has disappeared, and suggest a possible reason for the weakening of the anomaly being due to transaction costs being too high to profit from this anomaly, so investors cannot exploit this pattern. Dzhabarov and Ziemba (2010) used daily returns for the Russell 2000 and S&P500 futures market and through subperiod analysis find that the turn-of-the-month effect still exists, but with a bit of anticipation. Also, Hudson and Atanasova (2009) find evidence of the turn-of-the-month effect for the FT30 using -1 to +3 days for the period July 1935 to March 2009. They also find that the effect has not declined since the publication of Lakonishok and

Smidt (1988) but has actually increased in strength, with excess mean returns increasing by 0.07% between the subsamples 1935-1969 and 1987-2009. Thus the literature suggests that the turn-of-the-month effect is still evident in stock returns.

4.3. Methodology

The three calendar anomalies examined in this chapter are the Monday effect, January effect and the turn-of-the-month effect. The Monday effect states that returns on Monday should be significantly less than other days of the week. The January effect reports that returns in January are significantly higher than other months of the year. Since most studies find that this anomaly is only present in the first half of January, only the first 15 trading days in January are studied. The turn-of-the-month effect states that returns on the last day of each month and the first three days of the next month are significantly higher than any other four day period. These are the days of the anomaly chosen to examine.

To examine the behaviour of these calendar anomalies, the excess returns of the anomalies is calculated before and after the first academic publication date of a paper relating to that anomaly. This is to determine whether the publication of the seminal paper caused a change in the return behaviour of that anomaly. The Monday effect was first published in the academic literature by Cross (1973), the January effect was first observed by Rozeff and Kinney (1976) and the turn-of-the-month was first examined by Ariel (1987). Thus these dates determine the subsamples chosen for each anomaly. Excess returns are calculated by;

$$R_t = \alpha + \beta D_t + \varepsilon_t \tag{4.1}$$

Where R_t is the return on a stock index, D_t is the calendar dummy and ε_t is the error term. D_{1t} = 1 if day t is Monday and zero otherwise; D_{2t} = 1 if day t is a Tuesday and zero otherwise, and so forth. This approach enables the analysis of returns of the given anomaly compared to the returns on non-anomaly days. For example if the dummy variable for Monday is included, α captures the mean of daily return of non-Mondays, and β is the excess return on Mondays, relative to non-Mondays. The t-test of β tells us if the excess returns on Monday are significant. This regression is similar to performing a two-group comparison test between the mean daily return of a specific day and the mean daily return of all other days.

Nevertheless the year of the first academic publication of each anomaly may not be the turning point in the return behaviour of the anomalies. The success of the anomaly may be declining well before or after the anomaly was first published in the academic field. To investigate this two structural break tests are conducted on the data. A structural break occurs when the estimated parameters in the model are unstable over time, i.e. there is a significant difference between the residual variance from one part of the data to another. To determine the breakpoint in our sample we perform two tests for structural breaks, the Chow Test for a known structural breaks and the Quandt-Andrews Test for an unknown breakpoint.

Both of these tests require time-series data and we calculate the yearly excess mean returns to create a proxy for yearly data. Daily and monthly excess returns cannot be calculated for all three anomalies since the January effect only creates excess returns in the month of January. Thus yearly excess returns are calculated for each anomaly in market for consistency. For the January effect in year *t*, the excess mean returns are calculated by;

$$excess\ mean\ return\ January_t = \{\mu_{Januaryt} - \mu_{non-Januaryt}\} \tag{4.2}$$

Where $\mu_{Januaryt}$ is the mean return in January in the year *t* and $\mu_{non\text{-}Januaryt}$ is the mean return in non-January days in the year *t*.

The Chow (1960) test investigates a known structural break. In this test the date of the break must be chosen prior to conducting the test. We specify the exact breakpoint by choosing the year that the first academic article was published identifying that anomaly to see if this was the defining point where the behaviour of the anomaly changed. The test performs three regressions where the first two regressions separate the sample period, while the last covers the entire period. Thus;

$$\begin{gathered}(a) Before\ Publication\ Y_t = \omega_1 + \omega_2 X_t + \mu_{1t} \\ (b) After\ Publication\ Y_t = \gamma_1 + \gamma_2 X_t + \mu_{2t} \\ (c) Full\ Sample\ Y_t = \alpha_1 + \alpha_2 X_t + \mu_{3t}\end{gathered} \tag{4.3}$$

In (a) and (b) we assume that the intercept and the slope of the coefficients are different. In regression (c) we assume that both the intercept and slope coefficient remain the same over the entire period. That is $\alpha_1 = \omega_1 = \gamma_1$ and $\alpha_2 = \omega_2 = \gamma_2$. If there is no structural change in the time series, the aggregated residual sum of squares (RSS_R) from regression (a) and (b) should equal the residual sum of squares (RSS_{UR}) obtained from regression (c) (Gujarati 2009). Thus Chow (1960) defines this relationship formally as;

$$F = \frac{\frac{(RSS_R - RSS_{UR})}{k}}{\frac{(RSS_{UR})}{(n1 + n2 - k)}} \tag{4.4}$$

Since the null hypothesis is parameter stability, an *F*-statistic greater than its critical value from the *F*-table will reject the null hypothesis and indicate a break in the data. The main limitation of the Chow test is that the breakdate must be known a priori. Although the breakdates chosen in this study are not chosen arbitrarily and chosen with reasonable logic, this test can be misleading as the breakdate is exogenous and the test is likely to falsely indicate a break when none actually exists. This can lead to different researchers reaching distinctly difference conclusions from the same data.

Therefore to avoid the bias of the Chow (1960) test, we also utilise a break test that treats the breakdate as unknown. The Quandt-Andrews break test calculates a single Chow breakpoint test at every observation between two dates. From each individual Chow test two statistics are retained, the Likelihood Ratio *F*-statistic and the Wald *F*-statistic. The Likelihood Ratio *F*-statistic is based on the comparison of the restricted and unrestricted sum of squared residuals. The Wald *F*-statistics are computed from a standard Wald test of the restriction that the coefficients on the equation parameters are the same in all subsamples. However, these statistics do not follow a standard distribution and when Quandt proposed its use in 1960, all the critical values were unknown. Andrews (1993) proposed critical values for the Quandt test and thus it is now referred to as the Quandt-Andrews test. The test is not conducted on the full sample as the test statistic becomes degenerate at both ends of the sample. Andrews (1993) suggests a 15% trimming to obtain a reliable statistical inference. However, the ideal trimming percentage may vary with sample size and nature of the data. Thus we use trimming percentages of 5% and 15% to avoid any bias. Therefore to be more precise, the null hypothesis indicates no breakpoints within the trimmed observations.

Nevertheless, the finding of the breakpoints in the previous analysis give little indication of the behaviour of the anomalies over time. Thus similarly to the previous chapter, five-yearly subsamples of excess returns are calculated in the same way as equation 4.1 but over five-year periods and plotted over time. Five-yearly subsamples are chosen to provide enough observations to gain reliable results and enough data points to understand how the anomalies have behaved over time. A polynomial trendline is included to smooth the picture of how the anomalies have behaved over time. Again, the suggested classification of return behaviour is used to categorize the anomalies through the behaviour of the polynomial trendline as in the previous chapter.

An important question to ask when dealing with any stock market anomaly is whether investors can use these calendar anomalies to gain returns greater than the market. In this section, the degree to which investors can earn profits that beat the buy-and-hold strategy using two simple trading strategies are analysed. This section considers two simple trading strategies, which are also used for the technical trading rules in Chapter 5.

This study prefers simple trading strategies to complicated strategies since calendar anomalies are straightforward to understand and thus it should be relatively simple to make profits from them. Many studies use a trading strategy that invests in the risk-free asset if they are not in the market. Even though this may give an equivalent risk to the buy-and-hold strategy since the investor is always in some market, investing in the risk-free rate may be costly and time consuming since investors may only be out of the market for one or two days. Since this thesis uses data from the US since 1897, from the UK since 1935 and from Japan since 1951, risk-free rate data was not available for the full sample and so is ignored in these trading strategies. Since the investor does not invest in risk-free assets when they are out of the market in either of the trading strategies examined, the overall returns for the trading strategy will be less than if the investor had invested in the risk-free asset, making it more difficult for these rules to gain returns greater than the buy-and-hold strategy than if investment in the risk-free asset was conducted for every sell signal, thus the figures generated are conservative. Nevertheless, a "double to out" trading strategy, which has broadly the same risk as the buy-and-hold strategy is studied, as well as a simple trading strategy which does not have comparable risk.

The first trading strategy adopted is similar to Fifield et al (2005; 2008) and is as follows. The investor is initially assumed to hold a buy position and upon the first buy signal, the trader buys and holds until a sell signal is generated. Upon this sell signal, the trader sells and goes short until the next buy signal. Upon the last sell signal, it is assumed that the investor liquidates his position. At the end of the sample period, the profit from the different trading rules are calculated and compared with the profit from the naïve buy-and-hold strategy. A buy signal is generated for the Monday effect every day of the week except Monday, when a sell signal is generated. A buy signal is generated on the first 15 days of January for the January effect and on the last day and first three days of the month for the turn-of-the-month effect. The profits from this strategies are calculated net of transaction costs (transaction costs taken from Ratner and Leal 1999 for the US and Japan, and Hudson et al 1996 for the UK[22]). The trading strategy evaluated here differs from those in the majority of the previous papers. For example, this rule assumes that the investor has a limited amount of wealth that is invested in full at each buy (sell) transaction. That is, this rule assumes that the investor can only sell after a buy transaction (and buy only after a sell transaction) whereas other studies assume that the investor has an unlimited amount of wealth and can implement multiple buys or sells after each price change. The strategy examined here can therefore be characterised as prudent, and as satisfying the risk-averse nature of many investors (Fifield et al 2005).

The second trading strategy examined follows the “double or out” rule suggested by Bessembinder and Chan (1998). An investor who conducts the previous simple trading strategy faces a lot less risk than an investor who conducted the buy-and-hold strategy. This is because they are out of the market for a considerable period of time and avoid the risk associated with being in the market all of the time. This is shown in Tables 4.7 and 4.8 where the trading strategies standard deviation is substantially less than the buy-and-hold strategy. Acknowledging this fact, a slightly modified version of the “double or out” trading strategy suggested by Bessembinder and Chan (1998) is applied to the various moving average rules previously examined. If a neutral signal[23] is generated there is an investment in the index. If a buy day is indicated the investment in the index is doubled whereas, if a sell day is

[22] Although these transaction costs are accurate for the period they were calculated from, they do not correspond to the costs faced in the total sample examined in this thesis. Nevertheless with no data available for the full sample, these transaction costs are employed.
[23] Neutral signals are never generated in this trading strategy since the calendar anomalies only generate buy or sell signals.

indicated, the funds are invested in cash thus giving broadly similar risk to a buy-and-hold strategy (the exact standard deviations are reported in Tables 4.7 and 4.8). Bessembinder and Chan (1998) invest in the daily risk-free rate when a sell signal is generated but since no risk-free rates are available for long periods of the data examined, the investor invests in cash with no return when a sell signal is generated. The profits from this strategy are also calculated net of transaction costs (transaction costs taken from Ratner and Leal 1999 for the US and Japan, and Hudson et al 1996 for the UK). These two trading strategies are conducted to determine if simple trading on the calendar anomalies can beat the buy-and-gold strategy for each index.

Finally this chapter studies the influence of the turn-of-the-month effect. The turn-of-the-month effect has produced some extraordinary results in the recent literature with McConnell and Xu (2008) reporting that the turn-of-the-month accounts for all of the positive return in the DJIA, while Hudson and Atanasova (2009) confirm this result for the FT30. To determine whether the turn-of-the-month anomaly is driving the excess returns in the January effect, regression (4.1) is repeated but with the turn-of-the-month days excluded. Thus if the turn-of-the-month effect is driving the January effect, the excess returns in January should decrease or even disappear after the turn-of-the-month days are excluded.

4.4. Data

For all indexes, daily returns are calculated as:

$$r_t = [(\ln P_t) - (\ln P_{t-1})] \times 100 \tag{4.5}$$

Where r_t is the daily return of the stock market index and P_t is the stock index at date t. Summary statistics are given in Table 4.1 for the full sample of each index, as well as after the seminal paper was published for each calendar anomaly.

Table 4.1: Descriptive Statistics of Calendar Anomalies. ***, **, *` indicate significance at 1%, 5% and 10%.

	Full Sample			Post Seminal Paper		
	DJIA	**FT30**	**TOPIX**	**DJIA**	**FT30**	**TOPIX**
All Days						
Mean	0.01885	0.01537	0.02834	-	-	-
Standard Deviation	1.09616	1.05851	1.02429	-	-	-
No. of Days	31050	19154	15390	-	-	-
Fraction of positive return days	0.52200	0.4988	0.50052	-	-	-
Monday Days						
Monday Mean	-0.09925	0.06139	-0.00007	0.00269	0.09346	-0.03262
Standard Deviation	1.22873	1.00086	1.17486	1.32995	1.20862	1.22323
No. of Mondays Days	5523	3731	3078	1789	1904	1931
Fraction of positive Monday return days	0.47384	0.55030	0.49578	0.51537	0.52521	0.47126
Non-Monday Mean	0.04440	0.00614	0.03544	0.03004	-0.00572	0.01871
Non-Monday Standard Deviation	1.06361	1.07255	0.98297	1.04630	1.29107	1.08685
***t*-statistic for difference of means**	-8.84***	2.79***	-1.72*	-0.94	3.04***	-1.81*
January Days						
January Mean	0.03664	0.06650	0.11618	0.04453	0.05614	0.04304
Standard Deviation	0.96872	1.10842	1.05183	1.07124	1.16459	1.18560
No. of January Days	2635	1607	641	718	746	753
Fraction of positive January return days	0.52182	0.50840	0.49156	0.51950	0.50134	0.44356
Non-January Mean	0.01719	0.01069	0.02021	0.02768	0.01487	0.00878
Non-January Standard Deviation	1.10724	1.05373	1.02136	1.09810	1.18651	1.13097
***t*-statistic for difference of means**	0.87	2.02**	3.24***	0.39	0.91	0.79
Turn-of-the-month Days						
TOTM Mean	0.11758	0.09413	0.09508	0.10242	0.12630	0.09241
Standard Deviation	1.05439	1.06376	0.99753	1.08639	1.13448	1.26418
No. of TOTM Days	5437	3573	2831	1104	1104	1104
Fraction of positive TOTM return days	0.42818	0.52393	0.49912	0.53623	0.52717	0.47645
Non-TOTM Standard Deviation	1.10371	1.06998	1.02967	1.21121	1.18951	1.32897
Non-TOTM Mean	-0.00211	0.00454	0.01330	0.01215	-0.02088	-0.03193
***t*-statistic for difference of means**	7.31***	4.52***	3.84***	2.27**	4.46***	2.83***

The mean and standard deviations of the three indices for the various sample periods were calculated for the anomaly days and the non-anomaly days and are reported in Table 4.1. The *t*-test for the difference in the means is also reported in Table 4.1, the calculations assume that the returns in the two samples are independent and that the return generating process has been constant over the period of the sample.

Examining the full sample results first, the Monday mean for the DJIA and the TOPIX are negative compared to a positive mean for non-Mondays. The corresponding *t*-statistic shows that the difference is highly significant for the DJIA, but only at 10% for the TOPIX. The results supports the idea that there is no Monday effect in the FT30, with Mondays actually producing a positive mean compared to non-Mondays generating a negative mean. All three markets reveal that the mean in January is higher than the mean in non-January days with the FT30 and TOPIX being statistically significant. Each of the three markets produce significantly higher means during turn-of-the-month days, indicating that the turn-of-the-month effect has been generating higher means than non-turn-of-the-month days for the full sample.

Focussing on the subsample results after the seminal paper of each anomaly was published shows similar results to that of the full sample for the Monday effect. Again means are greater on Mondays only for the FT30, with the *t*-statistic difference being significant at 1%. However, the Monday return in the DJIA is no longer negative, with the *t*-statistic for the difference in the means being no longer significant. This suggests that the Monday effect has disappeared in the DJIA. The means on January days are all still greater than the means on non-January days for all three series, but the difference is not as great. None of the *t*-statistics for the difference in means are significant, again suggesting that the January effect is disappearing/has disappeared since the publication of Rozeff and Kinney's paper in 1976. The turn-of-the-month anomaly seems to still exist in all three markets, with the *t*-statistic for the difference in means being significant in each market. However, this is partly due to the fact that the mean on non-turn-of-the-month days in the FT30 and TOPIX are now negative. The mean on turn-of-the-month days in the DJIA for both subsamples is very similar, with the huge drop in the *t*-statistic due to the now positive mean on non-turn-of-the-month days. This indicates that the turn-of-the-month effect is still strong in each market, but not as strong as during the full sample. These results show that the means of some of the anomalies have decreased since the seminal paper on the effect was published.

4.5. Empirical Results

4.5.1. Regression Analysis

Table 4.2 documents the excess return on the anomalies, relative to non-anomaly days for the full sample, and before and after the year of initial publication of a given anomaly for the DJIA. Moreover, the *t*-statistics are calculated to test whether the coefficient corresponding to the anomaly is zero and this enables an examination of the strength of the anomaly over time. These initial results show that the Monday effect has decreased quite considerably in value over time for the DJIA. Over the entire sample (1897-2009) the excess returns on Mondays compared to non-Mondays was -0.14%. The difference between the excess returns on Mondays before and after the publication of Cross's 1973 paper is 0.17%, which is quite considerable given the whole sample excess returns was of a magnitude of 0.14%. As suggested in the literature, there is little evidence of the Monday effect in the FT30, with each subsample producing positive excess returns. The Monday effect in the TOPIX appears to be getting stronger, with the magnitude of negative excess returns larger after 1973 than before. The regression analysis in Table 4.2 for the January effect shows that returns have diminished over time, with excess returns falling by 0.003 between the period before and after Rozeff and Kinney's (1976) paper for the DJIA. The FT30 January effect results report than the excess returns have decreased since 1976, with the excess returns being significant at 5% before 1976 and not significant after. A similar result is found in the TOPIX, with excess returns significant at 1% before 1976, but not significant after 1976. These results suggest that the January effect is not as strong as it was before 1976. The turn-of-the-month effect for the DJIA shows that returns have also diminished over time, but only by a small amount (0.03% after the 1987 paper by Ariel 1987). Even though returns have fallen, the excess returns post 1987 are significant at 5%, indicating that this rule is still profitable in the DJIA. The FT30 and TOPIX results both document a increase in the magnitude of excess returns since 1987, indicating that the turn-of-the-month effect is getting stronger in each market.

Table 4.2: The excess returns before and after the publication of the anomalies. ***, **, * indicate significance at 1%, 5% and 10%.

Anomaly	Market	Entire Sample	Before Paper	After Paper
The Monday Effect (Cross 1973)	**DJIA**	-0.1436463*** (-8.84)	-0.1969739*** (-10.08)	-0.0271977 (-0.94)
	FT30	0.0556057*** (2.88)	0.018350 (0.89)	0.0934588*** (2.83)
	TOPIX	-0.0355162* (-1.72)	-0.0088766 (-0.32)	-0.0513341* (-1.81)
January Effect (Rozeff and Kinney 1976)	**DJIA**	0.0194491 (0.87)	0.0205262 (0.78)	0.0168533 (0.39)
	FT30	0.0558152** (2.02)	0.0683766** (2.05)	0.0412701 (0.91)
	TOPIX	0.0959742*** (3.24)	0.1803914*** (4.78)	0.0342558 (0.79)
Turn-of-the-Month (Ariel 1987)	**DJIA**	0.1204146*** (7.36)	0.1252654*** (7.01)	0.0902722** (2.27)
	FT30	0.0968266*** (4.93)	0.074116*** (3.33)	0.1471778*** (3.74)
	TOPIX	0.0817814*** (3.84)	0.0545856*** (2.63)	0.1243334*** (2.83)

4.5.2. Breakpoint Analysis

The Chow (1960) test examines whether a break is found in the data at a pre-selected date. The results in Table 4.3 reveal that the Monday effect breakpoint in 1973 can be accepted for the DJIA and the FT30, with the *F*-statistic being significant at 5%. However the Monday effect does not produce a significant breakpoint in 1973 for the TOPIX, indicating that returns did not immediately change when the seminal paper was published. Nevertheless, for the January effect the breakpoint in 1976 is rejected for the DJIA and FT30, but accepted for the TOPIX. This result is the reverse of the Monday effect results, dismissing the idea that the calendar anomalies may have been recognised later in the TOPIX than the DJIA and the FT30. The results for the turn-of-the-month effect reveal that only the DJIA accepts a breakpoint in 1987 at 5% significance. The FT30 does accept the breakpoint, but only at 7% significance, while the TOPIX rejects the breakpoint. This suggest that the turn-of-the-month effect returns have changed significantly since 1987 for the DJIA, but not the FT30 and TOPIX.

Table 4.3: Test results for the Chow (1960) known structural break test on the calendar anomalies. The first column documents the calendar effect examined, the second column shows the chosen breakpoint, while the third column reports the F-statistic. The fourth column reports the probably of the F statistic, while the fifth column documents the log-likelihood ratio. Finally the sixth column reports the Wald statistic.

Calendar Effect	Chosen breakpoint	F-statistic	F Prob	Log Likelihood Ratio	Wald Statistic
Panel A: DJIA					
Monday Effect	1973	15.34415	0.00	14.63116	15.34415
January Effect	1976	0.045878	0.83	0.046695	0.045878
TOTM Effect	1987	4.321454	0.04	4.315841	4.321454
Panel B: FT30					
Monday Effect	1973	5.718111	0.02	5.644963	5.718111
January Effect	1976	0.163835	0.69	0.168195	0.163835
TOTM Effect	1987	3.457021	0.07	3.470200	3.457021
Panel C: TOPIX					
Monday Effect	1973	0.684182	0.41	0.703972	0.684182
January Effect	1976	5.831264	0.02	5.746689	5.831264
TOTM Effect	1987	1.602095	0.21	1.635431	1.602095

The Quandt-Andrews (Andrews 1993) test results for an unknown break point are documented in Table 4.4. The Monday effect is found to have a significant breakpoint in 1988 for the DJIA which is much later than the seminal paper in 1973. The FT30 and TOPIX however both produce breakdates that are insignificant, indicating no real breakdate in the data. There are no significant breakpoints for the DJIA or FT30 for the January effect suggesting there has been no real change in the behaviour of the anomaly over time.

However, the TOPIX produces significant breakpoints in 1954 for 5% trimming and 1995 for 15% trimming, demonstrating no clear breakpoint near the publication date of the January effect in 1976. The turn-of the-month effect does produce significant breakdates for the DJIA in 1973 and in the FT30 in 1999 for 5% trimming and 1998 for 15% trimming, indicating a change in the behaviour of the anomalies. However, the TOPIX reveals no significant breakdate for the turn-of-the-month effect.

Table 4.4: Test results for the Quandt-Andrews (1993) unknown structural break test on the calendar anomalies. The first column documents the calendar effect examined, the second column shows the trimming percentage while the third column reports the breakdate year. The fifth column documents the LR F-statistic and the sixth column shows the associated p-value.

	Trimming Percentage	Break Point Year		LR F-statistic	p-value
Panel A: DJIA					
Monday Effect	5%	1988	**Max F**	25.7095	0.00
			Exp F	8.9944	0.00
	15%	1988	**Max F**	25.709	0.00
			Exp F	9.2351	0.00
January Effect	5%	2000	**Max F**	4.7908	0.39
			Exp F	0.5288	0.47
	15%	1990	**Max F**	2.0349	0.78
			Exp F	0.1331	0.94
TOTM Effect	5%	1973	**Max F**	12.5539	0.01
			Exp F	3.8383	0.00
	15%	1973	**Max F**	12.5539	0.01
			Exp F	4.0482	0.00
Panel B: FT30					
Monday Effect	5%	1972	**Max F**	6.4439	0.20
			Exp F	1.0908	0.18
	15%	1972	**Max F**	6.4439	0.13
			Exp F	1.2444	0.14
January Effect	5%	1995	**Max F**	7.1153	0.15
			Exp F	1.7498	0.07
	15%	1995	**Max F**	7.1153	0.10
			Exp F	1.6883	0.09
TOTM Effect	5%	1999	**Max F**	11.4450	0.02
			Exp F	2.8990	0.02
	15%	1998	**Max F**	8.9443	0.04
			Exp F	2.2299	0.04
Panel C: TOPIX					
Monday Effect	5%	1987	**Max F**	6.9532	0.16
			Exp F	0.9886	0.22
	15%	1987	**Max F**	6.9532	0.11
			Exp F	1.1302	0.16
January Effect	5%	1954	**Max F**	12.8389	0.01
			Exp F	3.4045	0.00
	15%	1995	**Max F**	8.5489	0.05
			Exp F	3.0428	0.01
TOTM Effect	5%	1954	**Max F**	6.0280	0.24
			Exp F	1.0554	0.19
	15%	1960	**Max F**	4.6660	0.28
			Exp F	0.9067	0.23

The results for the breakpoint analysis are inconclusive. One cannot say for certain when the anomalies ceased producing significant returns. The Chow test tends to over accept the breakpoint, and the breakpoint tested may not be the determining break in the returns. The Quandt-Andrews results have however only revealed a single breakpoint where many may be present in our data. It may report the biggest breakpoint in the data but it may be due to other factors and not actually due to knowledge of the anomaly. However, given the Chow test accepts a breakpoint in 1973 for the Monday effect in the DJIA, and the Quandt-Andrews test find one in 1972, there is strong evidence of a change in behaviour around these two years.

4.5.3. Five-Yearly Behaviour Analysis

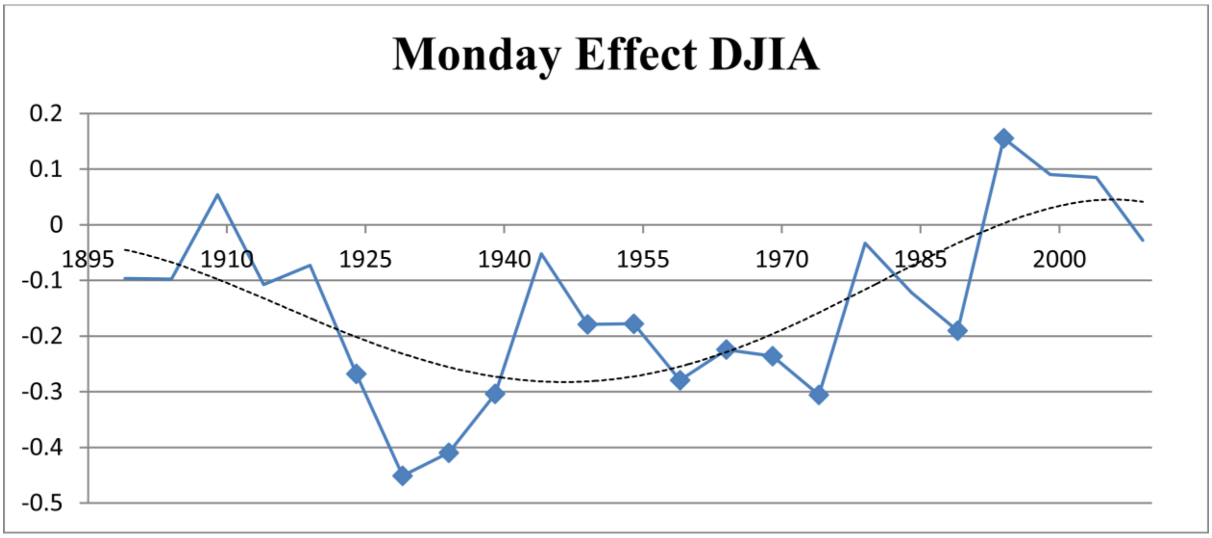
The above analysis is inconclusive and to examine the behaviour of the calendar anomalies in more detail, the five-yearly excess returns of each anomaly are calculated. The results for each year of our sample for each market are documented in Table 4.5 and Figures 4.1-4.3. The blotted points indicate which excess returns are statistically significant at 5% or more.

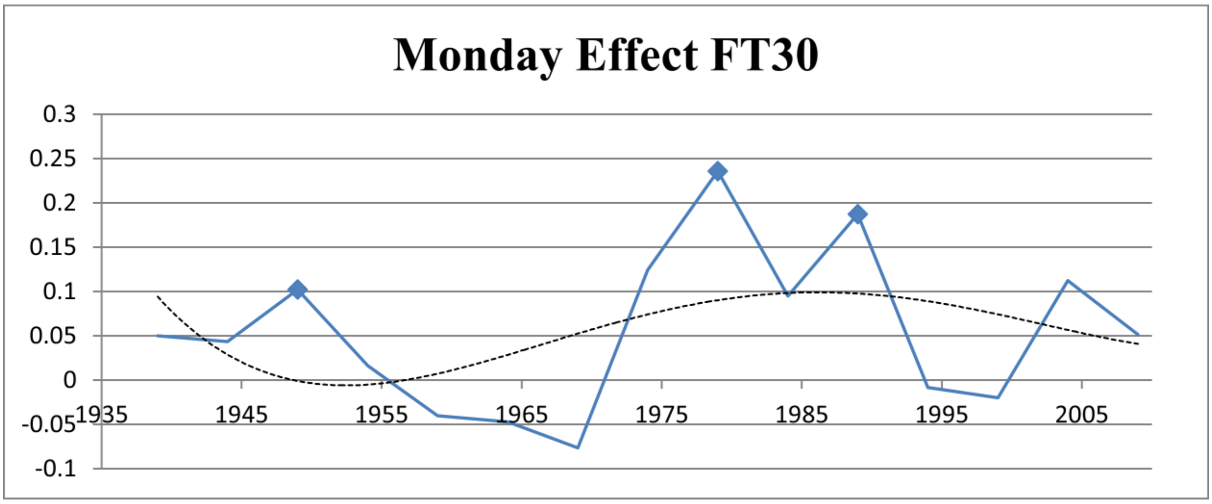
The results for the Monday effect for the three markets are documented in Figure 4.1. The dotted line is the polynomial trendline which documents how the excess returns of each anomaly behave over time. The results for the Monday effect in the DJIA reveal that the excess returns were negative throughout the sample until 1993 when excess returns turned positive. Thus the Monday effect appears to behave in a switching way in the DJIA and is type 3. The FT30 results suggest that the Monday effect has barely existed in the FT30. The only time the trendline is negative is between 1950-1955, albeit at a very low magnitude. Thus excess returns have been positive, then negative and then positive again in the FT30 so the effect can be deemed adaptive and type 4. The TOPIX results for the Monday effect indicate that excess returns are negative throughout the sample, even though the trendline gets quite close to the x-axis. Thus the TOPIX Monday effect can be deemed type 5 and the market inefficient through the sample.

The returns for the January effect for the three markets are documented in Figure 4.2. The excess returns for the DJIA do not produce any significant coefficients and appear to fluctuate around zero for the full sample, with the polynomial trendline starting above the x-axis and then turning below the x-axis, and then above and below it again. Thus excess returns appear fluctuate consistently over time and so can be deemed to be an efficient market type 4. The FT30 results for the January effect are quite similar to the results for the DJIA, with none of the five-yearly subsamples generating significant coefficients and the polynomial trendline crossing the x-axis three times. Also, it should be noted that since 1985 excess returns have been on a downward trend, indicating the fall in successfulness of the January effect in the FT30. This indicates that the behaviour can be deemed adaptive and type 4. The TOPIX results for the January effect reveal that only two of the subsamples generate positive significant coefficients and that the polynomial trendline is downward sloping throughout the sample. This indicates that excess returns in the TOPIX have decreased consistently over time and turn negative from 1992, suggesting a switching of behaviour and thus type 3.

Figure 4.3 depicts the turn-of-the-month regression analysis for the three markets studied. The DJIA shows that up to 1970, the majority of subsamples were positive and statistically significant, indicating the strong success of this anomaly. However since 1970, no subsample is significant and there is a downward trend, even though excess returns are still positive. Thus the DJIA turn-of-the-month effect has produced positive returns throughout the sample period can be classified as type 5. The FT30 results show that excess returns have remained positive over time, with the polynomial trendline being u-shaped indicating the greater strength of the anomaly over the last few subsamples. This again indicates the turn-of-the-month effect can be classified as type 5 since the trendline is always above the x-axis. The turn-of-the-month in the TOPIX has produced positive returns in nearly all of the subsamples, with only two subsamples generating slightly negative excess returns. Nevertheless, the polynomial trendline is positive throughout and similar to the FT30 results, is a u-shape indicating that this anomaly has not decreased but actually increased in successfulness in recent years. Thus similarly to the other two markets for the turn-of-the-month effect, the TOPIX can be classified as type 5.

Figure 4.1: The five-yearly Monday effect plotted over time. Blotted points indicate significance at 5%.





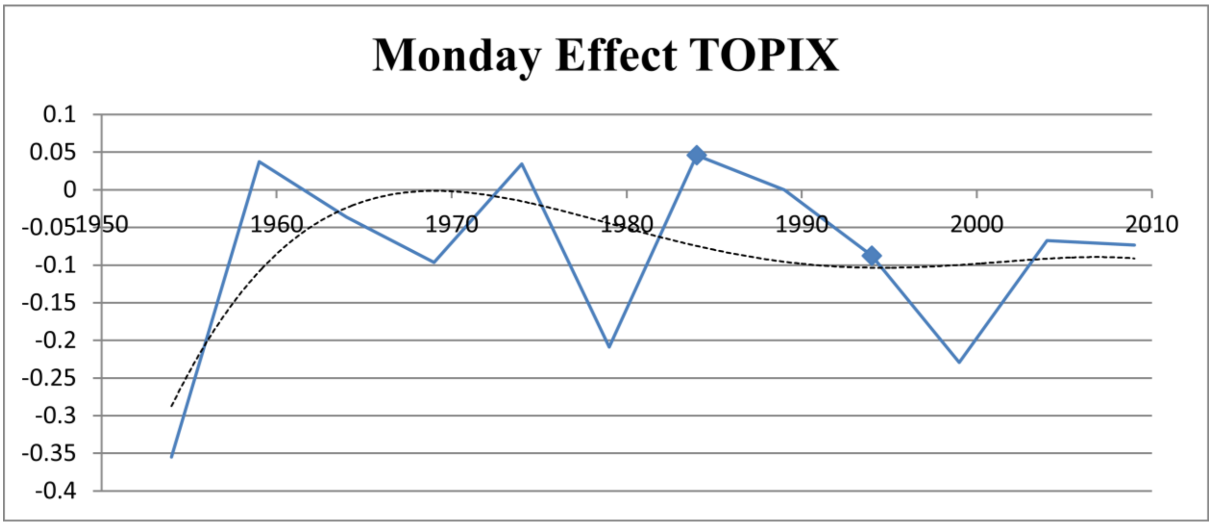


Figure 4.2: The five-yearly January effect plotted over time. Blotted points indicate significance at 5%.

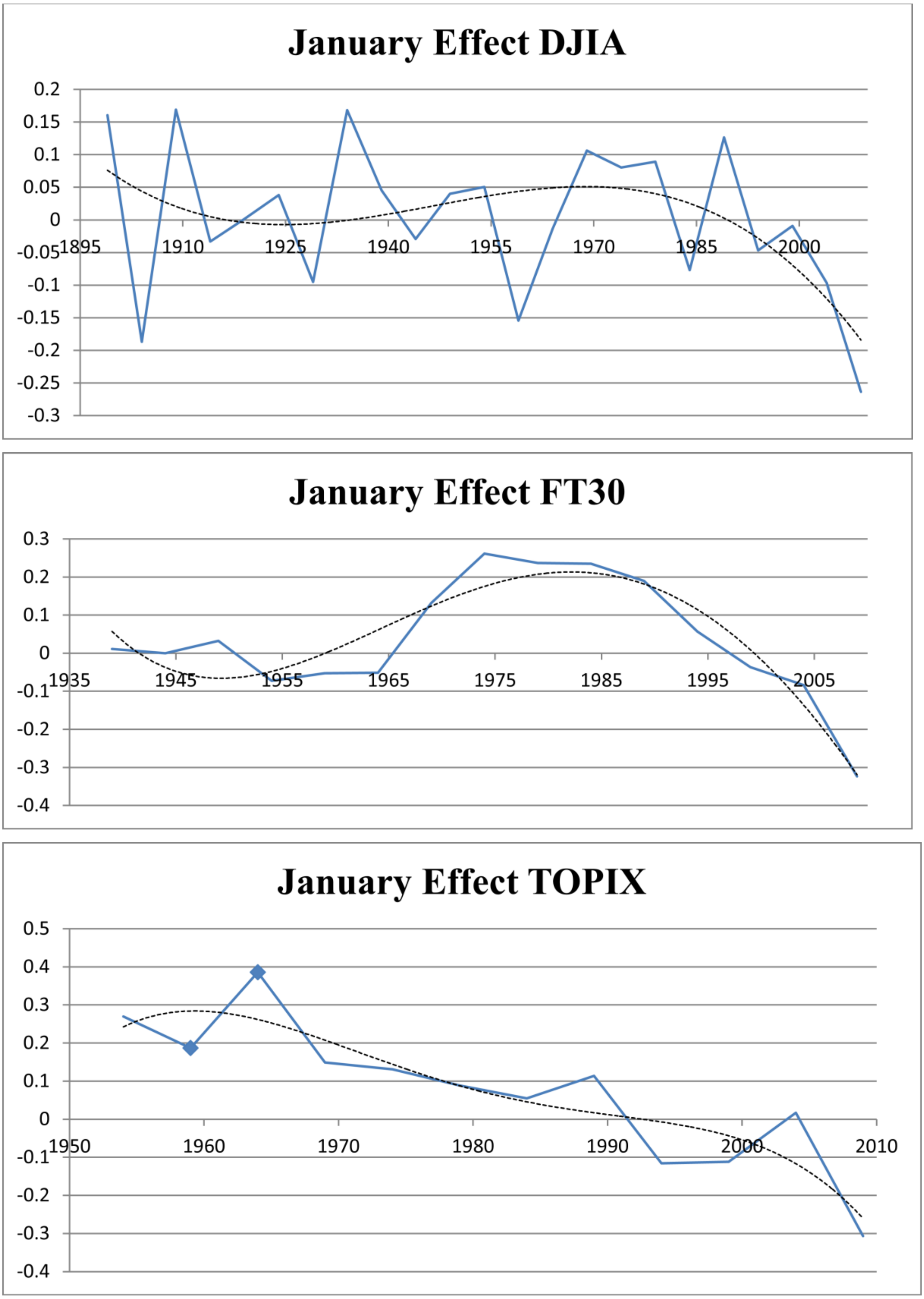


Figure 4.3: The five-yearly turn-of-the-month effect plotted over time. Blotted points indicate significance at 5%.

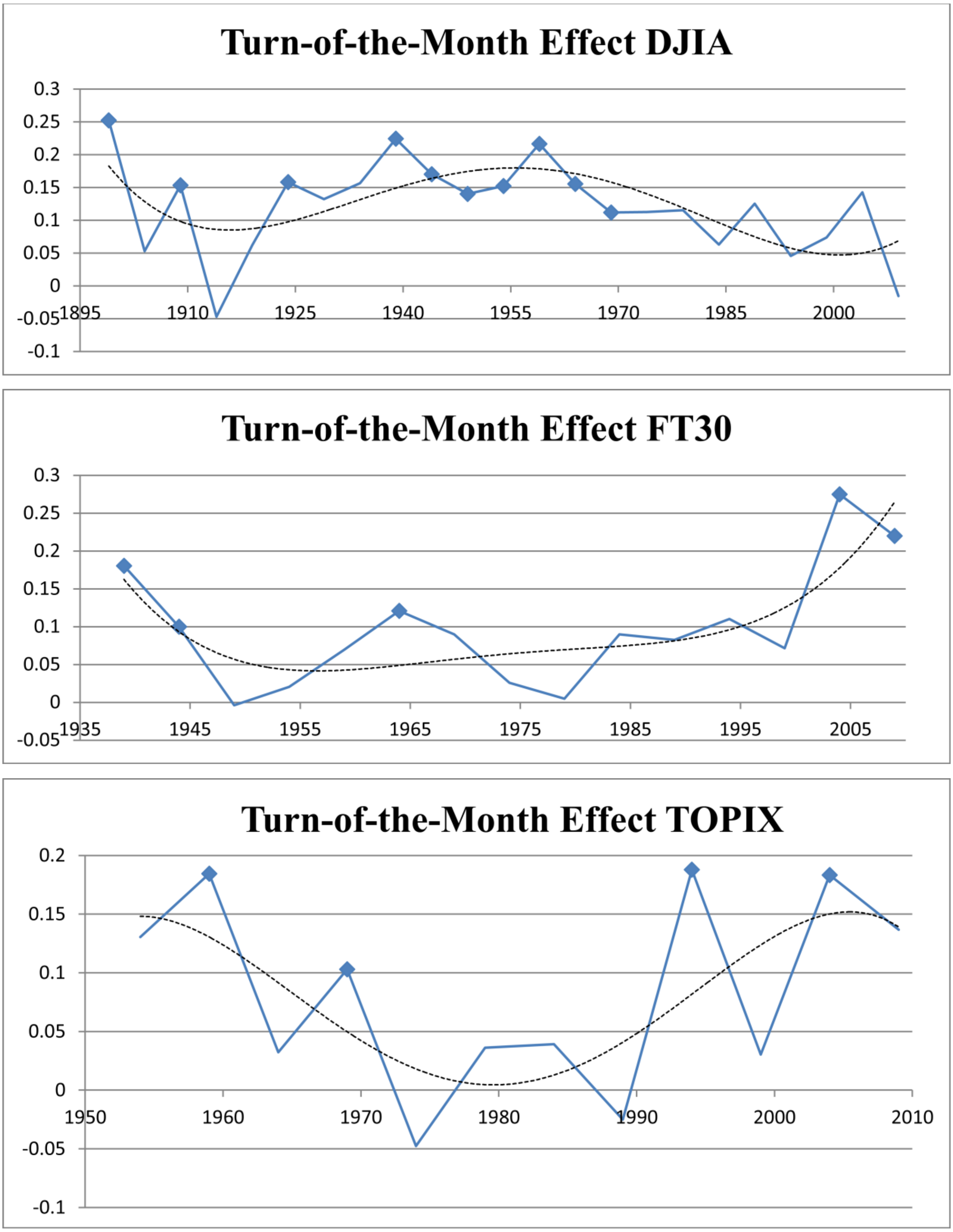


Table 4.5: Test results for regression 4.2 calendar effects on the DJIA, FT30 and TOPIX. Panel A documents the results for the DJIA, Panel B documents the results for the FT30 while Panel C documents the results for the TOPIX. ***, **, * indicate significance at 1%, 5% and 10%.

Sample Period		Monday Effect		January Effect		Turn-of-the-Month Effect	
		Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Panel A: DJIA							
Full Sample		-0.1436463***	(-8.84)	0.0011808	(0.04)	0.1196936***	(7.32)
1897	1899	-0.0962094	(-0.89)	0.1605907	(0.89)	0.2523137**	(2.35)
1900	1904	-0.0972839	(-1.30)	-0.1867101	(-1.46)	0.0528698	(0.70)
1905	1909	0.0539459	(0.79)	0.1691734	(1.45)	0.1533437**	(2.21)
1910	1914	-0.1074781*	(-1.89)	-0.0332134	(-0.36)	-0.0469102	(-0.82)
1915	1919	-0.0725844	(-0.91)	0.0017688	(0.01)	0.0621466	(0.77)
1920	1924	-0.2677891***	(-4.20)	0.0382623	(0.35)	0.1581739**	(2.46)
1925	1929	-0.4510391***	(-5.06)	-0.0949021	(-0.62)	0.1323803	(1.46)
1930	1934	-0.4095476***	(-2.56)	0.1682412	(0.62)	0.1564666	(0.97)
1935	1939	-0.3037017***	(-3.48)	0.0455367	(0.31)	0.2243837**	(2.55)
1940	1944	-0.0520022	(-1.01)	-0.0291069	(-0.33)	0.1701749***	(3.27)
1945	1949	-0.1788807***	(-3.40)	0.0399885	(0.45)	0.1401455***	(2.64)
1950	1954	-0.1777845***	(-4.20)	0.0506099	(0.71)	0.1522015***	(3.57)
1955	1959	-0.2792317***	(-5.62)	-0.1542201*	(-1.82)	0.2164325***	(4.27)
1960	1964	-0.2240496***	(-4.67)	-0.0129235	(-0.16)	0.155438***	(3.19)
1965	1969	-0.2359355***	(-5.34)	0.1062986	(1.43)	0.1118256**	(2.50)
1970	1974	-0.3056002***	(-4.29)	0.0802189	(0.67)	0.1126327	(1.56)
1975	1979	-0.0331369	(-0.56)	0.0891224	(0.90)	0.1151561*	(1.93)
1980	1984	-0.1218893*	(-1.77)	-0.0770569	(-0.67)	0.0630192	(0.91)
1985	1989	-0.1901199**	(-2.01)	0.1263909	(0.80)	0.125295	(1.32)
1990	1994	0.155704***	(2.77)	-0.046688	(-0.50)	0.0456211	(0.81)
1995	1999	0.0905212	(1.28)	-0.0009082	(-0.01)	0.0736912	(1.04)
2000	2004	0.0854678	(0.96)	-0.0960494	(-0.65)	0.1427204	(1.61)
2005	2009	-0.0279791	(-0.29)	-0.2633858	(-1.61)	-0.0156384	(-0.16)
Panel B: FT30							
Full Sample		0.0556057***	(2.88)	0.043834	(1.34)	0.0966365***	(4.93)
1935	1939	0.0501924	(0.80)	0.0110033	(0.10)	0.1804805***	(2.89)
1940	1944	0.043528	(1.20)	0.1131309*	(1.86)	0.1000202***	(2.73)
1945	1949	0.1023155**	(2.53)	0.0325857	(0.48)	-0.0039382	(-0.10)
1950	1954	0.0161634	(0.48)	-0.0723777	(-1.29)	0.0204363	(0.60)
1955	1959	-0.0402313	(-0.71)	-0.0525068	(-0.55)	0.0694119	(1.20)
1960	1964	-0.0471577	(-0.83)	-0.0511600	(-0.54)	0.1209588**	(2.13)
1965	1969	-0.0763483	(-1.09)	0.1320798	(1.14)	0.0899777	(1.28)
1970	1974	0.1242139	(1.21)	0.2614230	(1.52)	0.0258442	(0.25)
1975	1979	0.2358764**	(1.99)	0.2372067	(1.20)	0.0050104	(0.04)
1980	1984	0.0948711	(1.20)	0.2348724*	(1.72)	0.089784	(1.10)
1985	1989	0.1873412**	(2.39)	0.1895239	(1.41)	0.0826692	(1.02)
1990	1994	-0.0084414	(-0.13)	0.0567928	(0.53)	0.110396*	(1.71)
1995	1999	-0.0197367	(-0.32)	-0.0367500	(-0.35)	0.0716294	(1.14)
2000	2004	0.1124656	(1.24)	-0.0838486	(-0.54)	0.2750433***	(2.95)
2005	2009	0.0516633	(0.50)	-0.3237070*	(-1.82)	0.2200307**	(2.06)
Panel C: TOPIX							
Full Sample		-0.355162*	(-1.72)	0.0682586*	(1.92)	0.0817814***	(3.84)
1950	1954	0.0374024	(0.44)	0.2641706*	(1.81)	0.1304841	(1.48)
1955	1959	-0.0363902	(-0.79)	0.1871801**	(2.36)	0.1844637***	(3.89)
1960	1964	-0.0965355	(-1.61)	0.3860291***	(3.76)	0.032221	(0.52)
1965	1969	0.0344429	(0.71)	0.1488196*	(1.78)	0.103005**	(2.06)
1970	1974	-0.208634	(-0.32)	0.1313940	(1.19)	-0.0475438	(-0.72)
1975	1979	0.0460524	(1.34)	0.0884990	(1.50)	0.036248	(1.02)
1980	1984	0.0953626**	(2.31)	0.0549853	(0.77)	0.0391911	(0.92)
1985	1989	-0.0875416	(-1.25)	0.1141278	(0.95)	-0.0249972	(-0.34)
1990	1994	-0.2294963***	(-2.56)	-0.1156417	(-0.75)	0.1878847**	(2.02)
1995	1999	-0.0674739	(-0.83)	-0.1117756	(-0.80)	0.0303416	(0.36)
2000	2004	-0.0735377	(-0.82)	0.0171561	(0.11)	0.1833172**	(1.99)
2005	2009	-0.0126936	(-0.12)	-0.3068274*	(-1.64)	0.1367207	(1.22)

The above analysis shows that the excess returns of various calendar anomalies in three well established markets has fluctuated over time, with the behaviour of the excess returns differing in each case. In order to classify the behaviour of calendar anomalies, we use the classification of return behaviour suggested in the previous chapter. We use a polynomial trendline to distinguish between the five types of anomaly behaviour. The five possible types are perfectly efficient, a move towards efficiency, a switch to efficiency/inefficiency, an adaptive market, or market efficiency.

Table 4.6: Classification of the calendar test results. Key: Type 1 perfectly efficient, Type 2 move towards efficiency, Type 3 anomaly switches, Type 4 adaptive behaviour and Type 5 market inefficiency.

Market	Anomaly	Type
Monday Effect	DJIA	3
	FT30	4
	TOPIX	5
January Effect	DJIA	4
	FT30	4
	TOPIX	3
Turn-of-the-month Effect	DJIA	5
	FT30	5
	TOPIX	5

Table 4.6 shows that the Monday effect in the DJIA has behaved in a switching manner (type 3), while in the FT30 the Monday effect behaved in an adaptive manner (type 4). The TOPIX reports a strong Monday effect, with excess returns negative throughout the full sample (type 5). The January results show that the DJIA and the FT30 exhibit an adaptive behaviour (type 4), while excess returns appear to have reversed in the TOPIX (type 3), with positive excess returns followed by negative excess returns. The turn-of-the-month results indicate that the DJIA excess returns have switched (type 3), with the trendline turning negative at the end of the sample. The DJIA, FT30 and TOPIX all exhibit strong positive excess returns throughout the full sample (type 5), indicating that this anomaly in these markets is still evident.

These results show that the AMH can explain three of the behaviours of the anomalies in the three markets studied. They also show that there little evidence of the Monday effect in the FT30, which is supported by the literature. The newest anomaly, the turn-of-the-month effect, is the strongest of the three, since it can be described by type 5 in all three markets. Also the newest market, the TOPIX, also seems the most inefficient since two of the anomalies are earning excess returns and the other one has reversed. This is consistent with

Lo (2012) who stated that '*a relatively new market is likely to be less efficient than a market that has been in existence for decades*[24]'. There are no examples of type 1 or type 2 anomalies so there is no support for the EMH as set out by Fama. The EMH states that investors should not be able to earn above-average returns, since all information is reflected in the stock price. So if an anomaly is found to produce excess returns in a market, it should disappear quickly due to market forces. However, this is unlikely to be observed in this data given that this paper investigates well known anomalies, which have been found to produce excess returns in the literature.

4.5.4. Trading Strategy Analysis

The results from the simple trading strategy described earlier on the calendar anomalies are documented in Table 4.7 for the full sample and in Table 4.8 for the post publication samples. Table 4.7 reports that using a simple trading strategy over the full sample on the Monday effect does outperform the buy-and-hold strategy for the DJIA, however it cannot outperform the buy-and-hold strategy for the FT30 and TOPIX. Specially, the DJIA outperforms the buy-and-hold strategy by 0.81% per annum. The risk of the trading strategy and the buy-and-hold strategy are broadly similar for the Monday effect. The January anomaly results show that the buy-and-hold strategy outperforms the trading strategy for each market, even though the risk associated with the January effect is substantially less than the risk of the buy-and-hold strategy because the strategy is out of the market most of the time. This shows that the January effect could not be traded on using this simple trading strategy throughout the full sample in each market to gain returns greater than a buy-and-hold strategy. The TOTM anomaly results show that the DJIA and FT30 can outperform the buy-and-hold strategy using this trading strategy, but only by 0.07% and 0.18% per annum respectively. The TOPIX cannot outperform the buy-and-hold strategy for the TOTM, with returns 0.67% per annum less than the buy-and-hold strategy. The previous analysis suggested that the TOTM anomaly was quite strong in all three markets, however these results show that trading on the anomaly is not as successful. The risk of trading on the TOTM is substantially less than the buy-and-hold strategy because the strategy is out of the market most of the time, and may contribute to the success of the anomaly in the DJIA and FT30 markets.

[24] Although the TOPIX has been in existence for a number of decades, it is relatively new compared to the DJIA which was formed in 1896.

Table 4.8 presents the results for the simple trading rule since the first publication of each anomaly[25]. The simple trading rule does not outperform the buy-and-hold strategy for the Monday effect on the DJIA and FT30. The returns are less than the buy-and-hold strategy by 0.08% and 0.04% per annum respectively. This shows that the Monday effect has become less successful since the publication of the anomaly compared to the full sample. However the TOPIX does outperform the buy-and-hold strategy by 0.02% per annum. This shows that since 1973, trading on the Monday effect in the TOPIX has been successful but over the full sample it has been unsuccessful. Thus the Monday effect in the TOPIX has become a lot more successful since the publication of the seminal paper by Cross in 1973. The January results show the simple trading rule did not outperform the buy-and-hold strategy since 1976 for each market with the returns from the trading strategy being 3.13%, 0.03% and 0.03% per annum less than the buy-and-hold strategy. Further, the risk associated with the January effect from the simple trading rule is substantially less than that of the buy-and-hold strategy, further indicating the unsuccessfulness of trading on the January anomaly. The TOTM results show that the implementing this simple trading strategy after 1987 does not outperform the buy-and-hold strategy in the DJIA. However, the FT30 and TOPIX do outperform the buy-and-hold strategy by 0.12% and 0.13% per annum espectively. This shows that since 1987 the TOTM could have gained substantial returns, but over the full sample it generated negative returns. However, the risk associated with the TOTM effect is considerably less than the buy-and-hold strategy. Because of this, the “double or out” trading strategy is also conducted so make the risk of each trading rule fairly similar.

The results from Tables 4.9 and 4.10 document the “double or out” trading strategy to try to form a trading strategy that has comparable risk to that of the buy-and-hold strategy. It clear that the risk of the “double or out” trading strategy is double that of the simple trading strategy, and that the profit achieved from the rule is double that of the simple trading strategy. This is because there are no neutral signals generated so the investor is either out of the market or in the market by double the original amount. The results indicate that the risk of the “double or out” strategy for the Monday effect is now greater than the buy-and-hold strategy showing that the returns from this strategy are not just the result of a strategy with less risk. Even though the risk of the TOTM anomaly is still less than that of the buy-and-hold strategy, they are broadly comparable. However, the January standard deviations from

[25] 1973 for the Monday effect, 1976 for the January effect and 1987 for the turn-of-the-month effect.

the "double or out" trading strategy are still substantially less than that of the buy-and-hold strategy. Thus a "quadruple or out" strategy is now considered for the January anomaly in Table 4.11 to generate comparable risks between a trading strategy and the buy-and-hold strategy. The strategy is similar to the "double or out" strategy but the investor goes in the market with leverage of four times when a buy signal is generated. The strategy generates similar risks to the buy-and-hold strategy for the January anomaly and shows that none of the markets can outperform the buy-and-hold strategy.

The profitability of the three calendar anomalies previously examined through a simple trading strategy and a "double or out" trading strategy. The results show that using the simple trading strategy only the Monday effect in the DJIA, and the TOTM effect in the DJIA and FT30 can outperform the buy-and-hold strategy over the full sample. Further, studying the data after the seminal publication of that anomaly, the results show only Monday anomaly in the TOPIX and the TOTM anomaly in the FT30 and TOPIX can outperform the buy-and-hold strategy. All of the other anomalies cannot beat the buy-and-hold strategy, indicating that although these calendar anomalies are found in the market, they cannot be used to gain returns greater than the market using the simple trading strategy. The results from the "double or out" strategy are similar to the simple trading strategy but only the rule profits have doubled as have the standard deviations of the rules. Finally a "quadruple or out" trading strategy is also conducted for the January anomaly to enable the risk of the trading strategy to the comparable to that of the buy-and-hold strategy. The results show that the trading strategy cannot outperform the buy-and-hold strategy for all three markets. These results show that even though the earlier analysis shows that the calendar anomalies are strong and evident in the markets, it does not always guarantee that the anomaly will generate returns greater than the market.

Table 4.7: Test results for the calendar anomalies using the simple trading strategy on the full sample of each market. The number of trades (No. of buy/sell) are shown as well as the standard deviations associated with the trading rule and the buy-and-hold strategy. The profits from trading on the rule (Rule Profit) as well as the buy-and-hold strategy are shown. Further, the annualised difference between the rule returns and the buy-and-hold returns are also shown.

Anomaly	No. Buys	No. Sells	SD Rule	SD B&H	Rule Profit	B&H Profit	Difference	Annualised % Difference
	Panel A: DJIA							
Monday Effect	5522	5522	0.96	1.10	1124.00	585.14	538.87	0.81%
January Effect	113	113	0.23	1.10	33.81	585.14	-551.33	-0.83%
TOTM Effect	1360	1659	0.44	1.10	634.04	585.14	48.90	0.07%
	Panel B: FT30							
Monday Effect	3731	3731	0.95	1.06	69.44	294.40	-224.96	-1.01%
January Effect	74	74	0.25	1.06	62.39	294.40	-232.01	-1.05%
TOTM Effect	894	893	0.46	1.06	333.65	294.40	39.25	0.18%
	Panel C: TOPIX							
Monday Effect	3078	3078	0.87	1.02	432.80	436.15	-3.35	-0.01%
January Effect	59	59	0.25	1.02	82.22	436.15	-353.93	-1.40%
TOTM Effect	709	708	0.43	1.02	266.96	436.15	-169.76	-0.67%

Table 4.8: Test results for the calendar anomalies using the simple trading strategy on the post publication data. The number of trades (No. of buy/sell) are shown as well as the standard deviations associated with the trading rule and the buy-and-hold strategy. The profits from trading on the rule (Rule Profit) as well as the buy-and-hold strategy are shown. Further, the annualised difference between the rule returns and the buy-and-hold returns are also shown.

Anomaly	No. Buys	No. Sells	SD Rule	SD B&H	Rule Profit	B&H Profit	Difference	Annualised % Difference
	Panel A: DJIA							
Monday Effect	1788	1788	0.93	1.11	225.78	232.47	-6.68	-0.08%
January Effect	34	34	0.26	1.10	-7.85	250.42	-258.27	-3.13%
TOTM Effect	276	276	0.47	1.19	112.15	170.48	-58.33	-1.56%
	Panel B: FT30							
Monday Effect	1904	1904	1.15	1.28	-43.67	133.92	-177.59	-0.04%
January Effect	34	34	0.27	1.18	24.39	162.28	-137.89	-0.03%
TOTM Effect	276	276	0.49	1.18	138.32	138.32	101.07	0.12%
	Panel C: TOPIX							
Monday Effect	1931	1931	0.96	1.12	143.32	81.51	61.81	0.02%
January Effect	34	34	0.27	1.14	-10.77	103.68	-114.46	-0.03%
TOTM Effect	276	276	0.54	1.32	101.18	-54.33	155.51	0.13%

Table 4.9: Test results for the calendar anomalies using the "double or out" trading strategy on the full sample data. The number of trades (No. of buy/sell) are shown as well as the standard deviations associated with the trading rule and the buy-and-hold strategy. The profits from trading on the rule (Rule Profit) as well as the buy-and-hold strategy are shown. Further, the annualised difference between the rule returns and the buy-and-hold returns are also shown.

Anomaly	No. Buys	No. Sells	SD Rule	SD B&H	Rule Profit	B&H Profit	Difference	Annualised % Difference
	Panel A: DJIA							
Monday Effect	5522	5522	1.91	1.10	2248.00	585.14	1662.87	2.49%
January Effect	113	113	0.46	1.10	67.62	585.14	-517.52	-0.78%
TOTM Effect	1360	1659	0.88	1.10	1268.08	585.14	682.94	1.02%
	Panel B: FT30							
Monday Effect	3731	3731	1.90	1.06	138.89	294.40	-155.52	-0.70%
January Effect	74	74	0.50	1.06	294.40	294.40	-169.61	-0.77%
TOTM Effect	894	894	0.91	1.06	667.61	294.40	372.90	1.69%
	Panel C: TOPIX							
Monday Effect	3078	3078	1.74	1.02	865.60	436.15	429.44	1.70%
January Effect	59	59	0.49	1.02	164.44	436.15	-271.72	-1.07%
TOTM Effect	709	708	0.85	1.02	533.91	436.15	97.76	0.39%

Table 4.10: Test results for the calendar anomalies using the "double or out" trading strategy on the post publication data. The number of trades (No. of buy/sell) are shown as well as the standard deviations associated with the trading rule and the buy-and-hold strategy. The profits from trading on the rule (Rule Profit) as well as the buy-and-hold strategy are shown. Further, the annualised difference between the rule returns and the buy-and-hold returns are also shown.

Anomaly	No. Buys	No. Sells	SD Rule	SD B&H	Rule Profit	B&H Profit	Difference	Annualised % Difference
	Panel A: DJIA							
Monday Effect	1788	1788	1.87	1.11	451.57	232.47	219.10	2.62%
January Effect	34	34	0.53	1.10	-15.70	250.42	-266.12	3.22%
TOTM Effect	276	276	0.94	1.19	224.29	170.48	53.81	1.44%
	Panel B: FT30							
Monday Effect	1904	1904	1.90	1.06	138.89	133.92	-155.52	-1.47%
January Effect	34	34	0.54	1.19	48.77	162.28	-113.51	-2.12%
TOTM Effect	276	276	0.97	1.18	276.64	138.32	239.39	29.21%
	Panel C: TOPIX							
Monday Effect	1931	1931	1.93	1.12	286.64	81.51	205.13	6.99%
January Effect	34	34	0.53	1.14	-21.55	103.68	-125.23	-3.66%
TOTM Effect	276	276	1.08	1.32	202.36	-54.33	256.69	21.48%

Table 4.11: Test results for the "quadruple or out" trading strategy on the January anomaly. The number of trades (No. of buy/sell) are shown as well as the standard deviations associated with the trading rule and the buy-and-hold strategy. The profits from trading on the rule (Rule Profit) as well as the buy-and-hold strategy are shown. Further, the annualised difference between the rule returns and the buy-and-hold returns are also shown.

Anomaly	No. Buys	No. Sells	SD Rule	SD B&H	Rule Profit	B&H Profit	Difference	Annualised % Difference
	Panel A: Full Sample							
DJIA	113	113	0.93	1.10	135.23	585.14	-449.91	-0.67%
FT30	74	74	1.01	1.06	249.58	294.40	-44.83	-0.20%
TOPIX	59	59	0.98	1.02	328.87	436.15	-107.28	-0.42%
	Panel B: Post Publication Data							
DJIA	34	34	1.06	1.10	-31.39	250.42	-281.81	-3.41%
FT30	34	34	1.07	1.18	97.55	162.28	-64.73	-1.21%
TOPIX	34	34	1.06	1.14	-43.10	103.68	-146.78	-4.29%

4.5.5. January Anomaly Analysis Excluding TOTM Anomaly

Finally Table 4.12 reports the means and excess returns for the January anomaly with the turn-of-the-month days. The mean of January days without the turn-of-the-month days for the DJIA turns negative to -0.01961, compared to 0.03664 with the turn-of-the-month days included. The excess returns are also negative, indicating that the turn-of-the-month was driving the January returns. The results for the FT30 show that January's mean decreased by more than a half when the turn-of-the-month days are excluded. Although excess returns are still positive, they are no longer statistically significant. The TOPIX mean for January days excluding the turn-of-the-month days is also less than before, with the excess returns now only significant at the 10% level. These results show that the turn-of-the-month effect was driving the January anomaly in the DJIA, and contributed significantly to the January anomaly in the FT30 and TOPIX. Thus the January effect may not be as strong as first thought and that the turn-of-the-month effect may be the driving force behind the high returns documented in the first half of January.

Table 4.12: Summary statistics for the January effect excluding turn-of-the-month days. ***, **, * indicate significance at 1%, 5% and 10% respectively.

	Full Sample		
	DJIA	**FT30**	**TOPIX**
January Anomaly			
January Mean	0.03664	0.06650	0.11618
Standard Deviation	0.96872	1.10842	1.05183
No. of January Days	2635	1607	641
Fraction of positive January return days	0.52182	0.50840	0.49156
Non-January Mean	0.01719	0.01069	0.02021
Non-January Standard Deviation	1.10724	1.05373	1.02136
***t*-statistic for difference of means**	0.87	2.02**	3.24***
January – TOTM Anomaly			
January Mean	-0.01961	0.03076	0.09967
Standard Deviation	0.95507	1.01099	1.09523
No. of January Days	1347	888	708
Fraction of positive January return days	0.50	0.50	0.52
Non-January Mean	0.02059	0.01462	0.02490
Non-January Standard Deviation	1.10211	1.06078	1.02066
***t*-statistic for difference of means**	-1.32	0.44	1.90*
Excess Returns	-0.04007 (-1.32)	0.01614 (0.44)	0.07477 (1.90)*

4.6. Conclusion

Calendar anomalies are accepted in stock markets throughout the world due to the voluminous literature supporting them. However, recent evidence has suggested that these anomalies have diminished, or even reversed over time. In this chapter three of the most accepted calendar anomalies, the Monday effect, the January effect and the turn-of-the-month effect are examined. This chapter contributes to the literature by examining how the returns from these anomalies have behaved over time, whether they can be exploited to earn excess returns by using a simple trading strategy and whether the turn-of-the-month effect drives the January effect.

The key conclusions are;

(i) There is strong evidence of the Monday effect in the DJIA and TOPIX, but little evidence of it in the FT30. Since the publication of the seminal paper, the returns on the Monday effect have reversed in the DJIA but got stronger in the TOPIX.

(ii) The January effect is strong in the FT30 and TOPIX, but not so strong in the DJIA. Further, the January effect has decreased in magnitude since the publication of the seminal paper by Ariel in 1976.

(iii) The TOTM effect is strong in all three markets, although it has fallen in magnitude since the publication of the seminal paper in 1987.

(iv) The behaviour of the anomalies over time can be categorized into 5 types, with the DJIA presenting evidence of the AMH through the January effect, while evidence of the AMH is found through the January and Monday effect in the FT30. All of the other anomalies in the markets are characterized by a switch to efficiency or constant inefficiency indicating that market efficiency is not present.

(v) Using a simple trading strategy, only the Monday effect in the DJIA, and the TOTM effect in the DJIA and FT30 outperform the buy-and-hold strategy over the full sample. Further, studying the data after the seminal publication of each anomaly, only the Monday anomaly in the TOPIX as well as the TOTM anomaly in the FT30 and TOPIX outperforms the buy-and-hold strategy. All of the other anomalies do not beat the buy-and-hold strategy. “Double or out” and “quadruple or out” trading strategies are also conducted with results being very similar to the simple trading strategy but larger in magnitude.

(vi) The January anomaly excess returns can be accounted for by the turn-of-the-month effect in the DJIA, where January returns are not negative. In the FT30 and TOPIX, the January returns fall significantly when the turn-of-the-month days are excluded.

The fact that returns from some these calendar anomalies have decreased over time indicates the possibly these anomalies are not stylized facts about the stock market. It could be that investors caused these abnormal returns through irrational trades, but once they realized they were present, traded them away. This is consistent with the new AMH where profit opportunities go through cyclical fashions according to market conditions and investors learn these profit opportunities and take advantage of them. Simple investment strategies are able to generate returns greater than the market be exploiting these calendar effects over the full sample for only a few on the anomalies studied. This indicates that although these anomalies are evident in the data, they cannot be used consistently over time to generate excess returns. One explanation is that the trading strategies suggested is not sophisticated enough to take advantage of the anomalies. Another explanation is that the calendar anomalies may only work under certain market conditions, such as in booms, or bull markets. The turn-of-the-month effect appears to be responsible for the excess returns of the January anomaly in the DJIA. This is consistent with the findings of Xu and McConnell (2008) that the turn-of-the-month anomaly accounts for all the increases in the market. It also appears to have a significant impact on the excess returns of the January effect in the FT30 and TOPIX, with the FT30's excess returns turning insignificant and the TOPIX's decreasing to 10% significance. It may be that the turn-of-the-month effect may decrease over time, but since it is a relatively newly discovered anomaly it is still generating significant excess returns. However, it may also be the case that it is a stylized fact about the market and that it isn't a calendar anomaly after all. Future analysis of the returns of the turn-of-the-month effect will provide answers to this question.

Chapter 5: The Behaviour of the Moving Average Rule

5.1 Introduction

Technical analysis involves forecasting future prices through the identification and exploitation of recurring patterns in past prices. Thus it aims to identify patterns forced by economic, monetary, political factors or the psychological attitudes of investors. One of the most important and celebrated technical rule is the moving average rule, which is the focus of this chapter.

Technical analysis has a long history of widespread use by participants in financial markets. Park and Irwin (2007) note that its origins date back to the 18th century when the Japanese developed a form of technical analysis known as candlestick charting, that was not introduced to the west until the 1970s. Smidt (1965b) surveyed amateur traders in the US commodity futures markets and found that over half used charts exclusively to identify trends, while Billingsley and Chance (1996) also find that about 60% of commodity trading advisors (CTAs) rely heavily on computer-guided technical trading systems. More recently, Menkhoff (2010) finds that the vast majority of fund managers use technical analysis and it is preferred to fundamental analysis.

Academic interest in technical analysis can be traced back to Cowles (1933), who undertook an examination of stock price forecasting methods which included looking at technical trading and William Hamilton's use of the Dow Theory (Hamilton 1922). Dow Theory was developed by Charles Dow, the editor of the Wall Street, in the late 1800s. He believed that markets moved in trends, with major and minor trends being able to move in opposite directions to the main trend. There is an 'accumulation phase', where investors traded against the market at the start of the main trend, and sold towards the end of the main trend in a 'distribution phase'. In the distribution phase, investors were taking profits as new and less informed individuals bought too late. Dow also stated that the market quickly included new information into its stock price, which is consistent with the later proposed EMH. Dow himself was not interested in proposing profitable trading strategies, but later, editors of the Wall Street Journal developed his work and coined the expression Dow Theory (Lo and Hasanhodiz 2010). Cowles (1933) however found that investors who pursued these early theories were not very successful while Hamilton (1922) also found the results were insufficient to comprise a profitable trading strategy.

Academics however, tend to be sceptical about the use of technical analysis. This scepticism can be linked to acceptance of the EMH, which implies that trend analysis is futile in an attempt to make profits by exploiting currently available information such as past prices. This scepticism can also be linked to the early negative empirical findings regarding the profitability of technical analysis in stock markets, for example Fama and Blume (1966), Van Horne and Parker (1967), Van Horne and Parker (1968) and Jensen and Benington (1970).

The early rejection of the usefulness of technical analysis led to numerous studies investigating its validity since many traders used it in their trading strategies. These studies investigated various trading rules in a variety of markets, with the aim to uncover profitable trading rules or to confirm market efficiency. Due to the strong positive findings of technical analysis rules in the 1980s[26], there has been an explosion in the literature on technical analysis since the mid-1990s, with Park and Irwin (2007) noting that half of all empirical studies conducted after 1960 were published during the period 1995-2004.

This chapter examines the behaviour of one of the most celebrated and studied technical rules, the moving average rule and this chapter is organised in the following manner. Section 5.2 describes the literature while Section 5.3 outlines the methodology used. Section 5.4 presents the data while Section 5.5 reports the empirical results. Section 5.6 analyses and concludes the chapter.

5.2. Literature Review

The moving average rule is one of the most popular technical rules amongst practitioners and has been extensively studied in the academic literature. One of the first papers to investigate the moving average rule was by Cootner (1962). Cootner argued that Alexander's (1961) study of another technical rule, the filter rule, was not as effective when used on individual common stocks. So Cootner (1962) examined the average weekly change in 45 individual stocks from the NYSE from 1956 and tested the 200-day moving average against the buy-

[26] For example, Brock et al (1992).

and-hold strategy. He found that it was much more successful than a simple buy-and-hold strategy if only gross profits are considered. However due to the high frequency of trading, the rule is much inferior after allowing for transaction costs. To avoid the excessive movements between a long and short position, he introduced percentage bands which meant stocks were only bought if their price rose above the moving average by more than 5%. The results show a gross gain of 17% more than the simple buy-and-hold strategy, although the net gain is still negative. Thus the moving average rule was deemed not to be profitable. These results were further supported by Van Horne and Parker (1967), who investigated 30 industrial stocks on the NYSE between January 1960 and June 1966. They tested the 200-day, 150-day and 100-day rules with 0%, 2%, 5%, 10% and 15% bands. The results concluded that the various rules could not generate returns greater than a simple buy-and-hold strategy. Profits were considerably less after transaction costs were incurred and prices tended to move in a random nature. Van Horne and Parker (1968) furthered their work by employing a weighted moving average rule to account for the fact that investors tended to place more emphasis on the recent past, so more significance is placed on recent prices and less on historical data. They used various weightings with the 200-day rule and found that is it not possible to produce consistent profits by trading securities this way. They also showed that data from the recent past does not have more predictive power than price data from the more distant past. Further, James (1968) found similar results when investigating the moving average rule using monthly share price data for the period 1926-1960. By enabling investors to sell their securities near the peak price and repurchase when the security is near the lowest price, it was found that investors would be significantly worse off than if they had invested in the simple buy-and-hold strategy and thus the rule had no predictive power. Dale and Workman (1980) found similar results using US Treasury bill futures.

The study by Brock et al (1992) (BLL hereafter) is one of the most influential works on technical trading rules. The influence is due to the findings of strong, consistent and positive results about the forecasting power of technical trading rules, the use of a long price history (90 years of the DJIA) and the application for the first time of the model-based bootstrap method. BLL applied the model-based bootstrap approach to overcome the weaknesses of conventional *t*-tests when financial returns have distributions known to be leptokurtic, autocorrelated, conditionally heteroskedastic, and time varying (non-normal). In this approach, returns conditional on buy (or sell) signals from the original series are compared to conditional returns from simulated returns generated by widely used models for stock prices.

BLL applied the moving average rule to the DJIA data over the 1897-1986 period and the results indicate that buy (sell) signals from the moving average rule generates positive (negative) returns across all 26 rules and four sub-period tested. Thus all the buy-sell differences are positive and outperform buy-and-hold returns. All the buy-sell spreads are also positive with an annual return of 19%, which compares favourably with buy-and-hold returns of 5%. Moreover buy signals generate higher average returns than sell signals and have a lower standard deviation than sell signals. This implies that technical trading returns cannot be explained by risk. Hence BLL conclude '*the returns-generating process of stocks is probably more complicated than suggested by the various studies using linear models. It is quite possible that technical rules pick up some of the hidden patterns.*' However, the authors only report the gross returns of each trading rule without an adjustment for transaction costs, so their results are not sufficient to prove that the moving average rules generate returns greater than the simple buy-and-hold strategy.

The results from BLL have been subject to consider scrutiny with Bessembinder and Chan (1998) examining the same trading rules as BLL for dividend-adjusted DJIA data over the sample period 1926-1991. Incorporating these dividends tends to reduce the returns on short sales and thus decreases the technical trading returns. To avoid data snooping, they test the profitability and significance of the returns of the trading rules on portfolios as well as returns on individual stocks. The results show that the average buy-sell difference across all rules is 4.4% per year, with non-synchronous trading with a 1-day lag reducing the difference to 3.2%. Nevertheless as break-even transaction costs decline over time, they find that the transaction costs outweigh the returns. Thus it is unlikely that investors could have earned profits after transaction costs. Further, Sullivan et al (1999) examine the results of BLL by applying a bootstrap reality check for the same sample period. They use 8000 trading rules from five various technical trading systems (filter, moving average, channel break-outs, support and resistance and on balance volume averages). They find that the best rule is the 5-day moving average rule and that the results is not due to data snooping. However the out-of-sample results are not so successful. Using the 10-year out-of-sample period, the best rule is again the 5-day moving average rule although it does not continue to generate significant returns in the subsequent period. Thus Sullivan et al (1999) conclude that market efficiency has improved in recent years due to the inferior performance of the out-of-sample tests, relative to in-sample performance. Ready (2002) studies BLL results by comparing their moving average rules to technical trading rules formed by genetic programming. They find that the BLL best trading rule for the 1963-1986 sample period produces significantly higher excess returns than the average of the trading rules recognized by the genetic programming. However, the BLL moving average rule is less successful than the genetically generated rules over the 1957-1962 period. Thus Ready argues that investors would have been unlikely to choose the BLL moving average rule at the end of 1962 given its relatively poor performance and the results are just the result of data snooping. Furthermore, Day and Wang (2002) re-examine BLL findings by adjusting for both dividends and the interest earned on the proceeds from short sales. They show that adjusting for transaction costs and the impact of nonsynchronous prices on the reported closing levels of the DJIA eliminates the profits, reducing both the differential returns following buy and sell signals, and that the risk-adjusted excess profits are not statistically significant. Also, Atanasova and Hudson (2010) conducted an updated version of the BLL paper to include data from the DJIA from 1897 to 2009. They find that moving average rules to be highly predictive on the adjusted data to remove calendar effects and conclude that the removal of calendar effects does not make the rules insignificant. Thus while some rules exploit calendar effects, they are primarily being driven by other factors.

BLL results have been examined in great detail in the DJIA, but the moving average rule has also been examined in many markets, including the UK and Japan. Hudson et al (1996) examine BLL's methodology on the FT30 from 1935 to 1994. Although they confirm that these rules have predictive power, they do not generate excess returns after taking account of transaction costs of 1% per round trip. Mills (1997) investigate the FT30 from 1935 to 1994 and find that the first forty years of their sample are consistent with returns much higher than buy-and-hold returns. Goodarce et al (1999) also examine the UK market by utilising technical analysis methods such as relative strength, moving averages and the cumulative volume Relative Strength Moving Average ruler rule. Using the FTSE 350 index over 1988 to 1996, they find strong evidence that these trading rules are not predictive and the index moves randomly. Fifield et al (2005) study the moving average rule in 11 European stock markets (including the UK) from 1991 to 2000 and find that none of the rules examined outperformed the simple buy-and-hold strategy, suggesting deterioration in the profitability of the moving average rule. Also, Fifield et al (2008) examine the predictive power and profitability of the moving average rule in 15 emerging and 3 established markets (US, UK and Japan) from 1989 to 2003. They find that the moving average rule in developed markets is less profitable than that in developing markets. Further, Metghalchi et al (2012) examine the profitability of the moving average rule in 16 European stock markets (including the UK) from 1990 to 2006. They find that the simple moving average rule does have predictive power in all of the countries and that the two trading strategies studied do beat the buy-and-hold strategy.

Evidence from Japan has been sparse and mixed. Bessembinder and Chan (1995) assess the moving average rules and trade-breakout rules for five Asian stock market indices. They find that the rules have explanatory power in all five markets, with the three emerging markets (Malaysia, Thailand and Taiwan) generating more explanatory power than more developed markets (Hong Kong and Japan). However when transaction costs are considered, any gains from these trading strategies are eliminated. They also find that signals emitted by technical rules in the US contain forecast power for returns in the Asian markets. Ito (1999) also investigates the trading rules used by BLL data on the national equity indices of six Pacific-Basin countries. The results show that although the rules have predictive power in Japan, Canada, Indonesia, Mexico and Taiwan, the trading rules do not have any significant forecasting power in the US. Furthermore, the rules have stronger forecast power in emerging markets than developed markets. Jasic and Wood (2004) examine the profitability of the moving average rule based on univariate neural networks using untransformed data inputs to provide short-term predictions of stock market returns. The profitability of trading rule signals for the S&P 500, DAX, TOPIX and FTSE All-Share were evaluated over the period 1965-1999 using out-of-sample short-term predictions. The results suggest that each index produces returns above a simple buy-and-hold strategy even when transaction costs are accounted for. Chong and Chan (2008) study the Nikkei 225 from 1985 to 2006 and also split the whole subsample into two using the year 2000 as the cut-off year. They find the moving average rule has no predictive power in any of the samples thus indicating the efficiency of the Japanese stock market in this respect. Chen et al (2009) examine various technical trading rules from 1975 to 2006 in eight Asian markets (including the TOPIX) and find that the short term moving average rules are the most profitable for all markets when no transaction costs are implemented. However when transaction costs are taken into account, the most profitable rules are the long-run moving average rules, although there is a substantial decline in trading profits.

5.3. Methodology

The technical rule examined in this chapter is the popular and well documented moving average rule. A moving average is an average of observations of the level of the index over several consecutive time periods. The objective is to smooth out seasonal variations (volatility) in the data. The standard moving average rule, which utilizes the price line and the moving average of price, generates buy/sell signals on which the investor trades. This strategy is expressed as buying (or selling) when the short-period moving average rises above (or falls below) the long-period moving average. Thus buy and sell signals are generated by crossovers of a long moving average (calculated over L days) by a short moving average (S days, $S < L$). The buy signal is generated when the short-period moving average moves higher than the long-period moving average:

$$\left[\sum_{\lambda}^{S} P_{t-(\lambda-1)} \Big/ S\right] > \left[\sum_{\lambda}^{L} P_{t-(\lambda-1)} \Big/ L\right] \Rightarrow Buy\ at\ time\ t \qquad (5.1)$$

Where P_t is the price at time t and λ is the length of the moving average. Sell signals are generated when the inequality is reversed:

$$\left[\sum_{\lambda}^{S} P_{t-(\lambda-1)} \Big/ S\right] < \left[\sum_{\lambda}^{L} P_{t-(\lambda-1)} \Big/ L\right] \Rightarrow Sell\ at\ time\ t \qquad (5.2)$$

A x% band is included to reduce the number of signals by eliminating "whiplash" signals when the short and long period moving averages are close[27]. The most popular moving average rule in the literature is the (1,200), where the short period is one day and the long period is 200 days. However for completeness, the three most popular variations of the rule are used: (1,50), (1,150) and (1,200). The shorter the size of the moving average, the closer it follows the market, and the longer the size of the moving average, the more it smoothes market fluctuations. Thus a rule with $S = 1$ is very responsive, that is, whenever the actual returns rises above (below) the moving average, the signal is to buy (sell).

[27] Generally a 1% band is used in the literature.

The moving average rule is examined over the full sample for each market to examine if the rule has been successful over the full period[28] and these results are compared to the results of seminal paper by BLL to determine whether the returns of the rules have decreased since their examination of them. To investigate further how returns have fared since the BLL publication, the moving average rule is examined since 1987 (the end of BLL's sample period) for all markets. Also to examine how the moving average rules have behaved over time, five yearly subsamples of buy-sell returns are calculated and plotted over time as before. Similar to previous chapters, a dotted polynomial trendline is included to smooth the picture of how the anomalies have behaved over time. Again, the suggested classification of return behaviour in Chapter Two is used to categorize the trading rules behaviour as in the previous chapters.

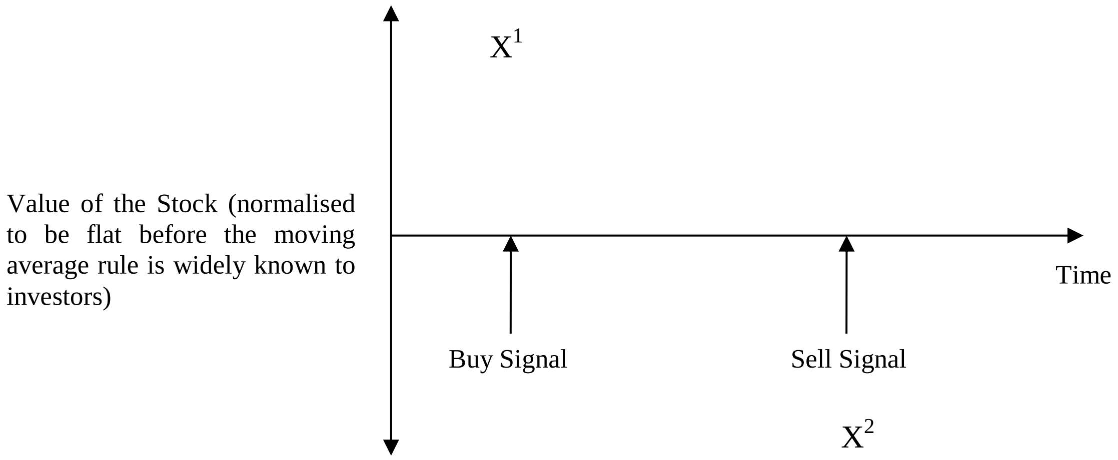
The fact that the moving average rule has been successful for such a long period of time suggests that the rule is picking up some intrinsic property of the market. This property was unknown to investors in general before the publication of the BLL paper but since its publication, investors may have known about the success of the rule and may have begun to implement the rule into their investment strategy. If many investors follow the moving average rule, it will force more buying (selling) pressure on the price when a buy (sell) signal is generated. Thus prices will go up (down) more (less) than they would have done before the publication of BLL due to the increased volume of trading caused by this rule. This means that the stock will become overvalued (undervalued) relative to what it would previous have been due to the high (low) buying pressure at the start of the buy period (which is beyond what was causing the phenomenon on the first place) which may result in the rule not doing so well in the future and explain why the rule after the BLL publication is not very successful.

Figure 5.1 presents the effect of investors knowing about the success of the moving average and trading on it. Initially it is assumed that the value of the stock before the rule is known to investors is zero for simplicity reasons (along the x-axis). However when investors begin trading on the moving average rule and a buy signal is generated, the increased volume of buying causes the stock's value to increase to X^1 beyond what it should be. The same can be said when a sell signal is generated and the increased volume of selling causes the stock's

[28] Atanasova and Hudson (2010) examined the DJIA up to March 2009 while this study investigates up to December 2009.

value to fall to X^2 less than it should be. Thus it is clear to see from Figure 5.1 that if many investors trade on the moving average rule, the value of the stock when a signal is created is distorted. This may cause the moving average rules predictability to diminish.

Figure 5.1: The effect on the value of the stock when investors know about the moving average rule and begin to trade on it.



Informed investors may realise this and begin to anticipate the next day's signal take advantage of the overvaluing/undervaluing of the price. To investigate this possibility, perfectly anticipated and imperfectly anticipated moving average rules are proposed and examined. These two rules anticipate the next day's signal and trade that signal today to take advantage of the overvalued/undervalued price. The perfectly anticipated moving average rule perfectly predicts the signal for the following day through the moving average rule. This is often quite possible since the long run moving average is often not close to the current price and so it is fairly certain what the following days signal is going to be. The imperfectly anticipated moving average rule incorporates the fact that investors will not always be 100% confident what the next day's signal is going to be. This rule is the same as the perfectly anticipated moving average rule except when the current price is very close to the long run moving average, a neutral signal is created like before. Bands of 0.25%, 0.50% and 1% are used, similar to before to create these neutral signals. That is, if the short run moving average is within the long run moving average by 0.25%, 0.5% and 1% the investor is faced with a neutral signal. Instead of not trading, when the investor is faced with a neutral signal they choose the current days signal and trade on that. That is, if the investor is uncertain what the following days signal is going to be, instead of predicting it they use the current days signal. These two rules are examined in section 5.4 of this chapter.

An important question to ask when dealing with any technical rule is whether an investor can use them to gain returns greater than the market. Thus the degree to which investors can earn profits that beat the buy-and-hold strategy using two simple trading strategies are analysed. This chapter considers two simple trading strategies, which are also used in the previous chapter for calendar anomalies.

This study prefers simple trading strategies to complicated strategies since calendar anomalies are straightforward to understand and thus it should be relatively simple to make profits from them. Many studies use a trading strategy that invests in the risk-free asset if they are not in the market. Even though this may give a more equivalent risk to the buy-and-hold strategy since the investor is always in some market, investing in the risk-free rate may be costly and time consuming since investors may only be out of the market for one or two days. Since this thesis uses data from the US since 1897, from the UK since 1935 and from Japan since 1951, risk-free rate data was not available for the full sample and so is ignored in these trading strategies. Since the investor does not invest in risk-free assets when they are out of the market in either of the trading strategies examined, the overall returns for the trading strategy will be less than if the investor had invested in the risk-free asset, making it more difficult for these rules to gain returns greater than the buy-and-hold strategy than if investment in the risk-free asset was conducted for every sell signal, thus the figures generated are conservative. Nevertheless, a “double to out” trading strategy, which has broadly the same risk as the buy-and-hold strategy is studied, as well as a simple trading strategy which does not have comparable risk.

The first trading strategy adopted is similar to Fifield et al (2005; 2008) and is as follows. The investor is initially assumed to hold a buy position and upon the first buy signal, the trader buys and holds until a sell signal is generated. Upon this sell signal, the trader sells and goes out of the market until the next buy signal. Upon the last sell signal, it is assumed that the investor liquidates his position. At the end of the sample period, the profit from the different trading rules are calculated and compared with the profit from the naïve buy-and-hold strategy. The profits from this strategies are calculated net of transaction costs (transaction costs taken from Ratner and Leal 1999 for the US and Japan, and Hudson et al

1996 for the UK[29]). The trading strategy evaluated here differs from those in the majority of the previous papers. For example, this rule assumes that the investor has a limited amount of wealth that is invested in full at each buy (sell) transaction. That is, this rule assumes that the investor can only sell after a buy transaction (and buy only after a sell transaction) whereas other studies assume that the investor has an unlimited amount of wealth and can implement multiple buys or sells after each price change. The strategy examined here can therefore be characterised as prudent, and as satisfying the risk-averse nature of many investors (Fifield et al 2005).

The second trading strategy examined follows the "double or out" rule suggested by Bessembinder and Chan (1998). An investor who conducts the previous simple trading strategy faces a lot less risk than an investor who conducted the buy-and-hold strategy. This is because they are out of the market for a considerable period of time and avoid the risk associated with being in the market all of the time. Acknowledging this fact, a slightly modified version of the "double or out" trading strategy suggested by Bessembinder and Chan (1998) is applied to the various moving average rules previously examined. If a neutral signal is generated there is an investment in the index. If a buy day is indicated the investment in the index is doubled whereas, if a sell day is indicated, the funds are invested in cash thus giving broadly similar risk to a buy-and-hold strategy. Bessembinder and Chan (1998) invest in the daily risk-free rate when a sell signal is generated but since no risk-free rates are available for long periods of the data examined, the investor invests in cash with no return when a sell signal is generated. The profits from this strategy are also calculated net of transaction costs (transaction costs taken from Ratner and Leal 1999 for the US and Japan, and Hudson et al 1996 for the UK). These two trading strategies are conducted to determine if simple trading on the calendar anomalies can beat the buy-and-gold strategy for each index.

One issue with this type of trading rule is that the issue of stocks indices were not easily tradable until the 1980s when futures on indices and exchange traded funds (ETFs) became available to investors. However this thesis assumes, similar to most other studies examining the profitability of trading rules, that investors can trade on the stock indices easily without any extra cost incurred.

[29] Although these transaction costs are accurate for the period in which they were calculated, they do not correspond to the costs faced in the total sample examined in this thesis. Nevertheless with no data available for the full sample, these transaction costs are employed.

5.4. Empirical Results

5.4.1. Moving Average Rules

Table 5.1 reports the moving average rule results for the three markets full samples. The number of buy and sell signals are denoted by N(Buy) and N(Sell) and the daily mean of the buy and sell periods are reported in columns 4 and 5, with their *t*-ratios below. The fraction of buy and sell returns that are greater than zero are reported in columns 6 and 7, while the last column lists the differences between the daily mean of the buy and sell returns, with their *t*-ratios below. If the moving average rule does not have any power to forecast price movements, then the returns on days when the rules generate buy signals should not be statistically different from the returns on days when the rule emits sell signals. In other words, if the last column is different from zero and significant, technical analysis can be used to forecast price movements, and thus is contrary to the EMH.

Panel A of Table 5.1 presents the moving average rule results for the DJIA. The results show that from 1896 to 2009 each rule produced positive buy-sell differences which were all significant at 1%. The (1,50,0.01) rule produces the greatest buy-sell difference of 0.0007485 per day, which equates to 18.71% per annum. However these buy-sell differences are lower than BLL's results, suggesting that the moving average rule is not as strong as it once was. Panel B documents the moving average results for the FT30 and show that five of the six rules produce positive buy-sell differences that are significant at 5%. The largest buy-sell difference of 18.06% is again associated with the (1,50,0.01) rule. The buy-sell differences are lower than ones found by Hudson et al (1996), again suggesting a weakening of the rule. Panel C reports the TOPIX results and indicate that all rules examined produce positive buy-sell differences that are significant at 1%. The most successful rule is the (1,150,0) rule which produces a buy-sell difference of 20.93% per annum, which is higher than any buy-sell difference in the DJIA or FT30. This preliminary analysis suggests that the moving rule is more successful in the TOPIX than the DJIA or FT30 and that the rule may have weakened in power in the DJIA and FT30.

Table 5.2 presents the moving average results for data after the data used in the BLL paper (1987-2009). Panel A presents the DJIA results and shows that all of the buy-sell differences are negative. This indicates that the moving average cannot be used to gain positive returns and that it actually generates negative returns. Although none of the rules are statistically significant, the fact that the buy-sell differences are now negative shows a complete reversal in the successfulness of the moving average rule. Panel B shows that five of the six rules generate buy-sell differences that are still positive for the FT30, but are no longer statistically significant. The *z*-statistics are not close to being significant at 5% indicating a weakening of the technical rule in the FT30. The TOPIX results in Panel C show that four of the six rules generate positive and significant buy-sell differences for the 1987-2009 subsample. However, the magnitudes of the buy-sell differences are lower than the full sample results, also indicating a weakening of the moving average rule.

The moving average rule in the DJIA from 1987-2009 does not generate positive buy-sell differences, suggesting investors may have taken advantage of the rule, eroding away the profits. The FT30 results suggest that although positive buy-sell differences can still be made, they are not of great value and none of them are statistically significant. The TOPIX however, still generates significant positive buy-sell differences, indicating that the moving average rule is a profitable strategy to use in this market although the magnitude of the predictability has fallen. Thus it is clear to see that there has been a fall in the success of the moving average rule since 1987.

Table 5.1: Test Results for the Moving Average Rules full sample**. "**N(Buys)" and" N(Sells)" are the number of buy and sell signals reported during the sample. "Buy" and "Sell" denote the daily mean buy and sell returns. The numbers in parentheses are standard *t*-ratios testing the difference of the mean buy and mean sell from the unconditional 1-day mean. "Buy > 0" and "Sell > 0" are the fraction of buy and sell returns greater than zero. "Buy-Sell" denotes the difference between the daily mean of the buy and sell returns, with the *t*-ratio in parentheses testing the difference of the buy-sell to zero. ***, **, * indicate significance at 1%, 5% and 10%.

Test – Moving Average Rules	**N(Buy)**	**N(Sell)**	**Buy**	**Sell**	**Buy > 0**	**Sell > 0**	**Buy-Sell**
Panel A: DJIA							
(1,50,0)	18116	12680	0.0004462 (2.50919)*	-0.0001770 (-3.18118)*	0.535714	0.504022	0.0006232 (4.58764)*
(1,50,0.01)	14861	3656	0.00053621 (2.92692)*	-0.0002123 (-3.04408)	0.537447	0.501243	0.0007485 (4.53284)*
(1,150,0)	18814	11679	0.0003887 (2.06246)*	-0.000157 (-2.8305)*	0.53519	0.50176	0.0005453 (3.83592)*
(1,150,0.01)	17163	10052	0.0004148 (2.26383)*	-0.000201 (-2.8389)*	0.53732	0.4999	0.0006158 (3.87923)*
(1,200,0)	19286	11157	0.0003791 (2.03981)*	-0.000181 (-2.9322)*	0.53448	0.50058	0.0005597 (3.82862)*
(1,200,0.01)	17890	9880	0.000397 (2.12766)*	-0.000222 (-3.0494)*	0.53628	0.49717	0.0006187 (3.87882)*
Panel B: FT30							
(1,50,0)	11200	7905	0.00039189 (1.53471)	-0.0001744* (-1.93551)	0.507143	0.486781	0.0005663* (3.050632)
(1,50,0.01)	9194	6172	0.0005021* (2.070352)	-0.0002203* (-2.79613)	0.506526	0.483474	0.0007224* (3.72152)
(1,150,0)	11491	7515	0.00031472 (1.0644)	-0.0000941 (-1.41141)	0.506744	0.486361	0.0004088* (2.15757)
(1,150,0.01)	10355	6503	0.00031647 (0.97204)	-0.000090 (-1.3266)	0.506229	0.48316	0.0004069* (1.93415)
(1,200,0)	11571	7385	0.00033330 (1.186685)	-0.0001293 (-1.59909)	0.510068	0.481517	0.0004623* (2.42732)
(1,200,0.01)	10768	6647	0.0003324 (1.07566)	-0.000108 (-1.4672)	0.50938	0.48157	0.0004407* (2.15202)
Panel C: TOPIX							
(1,50,0)	9048	6293	0.00060316 (2.00800)*	-0.00024220 (-2.55646)*	0.527741	0.460353	0.000845 (4.0019)*
(1,50,0.01)	7651	4990	0.00068249 (2.19998)*	-0.0002610 (-2.52581)*	0.534179	0.458517	0.000944 (3.7865)*
(1,150,0)	9458	5783	0.00063601 (2.21453)*	-0.0003611 (-3.06964)*	0.529182	0.452187	0.000997 (3.9144)*
(1,150,0.01)	8798	5146	0.0006373 (2.33812)*	-0.0001579 (-2.83454)*	0.530916	0.448504	0.000795 (3.9148)*
(1,200,0)	9598	5593	0.0004664 (1.26705)	-0.0001196 (-1.8127)	0.527506	0.451636	0.000586 (2.6955)*
(1,200,0.01)	9063	5107	0.0004734 (1.24061)	-0.0001361 (-1.8541)	0.529847	0.445467	0.000607 (2.6305)*

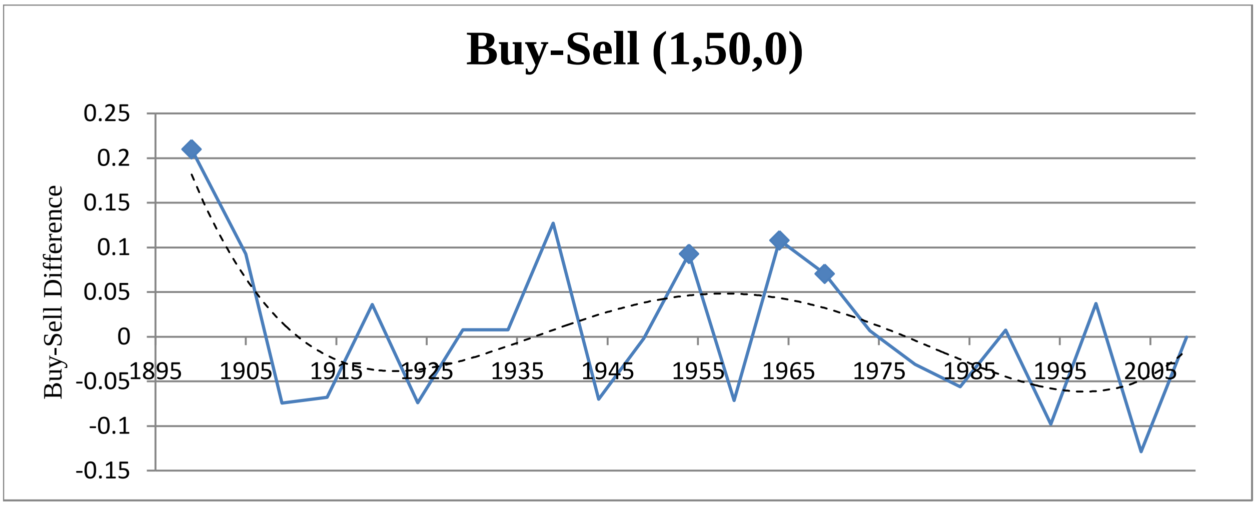
Table 5.2: Test Results for the Moving Average Rules 1987-2009. **"**N(Buys)" and" N(Sells)" are the number of buy and sell signals reported during the sample. "Buy" and "Sell" denote the daily mean buy and sell returns. The numbers in parentheses are standard *t*-ratios testing the difference of the mean buy and mean sell from the unconditional 1-day mean. "Buy > 0" and "Sell > 0" are the fraction of buy and sell returns greater than zero. "Buy-Sell" denotes the difference between the daily mean of the buy and sell returns, with the *t*-ratio in parentheses testing the difference of the buy-sell to zero. ***, **, * indicate significance at 1%, 5% and 10%.

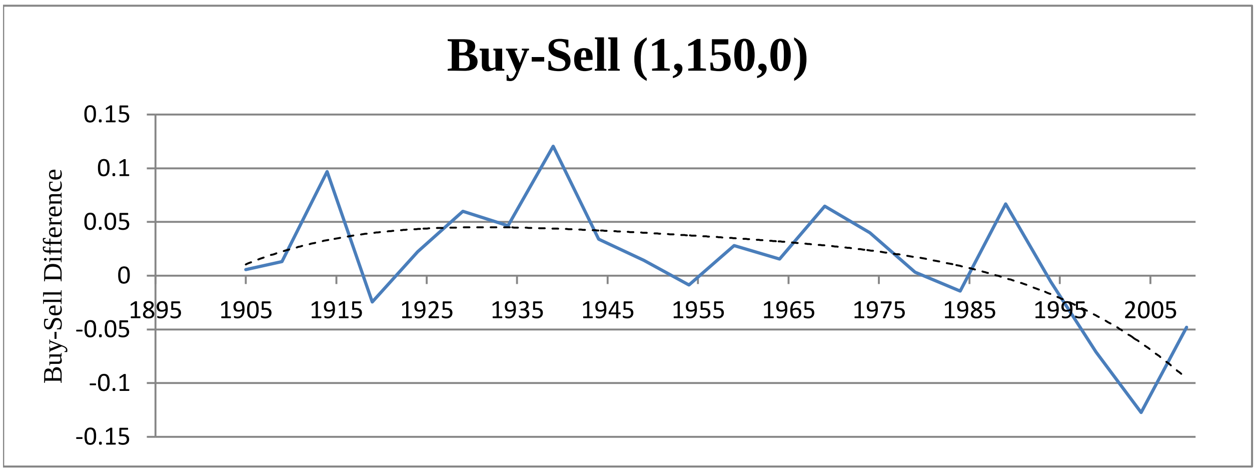
Test – Moving Average Rules	N(Buy)	N(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy-Sell
Panel A: DJIA							
(1,50,0)	3685	2071	0.0002396 (-0.21073)	0.0003871 (0.308717)	0.519946	0.537904	-0.000148 (-0.4441)
(1,50,0.01)	3016	1486	0.0001135 (-0.57766)	0.0004852 (0.624104)	0.511605	0.539704	-0.000372 (-0.7515)
(1,150,0)	3843	1813	0.0002069 (-0.17480)	0.0003432 (0.287004)	0.520687	0.535576	-0.000136 (-0.3208)
(1,150,0.01)	3498	1471	0.0002416 (0.195319)	0.0004104 (0.621166)	0.521441	0.536370	-0.000169 (-0.3368)
(1,200,0)	3915	1691	0.0002437 (-0.09834)	0.0003249 (0.171397)	0.525160	0.528090	-0.000081 (-0.1806)
(1,200,0.01)	3586	1408	0.0002907 (-0.05419)	0.0004575 (0.429378)	0.523982	0.526989	-0.000167 (-0.3207)
Panel B: FT30							
(1,50,0)	3433	2514	0.0000291 (-0.408192)	0.0002727 (0.502238)	0.49927	0.50438	-0.000244 (-0.7942)
(1,50,0.01)	2850	1946	0.0000245 (0.091329)	-0.000029 (-0.096506)	0.49614	0.50771	0.000053 (0.15197)
(1,150,0)	3376	2471	0.0002094 (0.437488)	-0.0000541 (-0.538466)	0.50948	0.48928	0.000264 (0.84807)
(1,150,0.01)	3036	2164	0.0002952 (0.711229)	-0.0000467 (-0.535069)	0.50889	0.48845	0.000342 (1.01891)
(1,200,0)	3296	2501	0.00014166 (0.28643)	-0.00002741 (-0.34421)	0.34557	0.48381	0.000169 (0.54678)
(1,200,0.01)	3087	2261	0.0000687 (0.07755)	0.0000254 (-0.08142)	0.51182	0.48607	0.000043 (0.13378)
Panel C: TOPIX							
(1,50,0)	2776	2980	0.0003741 (1.33187)	-0.0004180 (-1.2704)	0.48451	0.45369	0.0007923** (2.25356)
(1,50,0.01)	2320	2479	0.0003055 (1.50177)	-0.000515 (-1.1078)	0.49353	0.45583	0.0008200** (2.12314)
(1,150,0)	2692	2964	0.000416 (1.5703)	-0.000510 (-1.4727)	0.4970	0.4406	0.0009258*** (2.68628)
(1,150,0.01)	2496	2757	0.000339 (1.2864)	-0.000457 (-1.2278)	0.4956	0.4432	0.000796** (2.19706)
(1,200,0)	2620	2986	0.000256 (1.0811)	-0.000379 (-0.9909)	0.4927	0.4451	0.0006352* (1.842448)
(1,200,0.01)	2446	2814	0.000270 (0.9769)	-0.000340 (-0.9772)	0.4955	0.4442	0.00061038* (1.68856)

5.4.2. Five-Yearly Behaviour Analysis

The results for the moving average rules for the five yearly subsamples for the three stock indices are presented in Figures 5.2, 5.3, and 5.4 and discussed below. The blotted points indicate excess returns which are statistically significant at least at the 5% level. The dotted line is the polynomial trendline.

Figure 5.2: The five-yearly moving average rule plotted for the DJIA. The end year of sub sample is on the x-axis and the buy-sell difference is on the y-axis. The blotted points are buy-sell differences that are statistically significant at 5%.





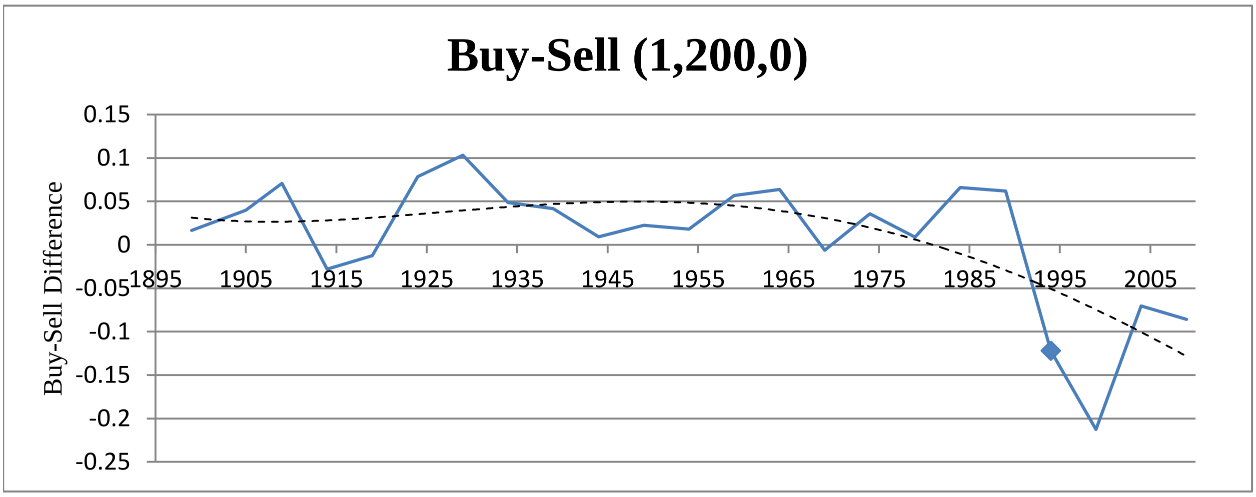


Figure 5.3: The five-yearly moving average rule plotted for the FT30. The end year of sub sample is on the x-axis and the buy-sell difference is on the y-axis. The blotted points are buy-sell differences that are statistically significant at 5%.

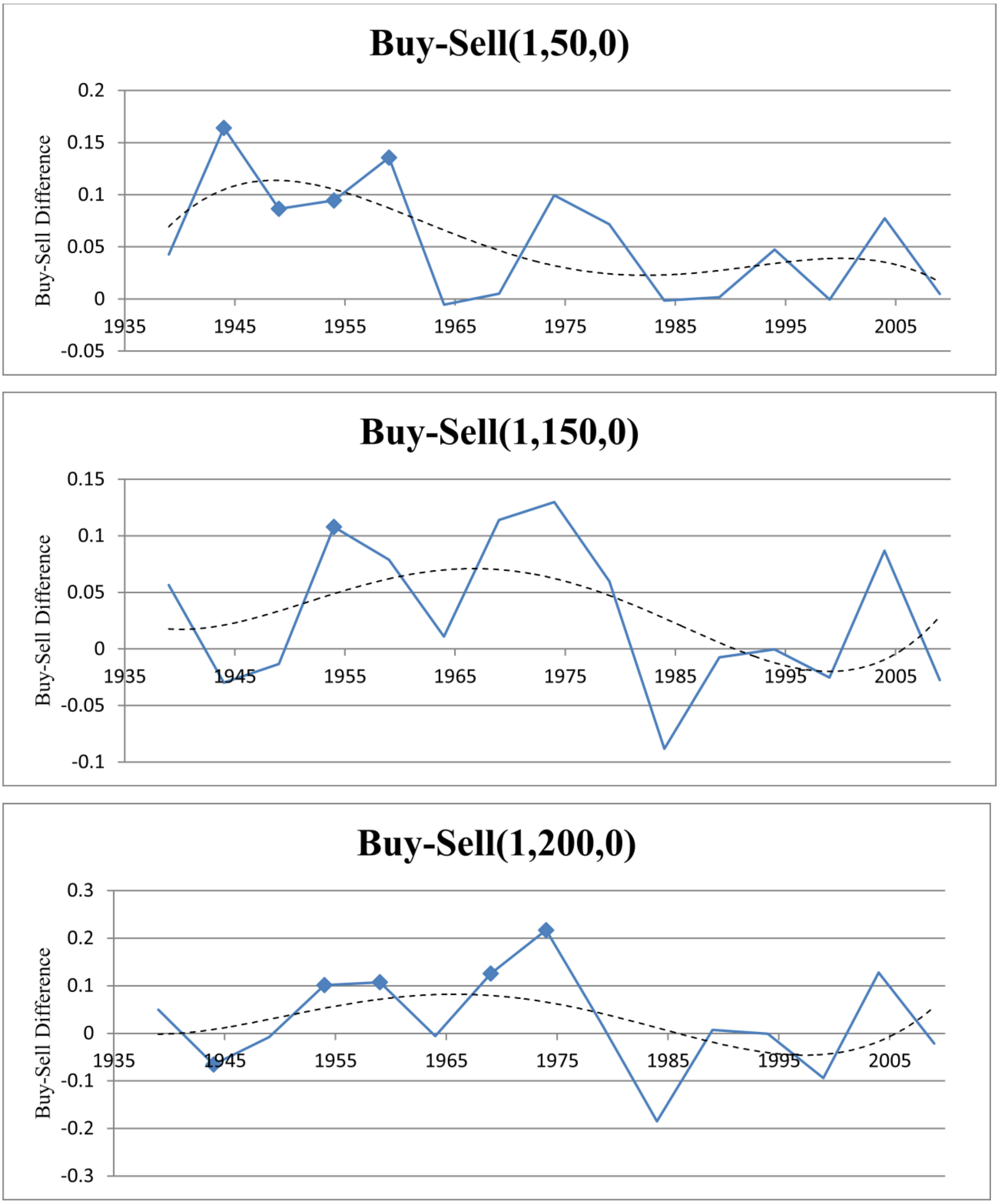
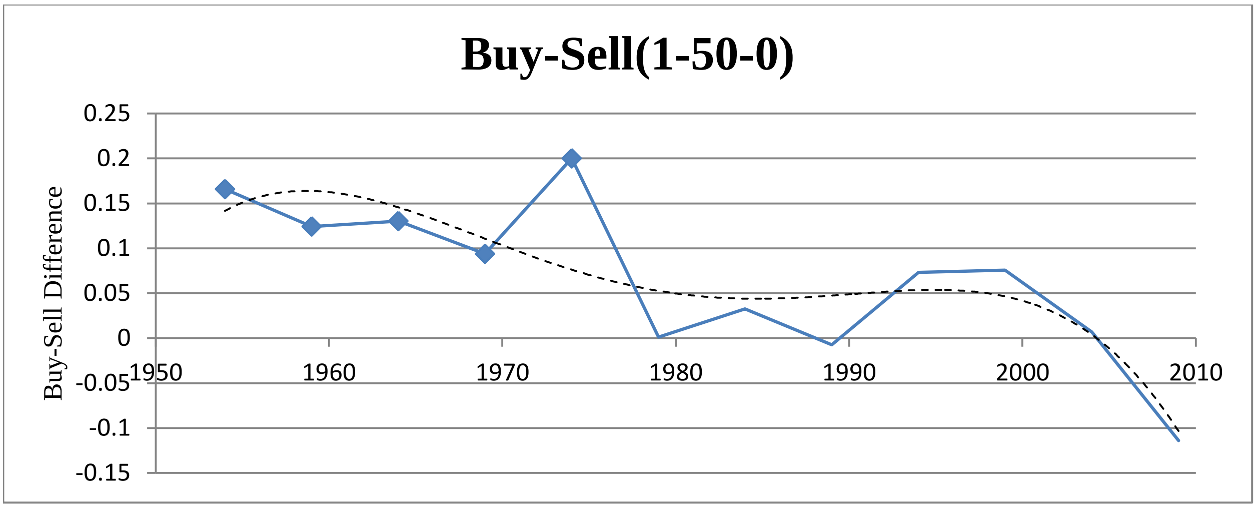
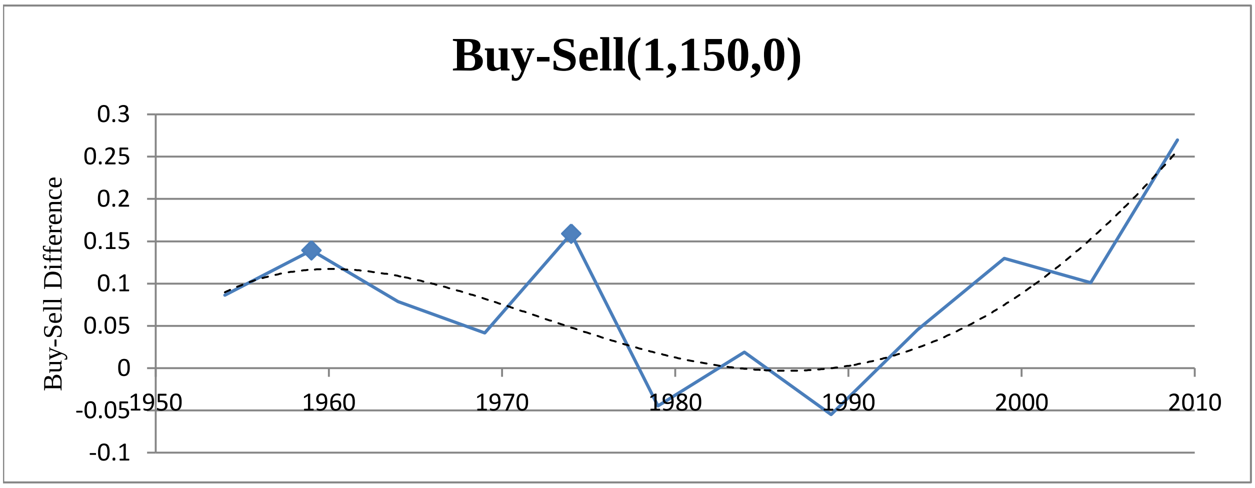


Figure 5.4: The five-yearly moving average rule plotted for the TOPIX. The end year of sub sample is on the x-axis and the buy-sell difference is on the y-axis. The blotted points are buy-sell differences that are statistically significant at 5%.





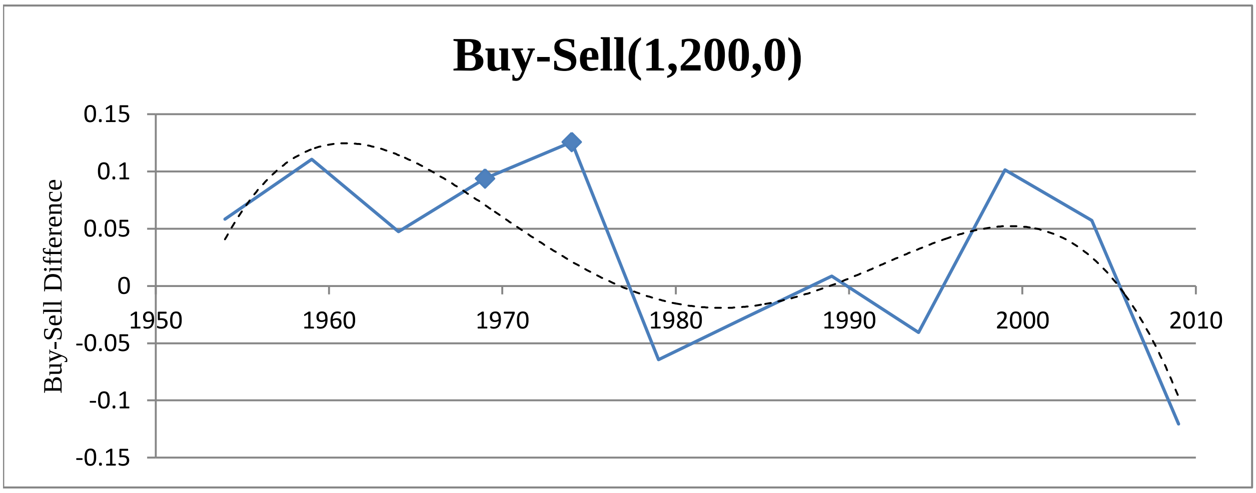


Figure 5.2 documents the results for the DJIA moving average rules. Only four of the 23 sub samples for the buy-sell differences of the (1,50,0) rule are statistically significant. Also, this trading rule has a clear downward trend in the buy-sell, with the polynomial trendline turning negative towards the end of the sample. The other two rules also have a clear downward trend, with their trendlines going negative in the early to mid-1980s. Thus these results suggest that the moving average rule for the DJIA has actually reversed over time, and is no longer profitable. Thus the (1,50,0) rule can be deemed adaptive (type 4) and the (1,150,0) and (1,200,0) rule have switched and are type 3 (switch). Figure 5.3 shows the results of the various moving average rules for the FT30. The (1,50,0) rule shows a clear downward trend throughout the sample, with four of the first five sub samples buy-sell differences being statistically significant. However, the trendline is still positive at the end of the sample, thus suggesting that this rule is still profitable and thus type 5. Nevertheless, the (1,150,0) and (1,200,0) rules do have a downward trend and do turn negative at the end of the sample. The last subsample is positive for both rules so both rule can be deemed adaptive thus type 4. The results for the TOPIX moving average rules are shown in Figure 5.4. The (1,50,0) rule has a number of positive and significant buy-sell differences at the beginning of the sample but from the mid-1970s onwards, the buy-sell differences decreases in magnitude. The polynomial trendline goes negative in the year 2000, and continues to the end of the sample, indicating that this rule is no longer profitable in the TOPIX stock index and type 3 (switch). However, the (1,150,0) rule appears to still be profitable. The trendline initially falls, but from the 1980s onwards, the trendline increases and continues to increase to the end of the sample. Thus the (1,150,0) rule has been profitable, and continues to produce positive buy-sell differences and can be deemed type 4. The (1-200-0) rule's profitability varies over time, with the trendline fluctuating above and below the x-axis indicating it's adaptive nature and type 4 behaviour.

Table 5.3: Classification of the of the moving average rules

Market	Anomaly	Type
DJIA	(1,50,0)	4
	(1-150-0)	3
	(1-200-0)	3
FT30	(1-50-0)	3
	(1-150-0)	4
	(1-200-0)	4
TOPIX	(1-50-0)	3
	(1-150-0)	4
	(1-200-0)	4

Table 5.3 reports the classification of the different moving average rulea according to the classifications prescribed in Chapter 2. The (1,50,0) rule for the DJIA is type 4, indicating the adaptive return behaviour. The (1,150,0) and (1,200,0) rules are both type 3 indicating a switch in the behaviour of returns. Two of the three rules for the FT30 and TOPIX are type 4, indicating evidence of the AMH. The other rule for these two markets indicates evidence of a switch in the behaviour of returns. These results are somewhat surprising, since one would expect type 4 would be more likely in the longer series (DJIA) rather than the shorter two. However, the fact that returns have changed from being positive to negative in the DJIA is an important finding, and could be evidence of an early stage adaptive market. Nevertheless, according to the classification, the AMH is an appropriate model and describing the behaviour of stock returns over time.

5.4.3. Perfectly and Imperfectly Anticipated Moving Average Rules

Table 5.4 presents the results for the perfectly anticipated moving average rule for the DJIA, FT30 and TOPIX for the sample period 1987-2009 i.e. the period after BLL studied. Panel A reports that the number of buy signals for each rule for the DJIA is greater than the number of sell signals. Also for each rule, the one-day buy returns are all positive and statistically significant, while the one-day sell returns are all negative and statistically significant. The buy-sell differences are all positive and significant, suggesting that if investors had perfectly anticipated the following days signal, they could make significant profits from 1987-2009. Panel B documents the results for the perfectly anticipated moving average rule of the FT30 for the sample period 1987-2009. The number of buy signals exceeds the number of sell signals for each rule and the one-day buy returns are all positive, while the one-day sell returns are all negative. However, all of the one-day returns are not statistically significant. The buy-sell differences are all positive (except one) with only the (1,50,0) rule being statistically significant. These buy-sell differences are greater than the original rules buy-sell differences for the same sample period, indicating that predicting the following days signal would increase returns. Panel C documents the results for the perfectly anticipated moving average rule for the TOPIX and shows that the number of buy and sell signals are quite similar and vary between rules to which one is greater. The one-day buy returns are all positive although none are statistically significant while one-day sell returns are all negative, with none of them being statistically significant. The buy-sell differences are all positive, with the rules with 50- and 150-days as the long run moving average being statistically significant. Three of the rules produce buy-sell differences that are greater than the corresponding buy-sell differences under the original rules indicating that predicting the following days signal does not always produce returns greater than the original rules for the TOPIX. For all three markets, the perfectly anticipated moving average rule substantially outperforms the original moving average rule for the 1987-2009 period.

In Table 5.5 the imperfectly anticipated moving average rules are presented. If investors are fairly certain what tomorrows signal is going to be, the investor uses that signal. However, if there is a high level of uncertainty about what tomorrows signal is going to be, the investor chooses the current days signal. The uncertainty comes from the fact that the short run moving average may be very close to the long run moving average implying that the following days return could generate either a buy or sell signal. The levels of uncertainty can be quantified by whether the short run and long run moving average are within say 1%, 2.5% or 5% of each other. Panel A presents the DJIA results for the three moving average rules examined. The results indicate that using all of the uncertainty bands produce significant returns. As expected, the value of returns decrease as the uncertainty bands increases as less true values are chosen. Although returns are less than the perfectly anticipated rules, it is clear that this more realistic rule produces significant returns in the DJIA. The results in Panel B indicate that two of the nine rules examined produce significant returns. The (1,50,0) rule with 0.25% and 0.50% bands generate returns that are significant at 5%. However, some of the imperfectly anticipated rules generate higher returns than the perfectly anticipated rule for the FT30. For instance, the (1,50,0) perfect rule generates 16.73% per annum, while the imperfect rule with 0.25% and 0.50% band 18.1% and 16.95% per annum respectively. This suggests the original FT30 moving average rule could be modified to generate higher returns. The TOPIX results in Panel C indicate that four of the rules examined produce significant returns. However, similarly to the DJIA results, the returns are less than the perfectly anticipated rules. This again indicates that even the imperfectly anticipated moving average can produce significant returns.

Table 5.4: Test Results for the perfectly anticipated moving average rule from 1987 – 2009. "N(Buys)" and" N(Sells)" are the number of buy and sell signals reported during the sample. "Buy" and "Sell" denote the daily mean buy and sell returns. The numbers in parentheses are standard *t*-ratios testing the difference of the mean buy and mean sell from the unconditional 1-day mean. "Buy > 0" and "Sell > 0" are the fraction of buy and sell returns greater than zero. "Buy-Sell" denotes the difference between the daily mean of the buy and sell returns, with the *t*-ratio in parentheses testing the difference of the buy-sell to zero. ***, **, * indicate significance at 1%, 5% and 10%.

Day Before Moving Average Rules – Perfectly Anticipated	N(Buy)	N(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy-Sell
Panel A: DJIA							
(1,50,0)	3684	2071	0.00174872*** (5.87)	-0.0023591*** (-8.60)	0.520087	0.537904	0.0041078*** (10.80)
(1,50,0.01)	3015	1486	0.00197458*** (6.07)	-0.0029833*** (-9.61)	0.511774	0.539704	0.0049579*** (10.16)
(1,150,0)	3842	1813	0.0009994*** (2.99)	-0.0013299*** (-4.90)	0.520562	0.535576	0.0023293*** (5.47)
(1,150,0.01)	3497	1471	0.00111548*** (3.58)	-0.0016908*** (-5.30)	0.521304	0.53637	0.0028062*** (5.56)
(1,200,0)	3915	1690	0.00096663*** (2.80)	-0.0013429*** (-4.87)	0.52516	0.528402	0.00230956*** (5.12)
(1,200,0.01)	3586	1408	0.0009448*** (2.77)	-0.0014852*** (-4.81)	0.523982	0.526989	0.00242998*** (4.64)
Panel B: FT30							
(1,50,0)	3433	2514	0.0003840 (1.12)	-0.0002849 (-1.38)	0.499272	0.504375	0.000669** (2.01)
(1,50,0.01)	2850	1946	0.00039845 (1.21)	-0.0003424 (-0.56)	0.49614	0.507708	-0.0007409* (1.85)
(1,150,0)	3376	2471	0.00029442 (0.86)	-0.0002275 (-1.06)	0.509479	0.489276	0.000522 (1.53)
(1,150,0.01)	3036	2164	0.00037672 (0.75)	-0.0002188 (-1.34)	0.508893	0.488447	0.000596 (1.57)
(1,200,0)	3296	2501	0.00034843 (1.06)	-0.0002884 (-1.28)	0.512743	0.483806	0.000637* (1.87)
(1,200,0.01)	3087	2261	0.00034944 (1.12)	-0.0002527 (-1.03)	0.511842	0.486068	0.000602* (1.65)
Panel C: TOPIX							
(1,50,0)	2904	3046	0.0004891 (1.75)	-0.000529 (-1.69)	0.48554	0.45371	0.001018*** (3.00)
(1,50,0.01)	2438	2537	0.0005622* (1.96)	-0.000516 (-1.47)	0.49426	0.45605	0.0010777*** (2.81)
(1,150,0)	2821	3029	0.000320 (1.22)	-0.000394 (-1.17)	0.4981	0.4407	0.000714** (2.10)
(1,150,0.01)	2608	2809	0.000457 (1.29)	-0.000341 (-1.30)	0.4969	0.4439	0.000798** (2.25)
(1,200,0)	2755	3045	0.0002093 (0.89)	-0.000307 (-0.83)	0.49292	0.44565	0.0005162 (1.52)
(1,200,0.01)	2569	2862	0.0002166 (0.78)	-0.0002729 (-0.81)	0.49513	0.44514	0.0004894 (1.37)

Table 5.5: Test results for the imperfectly anticipated moving average rule from 1987 – 2009. "Uncertainty Band" refers to the difference between the short and long run moving averages for which the previous signal was used. "% Signs not forecasted" denotes the percentage of days not forecasted. "N(Buys)" and" N(Sells)" are the number of buy and sell signals reported during the sample. "Buy" and "Sell" denote the daily mean buy and sell returns. The numbers in parentheses are standard *t*-ratios testing the difference of the mean buy and mean sell from the unconditional 1-day mean. "Buy > 0" and "Sell > 0" are the fraction of buy and sell returns greater than zero. "Buy-Sell" denotes the difference between the daily mean of the buy and sell returns, with the *t*-ratio in parentheses testing the difference of the buy-sell to zero. ***, **, * indicate significance at 1%, 5% and 10%.

Day Before Moving Average Rules	Uncertainty Band	% Signs not Forecasted	N(Buy)	N(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy-Sell
Panel A: DJIA									
(1,50,0)	0.25%	5.26%	3702	2053	0.001445*** (4.67)	-0.001847*** (6.90)	0.56	0.46	0.003292*** (8.57)
	0.5%	10.63%	3692	2063	0.001223*** (3.78)	-0.001433*** (-5.57)	0.55	0.48	0.002656*** (6.91)
	1%	21.79%	3701	2054	0.000868** (2.38)	-0.000805*** (-3.51)	0.54	0.51	0.001673*** (4.34)
(1,150,0)	0.25%	2.85%	3835	1820	0.000878** (2.50)	-0.001065*** (-4.09)	0.54	0.49	0.001943*** (4.56)
	0.5%	6.19%	3816	1839	0.0007796** (2.10)	-0.000840*** (-3.41)	0.54	0.50	0.001620*** (3.83)
	1%	12.15%	3802	1853	0.0006175 (1.45)	-0.000496** (-2.34)	0.53	0.51	0.001113*** (2.65)
(1,200,0)	0.25%	2.96%	3907	1698	0.000799** (2.12)	-0.000946*** (-3.68)	0.54	0.48	0.001746*** (3.88)
	0.5%	5.46%	3902	1703	0.000730* (1.85)	-0.000785*** (-3.19)	0.54	0.49	0.001516*** (3.37)
	1%	10.92%	3857	1748	0.000569 (1.20)	-0.000389** (-2.02)	0.54	0.51	0.000958** (2.18)
Panel B: FT30									
(1,50,0)	0.25%	4.76%	3418	2529	0.000409 (1.17)	-0.000315 (-1.57)	0.50	0.50	0.000724** (2.19)
	0.5%	9.43%	3410	2537	0.000390 (1.17)	-0.000287 (1.46)	0.50	0.50	0.000677** (2.05)
	1%	18.78%	3409	2538	0.000324 (1.10)	-0.000199 (-0.38)	0.50	0.50	0.000524 (1.59)
(1,150,0)	0.25%	2.75%	3373	2474	0.000296 (0.86)	-0.000229 (-1.10)	0.51	0.49	0.000525 (1.54)
	0.5%	5.49%	3366	2481	0.000307 (0.89)	-0.00024 (-1.18)	0.51	0.49	0.000550 (1.62)
	1%	10.98%	3307	2540	0.000356 (0.95)	-0.000293 (-1.55)	0.51	0.49	0.000649* (1.94)
(1,200,0)	0.25%	1.86%	3299	2498	0.000326 (0.99)	-0.000260* (-1.19)	0.51	0.49	0.000587* (1.73)
	0.5%	3.55%	3290	2507	0.000333 (0.96)	-0.000267 (-1.27)	0.51	0.49	0.000600* (1.77)
	1%	7.45%	3261	2536	0.000351 (1.25)	-0.000283 (-1.16)	0.51	0.49	0.000634* (1.89)
Panel C: TOPIX									
(1,50,0)	0.25%	3.95%	2894	3056	0.000384 (1.39)	-0.000426 (-1.34)	0.49	0.45	0.000810** (2.40)
	0.5%	7.63%	2916	3034	0.000322 (1.19)	-0.000373 (-1.16)	0.49	0.45	0.000695** (2.05)
	1%	16.08%	2909	3041	0.000204 (0.79)	-0.000258 (-0.77)	0.48	0.46	0.000462 (1.36)
(1,150,0)	0.25%	1.32%	2807	3043	0.000345 (1.30)	-0.000414 (-1.24)	0.50	0.44	0.000759** (2.24)
	0.5%	3.16%	2807	3043	0.000364 (1.37)	-0.000431 (-1.29)	0.50	0.44	0.000796** (2.35)
	1%	6.89%	2796	3054	0.000288 (1.11)	-0.000359 (-1.05)	0.50	0.44	0.000646* (1.90)
(1,200,0)	0.25%	1.62%	2748	3052	0.000221 (0.93)	-0.000317 (-0.86)	0.49	0.45	0.000539 (1.59)
	0.5%	3.31%	2747	3053	0.000208 (0.88)	-0.000305 (-0.82)	0.49	0.45	0.000513 (1.51)
	1%	5.97%	2756	3044	0.000166 (0.75)	-0.000268 (-0.70)	0.49	0.45	0.000435 (1.28)

5.4.4. Trading Strategy Analysis

The simple trading strategy and the “double-or-out” trading strategy are conducted on the original moving average rule, as well as the perfectly and imperfectly anticipated moving average rules described earlier on full sample data and the post BLL (1987-2009) data. Tables 5.6-5.8 present the moving average rule, perfectly anticipated moving average rule and imperfectly anticipated moving average rule trading strategy results for the full sample of each market. Table 5.6 reports the results for the moving average rules using the simple trading strategy on the full sample of each market. All three markets show that the simple trading strategy does outperform the buy-and-hold strategy over the full sample of each market. The most successful rule in each instance is the (1,50,0) rule, which is supported by the earlier findings. However as expected, the risk (standard deviation) of the sample trading strategy is about half the risk of the buy-and-hold strategy since there are long periods when the investor is out of the market and invested in cash. These results support the findings of BLL for the DJIA and Hudson et al (1996) for the FT30. Table 5.7 shows that the simple trading rule using the perfectly anticipated moving average rule does outperform the buy-and-hold strategy for all the rules and markets. These returns are substantially greater than the returns realised from the original moving average rule indicating that the perfectly anticipated moving average rule is optimal to the original moving average rule. Again it is noticeable that the risk of the trading strategy is only around half that of the buy-and-hold strategy and again the most successful rule is the (1,50,0) rule. Table 5.8 presents the results of the simple trading strategy when the imperfectly anticipated moving average rule is implemented. The trading rule again outperforms the buy-and-hold strategy for each version of the rule examined, with the standard deviation again being less than that of the buy-and-hold strategy. The returns from this rule are substantially greater than the returns from the original moving average rule, but as predicted are less than the perfectly anticipated moving average rule. Nevertheless, this shows that even if investors are unsure what the following days signal is going to be, they can still make substantial returns greater than the simple buy-and-hold strategy.

Tables 5.9–5.11 document the results from the trading strategy for the post-BLL data (1987-2009). This period is examined since previously this thesis found that the returns during this period were negative for the DJIA and returns for the FT30 and TOPIX were not as high as for the full sample. Table 5.9 shows that the returns from the simple trading strategy on the original moving average rules do not outperform the buy-and-hold strategy for the DJIA for any of the rules examined. The buy-and-hold strategy generates returns greater than the trading rule using the original moving average rule. This could be due to investors recognising the successful of the moving average rule and exploiting it. However, the trading rule does outperform the buy-and-hold strategy for the FT30 and TOPIX, supporting the results found earlier. Nevertheless when the perfectly anticipated moving average rule is examined in Table 5.10, the trading strategy outperforms the buy-and-hold strategy for all three markets. The returns are substantially greater than the returns generated from the original rule (up to six times greater) indicating that predicting the next day's signal accurately does generate substantially greater returns than the original moving average rule. When the imperfectly anticipated moving average rule is examined for the 1987-2009 data in Table 5.11, it is clear that all three markets outperform the buy-and-hold strategy. The returns are obviously less than the perfectly anticipated moving average rule, but all three markets still generate returns substantially greater than the buy-and-hold strategy. The rule is most successful in the TOPIX and least successful in the DJIA, which is constant with the previous results and the idea that a relatively new market is likely to be less efficient than an older one (Lo 2012).

Tables 5.12–5.14 document the results of using the "double or out" trading strategy on various versions of the moving average rule for the full samples. It is clear that risk associated with this trading strategy is comparable to the risk faced by the buy-and-hold strategy. It is clear to see from Tables 5.12-5.14 that the "double or out" trading strategy outperforms the buy-and-hold strategy for all of versions of the moving average rules examining the full samples. The perfectly anticipated moving average rule is the most successful and the original moving average rule the least successful rule. From Tables 5.15-5.17 it is clear that the original moving average rule on post BLL data outperforms the buy-and-hold strategy for all but one of the rules examined using the "double or out" strategy. Further, the trading strategy outperforms the buy-and-hold strategy substantially using the perfect and imperfectly anticipated rules. These results are consistent with the simple trading strategy used earlier. The magnitudes of the annualized % difference are quite substantial for all three markets. This can be explained by the fact that the trading strategy is investing double into the market when a buy signal is generated, and by the fact that the anticipated moving average rules are very successful. Further, the results may be so strong given the fact that the markets have been subject to a number of market crashes and recessions over the 1987-2009 period, with the TOPIX actually falling in value from 1987-2009.

This section has examined the original moving average rule, the perfectly anticipated moving average rule and the imperfectly anticipated moving average rule to determine whether returns can be generated that are greater than the buy-and-hold strategy using a simple trading strategy as well as the "double or out" trading strategy. The results show that both trading strategies using the original moving average rule can generate returns greater than the buy-and-hold strategy for all three markets when the full sample of each market is examined. Returns are substantially increased when the perfectly and imperfectly anticipated moving average rules are examined. The post BLL (1987-2009) data results show that the simple trading strategies cannot beat the buy-and-hold strategy for the DJIA, while the "double or out" strategy can for all but one of the rules. Nevertheless returns greater than the buy-and-hold strategy are generated for the FT30 and TOPIX. The perfect and imperfectly anticipated moving average rules do produce returns greater than the buy-and-hold strategy for all of the markets using both of the trading strategies. The "double-or-out" strategy results are very similar but double since the investor is double in the market when a buy signal is generated and still in the market when a neutral signal is generated. The results in this section show that if investors can successfully predict the following days signal, the moving average rule does produce substantial returns in all three markets greater than the original moving average rule and the buy-and-hold strategy. Even after the publication of BLL, substantial profits can be earned by predicting the next day's signal.

Table 5.6: Test results for the moving average rule using a simple trading strategy on the full sample for each market. The number of new trades (No. of buy/sell) is shown with the profit from trading on the rule (Rule Profit) and the buy-and-hold strategy as well as the difference between the rule returns and the buy-and-hold strategy returns. The final column is the annualised % difference in profit between the trading rules and the buy-and-hold strategies. All profits are the accumulation of log returns.

Rule	No. of Buy	No. of Sell	Rule SD	B&H SD	Rule Profit	B&H Profit	Difference	Annualised % Difference
Panel A: DJIA								
(1,50,0)	939	938	0.66	1.09	798.99	582.29	216.70	0.24%
(1,50,1)	623	851	0.60	1.09	781.33	582.29	199.29	0.22%
(1,150,0)	492	491	0.63	1.09	688.19	582.29	105.90	0.14%
(1,150,1)	501	470	0.61	1.09	668.56	582.29	86.27	0.11%
(1,200,0)	405	404	0.69	1.09	737.04	582.29	154.75	0.18%
(1,200,1)	423	369	0.67	1.09	718.69	582.29	136.40	0.17%
Panel B: FT30								
(1,50,0)	511	509	0.70	1.06	624.76	293.46	331.30	0.71%
(1,50,1)	529	482	0.65	1.06	565.64	293.46	272.18	0.64%
(1,150,0)	279	278	0.64	1.06	415.86	293.46	122.40	0.39%
(1,150,1)	274	263	0.62	1.06	435.11	293.46	141.65	0.43%
(1,200,0)	218	217	0.70	1.06	477.11	293.46	183.65	0.51%
(1,200,1)	226	222	0.68	1.06	450.45	293.46	156.99	0.44%
Panel C: TOPIX								
(1,50,0)	353	352	0.62	1.02	724.47	412.84	311.63	0.77%
(1,50,1)	354	358	0.58	1.02	692.53	412.84	279.69	0.72%
(1,150,0)	173	173	0.61	1.02	543.78	412.84	130.94	0.43%
(1,150,1)	183	170	0.57	1.02	558.63	412.84	145.79	0.47%
(1,200,0)	155	154	0.72	1.02	514.15	412.84	101.31	0.35%
(1,200,1)	156	137	0.65	1.02	516.59	412.84	103.75	0.36%

Table 5.7: Test results for the perfectly anticipated moving average rule using a simple trading strategy on the full sample for each market. The number of new trades (No. of buy/sell) is shown with the profit from trading on the rule (Rule Profit) and the buy-and-hold strategy as well as the difference between the rule returns and the buy-and-hold strategy returns. The final column is the annualised % difference in profit between the trading rules and the buy-and-hold strategies. All profits are the accumulation of log returns.

Rule	No. of Buy	No. of Sell	Rule SD	B&H SD	Rule Profit	B&H Profit	Difference	Annualised % Difference
Panel A: DJIA								
(1,50,0)	938	938	0.65	1.09	2993.76	582.29	2411.47	0.71%
(1,50,1)	955	851	0.60	1.09	2860.16	582.29	2277.87	0.70%
(1,150,0)	491	491	0.68	1.09	1892.11	582.29	1309.82	0.61%
(1,150,1)	500	470	0.65	1.09	1879.42	582.29	1297.13	0.61%
(1,200,0)	404	404	0.68	1.09	1709.15	582.29	1126.86	0.58%
(1,200,1)	422	369	0.66	1.09	1711.98	582.29	1129.69	0.58%
Panel B: FT30								
(1,50,0)	510	509	0.69	1.06	1802.55	293.46	1509.09	1.12%%
(1,50,1)	528	482	0.64	1.06	1729.68	293.46	1436.22	1.11%
(1,150,0)	278	278	0.62	1.18	1124.15	293.46	830.69	0.99%
(1,150,1)	273	263	0.66	1.06	1101.99	293.46	808.53	0.78%
(1,200,0)	217	217	0.69	1.06	975.20	293.46	681.74	0.93%
(1,200,1)	225	222	0.68	1.06	964.82	293.46	671.36	0.93%
Panel C: TOPIX								
(1,50,0)	352	352	0.61	1.02	1542.85	412.84	1130.01	1.31%
(1,50,1)	353	358	0.58	1.02	1463.71	412.84	1050.87	1.28%
(1,150,0)	172	173	0.64	1.02	991.54	412.84	578.70	1.04%
(1,150,1)	182	170	0.62	1.02	986.21	412.84	573.37	1.04%
(1,200,0)	154	154	0.64	1.02	912.31	412.84	499.47	0.98%
(1,200,1)	155	137	0.63	1.02	905.88	412.84	493.04	0.97%

Table 5.8: Test results for the imperfectly anticipated moving average rule using a simple trading strategy on the full sample for each market. The number of new trades (No. of buy/sell) is shown with the profit from trading on the rule (Rule Profit) and the buy-and-hold strategy as well as the difference between the rule returns and the buy-and-hold strategy returns. The final column is the annualised % difference in profit between the trading rules and the buy-and-hold strategies. All profits are the accumulation of log returns.

Rule	No. of Buy	No. of Sell	Rule SD	B&H SD	Rule Profit	B&H Profit	Difference	Annualised % Difference
	Panel A: DJIA							
(1,50,0.25)	953	951	0.66	1.09	2571.17	582.29	1988.88	0.68%
(1,50,0.5)	935	908	0.66	1.09	2230.09	582.29	1647.80	0.65%
(1,50,1)	955	851	0.66	1.09	1821.05	582.29	1238.76	0.57%
(1,150,0.25)	653	646	0.67	1.09	1964.94	582.29	1382.65	0.62%
(1,150,0.5)	641	651	0.67	1.09	1728.58	582.29	1146.29	0.58%
(1,150,1)	642	607	0.67	1.09	1419.96	582.29	837.67	0.52%
(1,200,0.25)	403	373	0.69	1.09	1527.70	582.29	945.41	0.54%
(1,200,0.5)	420	376	0.69	1.09	1388.87	582.29	806.58	0.51%
(1,200,1)	422	369	0.69	1.09	1198.29	582.29	646.00	0.47%
	Panel B: FT30							
(1,50,0.25)	499	507	0.69	1.06	1549.97	293.46	1256.51	1.08%
(1,50,0.5)	511	491	0.69	1.06	1368.95	293.46	1075.52	1.05%
(1,50,1)	528	482	0.69	1.06	1112.92	293.46	819.46	0.98%
(1,150,0.25)	378	348	0.68	1.06	1165.86	293.46	872.40	1.00%
(1,150,0.5)	383	350	0.68	1.06	1025.70	293.46	732.24	0.95%
(1,150,1)	397	321	0.69	1.06	860.54	293.46	567.08	0.88%
(1,200,0.25)	209	205	0.69	1.06	879.44	293.46	585.98	0.89%
(1,200,0.5)	202	210	0.69	1.06	793.95	293.46	500.46	0.84%
(1,200,1)	225	222	0.69	1.06	696.43	293.46	402.97	0.77%
	Panel C:TOPIX							
(1,50,0.25)	356	353	0.61	1.02	1360.29	412.84	947.45	1.24%
(1,50,0.5)	351	349	0.61	1.02	1234.20	412.84	821.36	1.19%
(1,50,1)	350	354	0.62	1.02	1069.82	412.84	656.98	1.10%
(1,150,0.25)	164	179	0.64	1.02	910.50	412.84	497.66	0.98%
(1,150,0.5)	171	177	0.64	1.02	861.31	412.84	448.47	0.93%
(1,150,1)	182	170	0.64	1.02	777.32	412.84	364.48	0.84%
(1,200,0.25)	151	152	0.64	1.02	832.00	412.84	419.16	0.91%
(1,200,0.5)	155	145	0.64	1.02	786.82	412.84	373.98	0.85%
(1,200,1)	155	137	0.65	1.02	705.69	412.84	292.85	0.74%

Table 5.9: Test results for the moving average rule using a simple trading strategy on the 1987-2009 data for each market. The number of new trades (No. of buy/sell) is shown with the profit from trading on the rule (Rule Profit) and the buy-and-hold strategy as well as the difference between the rule returns and the buy-and-hold strategy returns. The final column is the annualised % difference in profit between the trading rules and the buy-and-hold strategies. All profits are the accumulation of log returns.

Rule	No. of Buy	No. of Sell	Rule SD	B&H SD	Rule Profit	B&H Profit	Difference	Annualised % Difference
Panel A: DJIA								
(1,50,0)	216	216	0.69	1.19	89.78	170.49	-80.71	-3.91%
(1,50,1)	246	186	0.62	1.19	40.68	170.49	-129.81	-13.87%
(1,150,0)	121	121	0.65	1.19	97.31	170.49	-73.17	-3.27%
(1,150,1)	127	112	0.62	1.19	101.94	170.49	-68.54	-2.92%
(1,200,0)	113	113	0.71	1.19	114.19	170.49	-56.29	-2.14%
(1,200,1)	98	100	0.67	1.19	121.53	170.49	-48.95	-1.75%
Panel B: FT30								
(1,50,0)	192	192	0.69	1.18	134.41	39.42	94.99	3.07%
(1,50,1)	193	177	0.62	1.18	118.87	39.42	79.45	2.91%
(1,150,0)	100	100	0.58	1.18	112.47	39.42	73.05	2.82%
(1,150,1)	91	101	0.56	1.18	127.09	39.42	87.67	3.00%
(1,200,0)	73	73	0.62	1.18	137.59	39.42	98.17	3.10%
(1,200,1)	60	84	0.60	1.18	131.47	39.42	92.05	3.04%
Panel C: TOPIX								
(1,50,0)	170	170	0.71	1.32	143.18	-54.33	197.51	6.00%
(1,50,1)	161	179	0.66	1.32	140.23	-54.33	194.56	6.03%
(1,150,0)	74	75	0.67	1.32	120.80	-54.33	175.13	6.30%
(1,150,1)	71	86	0.62	1.32	118.69	-54.33	173.02	6.34%
(1,200,0)	69	69	0.71	1.32	75.28	-54.33	129.61	7.49%
(1,200,1)	70	72	0.69	1.32	74.02	-54.33	128.35	7.54%

Table 5.10: Test results for the perfectly anticipated moving average rule using a simple trading strategy on the 1987-2009 data for each market. The number of new trades (No. of buy/sell) is shown with the profit from trading on the rule (Rule Profit) and the buy-and-hold strategy as well as the difference between the rule returns and the buy-and-hold strategy returns. The final column is the annualised % difference in profit between the trading rules and the buy-and-hold strategies. All profits are the accumulation of log returns.

Rule	No. of Buy	No. of Sell	Rule SD	B&H SD	Rule Profit	B&H Profit	Difference	Annualised % Difference
Panel A: DJIA								
(1,50,0)	216	216	0.67	1.19	658.16	170.49	487.68	3.22%
(1,50,1)	246	186	0.60	1.19	611.70	170.49	441.42	3.14%
(1,150,0)	121	121	0.69	1.19	412.74	170.49	242.26	2.55%
(1,150,1)	127	112	0.65	1.19	415.98	170.49	245.50	2.57%
(1,200,0)	113	113	0.70	1.19	406.12	170.49	235.64	2.52%
(1,200,1)	98	100	0.66	1.19	362.57	170.49	192.09	2.30%
Panel B: FT30								
(1,50,0)	192	192	0.68	1.18	604.20	39.42	564.78	4.06%
(1,50,1)	193	177	0.61	1.18	571.70	39.42	532.28	4.05%
(1,150,0)	100	99	0.62	1.18	368.01	39.42	328.59	3.88%
(1,150,1)	91	101	0.59	1.18	346.01	39.42	306.59	3.85%
(1,200,0)	73	72	0.61	1.18	306.35	39.42	266.93	3.79%
(1,200,1)	60	83	0.59	1.18	294.74	39.42	255.32	3.77%
Panel C: TOPIX								
(1,50,0)	170	170	0.71	1.32	607.73	-54.33	662.06	4.74%
(1,50,1)	161	179	0.66	1.32	567.50	-54.33	621.83	4.76%
(1,150,0)	74	75	0.69	1.32	319.04	-54.33	373.37	5.09%
(1,150,1)	71	86	0.67	1.32	323.60	-54.33	377.93	5.08%
(1,200,0)	69	69	0.68	1.32	286.50	-54.33	340.83	5.17%
(1,200,1)	70	72	0.66	1.32	279.08	-54.33	333.41	5.19%

Table 5.11: Test results for the imperfectly anticipated moving average rule using a simple trading strategy on the 1987-2009 data for each market. The number of new trades (No. of buy/sell) is shown with the profit from trading on the rule (Rule Profit) and the buy-and-hold strategy as well as the difference between the rule returns and the buy-and-hold strategy returns. The final column is the annualised % difference in profit between the trading rules and the buy-and-hold strategies. All profits are the accumulation of log returns.

Rule	No. of Buy	No. of Sell	Rule SD	B&H SD	Rule Profit	B&H Profit	Difference	Annualised % Difference
Panel A: DJIA								
(1,50,0.25)	222	214	0.68	1.19	553.94	170.49	383.46	3.01%
(1,50,0.50)	225	203	0.68	1.19	466.00	170.49	295.52	2.76%
(1,50,1)	246	186	0.69	1.19	335.82	170.49	165.34	2.14%
(1,150,0.25)	158	135	0.68	1.19	420.98	170.49	250.50	2.59%
(1,150,0.50)	158	136	0.68	1.19	363.62	170.49	193.14	2.31%
(1,150,1)	167	137	0.69	1.19	301.86	170.49	131.38	1.89%
(1,200,0.25)	111	104	0.70	1.19	338.41	170.49	167.93	2.15%
(1,200,0.50)	110	105	0.70	1.19	311.14	170.49	140.66	1.97%
(1,200,1)	98	100	0.70	1.19	238.00	170.49	67.52	1.23%
Panel B: FT30								
(1,50,0.25)	178	194	0.67	1.18	499.58	39.42	460.16	4.00%
(1,50,0.5)	184	186	0.67	1.18	435.06	39.42	395.64	3.95%
(1,50,1)	193	177	0.68	1.18	348.75	39.42	309.33	3.86%
(1,150,0.25)	142	124	0.64	1.18	364.79	39.42	325.37	3.88%
(1,150,0.5)	145	126	0.64	1.18	305.59	39.42	266.17	3.79%
(1,150,1)	151	117	0.64	1.18	254.77	39.42	215.35	3.68%
(1,200,0.25)	72	72	0.61	1.18	282.47	39.42	243.05	3.74%
(1,200,0.5)	67	80	0.60	1.18	251.84	39.42	212.42	3.67%
(1,200,1)	60	83	0.61	1.18	225.01	39.42	185.59	2.28%
Panel C:TOPIX								
(1,50,0.25)	164	177	0.71	1.32	505.83	-54.33	560.16	4.81%
(1,50,0.5)	157	174	0.71	1.32	434.66	-54.33	488.99	4.89%
(1,50,1)	161	179	0.71	1.32	357.46	-54.33	411.79	5.01%
(1,150,0.25)	73	75	0.70	1.32	292.82	-54.33	347.15	5.15%
(1,150,0.5)	65	79	0.69	1.32	267.72	-54.33	322.05	5.23%
(1,150,1)	71	86	0.69	1.32	223.34	-54.33	277.67	5.41%
(1,200,0.25)	68	71	0.64	1.32	245.53	-54.33	299.86	5.31%
(1,200,0.5)	71	66	0.68	1.32	222.04	-54.33	276.37	5.41%
(1,200,1)	70	72	0.68	1.32	191.97	-54.33	246.30	5.58%

Table 5.12: Test results for the moving average rule using the double or out trading strategy on the full sample for each market. The number of new trades (No. of buy/sell) is shown with the profit from trading on the rule (Rule Profit) and the buy-and-hold strategy as well as the difference between the rule returns and the buy-and-hold strategy returns. The final column is the annualised % difference in profit between the trading rules and the buy-and-hold strategies. All profits are the accumulation of log returns.

Rule	No. of Buy	No. of Sell	Rule SD	B&H SD	Rule Profit	B&H Profit	Difference	Annualised % Difference
Panel A: DJIA								
(1,50,0)	939	938	1.33	1.09	1597.98	582.29	1015.69	1.53%
(1,50,1)	623	851	1.27	1.09	1561.39	582.29	979.10	1.47%
(1,150,0)	492	491	1.26	1.09	1376.38	582.29	798.93	1.21%
(1,150,1)	501	470	1.24	1.09	1378.64	582.29	801.18	1.22%
(1,200,0)	405	404	1.38	1.09	1474.09	582.29	915.21	1.44%
(1,200,1)	423	369	1.36	1.09	1474.43	582.29	915.55	1.44%
Panel B: FT30								
(1,50,0)	511	509	1.39	1.06	1285.70	293.46	992.24	4.51%
(1,50,1)	529	482	1.34	1.06	1195.96	293.46	902.50	4.10%
(1,150,0)	279	278	1.28	1.06	831.73	293.46	538.27	2.45%
(1,150,1)	274	263	1.26	1.06	865.42	293.46	571.96	2.60%
(1,200,0)	218	217	1.40	1.06	954.22	293.46	660.76	3.00%
(1,200,1)	226	222	1.38	1.06	911.21	293.46	617.75	2.81%
Panel C: TOPIX								
(1,50,0)	353	352	1.24	1.02	1448.94	412.84	1036.10	3.35%
(1,50,1)	354	358	1.21	1.02	1400.73	412.84	987.89	2.92%
(1,150,0)	173	173	1.22	1.02	1087.56	412.84	674.72	2.92%
(1,150,1)	183	170	1.18	1.02	1078.92	412.84	666.09	2.88%
(1,200,0)	155	154	1.33	1.02	1028.29	412.84	615.45	2.66%
(1,200,1)	156	137	1.32	1.02	1043.86	412.84	631.02	2.73%

Table 5.13: Test results for the perfectly anticipated moving average rule using the double or out strategy on the full sample for each market. The number of new trades (No. of buy/sell) is shown with the profit from trading on the rule (Rule Profit) and the buy-and-hold strategy as well as the difference between the rule returns and the buy-and-hold strategy returns. The final column is the annualised % difference in profit between the trading rules and the buy-and-hold strategies. All profits are the accumulation of log

Rule	No. of Buy	No. of Sell	Rule SD	B&H SD	Rule Profit	B&H Profit	Difference	Annualised % Difference
Panel A: DJIA								
(1,50,0)	938	938	1.31	1.09	5987.53	582.29	5405.24	8.14%
(1,50,1)	955	851	1.26	1.09	5797.16	582.29	5214.88	7.86%
(1,150,0)	491	491	1.35	1.09	3784.23	582.29	3201.94	4.82%
(1,150,1)	500	470	1.33	1.09	3777.50	582.29	3195.21	4.81%
(1,200,0)	404	404	1.37	1.09	3418.29	582.29	2836.00	4.25%
(1,200,1)	422	369	1.34	1.09	3381.64	582.29	2799.35	4.23%
Panel B: FT30								
(1,50,0)	510	509	1.37	1.06	3605.01	293.46	3311.55	15.05%
(1,50,1)	528	482	1.32	1.06	3485.98	293.46	3192.52	14.51%
(1,150,0)	278	278	1.38	1.06	2248.29	293.46	1964.08	9.24%
(1,150,1)	273	263	1.43	1.06	2213.46	293.46	1929.25	9.05%
(1,200,0)	217	217	1.38	1.06	1950.40	293.46	1656.94	7.53%
(1,200,1)	225	222	1.42	1.06	1973.05	293.46	1679.59	7.63%
Panel C: TOPIX								
(1,50,0)	352	352	1.22	1.02	3085.71	412.84	2672.87	11.56%
(1,50,1)	353	358	1.31	1.02	3089.33	412.84	2676.49	11.58%
(1,150,0)	172	173	1.28	1.02	1983.08	412.84	1570.24	6.79%
(1,150,1)	182	170	1.26	1.02	1996.72	412.84	1583.20	6.84%
(1,200,0)	154	154	1.28	1.02	1824.62	412.84	1411.78	6.11%
(1,200,1)	155	137	1.27	1.02	1796.24	412.84	1383.40	5.98%

Table 5.14: Test results for the imperfectly anticipated moving average rule using the double or out strategy on the full sample for each market. The number of new trades (No. of buy/sell) is shown with the profit from trading on the rule (Rule Profit) and the buy-and-hold strategy as well as the difference between the rule returns and the buy-and-hold strategy returns. The final column is the annualised % difference in profit between the trading rules and the buy-and-hold strategies. All profits are the accumulation of log returns.

Rule	No. of Buy	No. of Sell	Rule SD	B&H SD	Rule Profit	B&H Profit	Difference	Annualised % Difference
	Panel A: DJIA							
(1,50,0.25)	953	951	1.32	1.09	5142.34	582.29	4560.05	6.85%
(1,50,0.5)	935	908	1.32	1.09	4460.18	582.29	3877.89	5.84%
(1,50,1)	955	851	1.32	1.09	3642.1	582.29	3059.81	4.61%
(1,150,0.25)	653	646	1.34	1.09	3929.88	582.29	3347.59	5.04%
(1,150,0.5)	641	651	1.34	1.09	3457.16	582.29	2874.87	4.33%
(1,150,1)	642	607	1.34	1.09	2839.92	582.29	2257.63	3.40%
(1,200,0.25)	403	373	1.38	1.09	3055.40	582.29	2473.11	3.73%
(1,200,0.5)	420	376	1.38	1.09	2777.74	582.29	2195.45	3.31%
(1,200,1)	422	369	1.38	1.09	2396.58	582.29	1814.29	2.73%
	Panel B: FT30							
(1,50,0.25)	499	507	1.38	1.06	3099.94	293.46	2806.48	6.43%
(1,50,0.5)	511	491	1.38	1.06	2737.90	293.46	2444.44	5.60%
(1,50,1)	528	482	1.38	1.06	2225.84	293.46	1932.38	4.16%
(1,150,0.25)	378	348	1.36	1.06	2331.72	293.46	2038.26	4.03%
(1,150,0.5)	383	350	1.36	1.06	2051.40	293.46	1757.94	4.03%
(1,150,1)	397	321	1.38	1.06	1721.08	293.46	1427.62	3.27%
(1,200,0.25)	209	205	1.38	1.06	1758.88	293.46	1465.42	2.96%
(1,200,0.5)	202	210	1.38	1.06	1587.90	293.46	1294.44	2.96%
(1,200,1)	225	222	1.38	1.06	1392.86	293.46	1099.4	2.52%
	Panel C:TOPIX							
(1,50,0.25)	356	353	1.22	1.02	2720.58	412.84	2307.74	7.08%
(1,50,0.5)	351	349	1.22	1.02	2468.40	412.84	2055.56	6.30%
(1,50,1)	350	354	1.24	1.02	2139.64	412.84	1726.80	5.30%
(1,150,0.25)	164	179	1.28	1.02	1821.00	412.84	1408.16	4.32%
(1,150,0.5)	171	177	1.28	1.02	1722.62	412.84	1309.78	4.02%
(1,150,1)	182	170	1.28	1.02	1554.64	412.84	1141.80	3.50%
(1,200,0.25)	151	152	1.28	1.02	1664.00	412.84	1251.16	3.84%
(1,200,0.5)	155	145	1.28	1.02	1573.64	412.84	1160.80	3.56%%
(1,200,1)	155	137	1.30	1.02	1411.38	412.84	998.54	3.06%

Table 5.15: Test results for the moving average rule using the double or out strategy on the 1987-2009 data for each market. The number of new trades (No. of buy/sell) is shown with the profit from trading on the rule (Rule Profit) and the buy-and-hold strategy as well as the difference between the rule returns and the buy-and-hold strategy returns. The final column is the annualised % difference in profit between the trading rules and the buy-and-hold strategies. All profits are the accumulation of log returns.

Rule	No. of Buy	No. of Sell	Rule SD	B&H SD	Rule Profit	B&H Profit	Difference	Annualised % Difference
Panel A: DJIA								
(1,50,0)	216	216	1.38	1.19	179.57	170.49	9.08	0.23%
(1,50,1)	246	186	1.31	1.19	137.48	170.49	-33.00	-0.84%
(1,150,0)	121	121	1.30	1.19	194.61	170.49	24.13	0.62%
(1,150,1)	127	112	1.28	1.19	199.46	170.49	28.98	0.74%
(1,200,0)	113	113	1.42	1.19	228.38	170.49	57.90	1.48%
(1,200,1)	98	100	1.38	1.19	227.13	170.49	56.65	1.44%
Panel B: FT30								
(1,50,0)	192	192	1.38	1.18	268.81	39.42	229.39	25.30%
(1,50,1)	193	177	1.31	1.18	248.79	39.42	209.37	23.09%
(1,150,0)	100	100	1.16	1.18	224.93	39.42	185.51	20.46%
(1,150,1)	91	101	1.14	1.18	232.808	39.42	193.39	21.33%
(1,200,0)	73	73	1.24	1.18	275.18	39.42	235.76	26.00%
(1,200,1)	60	84	1.22	1.18	253.27	39.42	213.85	23.58%
Panel C: TOPIX								
(1,50,0)	170	170	1.41	1.32	286.36	-54.33	340.68	27.26%
(1,50,1)	161	179	1.38	1.32	249.75	-54.33	304.08	24.34%
(1,150,0)	74	75	1.34	1.32	177.60	-54.33	231.93	18.56%
(1,150,1)	71	86	1.27	1.32	187.37	-54.33	241.70	19.34%
(1,200,0)	69	69	1.42	1.32	150.57	-54.33	204.99	16.40%
(1,200,1)	70	72	1.40	1.32	133.25	-54.33	187.58	15.01%

Table 5.16: Test results for the perfectly anticipated moving average rule using the double or out strategy on the 1987-2009 data for each market. The number of new trades (No. of buy/sell) is shown with the profit from trading on the rule (Rule Profit) and the buy-and-hold strategy as well as the difference between the rule returns and the buy-and-hold strategy returns. The final column is the annualised % difference in profit between the trading rules and the buy-and-hold strategies. All profits are the accumulation of log returns.

Rule	No. of Buy	No. of Sell	Rule SD	B&H SD	Rule Profit	B&H Profit	Difference	Annualised %Difference
Panel A: DJIA								
(1,50,0)	216	216	1.34	1.19	1316.31	170.49	1145.84	29.22%
(1,50,1)	246	186	1.29	1.19	1227.46	170.49	1056.98	26.96%
(1,150,0)	121	121	1.37	1.19	825.47	170.49	655.00	16.70%
(1,150,1)	127	112	1.30	1.19	831.96	170.49	661.48	16.87%
(1,200,0)	113	113	1.39	1.19	812.24	170.49	641.75	16.37%
(1,200,1)	98	100	1.36	1.19	740.19	170.49	569.70	14.53%
Panel B: FT30								
(1,50,0)	192	192	1.35	1.18	1202.40	39.42	1162.98	128.26%
(1,50,1)	193	177	1.29	1.18	1165.80	39.42	1126.37	124.22%
(1,150,0)	100	99	1.23	1.18	736.03	39.42	696.60	76.82%
(1,150,1)	91	101	1.30	1.18	746.21	39.42	706.79	77.95%
(1,200,0)	73	72	1.21	1.18	612.70	39.42	573.28	63.22%
(1,200,1)	60	83	1.26	1.18	656.00	39.42	616.58	68.00%
Panel C: TOPIX								
(1,50,0)	170	170	1.43	1.32	1215.46	-54.33	1269.78	101.62%
(1,50,1)	161	179	1.54	1.32	1259.08	-54.33	1313.41	105.11%
(1,150,0)	74	75	1.39	1.32	638.08	-54.33	692.41	55.41%
(1,150,1)	71	86	1.36	1.32	665.01	-54.33	719.34	57.57%
(1,200,0)	69	69	1.35	1.32	572.90	-54.33	627.23	50.20%
(1,200,1)	70	72	1.34	1.32	561.72	-54.33	616.05	49.30%

Table 5.17: Test results for the imperfectly anticipated moving average rule using the double or out strategy on the 1987-2009 data for each market. The number of new trades (No. of buy/sell) is shown with the profit from trading on the rule (Rule Profit) and the buy-and-hold strategy as well as the difference between the rule returns and the buy-and-hold strategy returns. The final column is the annualised % difference in profit between the trading rules and the buy-and-hold strategies. All profits are the accumulation of log returns.

Rule	No. of Buy	No. of Sell	Rule SD	B&H SD	Rule Profit	B&H Profit	Difference	Annualised % Difference
Panel A: DJIA								
(1,50,0.25)	222	214	1.36	1.19	1107.88	170.49	937.39	7.00%
(1,50,0.50)	225	203	1.36	1.19	932.00	170.49	761.51	5.69%
(1,50,1)	246	186	1.38	1.19	671.64	170.49	501.15	3.74%
(1,150,0.25)	158	135	1.36	1.19	841.96	170.49	671.47	5.01%
(1,150,0.50)	158	136	1.36	1.19	727.24	170.49	556.75	4.16%
(1,150,1)	167	137	1.38	1.19	603.72	170.49	433.23	3.23%
(1,200,0.25)	111	104	1.40	1.19	676.82	170.49	506.33	3.78%
(1,200,0.50)	110	105	1.40	1.19	622.28	170.49	451.79	3.37%
(1,200,1)	98	100	1.40	1.19	476.00	170.49	305.51	2.28%
Panel B: FT30								
(1,50,0.25)	178	194	1.34	1.18	999.16	39.42	959.74	7.17%
(1,50,0.5)	184	186	1.34	1.18	870.12	39.42	830.70	6.20%
(1,50,1)	193	177	1.36	1.18	697.50	39.42	658.08	4.91%
(1,150,0.25)	142	124	1.28	1.18	729.58	39.42	690.16	5.15%
(1,150,0.5)	145	126	1.28	1.18	611.18	39.42	571.76	4.27%
(1,150,1)	151	117	1.28	1.18	509.54	39.42	470.12	3.51%
(1,200,0.25)	72	72	1.22	1.18	564.94	39.42	525.52	3.92%
(1,200,0.5)	67	80	1.20	1.18	503.68	39.42	464.26	3.47%
(1,200,1)	60	83	1.22	1.18	450.02	39.42	410.60	3.07%
Panel C:TOPIX								
(1,50,0.25)	164	177	1.42	1.32	1011.66	-54.33	1065.99	7.96%
(1,50,0.5)	157	174	1.42	1.32	869.32	-54.33	923.65	6.90%
(1,50,1)	161	179	1.42	1.32	714.92	-54.33	769.25	5.74%
(1,150,0.25)	73	75	1.40	1.32	585.64	-54.33	639.97	4.78%
(1,150,0.5)	65	79	1.40	1.32	535.44	-54.33	589.77	4.40%
(1,150,1)	71	86	1.38	1.32	446.68	-54.33	501.01	3.74%
(1,200,0.25)	68	71	1.28	1.32	491.06	-54.33	545.39	4.07%
(1,200,0.5)	71	66	1.36	1.32	444.08	-54.33	498.41	3.72%
(1,200,1)	70	72	1.36	1.32	383.94	-54.33	438.27	3.27%

5.5. Conclusion

Technical trading rules have been documented in many stock markets throughout the world and this chapter has examined one of the simplest and most popular rules, the moving average rule in three important stock markets. The behaviour of the moving average since BLL's paper has been examined, as has the behaviour of the rule for long sample periods for the DJIA, FT30 and TOPIX. This chapter contributes to the literature by reporting the successfulness of the rule since its seminal paper, how it has behaved over time, if predicting tomorrows signal can gain higher returns than the normal moving average rule, and whether a simple trading rule can generate returns than a simple buy-and-hold strategy.

They key conclusions are;

(i) The moving average technical trading rule produces returns for each full sample that are positive and significant, although the magnitude of returns is lower than the seminal BLL paper.

(ii) The moving average rule returns have diminished in all three markets since 1987, with all of the rules producing negative returns in the DJIA.

(iii) The behaviour of the anomalies over time can be categorized into 5 types, with each of the three markets presenting evidence of the Adaptive Market Hypothesis.

(iv) The perfectly and imperfectly anticipated moving average rules both produce returns greater than the original since 1987, indicating the rule is still successful.

(v) Two simple trading strategies can outperform the buy-and-hold strategy for all markets full samples, however the post BLL data shows mixed results for the DJIA but positive results for the FT30 and TOPIX.

(vi) The perfectly and imperfectly anticipated moving average rules can outperform the buy-and-hold strategy for all markets examined and substantially outperform the original moving average rules.

Similarly to the calendar effect analysis in the previous chapter, the moving average returns have decreased over time indicating that the rule itself is not a stylized fact in the stock market, but could be the result of the investors' activity. Informed investors may have become familiar with the rule before uninformed investors and traded on it, which may have eliminated the predictability from the moving average rule through overvaluing (undervaluing) the index. Thus to discover whether forecasting the follow days signal could produce significant returns, the perfectly anticipated moving average rule is conducted. It finds that significant returns can be made, although it is unlikely an investor will successfully predict the next day's signal 100% of the time. Thus an imperfectly anticipated moving average rule is also examined and still finds positive significant returns. To further analyse these results, two simple trading strategies are examined and find that the original moving average rule can outperform the buy-and-hold strategy for the full samples of each market, but cannot for the DJIA post BLL data. However the perfect and imperfectly anticipated moving average rules show that these trading strategies can substantially beat the buy-and-hold strategy for all markets, including the DJIA. This shows that although the moving average rule is not that successful since 1987, if investors can successfully predict what the following days signal is going to be, they can quite substantially outperform the buy-and-hold strategy. Thus this chapter has shown that a modified version of the moving average rule can gain substantial returns in the DJIA, FT30 and TOPIX, even when the original moving average rule generates negative returns in the DJIA from 1987-2009. Further, this chapter has demonstrated that each market provides evidence of the AMH for the moving average rule. Future research could examine the perfectly and imperfectly anticipated moving average rule is more detail and discover when it became a successful rule. However, this is beyond the scope of this chapter and thesis.

Chapter 6 – Investor Sentiment during World War Two Britain

6.1. Introduction

Britain declared war on Germany[30] on 3rd September 1939 and although this was the official start of World War Two (WW2 hereafter), the outbreak of war had been expected for some time and was of no great surprise. WW2 dominated events in Europe and the rest of the world until the official surrender of Germany on 7th May 1945 (although Japan surrendered 2nd September 1945, Britain was not heavily involved in the conflict in the Pacific), yet the effects of the war were long-lasting in Britain. The war cost Britain over 450,000 lives and the economic impact was huge. More than a quarter of Britain's national wealth was spent during the war and Britain had mounting debts, while 55% of the labour force were employed in war production so after the war Britain faced huge unemployment issues (Harrison 1998).

Surprisingly given the expanding literature on investor sentiment, the impact of WW2 on stock market returns has not been examined in great detail in the financial literature. Further, the literature on investor sentiment tends to examine seemingly economically unimportant events and ignores major, economically significant events. Thus the aim of this chapter is to examine the effect WW2 had on the main British stock market represented at the time by the FT30. It examines investor sentiment in stock returns and whether the major events of the war had an impact on the FT30. This is a period of the FT30 that has not been examined in great detail and it also provides an opportunity to examine investor sentiment in extreme circumstances through major events of WW2. This chapter also investigates the effect naval disasters had on the FT30 with an examination of British, German, US and Japanese capital ship sinkings and whether these unexpected sinkings caused investor sentiment on the FT30[31]. Capital vessels were held in much esteem during WW2 and their loss could have had an effect on moral and the war effort. Finally, this chapter studies a period likely to have an extreme effect on investor sentiment during the war, the Blitz. The Blitz was the period when German bombers bombed major UK cities every night from 7th September 1940 until 12th May 1941. Many of the biggest bombings were on London, where financial markets and

[30] Along with France, Australia and New Zealand.
[31] Kaplanski and Levy (2010) examine the effect of aviation disasters on the US market and whether these unexpected crashes cause investor sentiment.

investors were situated, providing an opportunity to examine investor sentiment in the most extreme case when the lives of investors and market participants are at risk.

The first section of this chapter provides a background of WW2, a review of the investor sentiment literature as well as the methodology employed throughout this chapter. The second section examines investor sentiment in major events during WW2, while the third section examines investor sentiment due to major vessel sinkings. Finally the fourth section examines the effect of the Blitz on the FT30 during WW2 and section five provides a chapter summary.

6.1.1. The History of World War Two

WW2 was a global war that began in 1939 and ended in 1945 which involved almost all of the world's great powers. With more than 100 million people serving in military units, it was the most widespread war in history and the deadliest conflict (Sommerville 2008).

WW2 officially began for Britain with the invasion of Poland by Germany and the subsequent declarations of war by France and Britain on Germany on 3rd September 1939. British troops were deployed to the Continent but neither side launched major operations against the other until April 1940 (Weinberg 1995). An Axis alliance was formed between Germany, Japan (after Pearl Harbour) and Italy, with only Britain and other Commonwealth nations (called the Allied forces) fighting the Axis. Germany invaded France, Belgium, the Netherlands and Luxembourg on 10th May 1940, with the Netherlands and Belgium overrun in a few days. British troops evacuated the continent at Dunkirk on 27th May 1940 and on 10th June 1940 Italy invaded France, declaring war on France and Britain. France was now under the control of the Axis, and Germany began the aerial bombardment of Britain to prepare for the invasion. The campaign failed and the invasion was cancelled however this marked the beginning of the Blitz (more information is provided in section 6.3). Nevertheless, the Axis expanded in November 1940 when Hungary, Slovakia and Romania joined after the takeover of the Balkans on 7th December 1941 and Japan attacked British and American Navy holdings at Pearl Harbour to prevent American intervention. This led to the Allied nations declaring war on Japan and the US formally entering the war. Initially there was great Japanese success against the US in the naval battles as they took over much of Asia and the Pacific, as well as Malaysia, Singapore, Burma, Philippines and Java. However this was halted at the Battle of Midway, where the US sunk 4 carriers, one cruiser and 248 carrier aircrafts, killing 3057 Japanese soldiers.

The Allies gained momentum in 1943 and in September of that year, invaded and seized Italy following an armistice with Italian leaders. With German defeats in Eastern Europe, the Allied invasion of Italy and American victories in the Pacific, the Axis was in strategic retreat on all fronts in 1943. The Allies advance continued in Asia and on the Atlantic Ocean and on 6th June 1944 (known as D-Day), the Allies invaded France which led to the defeat of German forces in France. Paris was liberated on 25th August 1944 and the German forces were pushed back and although an attempt to advance into northern Germany ended in failure, German forces were continually retreating. Meanwhile in the Pacific, the US defeated the Japanese Navy and captured key Western Pacific islands during 1944 and 1945. The war in Europe concluded with the capture of Berlin by Soviet and Polish troops and the German unconditional surrender on 8th May 1945. Japan officially surrendered on 15th August 1945 after the Hiroshima and Nagasaki bombings on the 6th and 9th August 1945 respectively. Estimates of total casualties of the war vary, but most suggest some 60 million people died, with 20 million soldiers and 40 million civilians[32]. WW2 altered the social structure and political alignment of the world and the United Nations (UN) was a direct result of the war to prevent future conflicts and foster international cooperation.

6.1.2. Investor Sentiment Literature Review

The existence of investor sentiment has been well documented in the literature, with many routine and seemingly economically unimportant events having a significant effect on stock returns, such as cloud cover, (Saunders 1993) daylight (Kamstra et al 2000; 2003), sunshine (Hirshleifer and Shumway 2003), temperature (Cao and Wei 2005) and even sports results (Edmans et al 2007). Saunders (1993) showed that less cloud cover is associated with higher returns and the returns difference between the most cloudy days and the least is statistically significant for the NYSE. Kamstra et al (2000) find that daylight saving time changes cause desynchronosis and anxiety, which in turn negatively impacts stock markets. Further Kamstra et al (2003) show evidence of a link between seasonal variations of daylight and seasonal variations in stock returns. Hirshleifer and Shumway (2003) show that sunshine is strongly

[32] Beevor (2012).

significantly correlated with stock returns while Cao and Wei (2005) show a negative correlation between temperature and stock returns in twenty international markets. Also Edmans et al (2007) show that soccer matches have a significant impact on stock returns, with negative results have a stronger negative effect on returns than positive results.

With such strong and varied evidence of investor sentiment for small and economically unimportant events, it is quite surprising that major events have not received the same level of attention in the academic literature. However, some major events have been explored such as airplane crashes (Barrett et al 1987; Davidson et al 1987; Kaplanski and Levy 2010), hurricanes (Lamb 1995, 1998; Angbazo and Narayanan 1996; Huerta and Perez-Liston 2010) and earthquakes (Shan and Gong 2012) which have all found that these unexpected disasters have a significant negative impact on stock returns across the market. Barrett et al (1987) show that fatal commercial airline crashes have an immediate negative market reaction in the US market for one day, even if the crash occurs in a remote geographic location. Davidson et al (1987) employ a sample of 57 crashes from 1965-1984 and observe a significant price decline for airlines on the day of the crash with the negative returns reversing in the days following a crash. Further, Kaplanski and Levy (2010) examine 228 aviation disasters from January 1950 to December 2007 and find evidence of a significant negative effect. They document a greater effect in small and riskier stocks and in firms belonging to less stable industries. With regard to hurricanes, Lamb (1995) examines the impact of the 1992 hurricane Andrew and its impact on property liability insurers. The study reports that hurricane Andrew produced a significant negative stock price reaction on property-liability insurers with direct premiums written in the affected areas (Florida and Louisiana) while an unexposed firm sustained no significant price response. Angazo and Narayanan (1996) examine the impact of hurricane Andrew on insurance firms and find that it had a large negative effect on insurance stocks that were ameliorated to some extent by a smaller positive effect, while that Andrew also had an industry-wide effect with firms not exposed to Andrew also affected. Lamb (1998) examined the effect of hurricanes Andrew and Hugo and find that the property industry was generally unaffected by Hugo but Andrew generated a significant negative impact on property firms. The study concludes by stating that the market is able to discriminate by the magnitude of the hurricane and by the property firm's degree of loss exposure. More recently, Huerta and Perez-Liston (2010) examine 66 hurricanes in the US from 1966 to 2008 and find that there is a significant decrease in stock returns on the day the hurricane hits the US and one day prior. Further, they show that not all industries are significantly impacted and an increase in investor fear on the day of the hurricane hitting the US. Shan and Gong (2012) examine the Wenchuan earthquake in China and find that during the 12 months following the earthquake, stock returns are significantly lower for firms located nearer the epicentre than for firms further away. Further, they show that this pattern in stock returns does not exist before or long after the earthquake, thus it must be a temporal shock to stock returns.

Recently, there has been a growing attention in the financial literature to the influence of terrorist attacks on capital markets. Abadie and Gardeazabel (2003) study the case of the Basque region in Spain and find evidence that terrorism related news has a significant impact on equity prices. They use three event study methods to estimate Basque firms' abnormal return following new announcements related to peace talks during the cease-fire around 1998. They find that following the release of good news the Basque portfolio outperformed the non-Basque portfolio and following the release of bad news the Basque portfolio underperformed the non-Basque portfolio. Carter and Simkins (2004) examine the effect of the September 11^{th} attacks on New York in 2001 and find large significant negative abnormal returns for airfreight firms and international airlines. Further Chen and Siems (2004) examine the US capital markets response to various terrorism attacks dating back to 1915 and up to the September 11^{th} attacks in 2001. They show that these attacks had a significant negative impact on the US capital markets but that they are more resilient than in the past and recover sooner from terrorist attacks than other global markets. Charles and Darné (2006) perform a study on the impact of the September 11^{th} attacks in 2001 on international stock markets by estimating abnormal price changes using an outlier detection method based on an ARIMA model. This model has the ability to identify whether the changes in the market are endogenous, exogenous, permanent or temporary. The results show that the September 11^{th} bombings produced outliers in all indices examined with the US markets less affected by the attack than other international markets. Further, Nikkinen and Vahamaa (2010) examine the behaviour of the FTSE100 index around the terrorist attacks of September 11^{th} 2001, the 2004 attacks in Madrid and the July 7^{th} attacks in London in 2005. They show that terrorism had a strong adverse effect on stock market sentiment with a pronounced downward shift in the expected value of the FTSE 100 and that these attacks caused 3 of the 5 largest daily increases in implied volatility from January 2000 through to December 2005. Further Kollias et al (2011) examine the effect of the bomb attacks in Madrid on 11^{th} March 2004 and in London on 7^{th} July 2005 on the equity sectors. They find significant negative abnormal returns across the majority of sectors in the Spanish markets but not so for London. Further they find that the market rebound was much quicker in London compared to the Spanish markets and that the bombings had only a transitory impact on returns and volatility that did not last for a long period.

Give the recent literature on terrorist attacks, it is surprising the literature on financial markets and wars is limited, with very little written on WW2. Choudhry (2010) investigates the DJIA to determine endogenously the structural breaks during WW2 by examining price changes and volatility through an exponentially weight moving average. The paper distinguishes between two possible types of breaks; turning points and blips. Turning points are breaks that cause a price change in the same direction for at least five days, while blips are breaks that cause a price change in the same direction for less than five days. The results show that many events deemed by historians as important are reflected in the data as turning points. However, some major events are only blips (German invasion of Poland), or fail to generate a break point (Battle of Britain, Invasion of France, Operation Market Garden[33] etc). The paper concludes by stating that news seen as good by the investors tends to increase the price the next day after the event and for the next five working days and leads to a fall in volatility. Frey and Kucher (2000) examine government bond prices of five European countries traded on the Swiss bourse during WW2. They find that the loss and gain of national sovereignty during WW2 influenced the bond prices of the European countries involved. Further, Frey and Kucher (2001) analyse government bond prices of Germany and Austria traded on the Swiss bourse during WW2. They show that war events considered crucial by historians are clearly reflected in government bond prices; however some events, such as Germany's capitulation in 1945 is not reflected in bond prices. Schneider and Troeger (2006) examine the effect of political developments within three war regions from 1990 to 2000 in the CAC, DJIA and FTSE. They show that the conflicts caused a negative reaction in the three markets, with the notable exception of the DJIA and the Gulf war. Given the lack of studies examining investor sentiment in WW2, this chapter will significantly contribute to the literature on investor sentiment during wars.

[33] An airborne attempt to the seize the Rhine bridges by the allies from 17th-25th September 1944.

6.2. Methodology

This chapter examines the effect of the WW2 on stock returns and whether investor sentiment in present in extreme circumstances. Given the previous literature on routine and economically unimportant factors having a significant impact on stock returns as well as terrorist attacks generating negative investor sentiment, the null hypothesis is that the events of WW2 should have a strong degree of investor sentiment on returns since investors lives were at risk. Major events of the war, major naval disasters as well as the Blitz period are examined to provide a detailed analysis of the effect of WW2 on British stock returns.

6.2.1. Major Events

Initially the major events of the war are examined, followed by naval disasters and then the Blitz period. Abnormal returns (ARs) and the cumulative abnormal returns (CARs) are initially examined. Daily excess returns are measured by the mean-adjusted-returns approach discussed by Brown and Warner (1985). An AR is the deviation of returns on day *t* from an expected return generated by a mean of returns calculated on a pre-event period. The mean is estimated over a 20-day estimation period starting 30-days prior to the event day *t* and closing 11 days before the event. That is, ARs are computed following;

$$AR_{jt} = R_{jt} - \overline{R_J} \qquad (6.1)$$

Where AR_t is the abnormal return for the stock index at time *t*, R_{jt} is the actual observed rate of returns for this index, and $\overline{R_J}$ is the mean of this index daily returns in the (-30,-11) estimation period. $\overline{R_J}$ is computed as follows;

$$\overline{R_J} = \frac{1}{20} \sum_{t=-30}^{-11} R_{jt} \qquad (6.2)$$

The date of the event is $t = 0$, the mean adjusted returns model is estimated over 20 days from $t = -30$ to $t = -11$ relative to the event date. The *t*-test also follows Brown and Warner (1985) to obtain a level of statistical significance of the portfolio abnormal returns such that;

$$t_o = \frac{AR_t}{SD_{AR}} \tag{6.3}$$

Where t_o is the *t*-value indicating significance of the FT30, *AR* is the abnormal return on day *t*, and SD_{AR} is the standard deviation of all of the abnormal returns. The SD_{AR} is computed as follows;

$$SD_{AR} = \sqrt{\frac{\sum_{n=1}^{n}(AR - \overline{AR})^2}{(n-1)}} \tag{6.4}$$

Where $\overline{AR}$ is the mean of the abnormal returns and n is the total number of *AR*s calculated.

Additionally, two longer event windows are examined by computing the CARs six (t = 6) and eleven (t = 11) days following the event. The CARs were estimated using the following equation;

$$CAR_t = \sum_{t=T_1}^{T_2} AR_t \tag{6.5}$$

Where T_1 is the event day and T_2 is consequently 5 and 10 days after the event. The same t-statistic for the ARs is calculated for the CARs only that;

$$t_o = \frac{CAR_t}{SD_{CAR}} \tag{6.6}$$

Where t_o is the *t*-value indicating significance of the FT30, C*AR* is the cumulative abnormal return on day *t*, and SD_{CAR} is the standard deviation of all of the cumulative abnormal returns. The SD_{CAR} is computed as follows;

$$SD_{CAR} = \sqrt{\frac{\sum_{n=1}^{n}(CAR - \overline{CAR})^2}{(n-1)}} \tag{6.7}$$

Where $\overline{CAR}$ is the mean cumulative abnormal returns and n is the total number of *CAR*s calculated.

Also, the cumulative mean rate of return (CMR) is calculated to explore whether there is a time delay in investors reacting to the major events studied. The CMR shows the total return of major events after various days in order to document whether the major events affects the next day or other days after the event. Thus the mean rate of return for each of the first 10 days following major positive and negative events is plotted. Following Kaplanski and Levy (2010), the ten largest increases and decreases in the FT30 during the war are identified to determine whether the major events studied are the associated with the largest price changes in the FT30.

To further examine the major events of WW2, an OLS regression is run similar to that of Kaplanski and Levy (2010). However unlike Kaplanski and Levy (2010), this chapter pre-examines whether the seasonality's are evident in the data before the regression analysis. If the seasonality's are found to be significant, they are included in the regression analysis but if they are not found they are excluded from the analysis. The seasonality's are examined over the period from the beginning of the FT30 to the end of the war. The seasonality's examined are the well-known Monday effect, January effect, turn-of-the-month effect, tax year effect, as well as serial correlation in the returns. Thus the main seasonality's are examined through a simple regression analysis such that;

$$r_t = \gamma_0 + \beta_1 D_{1it} + \varepsilon_t \qquad (6.8)$$

Where r_t is the daily rate of return on the FT30, γ_0 is the regression intercept, and D_{1it} is a dummy variable for the seasonality's examined. β_1 is the parameter to measure whether the dummy variable examined is significant. For instance, in the investigation of the January effect, the dummy equals one for January returns and zero otherwise, hence alpha measures the average daily return in months other than January, and beta measures the difference between January and non-January returns. Thus a positive and significant beta would indicate the existence of the January effect, i.e., the average daily return in January being statistically higher than in other months, on average. An analogous interpretation holds for other seasonality's. If all of the seasonality's are found in the data, the following regression is run;

$$r_{it} = \gamma_0 + \sum_{i=1}^{5} \gamma_{1i} r_{t-i} + \gamma_{2i} Mon_{it} + \gamma_{3i} J_{it} + \gamma_4 TOTM_{it} + \gamma_5 T_{it} + \sum_{i=3}^{3} \gamma_6 NE_{i,t} \sum_{i=3}^{3} \gamma_7 PE_{i,t} + \varepsilon_t \quad (6.9)$$

Where r_t is the daily rate of return on the FT30, γ_0 is the regression intercept, r_{t-1} is the i^{th} previous day rate of return. Mon_{it} is a dummy variable for the Monday effect. J_{it} is the dummy variable for the January effect where i = 1 for the first 15 days in January. $TOTM_{it}$ is a dummy variable for the turn-of-the-month days and T_{it} is a dummy variable for the first five days of the taxation year. NE_{it} is the dummy variable for a negative event while PE_{it} is the dummy variable for a positive event. However, if any of the seasonality's are not found to be significant from equation 6.4, they are excluded from the subsequent regression analysis.

Nevertheless, the OLS regression estimated above may be affected by a few extreme values. These extreme values may bias the regression results and since the war period was quite a volatile period for the FT30, this is a distinct possibility. Acknowledging this fact, a quantile regression (QR) which was introduced by Koenker and Bassett (1978) is estimated. A major benefit of quantile regressions are that they not as sensitive to extreme observations as the typical OLS regressions (Koenker and Hallock 2001). The QR method is employed to estimate the conditional median, rather than the conditional mean via the OLS method. The linear regression takes the form;

$$y_t = x_t\beta + \varepsilon_t \quad (6.10)$$

Where x_t is a row vector of the explanatory variables with the first element equal to 1; ε_t is an error term independent of x_t and β is a vector of the parameters. The conditional quartile function can be written as;

$$Q(\psi)_t = x_t\beta(\psi) \quad (6.11)$$

Where $\beta(\psi)$ is a vector of parameters dependent on ψ. In our case the ψ equals 0.50. Koenker and Basset (1978) define the ψ^{th} regression quartile (0< ψ<1) as any solution $\beta(\psi)$, to the quartile regression minimization problem;

$$\min_{\beta}\left[\sum_{t:y_t>x_t\beta}\psi|y_t-x_t\beta|+\sum_{t:y_t<x_t\beta}(1-\psi)|y_t-x_t\beta|\right] \tag{6.12}$$

A further issue with the original OLS regression is its constant-volatility assumption. Bollerslev, Engle and Nelson (1994) show that stock index returns have time-varying volatility properties and if any of the major events examined occurs during periods of high volatility, the magnitude of the standard errors could be biased. Therefore a Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model is estimated. The GARCH model allows for time-varying volatility and adds robustness to the results. Specially, the model estimated is;

$$\begin{gathered} r_{it}=\gamma_0+\sum_{i=1}^{5}\gamma_{1i}\,r_{t-i}+\gamma_{2i}Mon_{1it}+\gamma_{3i}J_{2it}+\gamma_4H_t+\gamma_5T_4+\sum_{i=3}^{3}\gamma_6NE_{i,t}\sum_{i=3}^{3}\gamma_7PE_{i,t}+\varepsilon_t \\ \varepsilon_t\sim N(0,h_t) \\ h_t=\alpha_0+\alpha_1\varepsilon_{t-1}^2+\beta_1h_{t-1} \end{gathered} \tag{6.13}$$

Where all variables are described in equation 6.5 and ε_t is the error term with conditional mean zero and conditional variance h_t. The estimation of equation 6.5 using quartile regression and GARCH modelling for volatility, are done to add power to the results.

The above analysis examines the impact of pre-determined major events on the FT30. However, these events are only deemed important with regards to the outcome of the war by historians. They may not have been important to investors in Britain and even more importantly, there may be a number of events that were hugely important for investors in Britain that the previous analysis has ignored. Thus this chapter examines structural breaks during the war period similar to Choudhry (2010), to pick up any events that the previous analysis has ignored. Breaks in a time-series are shocks that permanently affect the series, and that they do not occur each period. That is, while some shocks permanently shift the trend function of a series, the majority of shocks have only a temporary effect. Thus events during the course of WW2 that have produced permanent and temporary effects on the British stock market are examined. Zivot and Andrews (1992) provide a test that takes into account possible structural shifts in a series, and its intercept. The test can be formalised by;

$$InP_t = \alpha_0 + \beta t + \alpha_1 DU_t + \alpha_2 DTB_t + \alpha_3 DT_t + \rho InP_{t-1} + \sum_{i=1}^{N} \psi_i \Delta InP_{t-1} + u_t \quad u_t \sim (0, \sigma^2) \tag{6.14}$$

Where InP_t is the log of the FT30, if T_b is the break point, $DTB_t = 1$ if $t = T_b + 1$ (otherwise it is equal to zero), $DU_t = 1$ if $t > T_b$, zero otherwise, and $Dt_t = (t - T_b)$ if $t > T_b$, zero otherwise. Thus this test allows a change in both the intercept and the slope of the trend function. Dummies DTB_t, DU_t, *and* DT_t allow for a break in the level of the trend function, in the slope, and for breaks in both the level and the slope respectively. Thus this test is more powerful than a number of other structural break tests (for example the Chow test). The Zivot Andrews test also includes lags of ΔInP_t to eliminate potential serial correlations. Application of zero lags implies no serial correlation.

According to Willard et al (1996), one of the main problems of finding a break in a series is determining the length of the break. This test only assumes a single break point in the series, thus if two breaks happen within a short space of time there may be difficulty in finding both, or it may locate one with an inflated effect. This problem can be addressed by investigating potential breaks that last for periods shorter than the rest of the remaining sample period. As the period gets shorter, it becomes easier for a break to be labelled as long lasting. Thus there is a trade off in choosing between a short time period and a long period for analysis; as the period gets shorter breaks may falsely be deemed long lasting and as the period gets longer important breaks may be missed. In this investigation the search for potential breaks in the FT30 is based on one sample size but with different rolling windows. A three-month sample size with a rolling window of two weeks and one month are used similar to Choudhry (2010).

There are two types of break possible in the stock prices according to Choudhry (2010), turning points and blips. Blips are shocks that last for only a day or so, while turning points persist for much longer. Turning points may induce a change in the prices without any further change in the near future. On the other hand, blips may reflect reaction to earlier news that later turned out to be false, or market reaction over events on which there is little information. Thus this chapter uses this identification with investors considering turning points much more important and impact the market much more than blips.

6.2.2. Naval Disasters

Naval disasters are also examined in this chapter to determine whether key sinkings during WW2 caused any investor sentiment in stock returns. Naval ships during the war were held with great prestige, and an unexpected sinking caused thousands of deaths and huge financial losses. British ships, German ships and Japanese ships are all examined to understand the impact of these sinkings. Similar to the major event analysis, ARs and CARs are estimated, as well as an OLS regression, QR and GARCH regression similar to regression 6.5. Again the seasonality's are pre-examined over the same period as the major events, so the same seasonality's used in the major events section are used again in this section.

6.2.3. The Blitz

Finally, the continual bombings of British Isles, the period known as the Blitz, is examined in this chapter to examine the level of investor sentiment when the war came to British shores and investors lives were at risk. Initially the Blitz period itself is examined, and then the major London and non-London bombings are examined to determine whether the location of the bombings had a significant impact on the level of investor sentiment in stock returns. Firstly ARs and CARs are estimated, and then an OLS regression, QR and GARCH regression are examined, similar to the major events and naval analysis. However unlike previously, the seasonality's are pre-examined from the start of the FT30 to the end of the Blitz to find only the seasonality's relative to the Blitz period. Thus the seasonality's are examined from 1st July 1935 to 12th May 1941.

6.3. Major Events

6.3.1. Data

The empirical tests employ closing FT30 data from 3rd January 1939 to 31st December 1945 which represents the WW2 period. Although the war did not officially begin until 3rd September 1939, many of the leading players had been planning for the outbreak of war for some time and saw it as only a matter of time. Further, this is the period of WW2 used in the previous literature. To gauge an overview of how the returns during the war compare to non-war returns, descriptive statistic during WW2 with periods before and after it are compared in Table 6.1. Figure 6.1 and 6.2 present the log prices and log returns over the war period.

Figure 6.1: FT30 during WW2.

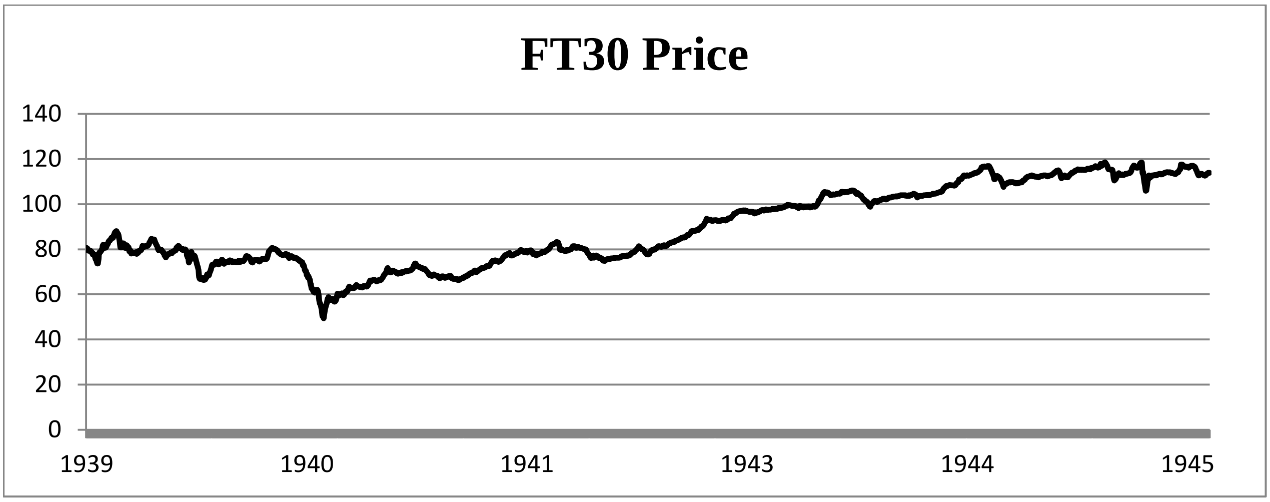


Figure 6.2: Log returns of the FT30 during WW2.

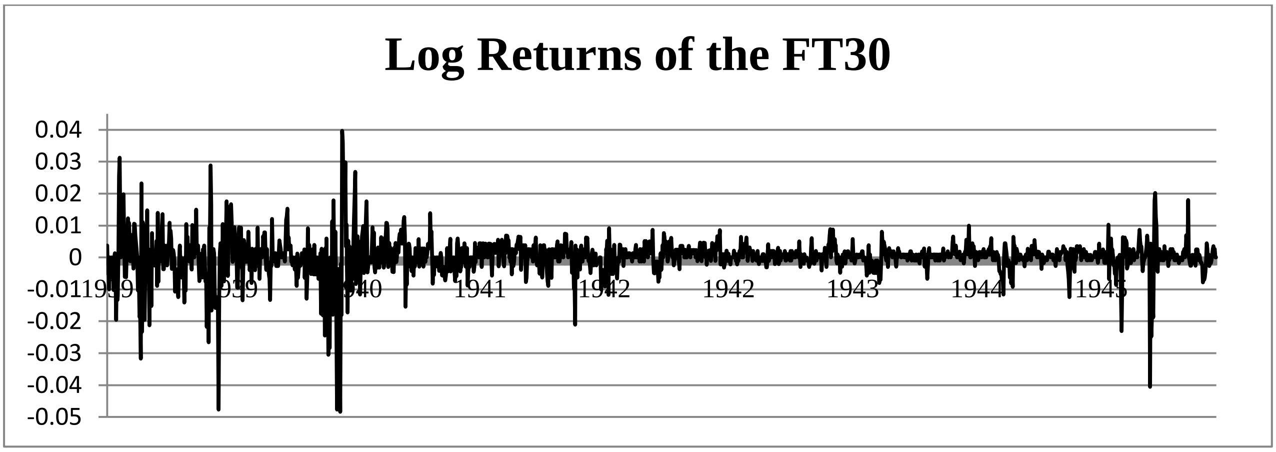


Table 6.1: Descriptive Statistics of daily returns during World War Two. Significance tests are only applied to the skewness, kurtosis and Jarque-Bera statistics. ***, **, * indicate significance at 1%, 5% and 10% respectively.

Period	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Obs
1935 - 1938	-0.000245	0.080773	-0.055534	0.008006	0.470900***	21.44520***	12649.58***	890
World War Two	0.000195	0.039688	-0.0484122	0.005881	-1.215714***	17.9953***	17173.25***	1786
1946 - 1952	0.000009	0.041925	-0.037166	0.005407	-0.739001***	11.02905***	4946.223***	1780
1935-2009	0.000154	0.107810	-0.124000	0.010581	-0.19629***	12.69284***	75169.29***	19155

Summary statistics for the FT30 before the war, during the war period and after the war are presented in Table 6.1. The war period is from 1939 to 1945 and is compared to the following seven years, the previous four years and the full data period 1935-2009. This study does not have access to data pre-1935 so the pre-war sample period is just four years. Table 6.1 shows that the mean returns during the war period are greater than the mean returns after the war period and for the full sample, while the mean returns before the war were negative. The reason why the mean returns during the war are greater than the returns after the war may be explained by the fact that Britain in the post-war years were days of austerity and of fuel shortages, which strangled production and dragged the market lower than it had been during WW2 (Harrison 1998). The skewness and kurtosis statistics for each subsample show that the frequency distribution of the returns is not normal. Table 6.1 shows that the war period, as well as the post-war period, has significant left skewed data which is what is generally found in stock markets (see for example Premaratne and Bera 2001). Kurtosis is a measure of whether the data is peaked or flat relative to a normal distribution. All of the subsamples have kurtosis coefficients that are greater than three and significant, indicating a leptokurtic distribution. Thus the skewness and kurtosis coefficients for each subsample indicate that the returns series deviates from the normal distribution at 1% significance, indicating the non-normal nature of the data. Further, the Jarque-Bera statistic is commuted to further assess the extent of non-normality in the distributions of the returns series. The probabilities of the JB statistic for each subsample are all less 0.01 which is statistically significant at 1% and confirms that the distribution of the returns of each subsample is not normal. Thus the WW2 period for the FT30 generated higher returns than periods before and after it and the full sample, but as with most time series data, the returns series is not normal.

Table 6.2 documents the major positive and negative events examined, along with the rationale for choosing them as major events and are taken from Beevor (2012). The main criteria for the chosen events are that they are believed by historians to significantly contribute to the outcome of the war to Britain. For example, the Nazi invasion of Poland which led to the declaration of war from the allies is generally deemed to be the official beginning of the war and so is an important event. However the Battle of Midway is not chosen as even though it was important for victory in the Pacific, it was fought by the US and Japan far away from Britain and is not deemed important to British investors at the time.

Table 6.2: The major war events studied in this chapter and a brief note about each event. Panel A documents the negative events while Panel B shows the positive events from a British viewpoint during WW2.

Date	Event	Rationale
		Panel A: Negative Events
23rd Aug 1939	Nazis and Soviets sign Pact	Russia and Germany sign a non-aggression Pact to ensure Germany would not have to fight a war on two fronts.
1st Sep 1939	Germany invades Poland	The Nazis invade Poland which leads to the declaration of war from the Allies.
3rd Sep 1939	Britain, France, Australia and New Zealand declare war on Germany	British Ambassador in Germany Neville Henderson delivered the British declaration of war to German Foreign Minister Joachim von Ribbentrop, effective at 1100 hours. British Commonwealth nations of New Zealand and Australia followed suit and France also declared war later on this day.
27th Sep 1939	Warsaw falls to Germany	Warsaw, Poland fell to the Germans after two weeks of siege. The Polish government in exile was established in Paris, France.
10th May 1940	Germany invades France, Belgium, Luxembourg and the Netherlands	Germany invaded France as well as Belgium, Luxembourg and the Netherlands.
15th May 1940	Surrender of Holland	The Netherlands surrendered to Germany at 1015 hours; Dutch General Winkelman signed the surrender document.
10th June 1940	Italy declares war on Britain and France	Italy declared war on France and Britain, to be effective on the following day.
14th June 1940	Fall of Paris	In France, German troops captured the open city of Paris without any opposition. To the north, the coastal city of Le Havre fell under German control. To the east, the German 1st Army broke through the Maginot Line near Saarbrücken. Also on this date, all remaining British troops in France were ordered to return.
10th July 1940	Start of the Battle of Britain	A large German aerial formation attacked one of the eight British convoys in the English Channel. Upon detecting the incoming aircraft, four squadrons of British fighters were launched to counter the attack. At the end of the battle, seven British aircraft were destroyed and one of the Bread ships was sunk. The Germans lost 13 aircraft and this surprising victory led to the British announcing that 10th July was the start of the Battle of Britain.
7th Sep 1940	Start of the Blitz	German bombers attacked London as the new Operation Loge commenced. During the day, 53 German bombers were shot down, as was 21 BF 109 fighters; the British lost 27 fighters. Overnight, German bombers continued to attack the East End, which saw 490 killed and 1,200 wounded on this day. This would mark the first of 57 consecutive nights of German bombings on the British capital.
7th Dec 1941	Pearl Harbour	360 Japanese carrier aircrafts attack Pearl Harbour sinking or damaging 8 battleships, 3 cruisers, 3 destroyers, 1 anti-aircraft training ship, 1 minelayer. In total 2,459 were killed of which 57 were civilians.
		Panel B: Positive Events
31st Oct 1940	Battle of Britain won	According to a British Air Ministry pamphlet published in 1941, this date was the official end of the Battle of Britain, but bombings in London would continue.
8th Dec 1941	US joins Allied forces	United States declared war on Japan after Franklin Roosevelt's "a date which will live in infamy" speech. United Kingdom, Canada, Costa Rica, Dominica, Haiti, Honduras, Nicaragua, Free France, and the Dutch government-in-exile also declared war on Japan. Meanwhile, China declared war on both Germany and Italy; China had been fighting with Japan since July 1937.
2nd Feb 1943	Germans surrender to Stalingrad in the first big defeat of Hitler's armies	The last of the German Sixth Army surrendered in Stalingrad, Russia.
25th July 1943	Moussolini's government overthrown	The Fascist Grand Council in Rome voted 19 to 7 for King Vittorio Emanuele III to retake command of the Italian military from Mussolini. Mussolini was arrested immediately.
8th Sep 1943	Badoglio signs armistice with the Allies made public	Italy sign a treaty with the Allies to support them against Germany.
12th Aug 1944	Battle of Normandy won	The German failure to successfully defend the Normandy area from the Allied liberation forces in essence doomed Hitler's dream of a Nazi controlled "Fortress Europe" and marked the beginning of the end for Germany.
25th Aug 1944	Liberalisation of Paris	The French 2nd Armoured Division entered Paris, France. De Gaulle moved his headquarters into the War Ministry in Paris on the same day with the approval of Eisenhower.
21st Oct 1944	Massive German surrender at Aachen, Germany	German troops surrender at Aachen, Germany.
30th Apr 1945	Hitler commits suicide	The recently married Hitler and Braun committed suicide in Berlin, Germany.
2nd May 1945	German troops in Italy surrender	German troops in Italy surrendered in accordance with secret negotiations, followed by an announcement for the cessation of hostilities.

7th May 1945	Unconditional surrender of Germany	General Jodl signed the unconditional surrender of all German forces to the Allies, to take effect the following day at Eisenhower's headquarters near Rheims, France.

6.3.3. Empirical Results

Table 6.3 documents the abnormal returns (ARs) and cumulative abnormal returns (CARs) for the major positive and negative events during WW2 in FT30. Some of the CARs are overlapping such as the German invasion of Poland and the declaration of war on Germany by the Allies and so may affect the results. The results show that of the 11 negative events studied, 8 events experienced negative abnormal returns on the day after the event. The only negative events with positive ARs are the fall of Warsaw to Germany, the German invasion of France, Belgium, Luxembourg and Holland, and the start of the Battle of Britain. The signing of the Nazi Soviet Pact generated significant negative abnormal returns, as did the fall of Paris and the attack on Pearl Harbour. Regarding the positive events, only 3 of the 11 events produce positive ARs the day following the positive event. This suggests that many of these positive events may not have been deemed that positive at the time by investors or it took some time for the event to be incorporated in stock returns. None of the positive events produced significant positive abnormal returns.

While the ARs are interesting in that they show immediate investor reaction to these major events, the CARs (6- and 11-day) provide a stronger indication of the stock market's resilience and ability (or inability) to bounce back from these events. Only the attack on Pearl Harbour generates significant negative CARs for both the two windows examined. However, the fall of Paris produces significant negative CARs for 5-days after the event indicating its lasting impact. A number of negative events produce little or no significant evidence regarding their ARs but the 10-day CARs are significant. This indicates that the actual event studied had little or no impact on the FT30 and that some other factor may be driving the result. None of the positive events produce CARs that are statistically significant suggesting the limited and short impact of these positive events on the FT30. The final column to Table 6.3 shows that the number of days it took the market to return to its pre-event value. The FT30 remained down for 169 days after the invasion of Germany into France, Belgium, Luxembourg and the Netherlands. After the surprise attack on Pearl Harbour the FT30 did not recover for another 174 trading days., however the other negative events recovered quite quickly. Positive events to have a strong impact on the FT30 were the Allies declaration of war on Japan when the FT30 did not fully rebound for 164[34], while after the Battle of Normandy, the FT30 recovered in 160 days, nearly 8 months. The other positive events rebounded quite quickly but the suicide of Hitler and the German surrender in Italy still took over 50 trading days to recover.

Table 6.3: ARs and CARs for the FT30 after major events of WW2. [a] Number of trading days for the market index to return to the pre-event level.

Date	Event	Return	AR	5-day CAR	10-day CAR	Days to rebound[a]
Panel A: Negative Events						
23rd Aug 1939	Nazis and Soviets sign Pact	-2.63%	-2.77%*** (-4.73)	3.06% (1.44)	1.15% (0.33)	4
1st Sep 1939	Germany invades Poland	-0.65%	-0.63% (-1.03)	-1.90% (-0.90)	10.92%*** (-3.14)	3
3rd Sep 1939	Britain, France, Australia and New Zealand declare war on Germany	-0.65%	-0.63% (-1.03)	-1.90% (-0.90)	10.92%*** (-3.14)	3
27th Sep 1939	Warsaw falls to Germany	-0.30%	0.15% (0.25)	3.87%* (1.83)	9.72%*** (2.80)	3
10th May 1940	Germany invades France, Belgium, Luxembourg and the Netherlands	-0.27%	0.38% (0.62)	-2.91% (1.37)	-6.85%** (1.97)	169
15th May 1940	Surrender of Holland	-0.85%	-0.67% (-1.10)	-4.04%* (1.91)	-7.58%** (2.18)	1
10th June 1940	Italy declares war on Britain and France	-0.65%	-0.01% (-0.02)	-3.59%* (-1.69)	-11.64%*** (-3.35)	2
14th June 1940	Fall of Paris	-4.66%	-3.77%*** (-3.17)	-7.89%*** (3.72)	-3.12% (-0.90)	13
10th July 1940	Start of the Battle of Britain	0.52%	1.82%*** (2.99)	3.97%* (1.87)	5.90%* (5.90)	0
7th Sep 1940	Start of the Blitz	-0.31%	-0.53% (-0.87)	-2.32% (-1.10)	-3.72% (-1.07)	18
7th Dec 1941	Pearl Harbour	-0.96%	-1.21%** (-1.99)	-5.16%** (-2.44)	-6.91%** (-1.99)	174
Panel B: Positive Events						
31st Oct 1940	Battle of Britain won	0.15%	-0.11% (-0.19)	1.96% (0.92)	4.83% (1.39)	0
8th Dec 1941	US join the Allied forces/ Allies declare war on Japan.	-0.85%	-1.11%* (1.82)	-3.93%* (1.85)	-6.31%* (1.82)	164
2nd Feb 1943	Germans surrender to Stalingrad in the first big defeat of Hitler's armies	0.21%	-0.01% (0.01)	-1.21% (-0.57)	-2.29% (-0.66)	0
25th July 1943	Moussolini's government overthrown	0.88%	0.87% (1.43)	2.51% (1.18)	2.08% (0.60)	0
8th Sep 1943	Badoglio signs armistice with the Allies made public	0.57%	0.55% (0.90)	0.43% (0.20)	0.73% (0.22)	0
12th Aug 1944	Battle of Normandy won	-0.43%	-0.58% (-0.96)	-3.52%* (-1.66)	-5.05% (-1.45)	160
25th Aug 1944	Liberalisation of Paris	0.27%	0.17% (0.27)	-0.34% (-0.16)	-1.76% (-0.51)	0
21st Oct 1944	Massive German surrender at Aachen, Germany	-0.09%	-0.10% (-0.17)	0.81% (0.38)	1.92% (0.55)	1
30th Apr 1945	Hitler commits suicide	-0.25%	-0.30% (-0.49)	-2.40% (-1.13)	-3.52% (-1.01)	56
2nd May 1945	German troops in Italy surrender	-0.51%	-0.55% (-0.90)	-2.54% (-1.20)	-3.21% (-0.92)	53
7th May 1945	Unconditional surrender of Germany	-0.43%	-0.49% (-0.80)	-1.13% (-0.53)	-5.68% (-1.63)	38

[34] However, this could be due to it being the day after the surprise attack at Pearl Harbour.

Following Kaplanski and Levy (2010), the ten largest increases and decreases in the FT30 during the war are identified to determine whether the major events studied in this section are the associated with the largest price changes in the FT30. Table 6.4 reveals that only one of the largest changes in the FT30 during WW2 can be explained by a major event. The large negative return experienced on the 24th June 1940 is the next trading day after the fall of France to Germany. In the next section naval disasters are examined but the 18th September 1939 is the next trading day after the Courageous Carrier ship was sunk, while the 3.02% increase on the 4th July 1940 could be attributed to the Royal Navy's sinking of the Provence and Bretagne Battleships which occurred the previous day. The fall in returns of 2.45% on 30th July 1945 is the first trading day after the Amagi CV was sunk, however this fall in returns is likely to be the effect of the surprise election result on the 26th July 1945 in which Winston Churchill lost office and Clement Attlee won power. Thus the fall of France had a huge bearing on the FT30 as the threat of invasion of Britain was quite real, while some naval sinkings that are examined in the next section also could have caused a large change in the FT30 stock price.

Table 6.4: Rates of return on the best and worst trading days. Reported are the ten highest rate of return and the ten lowest rates of return on the FT30 from 3rd January 1939 to 31st January 1945. The fourth column provides the common explanation for the market movement. The fifth column reports if these days coincided with an event corresponding to a major event covered in this study.

Date	Largest Positive Returns	Largest Negative Returns	Possible War Event Explanation	Major Event Day?
30/01/1939	2.58%	-	-	No
31/01/1939	3.17%	-	-	No
20/03/1939	-	-3.12%	-	No
21/03/1939	2.35%	-	-	No
24/08/1939	-	-2.63%	-	No
29/08/1939	2.92%	-	-	No
18/09/1939	-	-4.65%	First trading day after the Carrier Courageous was sunk	No
28/05/1940	-	-3.01%	-	No
30/05/1940	-	-2.80%	-	No
17/06/1940	-	-4.66%	-	No
21/06/1940	-	-2.76%	-	No
24/06/1940	-	-4.73%	France surrendered on 22nd June (Saturday) and this was the next trading day.	Yes
27/06/1940	4.05%	-	-	No
28/06/1940	3.70%	-	-	No
01/07/1940	2.06%	-	-	No
04/07/1940	3.02%	-	Day after British sinkings of the Provence and Bretagne Battleships	No
26/07/1940	2.72%	-	-	No
26/07/1945	-	-3.97%	General Election	No
30/07/1945	-	-2.45%	First trading day after Churchill leaves office Carrier Amagi sunk on 28th July (Saturday)	No
08/08/1945	2.04%	-	-	No

To explore whether there was a time delay in investors reflecting the major event in stock returns, the cumulative mean rate of return (CMR) is plotted for days following a major positive and major negative event. Figure 6.3 shows that the first day following a major negative event (t = 1), the mean rate of return falls but not by much. However, there is sharp decline in returns two days following a major negative event. This could be due to either the time it takes investors to find out about the negative event taking palce, or the time it takes for the severity of the event to be realised by investors. There does not appear to be a reversal effect following a negative event. This could either suggest that the negative event had a lasting impact on the market or the market was affected by other events days after the negative events studied and thus affected by high volatility. Figure 6.3 also presents the cumulative rates of return for days following a positive event. The first day after a positive event (t = 1) shows an increase in the mean rate of return. Even though this is still negative, it does show a positive reaction in stock returns. However, the following day exhibits a reversal effect where there is a decrease in the mean rate of return lower than the original mean rate of return (t = 0). This suggests that the positive event had a short-term (one day) effect on the rate of return of the FT30. The remaining days appear to behave in a random nature, fluctuating below zero indicating that any event (positive or negative) causes future days returns to be negative.

Figure 6.3: Test results for the mean cumulative rate of return (CMR). The figure depicts the cumulative mean return around the event date (t=0). The CMR is calculated as the average rate of return on day t.

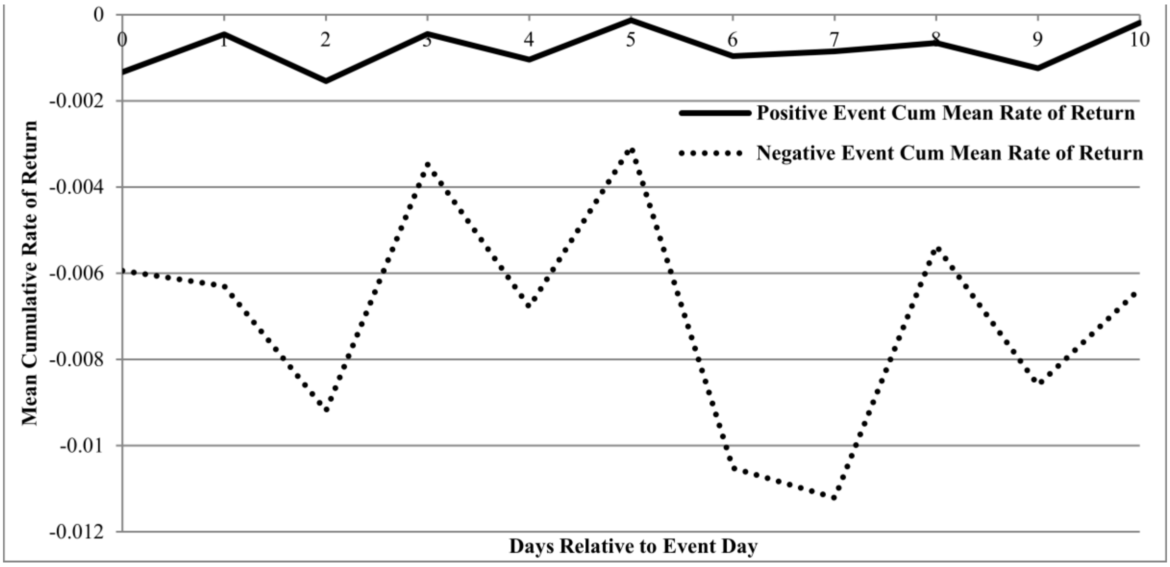


Table 6.5 presents the results from regression 6.4. to determine which seasonality's are evident in the FT30 from the beginning of the sample to the end of the war. The results show

that there is a positive and significant serial correlation at lags 1 and lags 2, while there is also a positive and significant turn-of-the-month effect. Further, there is a negative and significant serial correlation at lag 3, thus the regression to be estimated will be;

$$r_{it} = \gamma_0 + \gamma_1 r_{t-1} + \gamma_2 r_{t-2} + \gamma_3 r_{t-3} + \gamma_4 TOTM_4 + \sum_{i=3}^{3} \gamma_5 NE_{i,t} \sum_{i=3}^{3} \gamma_6 PE_{i,t} + \varepsilon_t \tag{6.15}$$

Where r_{t-1} is the serial correlation at lag 1, r_{t-2} is the serial correlation at lag 2, r_{t-3} is the serial correlation at lag 3 and *TOTM* is the turn-of-the-month anomaly.

Table 6.5: Pre-regression results for the known market anomalies during the war period. ***, **, * indicate significance at 1%, 5% and 10% respectively.

Monday Effect	January Effect	TOTM Effect	Tax Effect	Returns^{-1}	Returns^{-2}	Returns^{-3}	Returns^{-4}	Returns^{-5}
0.034621 (0.66)	0.017784 (0.24)	0.145401*** (2.72)	0.062413 (0.42)	0.269675*** (10.39)	0.083316*** (3.10)	-0.054181** (-2.01)	-0.018264 (-0.68)	0.018672 (0.72)

Table 6.6 documents the results from regression 6.11 for the day after a major event during WW2. The OLS regression results show that although positive events had a negative effect on the FT30, the first three days after the event day did not produce significant coefficients. This suggests that the positive events examined had little or no impact on the FT30. The negative events however produce negative and significant coefficients for the first and third day after a negative event indicating the markets adverse reaction to the negative events examined. The coefficients are significant at 1% and 5% respectively indicating that the impact of negative events may be immediate and last up to three days, however the second day after the negative event generates a positive coefficient. The results for the QR in Table 6.6 show that the first three days following a major positive event again produce negative coefficients, although now the third day is statistically significant at 5%. The QR generates a highly significant coefficient the first day after a major event, suggesting that the previous OLS regression results were affected by extreme values and the impact of negative events is stronger than first thought. However in the QR, the 2nd day after a major negative event now generates a negative coefficient while the 3rd day generates a positive coefficient. These two results are again different to the results generated from the OLS regression, suggesting that extreme values have had an effect on the OLS results. To account for possible time-varying

volatility in the stock returns, an ARCH(1)[35] model is estimated. Table 6.6 shows that the first three days after a major positive event all generate insignificant coefficients, with the first day coefficient being positive and the second and third day being negative. However, all of the first three days following a major negative event generate negative significant coefficients indicating the substantial level of negative investor sentiment in stock returns after major negative events of WW2. The fact that negative events have a stronger impact on stock returns than positive events is consistent with some literature, which finds asymmetric effects. For example, Brown and Hartzell (2001) and Edmans et al (2007) find that stock price changes following sporting losses are substantially larger in magnitude than those following wins. Thus the results from Table 6.6 show that negative vents had a significant negative impact on FT30 returns while positive events had little impact.

Table 6.6: The OLS, Quantile and ARCH regression results from equation 6.4. Positive 1st day denotes the 1st day following a positive event, positive 2nd day denotes the 2nd day following a positive events and so on. ***, ** and * indicate significant at 1%, 5% and 10%.

		OLS Regression	QR	ARCH(1)
The Conditional Mean Equation	γ_0	0.00005 (0.32)	0.00025*** (3.94)	0.00031*** (4.50)
	R_{t-1}	0.29339*** (12.36)	0.32393*** (30.39)	0.30602*** (29.93)
	R_{t-2}	0.21157*** (8.75)	0.17284*** (15.78)	0.10914*** (11.57)
	R_{t-3}	-0.05058** (-2.15)	-0.01458 (-1.37)	-0.02454*** (-3.57)
	TOTM	0.00070** (2.16)	0.00020 (1.34)	0.00015 (0.63)
	Positive 1st day	-0.00050 (-0.31)	-0.00128* (-1.82)	0.00088 (1.05)
	Positive 2nd day	-0.00096 (-0.59)	-0.00133* (-1.91)	-0.00025 (-0.19)
	Positive 3rd day	-0.00010 (-0.06)	-0.00153** (2.19)	-0.00172 (-1.36)
	Negative 1st day	-0.00799*** (-4.72)	-0.00599*** (-8.21)	-0.01307*** (-21.87)
	Negative 2nd day	0.00011 (0.07)	-0.00074 (-1.01)	-0.00164** (-2.35)
	Negative 3rd day	-0.00340** (-1.99)	0.00035 (0.48)	-0.00388*** (-4.89)
The Conditional Variance Equation	**Constant**	-	-	9.58e-6*** (6.85)
	ARCH(1)	-	-	0.87915*** (19.78)

[35] A GARCH(1,1) model was estimated first (as in line with the literature) however the sum of the coefficients were greater than unity indicating inappropriateness. The only model that fits is an ARCH(1) model.

Table 6.7: Test results for the Zivot-Andrews (1992) structural break test. The data used is a 3-month weekly rolling subsample, similar to Choudhry (2010). The final column denotes whether the break point is associated with an important event. *** and ** indicate significance at 1% and 5%.

Date	Minimum t-statistic	One day percent change in price	Percentage change in price over the next 5 working days	Possible Explanations for breaks	Important Event?
11/04/1939	-5.510***	-2.10	-0.76%	Adolf Hitler issues a Directive for the Armed Forces regarding the invasion of Poland	No
09/10/1939	-5.483***	-0.58%	5.86%	Adolf Hitler issues a memorandum to senior commanders justifying a policy of full-scale attack on Britain and France, if possible, that autumn. Adolf Hitler issues Directive No. 6 "for the Conduct of the War", ordering an offensive planned through Luxembourg, Belgium, and Holland, as soon as armoured units are ready and favourable weather conditions allow. The purpose of the offensive is to defeat the French Army, gain territory in Holland, Belgium, and Northern France to serve as a base against England and protect the Ruhr area. Adolf Hitler fears a delay would lead to an invasion of Belgium and possibly Holland by Western forces.	No
20/02/1940	-4.891**	-1.18%	3.88	-	No
14/06/1940	-4.978**	-2.12%	-13.6%	Germany enters Paris	Yes
03/07/1940	-7.111***	1.63%	2.27%	The last of the British Expedition Force is evacuated from Dunkirk, France	No
13/09/1940	-5.004**	-0.16%	-0.16%	The Japanese Foreign Minister Yosuke Matsuoka and German aide to Ribbentrop Heinrich Stahmer reach a general agreement for a joint alliance.	No
08/12/1941	-5.603***	-0.96%	-2.75%	Allies declare war on Japan and on the 7th December, Japanese attacked Pearl Harbour	No
03/07/1942	-4.919**	0.77%	1.65%	Off Georges' Bank, Nova Scotia, Canada, British warship HMS *Le Tigre* sinks German submarine U-215.	No
30/09/1942	-5.870***	0.50%	1.93%	29th September - For the second time, Japanese submarine I-25 launches a floatplane off the coast of Oregon, bombing the coast	No
04/01/1943	-4.972**	0.43%	1.91%	General Hideki Tojo, Prime Minister of Japan, ordered Japan's forces to evacuate Guadalcanal,	No
12/08/1943	-4.910**	-0.48%	-0.38%	10th August - British bombers attack Nuremberg, Germany. Great damage is achieved at little cost.	No
18/11/1943	-6.800***	-0.10%	0.70%	395 British bombers attack Mannheim and Ludwigshafen, Germany, as a diversion from the main attack on Berlin. 444 British heavy bombers attack Berlin, Germany, in the first attack of the Battle of Berlin. Nine British planes are lost. Little damage is done, mainly due to much cloud cover.	No
24/02/1944	-5.267**	-0.29%	-0.48%	Over the day, the US 8th Air Force launches bomber attacks on Gotha, Rostock, and Schweinfurt. In the North Atlantic, Royal Canadian Navy frigate *Waskesiu* sinks German submarine U-257. (evening) 734 British bombers attack Schweinfurt, Germany	No
26/04/1944	-5.356**	0.47%	1.70%	German destroyer T-29 sinks in the English Channel, after shelling from Royal Canadian Navy destroyer *Haida*, and three other British and Canadian ships. (evening) 493 British bombers attack targets in Essen, Germany. Enormous damage is inflicted. Seven planes are shot down. (evening) 225 British bombers attack the ball-bearing industry centre at Schweinfurt, Germany. About 21 planes are shot down	No
24/10/1944	-5.247**	0.36%	1.36%	Allied forces seal off the South Beveland isthmus near the port of Antwerp, Belgium	No
19/01/1945	-5.579***	-0.71%	-0.88%	Soviet forces reach the German frontier in Silesia	No
12/02/1945	-5.873***	0.27%	0.80%	Poland issues ten postage stamps noting the dates of liberation of various Polish cities	No
27/07/1945	-7.467***	0.44%	-7.09%	Winston Churchill leaves office	Yes
30/07/1945	-5.253**	-2.45%	-3.05%	Monday after Churchill leaves office	Yes
14/08/1945	-5.789***	-0.45%	0.81%	The US receives the Japanese acceptance of unconditional surrender. (evening) US President Harry Truman announces the end of the Second World War	Yes

Table 6.7 presents the structural break dates, the major event(s) associated with the date, the change in the stock price between the day of the event and the day after, and the sum of the change in price over the next five working days. Five working days[36] are applied because of the high intensity of the war since many battles and conflicts were fought very close to each other so in order to avoid over lapping, and to also capture the potential long-run effect of each major battle or event.

The results show a total of 23 breaks found it the data. Some of the breaks found have obvious explanations, such as the entry of Paris by Germany on 14th June 1940, or 8th December 1940 which is the day after the Japanese attack on Pearl Harbour. However, there are a number of breaks found on days when no event took place. For example the analysis shows a break on 19th January 1945 when the only event was the Soviet forces reaching the German frontier in Silesia. It is very unlikely that this is a major event for British investors and there may have been other factors that caused this break to be found. Further, it is quite surprising that not more well-known events have not been picked up as breaks. In the previous analysis 22 of the most important event during the WW2 were examined, but through this exogenous test, only two of them are found. This could suggest that the previous events studied were not the real major events of WW2 as far as the investors were concerned or that the major events that determined the outcome of WW2 did not have a bearing on the behaviour of British investors. These results are quite different to the ones found by Choudhry (2010), who used the same testing procedure to find that major events during WW2 for DJIA data. They found that the majority of events deemed as important by historians were picked up in the structural break test. This could be due to the DJIA being more efficient than the FT30 and the market reacting to major events of the war in a timelier manner. Another possible explanation is that the volume of trading in the FT30 during the war was relatively low since investors were either at war themselves or trading didn't seem very important at the time. Blips are breaks that persist for only a day or so, thus the five-day change in price should be of an opposite sign to the one day price change. Blips reflect reaction to early news that later turned out to be false, or market reaction over events on which there is little information. Turning points however induce a persistent change in prices in a certain direction and can be viewed as important events during the war. The results from Table 6.7 show that 15 of the 23 break points found were turning points, with the price

[36] Similar to Choudhry (2010).

change continuing in the same direct for five-days. None of the blips were major events in the previous analysis and there is little rationale to deem them as important.

6.3.4. Major Events Conclusion

This section examined major events during WW2 through exogenous and endogenous tests. The first section examined whether investor sentiment was present in the FT30 during WW2 through an examination of major positive and negative events. The next day returns analysis shows that major negative events had a strong negative effect on the FT30 while major positive events had a small negative effect. This is not surprising since the majority of the literature on investor sentiment reveals that negative events seem to have a stronger impact on stock returns than positive events (for example Edmans et al 2007). To examine whether there is a time-delay in investors reacting to these events, the cumulative mean rate of return is plotted for the first 10 days following the event. The figure shows that negative events seem to produce larger than normal returns for all the days following the events, while positive events seem to produce a smaller than normal rate of return. Further, the OLS, QR and ARCH regressions are conducted to examine the effect of these events when accounting for known anomalies in market returns. The results from the OLS regression, quantile regression and the ARCH model show that major negative events during WW2, have a significant negative impact on FT30 stock market returns. This is not that surprising given the negative events chosen were key events that must have caused anxiety among investors due to the threat of losing the war. Thus major positive events of WW2 had a small effect on the FT30 while major negative events had a strong significant effect on the FT30. Overall our results are consistent with the majority of literature on investor sentiment in that negative events tend to have a stronger effect on the FT30 than positive events. However, there is limited evidence of strong investor sentiment during WW2, which is contrary to the literature that finds strong investor sentiment for economically unimportant events. The results from the break analysis shows that only two events examined in the previous section are found using the break analysis; namely the German entry into Paris and Pearl Harbour. This suggests that many events deemed as important by historians in regards to the war effort were not that important for British investors. Thus the break analysis shows that only the very biggest WW2 event had an impact on the FT30. Overall, the major events examined had a negative impact on the FT30, however given the break analysis fails to pick up the majority of them, they may not be the cause of the biggest effect on the FT30 during the WW2 period.

6.4. Naval Disasters

The previous section examined the major events of WW2 and whether they had an impact on stock returns in the FT30. These major events were selected due to their impact on the war as whole and included major victories, losses as well as declarations of war and surrenders. Nevertheless the battles at sea had an important impact on the outcome of WW2 with thousands of crew being killed instantly at sea and the sinkings being as unpredictable as airline crashes today. Churchill demonstrates the importance of naval ships during WW2 by stating '*In all the war I never received a more direct shock*'[37], which was his response to hearing the sinking of the battleships Prince of Wales and Repulse on 10th December 1941. A loss of a large ship not only was a huge loss financially and strategically in the war effort, but some ships had a huge prestige value. For example, the Battleship HMS Hood was the pride of the British fleet and its loss was felt deeply. '*The destruction of the battle-cruiser Hood is a heavy calamity. With her 42,000 tons displacement she was the largest and most powerful warship afloat… the loss of this mighty unit makes an acknowledged gap in a fighting line that, especially since the defection of our French ally, has had to be stretched round the globe to the utmost limit of its elasticity*[38].'

This section examines the impact of major naval sinkings during WW2 had on the FT30. The null hypothesis is that these unexpected sinkings have a negative sentiment on stock returns. The major sinkings of British, German, US and Japanese vessels are examined to determine what impact (if any) they had on investor decision making. The next day return, ARs, CARs, and regression analysis are used to understand major vessel sinkings impact on the FT30. Table 6.8 documents the ships sunk during WW2 that are examined and it is a comprehensive list of major ships sunk during WW2 which are taken from Stephens (1983) and Heden (2006). Also included is the date the sinking was published in the Times to examine whether there is a time delay between the sinking and the public being made aware the sinking. British ships (Battleships and Aircraft Carriers) are examined as well as enemy ships and allied ships sunk to determine whether the nationality of the ships is significant. Enemy ships include German, Italian and Japanese ships, while allied ships consist of British and US vessels.

[37] Churchill, W.S. , 1948-55, The Second World War (6 Vols), London.
[38] The Times, 26th May 1941.

6.4.1. Background on Naval Warfare

Naval power had been assessed primarily by the number of battleships possessed by a nation since the British admiralty authorised the construction of the revolutionary HMS Dreadnaught in 1905. This warship was far larger and more advanced than existing ships and rendered all existing battleships obsolete (Lambert, 1995). These ships were also hugely expensive and demanding to construct and maintain. Even the largest economies struggled to build substantial forces of post dreadnaught battleships. Before the First World War there was a huge and enormously emotive naval arms race between Britain and Germany to construct the largest possible battleship fleet. This naval rivalry is often considered a major contributory factor to the war. The cost of producing the ships can be gauged by the fact that after almost a decade of extreme rivalry and all-out construction by two of the greatest industrial powers Britain possessed approximately a couple of dozen dreadnaughts and Germany somewhat less. Given the small number of ships involved and their enormous power and expense the loss of any ship was of considerable strategic, economic and moral importance.

Although the battleship played a less than decisive role in the First World War it emerged as still the overwhelming determinant of naval power. After the war all the major powers put in hand major programs for the construction of even larger battleships. These promised to be so ruinously expensive that at the Washington naval treaty of 1922 the powers agreed to severe limits on the size of their fleets. Although there was a flurry of construction just before the Second World War as war appeared inevitable (the UK for example laying down five King George V-class battleships) the major powers entered the war with relatively small fleets of battleships with each ship representing a substantial proportion of its naval might. At the start of the war in Europe in 1939 the British Navy possessed about 12 operational Battleships with the 5 mentioned above under construction, three battle cruisers and eight aircraft carriers (Konstam 2009) while the Germans 5 (including 3 of the relative small pocket battleships) with 2 under construction. At the start of the war in the Pacific in 1941 the US possessed 17 battleships and Japan 10 (Ellis, 1990, Statistical Appendix, Table 56)

Between the wars the aircraft carrier started to emerge as a rival to the battleship. Normally of similar size and expense to battleships their offensive power was provided by aircraft as opposed to huge guns. The issue of whether aircraft were of more value than big guns and indeed whether aircraft could sink battleships, which were enormously armoured and bristling with anti-aircraft guns, was hugely controversial between the wars (see, for example, Hough, 1979). This dispute was certainly not resolved by the start of the Second World War and the largest navies of the UK, US and Japan hedged their bets with substantial forces of aircraft carriers as well as battleships. During the war the battleship was shown to be vulnerable to air attack on many occasions and was considered of secondary importance to the aircraft carrier by the end of the war. The aircraft carrier can be considered to have taken over as the modern capital ship but is so expensive that it is only operated in significant numbers by the US navy. In our analysis of war events we look at both battleships and aircraft carriers both because both classes of ship were important and in an effort to determine whether the market was informed about the greater military value of aircraft carriers.

6.4.2. Empirical Results

The ARs and CARs of the naval sinking days when capital ships were sunk are documented in Table 6.9. Allied ships sinking include all British and US ships, while enemy ships sinking include all German, Italian and Japanese ships. All abnormal returns are not significant, indicating that none of the sinkings had a strong impact on the FT30. However, it is obvious that British, allied and Japanese ships sinking had a detrimental effect on the FT30 since the next day abnormal returns are negative. This is surprising for the Japanese ships sinking but the likelihood is that other factors are driving the negative result. The day after British ships sinking has the largest negative abnormal return which is expected but the next two days are positive indicating that it only had a temporary effect on the FT30. German ships sinking produce a next day abnormal returns which is positive, but the following day is negative possibly indicating again the temporary impact on the FT30. When British battleships and carrierships are separated it is clear that carrierships had a much stronger negative impact than battleships, with the abnormal return at -0.58% for carrierships and only -0.04% for battleships. The 5-day and 10-day cumulative abnormal returns are all insignificant again suggesting the limited impact of naval disasters on the FT30. The results are quite similar to the abnormal return results except that the first day after a German sinking now produces a negative return, further suggesting the temporal impact on FT30 returns. Further, battleships sinkings appear to have a positive effect on the FT30, again suggesting the temporal impact on FT30 returns. Nevertheless, carrierships continue to produce a negative return for the 5-day and 10-day cumulative abnormal return indicating the negative effect they appear to have on FT30 returns. None of the ARs or CARs are statistically significant, which is not that surprising since the t-statistics are calculated by comparing the abnormal return to the standard deviation of the abnormal return, thus the probability of a significant result is not that high.

Table 6.8: The major naval disasters studied in this chapter.

Ship BB – Battleship CV Carrier	Nationality	Sunk Date	Date Sinking was Published in the Times	Comments	Next Day Return
Courageous CV	British	17 Sept 1939	19 Sep 1939	Sunk by U-29 boat near UK, 519 deaths.	-0.0477
Royal Oak BB	British	14 Oct 1939	16 Oct 1939	Sunk at anchor in Scapa Flow by U-47 with the loss of 833 lives.	0.0167
Graf Spee Pocket BB (approx 15,000 tons)	German	17 Dec 1939	18 Dec 1939	Scuttled after Battle of River Plate in South America	0.0013
Glorious CV	British	8 June 1940	10 June 1940	Sunk by Scharnhorst and Gneisenau off Norway over 1,200 dead	-0.0065
Provence BB, Bretagne BB	French	3 July 1940	5 July 1940	British attacks on Oran et Mers-el-Kebir in North Africa to stop French ships falling into German hands. 1,300 lives lost.	0.0103
Conte di Cavour BB, Caio Duilio BB, Andrea Doria, BB, Littorio BB	Italian	11 Nov 1940	14 Nov 1940	Conte di Cavour BB was sunk by Royal Navy aircraft in Taranto Harbour in Italy The other ships did not fully sink in the shallow harbour and some were repaired	0.0043
Hood BB	British	24 May 1941	26 May 1941	Sunk by Bismark in North Atlantic with only 3 men escaped from crew of 1,419.	0.0000
Bismarck BB	German	27 May 1941	28 May 1941	Sunk by Royal Navy in North Atlantic with only 110 survivors out of acrew of over 2,200.	0.0043
Ark Royal CV	British	14 Nov 1941	15 Nov 1941	Sunk by U-81 boat near Gibraltar	0.0025
Barham BB	British	25 Nov 1941	28 Jan 1941	Sunk by U-331 boat in Med. With 862 deaths. The Germans didn't initially realise they had sunk it. Sinking kept secret until 27 January 1942 when admiralty informed the press.	0.0012
Arizona BB, Oklahoma BB, West Virginia BB, California BB, Nevada BB, Tennessee BB, Maryland BB	US	7 Dec 1941	8 Dec 1941	Pearl Harbour. All the ships except Arizona and Oklahoma were later repaired and brought back into service. About 2,400 US deaths	-0.0097
Prince of Wales BB, Repulse BB	British	10 Dec 1941	11 Dec 1941	Sunk by Japanese aircraft off Malaya, with 327 deaths on Prince of Wales and 508 deaths on Repulse	0.0038
Valiant BB, Queen Elizabeth BB	British	19 Dec 1941	9 Jan 1942	Sunk in Alexandria harbour in Egypt by Italian divers on manned torpedoes. Sank in shallow water and repaired within a few months although it was kept secret from the press.	0.0012
Hermes CV	Britain	9 April 1942	11 April 1942	Japanese planes sunk the Hermes in Indian Ocean	0.00
Shoho CV	Japan	7 May 1942	-	Sunk at the Battle of Coral Sea	-0.0013
Lexington CV	US	8 May 1942	-	Sunk at the Battle of Coral Sea	0.0026
Kaga CV, Soryu CV	Japan	4 June 1942	-	Battle of Midway	0.0050
Akagi CV, Hiryu CV	Japan	5 June 1942	-	Battle of Midway - over 2000 casualties on Japanese carriers.	0.0050
Yorktown CV	US	7 June 1942	-	Battle of Midway	0.0037
Eagle CV	Britain	11 Aug1942	13 Aug 1942	Sunk by U-73 boat	0.0037
Ryuyi CV	Japan	24 Aug 1942	-	Battle of Eastern Solomans	0.00
Wasp CV	US	15 Sept 1942	-	Hit by submarine torpedo Sunk by US forces	0.0024
Hornet CV	US	27 Oct 1942	-	Dive bombers, torpedo bombers and destroyer torpedos	0.0033
Hiei BB	Japan	13 Nov 1942	-	Aircraft and submarine attacks Guadalcanal	0.00
Kishima BB	Japan	15 Nov 1942	-	Naval gunfire Guadalcanal	0.00

Mutsu BB	Japan	8 June 1943	-	Accidental explosion – over 1,000 deaths – survivors dispersed to remote outposts to suppress the news.	-0.0010
Roma BB	Italy	9 Sept 1943	-	Sunk by German guided bombs while proceeding to join allies after Italian surrender	0.0009
Chuyo Escort Carrier (approx 20,000 tons)	Japan	4 Dec 1943	-	Sunk by submarine Sailfish of southeast of Honshu, Japan.	0.0020
Scharnhorst BB	German	26 Dec 1943	28 Dec 1943	Sunk by British surface forces in battle of North Cape. Only 36 men were pulled from the icy seas, out of a crew of 1,968	0.0010
Shokaku CV, Taiho CV, Hitaka CV	Japan	19 June 1944	-	Two submarines and carriership sunk in the Battle of Philippine Sea	0.0018
Hiyo CV	Japan	20 June 1944	-	Carrier Aircraft sunk in the Battle of Philippine Sea	0.00
Otaka Escort Carrier	Japan	18 Aug 1944	-	Sunk by submarine Rasher off the Philippine Islands,	-0.0071
Princeton Light Carrier	US	24 Oct 1944	-	Aircraft but sunk by own forces Battle of Leyte Gulf	0.0036
Musahi BB	Japan	24 Oct 1944	-	Aircraft sunk in the Battle of Leyte Gulf with approximately 1,000 deaths	0.0036
Zuikaku CV, Chitose Light CV, Chiyoda Light CV, Zuiho Light CV, Fuso BB, Yamashiro BB	Japan	25 Oct 1944	-	Sunk in the Battle of Leyte Gulf	0.0009
Tirpitz BB	German	12 Nov 1944	14 Nov 1944	Sunk by RAF Lancaster bomber Approx. 1,000 deaths.	0.0009
Kongo BB	Japan	21 Nov 1944	-	Submarine	0.00
Unryu CV	Japan	19 Dec 1944	-	Submarine	0.0027
Yamato BB	Japan	7 Apr 1945	-	The world's biggest battleship sinks with the loss of nearly 2,500 lives.	0.0017
Admiral Scheer, Pocket BB	Germany	10 Apr1945	12 Apr 1945	Sunk by RAF	-0.0009
Lutzow Pocket BB	Germany	16 Apr 1945	21 Apr 1945	Made unfit for sea by RAF attack - later scuttled	0.0017
Hyuga BB, Ise BB Haruna BB, Kaiyo, Escort Carrier	Japan	24 July 1945	-	Sunk by carrier aircraft	0.00
Amagi CV	Japan	28 July 1945	-	Sunk by carrier aircraft	-0.0248

Table 6.9: ARs and CARs for the FT30 after major naval disasters. The second column denotes the abnormal returns while the fourth and fifth columns document the 5-day and 10-day cumulative abnormal returns. ***, **, * indicate significant at 1%, 5% and 10% respectively. Allied ships sinking includes British and US ships as well as the Italian ship the Roma BB which was sunk on 9th September 1943 when on its way to join the allied forces. Finally Enemy sinkings include German and Japanese ships as well as the French ships sunk on 3rd July 1940 and the Italian ships sunk on 11th November 1940.

Data	Day post sinking	AR	5-day CAR	10-day CAR
FT30	-	-0.0003%	-0.003%	0.01%
British Ships Sunk	1st	-0.31% (0.51)	-0.09% (0.05)	-0.07% (-0.02)
	2nd	0.05% (0.07)	0.07% (0.04)	0.30% (0.10)
	3rd	0.37% (0.61)	0.28% (0.14)	0.62% (0.21)
Allied Ships Sunk	1st	-0.19% (-0.31)	0.04% (0.02)	0.14% (0.04)
	2nd	-0.06% (-0.10)	0.00% (0.00)	0.31% (0.10)
	3rd	0.02% (0.04)	0.18% (0.09)	0.34% (0.11)
German Ships Sunk	1st	0.04% (0.06)	-0.06% (-0.03)	-0.63% (-0.21)
	2nd	-0.16% (-0.26)	-0.28% (-0.14)	-0.89% (-0.29)
	3rd	0.09% (0.15)	-0.57% (-0.28)	-1.04% (-0.34)
Japanese Ships Sunk	1st	-0.17% (-0.28)	-0.93% (-0.46)	0.15% (0.05)
	2nd	-0.38% (-0.63)	-0.93% (-0.46)	-0.32% (-0.11)
	3rd	-0.10% (-0.16)	-0.99% (-0.49)	-0.47% (-0.16)
Enemy Ships Sunk	1st	0.05% (0.07)	0.39% (0.19)	0.77% (0.25)
	2nd	-0.23% (-0.37)	-0.07% (-0.03)	0.52% (0.17)
	3rd	0.06% (0.10)	-0.22% (-0.11)	0.64% (0.21)
British Battleships Sunk	1st	-0.04% (-0.06)	0.52% (0.26)	1.38% (0.45)
	2nd	0.03% (0.05)	0.57% (0.28)	1.51% (0.50)
	3rd	0.14% (0.23)	0.57% (0.28)	1.75% (0.58)
British Carrier Ships Sunk	1st	-0.58% (-0.95)	-0.70% (-0.35)	-1.52% (-0.50)
	2nd	0.06% (0.10)	-0.42% (0.21)	-0.92% (-0.30)
	3rd	0.61% (1.00)	-0.01% (-0.01)	-0.50% (-0.17)

Table 6.10 documents the results from regression 6.5 on naval ships sinking on the FT30. The seasonality's are examined in the previous section and are the serial correlation up to lag 3 and the turn-of-the-month effect are found to be significant. The results for British ships sinking reveals that the first day coefficient is negative (-0.00107) but the next two days have positive coefficients. The results for the Allied ships sinking (this includes British and US

ships) are nearly identical due to the small number of US ships sunk during WW2[39]. This suggests that British and Allied ships sinking did not have lasting impact on the stock market and only caused a temporary shock. The German ships sinking during WW2 appear to have little impact on the British stock market as the first day after the sinking generates a coefficient that is positive and very small 0.00073). But the second day after a German sinking produces a negative coefficient, while the third day after produces a positive coefficient again. This suggests that German ships sinking had little immediate impact upon FT30 prices and any effect they did have was only temporary. However, when Japanese ships sunk, the first day after a sinking produces a positive coefficient (0.00051), which is expected. However, the second day after the sinking produces a negative (-0.00400) coefficient which is significant at 1%, suggesting that Japanese ships must have had a temporary effect on the market for one day, with the market going negative in the second day. Also the first three days after a Battleship is sunk produces positive coefficients, with the first day being significant at 10%. Conversely, when just carrier ships are examined, the 1st day after the sinking produces a negative coefficient (-0.00676) which is significant at 1%, suggesting that carrier ships sinking during WW2 had a detrimental effect on the British market. The 2nd and 3rd day after the sinkings are positive, with the 3rd day being significant at 1% signifying that impact of carrier ships sinking did not have a long lasting impact on the FT30. This also suggests that the carrier ship results were driving the result for all British ships sinking and that battleship sinkings had little or no effect on the market as a whole. This shows the possible importance of Carrier ships during WW2 to Britain and the relative importance of Battleships to the FT30 during WW2.

[39] See Table 6.10 for details.

Table 6.10: The OLS regression results from equation 6.11 on naval ship disasters. ***, **, * indicate significance at 1%, 5% and 10% respectively.

		OLS Regression						
		British Ships	**Allied Ships**	**German Ships**	**Japanese Ships**	**Enemy Ships**	**British Battle Ships**	**British Carrier Ships**
The Conditional Mean Equation	γ_0	0.00032	0.00034	0.00033	0.00033	0.00033	0.00033	0.00034
		(1.09)	(1.14)	(1.12)	(1.12)	(1.11)	(1.12)	(1.16)
	R_{t-1}	0.30579***	0.3039***	0.30666***	0.30739***	0.30916***	0.30650***	0.30849***
		(12.60)	(12.62)	(12.63)	(12.66)	(12.74)	(12.61)	(12.72)
	R_{t-2}	0.23335***	0.23271***	0.23259***	0.23500***	0.23390***	0.23365***	0.23235***
		(9.21)	(9.18)	(9.18)	(9.29)	(9.25)	(9.22)	(9.16)
	R_{t-3}	-0.05855**	-0.05946**	-0.05927**	-0.06457**	-0.06368**	-0.06031**	0.06068**
		(-2.26)	(-2.29)	(-2.29)	(-2.49)	(-2.46)	(-2.33)	(-2.35)
	TOTM	0.00082**	0.00071**	0.00215**	0.00004	0.00004	0.00089***	0.00079
		(2.17)	(2.15)	(2.01)	(1.19)	(1.20)	(2.22)	(2.11)
	Returns Post Events 1st Day	-0.00107	-0.00059	0.00073	0.00051	0.00132	0.00458*	-0.00676***
		(-0.56)	(-0.44)	(0.33)	(0.38)	(1.20)	(1.88)	(-2.77)
	Returns Post Events 2nd Day	0.00128	0.00036	-0.00161	-0.00400**	-0.00319***	0.00237	0.00012
		(0.74)	(0.27)	(-0.72)	(-2.93)	(-2.88)	(0.97)	(0.05)
	Returns Post Events 3rd Day	0.00307*	0.00042	0.00160	0.00129	0.00149	0.00039	0.00572**
		(1.78)	(0.32)	(0.72)	(0.96)	(1.36)	(0.16)	(2.35)
	R^2	0.19	0.19	0.19	0.19	0.19	0.19	0.19
	F	26.18	25.88	25.94	26.57	26.69	26.22	26.94

Table 6.11 further examines the level of investor sentiment by examining the QR and GARCH regressions[40]. The QR regression results show that the sinking of British ships had no impact on stock returns, since all three post event days produce positive coefficients when negative coefficient should be associated with British sinkings. German ships sinking produce very similar results to the OLS regression in Table 6.10, although now the 3rd day after the sinking is statistically significant at 5%. Further, British battle ship sinkings generate positive coefficients for the first three days, with the 2nd and 3rd day statistically significant at 1% and 5% respectively. This result is a lot stronger than the OLS regression results for battle ships, indicating that the OLS regression may have been affected by extreme values. The British carrier ship QR regression results are similar to the OLS regression results except the magnitude of the coefficients are less and no longer statistically significant, indicating the strong negative sentiment associated with the carrier ship sinkings in Table 6.10 may be due to extreme values. Table 6.11 also presents the GARCH regression results, which allow for varying volatility in stock returns. Again, British sinkings appear to have no impact on stock returns, since each of the first three days after the sinking are all associated with positive coefficients. Further the days following German sinkings produce negative coefficients, contradicting the null hypothesis that British sinkings should have a negative impact on stock returns and German sinkings a positive impact. British battle ships and carrier ships both generate positive coefficients, again contradicting the null hypothesis.

In Section 6.2 in this chapter, the 10 largest positive and negative returns of the FT30 during the war period are examined. It is found that the day following the Courageous carrier ship's sinking is associated with a strong negative returns. To ensure that the British ships results are not driven by just one value, the regressions are run again but with the Courageous carrier ships excluded from the data. Table 6.12 reveals the results for the British ships excluding the Courageous carrier ship. The results show that British ships sinking without the Courageous CV included produces a positive next day coefficient, which is significant at 10%. The results are confirmed when carrier ships are examined, indicating that this one observation may have been driving the negative coefficient. Further, the British carrier ships data excluding the Courageous carrier ships are examined and find that the next day coefficient is positive but not significant, indicating that the Courageous CV was also driving the results for the Carrier ships analysis. To investigate the sentiment of investors in more

[40] Allied ships results are not presented since the results are very similar to the British ship results. Japanese ships and enemy ships are also not reported since they showed no evidence of sentiment in Table 6.10.

detail, the OLS regression is run again for war data but when each individual British sinking was announced in the Times newspaper. Some of the sinkings were not reported until a couple of days after their sinking and so the majority of investors would not have been aware of the sinking until it was reported in the Times. There was a lot of propaganda from both sides during the war and many losses were not published for public consumption to avoid a fall in moral. The information for the Times was retrieved from the Times online archive. The results in Table 6.12 reveal that the day a British sinking was announced in the Times produces a coefficient of 0.00373, which is significant at 5%. This suggests that the announcement of the sinkings in the Times had no effect on the investor sentiment since one would suspect the coefficient to be negative.

Table 6.11: The QR and GARCH regression results from equation 6.11 on naval ship disasters. ***, **, * indicate significance at 1%, 5% and 10%.

		Quantile Regression				GARCH Regression			
		British Ships	**German Ships**	**British Battle Ships**	**British Carrier Ships**	**British Ships**	**German Ships**	**British Battle Ships**	**British Carrier Ships**
The Conditional Mean Equation	γ_0	0.00039***	0.00042***	0.00042***	0.00042***	0.00029*	0.00029*	0.00030*	0.00029*
		(2.63)	(2.99)	(2.92)	(2.75)	(1.68)	(1.71)	(1.72)	(1.69)
	R_{t-1}	0.30461***	0.30677***	0.30537***	0.30507***	0.29391***	0.29423***	0.29535***	0.29475***
		(25.02)	(26.79)	(25.94)	(24.33)	(10.51)	(10.30)	(10.57)	(10.53)
	R_{t-2}	0.20687***	0.20381***	0.20335***	0.20672***	0.11966***	0.11722***	0.12042***	0.11944***
		(16.25)	(17.08)	(16.57)	(15.73)	(3.71)	(3.50)	(3.75)	(3.69)
	R_{t-3}	-0.04003***	-0.03011**	-0.02164*	-0.03571***	0.002635	0.00610	0.00091	0.00156
		(-3.08)	(-2.46)	(.73)	(-2.65)	(0.08)	(0.19)	(0.03)	(0.05)
	TOTM	0.03214**	0.03482**	0.05498**	0.07159**	0.02804**	0.02084**	0.04896**	0.03879**
		(2.11)	(2.22)	(2.00)	(2.14)	(1.98)	(2.07)	(1.99)	(2.28)
	Returns Post	0.00019	0.00035	0.00072	-0.00004	0.00070	-0.00070	0.00073	0.00065
	Events 1st Day	(0.22)	(0.40)	(0.68)	(-0.03)	(0.42)	(-0.52)	(0.23)	(0.33)
	Returns Post	0.00151*	-0.00097	0.00374***	0.00039	0.00166	-0.00216**	0.00290	0.00123
	Events 2nd Day	(1.82)	(-1.01)	(3.53)	(0.34)	(1.55)	(-2.28)	(0.77)	(1.06)
	Returns Post	0.00242***	0.00223**	0.00267**	0.00209*	0.00187	0.00006	0.00205	0.00179
	Events 3rd Day	(2.93)	(2.33)	(2.52)	(1.85)	(0.94)	(0.11)	(0.78)	(0.39)
The Conditional Variance Equation	**Constant**	-	-	-	-	0.0000003**	0.0000003***	0.0000003**	0.000004**
						(1.99)	(2.58)	(2.02)	(1.97)
	ARCH(1,1)	-	-	-	-	0.13001***	0.13664*	0.13011*	0.17912**
						(2.55)	(1.80)	(1.81)	(2.12)
	GARCH(1,1)	-	-	-	-	0.80013***	0.79700***	0.72494***	0.80111***
						(3.41)	(2.95)	(3.20)	(3.21)

Table 6.12: The OLS regression results from equation 6.11 on naval ship disasters. ***, **, * indicate significance at 1%, 5% and 10%.

		OLS Regression		
		British Ships excluding the Courageous CV (17/09/1939)	**British Carrier Ships excluding the Courageous CV (17/09/1939)**	**British Ships with the Times dates**
The Conditional Mean Equation	γ_0	0.00032	0.00033	0.00031
		(1.08)	(1.11)	(1.05)
	R_{t-1}	0.30484***	0.60597***	0.30559***
		(12.55)	(12.58)	(12.59)
	R_{t-2}	0.23400***	0.23414***	0.23475***
		(9.24)	(9.22)	(9.27)
	R_{t-3}	-0.06092**	-0.06277**	-0.05905**
		(-2.35)	(-2.41)	(-2.28)
	TOTM	0.07549**	0.05978**	0.06879**
		(2.44)	(2.22)	(2.33)
	Returns Post Events 1st Day	0.00326*	0.00154	0.00373**
		(1.79)	(0.56)	(2.17)
	Returns Post Events 2nd Day	0.00081	-0.00121	0.00207
		(0.45)	(-0.44)	(1.20)
	Returns Post Events 3rd Day	0.00171	0.00335	0.00185
		(0.94)	(1.23)	(1.07)
	R^2	0.19	0.19	0.19
	F	26.20	26.01	26.44

6.4.3. Naval Disaster Conclusion

The aim of this section was to examine the effect major naval sinkings had on British and US markets. The initial analysis on the AR and CARs show that British ships sinking had a negative impact on the next day return of the FT30 and German sinkings had a positive effect, although neither are statistically significant. When British carrier and battle ships are separated it is clear to see that carrier ships generate a larger negative next day return than battle ships. The OLS regression results in Table 6.10 support the findings from the AR and CARs, however the day following a British carrier ships sinking does generate a significant negative coefficient. To test the robustness of our results, the regressions are re-estimated through a QR and GARCH regression to account for extreme values and varying volatility in stock returns. The QR results in Table 6.11 show that the coefficient the day after a British sinking changes from negative to positive, while the day after a carrier ship sinking coefficient changes from being significant to insignificant and very small. This suggests that the results found in Table 6.9 could be due to extreme values. The GARCH results in Table 6.11 support this finding, with the coefficient the day after a carrier ships sinking now turning positive. Previous analysis in section 6.2 showed that the Courageous carrier ships was preceded by one of the largest negative returns of the war period. Thus after excluded the sinking of the Courageous CV, the next day's coefficients for British sinkings indicating that these two observations were driving our results. Further, the announcement of the sinkings in the Times had no investor sentiment on the FT30 since one would suspect the coefficient to be negative. All of these results show that ships sinking during WW2 produced little or no sentiment in stock returns.

This chapter can conclude that the unexpected sinkings of naval ships during WW2 are not associated with much investor sentiment. This is contrary to the much of the literature that finds disaster events have a negative impact on stock returns, and especially with the study by Kaplanski and Levy (2010) who found a strong degree of investor sentiment associated with unpredictable airplane crashes. This is puzzle in that these naval sinkings damaged national pride and caused many deaths, and the recent literature on investor sentiment indicates that bad moods and anxiety can be expected to have a substantial negative influence on stock prices.

6.5. The Blitz

The previous two sections have examined the effect major events and naval disasters had on the FT30. Nearly all of these events and sinkings took place outside of the British Isles and had no direct impact on investors and civilians in Britain. The Blitz, from 7th September 1940 to 12th May 1941, was a period of almost continual air attack by German forces on Britain during WW2. The bombings caused many causalities and great damage with over 40,000 civilians killed and 46,000 injured, and more than one million houses were destroyed or damaged. This was accomplished with the loss of about 600 German aircrafts (Richards, 1952). The majority of the bombings were on London[41], with other major cities heavily bombed due to their significance in the war effort. The period of the Blitz is very interesting in terms of finance theory in that one of the world's major financial centres was under prolonged and serious attack. Given that London is the hugely pre-eminent finance centre in the UK it is no exaggeration to say that most market participants were directly exposed to serious danger for a substantial period of time. Given the extensive recent literature on the effect of sentiment and particularly anxiety and fear on stock returns the conditions of the Blitz gives a unique opportunity to contribute to the literature by examining investor sentiment in extreme circumstances. The period also provides an excellent natural experiment to explore the local bias hypothesis in a natural experiment by investigating whether the Blitz bombings in London had a stronger adverse effect on the London Stock Exchange than bombings outside of London. This section examines the effect of the major bombings of the Blitz on the British stock market. ARs and CARs are calculated as in the previous two sections, as well as regressions similar to the previous sections including OLS regression, QR and GARCH regression.

6.5.1. The History of the Blitz

The London Stock Exchange (LSE) stayed open during the Blitz, although fear of destruction caused 514 of its 784 members to establish an emergency address (Michie 1999). Damage only closed the LSE from 16th to 24th September 1940, although trading was switched to the settlement room on the 17th, so only one day's business was lost. Consequently, the LSE stayed open virtually throughout the war although with slightly reduced hours. Nevertheless,

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[41] London was bombed every night bar one, for eleven weeks.

the LSE turnover was affected with it falling to half its pre-war level by 1941. By 1942 however, business began to increase and the LSE was recovering back to its pre-war state (Michie, 1999).

London was not the only major city to be bombed by German forces. One of the biggest and most damaging attacks during the Blitz was on the manufacturing city of Coventry on the 14th November 1940 where twelve important aircraft plants and nine other major industrial works were targeted with some 437 German aircrafts dropping bombs repeatedly for 10 hours, There was a loss of some 500 retail shops, as well as the blocking of railway lines, causing great disruption to the war effort (Richards, 1952). Other major cities were targeted due to their importance to the war effort, including Birmingham, Bristol, Clydebank, Manchester, Merseyside, Plymouth and Sheffield. For example Merseyside suffered sixty raids and was Hitler's number one target outside of London due to its granaries, power stations, dry docks, gasworks and its port which brought food and materiel across the Atlantic (Gardner p201).

6.5.2. Data

The data used is from the FT30 from 1st July 1935 to 31st December 2009 for the full sample, from 1st January 1939 to 31st December 1945 for WW2 period and from 7th September 1940 to 12th May 1941 for the Blitz period. Figures 6.4 and 6.5 show the index and the daily returns on the index. Descriptive statistics shown in Table 6.13 reveal the mean return during the Blitz is positive and higher than the mean during both the rest of the war and the full sample. The standard deviation of returns during the Blitz is lower than during the rest of war and during the whole sample period. It appears that there is no evidence of the Blitz period as a whole having a negative effect on stock prices. However further analysis on the major bombings on London and outside of London will provide a clearer picture.

Table 6.13: Descriptive statistics for daily returns of the Blitz period.

Data	Obs	Max	Min	Mean	Standard Deviation	Skewness	Kurtosis
Blitz	174	0.0138506	-0.0138506	0.0003225	0.0042991	0.20164	1.12256
Rest of War	1610	0.0590633	-0.0484122	0.0002139	0.0062050	-0.63744	18.10595
Full Sample	19155	0.1078119	-0.1240017	0.0001538	0.0105848	-0.19631	9.69967

Figure 6.4: FT30 price index during the Blitz.

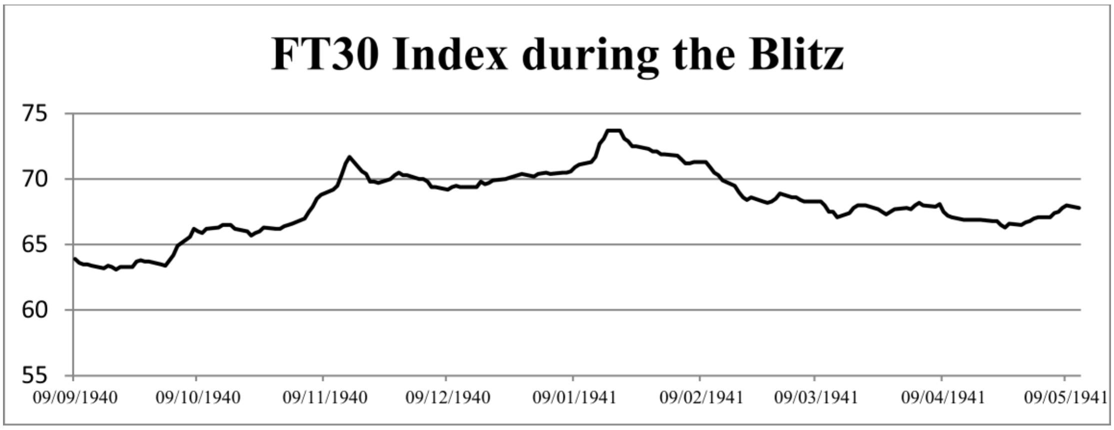
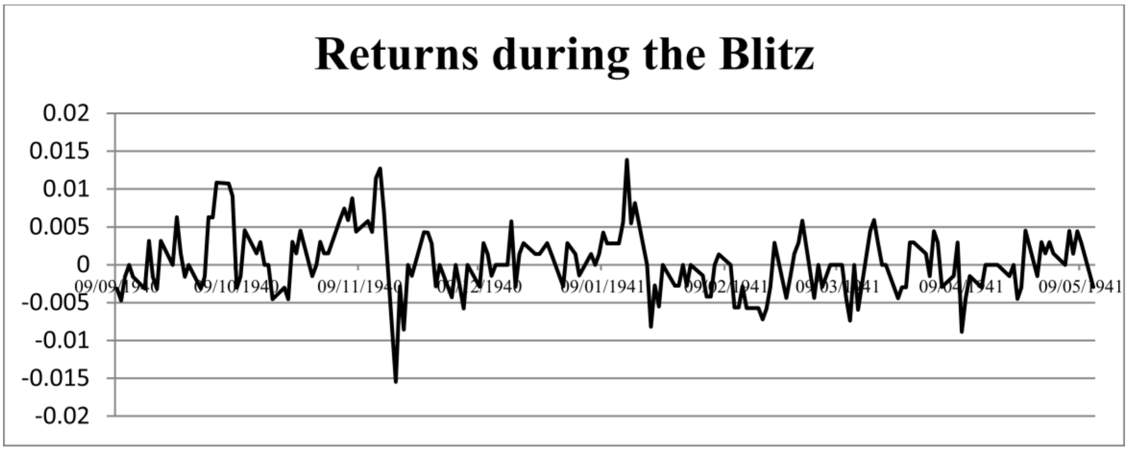


Figure 6.5: FT30 returns during the Blitz



As well as looking at the Blitz period as a whole, individual major bombings are also examined. Specifically, 8 air raids that caused the most deaths in London and outside of London studied. Thus this section analyses bombings that caused the most damage to human life rather than bombings that caused financial or infrastructural damage. For instance, the bombings on Belfast on 4th May 1941 destroyed two-thirds of the Harland and Wolff shipyards but only caused just over 100 deaths. The bombings selected are documented in Table 6.14 with a note describing the severity of the attack.

Table 6.14: The major bombings and cities studied in this chapter along with the date they took place as well as a brief description of the impact of the bombings, taken from Gardiner (2011).

City	Date	Notes
London	7th Sep	First real raid of the Blitz, with 300 bombers and more than 600 fighter planes over the city. 430 were killed, with 1600 seriously injured.
London	8th Sep	200 German planes pounded the City, with every railway line out of London to the south out of action. 412 Londoners were killed, and 747 seriously injured.
London	9th Sep	The raid lasted nearly 10 hours, killing 370 people and injuring 1400.
Coventry	14th Nov	500 tons of high-explosive bombs and 30,000 incendiaries fell, with 568 people killed and 1256 injured.
Birmingham	22nd+23rd Nov	682 dead, 1057 injured and 2000 houses damaged
Bristol	25th Nov	1540 tons of high explosives, 47 tons of oil bombs and 12500 incendiaries dropped, 207 dead and 187 seriously injured and 703 slightly hurt.
Sheffield	12th Dec	300 bombers, 750 dead and 500 injured
Merseyside	22nd Dec	119 fatalities and Wallasey suffered badly. The previous 3 nights caused 702 deaths and the same again injured.
Manchester	22nd +23rd Dec	On the first night, 272 tons of high explosive bombs and 100 incendiary, while on the second 195 tons of high explosive bombs dropped and 900 incendiaries. In total, 684 died 2364 wounded and 8000 houses uninhabitable.
London	27th Dec	48 German aircraft bombed the city from Chelsea to Dalston. Parachute mines caused many fires, killings 141 people and injuring 455.
London	29th Dec	120 tons of high explosives and 22000 incendiaries were dropped on the city, with 160 dead and 500 injured.
Clydebank	13th+14th Mar	268 tons of bombs and 1630 incendiaries were dropped on the first night and 227 tons of high explosive bombs and 781 incendiaries dropped on the second night, with a total of 1083 dead.
London	16th Apr	66 of the 101 London boroughs reported bomb damage and over 2250 fires burning, killing 1180 and seriously injuring 2230.
London	19th Apr	More than 1000 tons of high explosives were dropped plus 153,096 incendiaries, the most ever in a single night raid. 146 people died, with 46 missing. This was the biggest single raid on London during the war.
Plymouth	21st Apr	10000 incendiary dropped killing 750 civilians.
London	10th May	1436 people killed, 1800 seriously injured with 11000 houses damaged beyond repair.

6.5.3. Empirical Results

Table 6.15 reveals that the returns on the day after a major air raid in London are all negative, indicating that the bombings had a negative effect on the British stock market. However, the returns after the major air raids outside of London are all positive. The mean return the day following a major London bombings is -0.00264 while the return the day following a major non-London bombing is 0.00286. The t-test for the two samples is highly significant at 1%, indicating there is a significant difference in the return the day after a London and a non-London bombing, supporting the local bias hypothesis. Table 6.16 reveals that four of the eight London bombings studied generate a negative next day AR, all of which are not statistically significant. Non-London bombings generate five positive next day ARs, of which one is significant at 1%. The mean AR from London bombings is negative, while the mean of a non-London bombings is positive, indicating that London bombings in general had a negative effect on the FT30, while the non-London bombings had a positive effect. The CARs for the London bombings reveal that the bombings that produced a negative AR also produce a negative 10-day CAR indicating that the negative effect may be long lasting. However, the market after two of the four negative AR bombings rebounded in one day, indicating that other events or factors have caused the negative 10-day CARs. The non-London bombing CARs show that the Bristol bombing generated negative and significant at 10% CARs for 5- and 10-days. However, the FT30 rebounded 1-day after the bombing itself, so other factors may have caused this result. The Coventry bombing produces a negative AR and negative CARs, with the market taking 40 trading days to recover, which suggests that this bombing had a long lasting effect on the FT30. Panel C reports the two sample t-test and shows that there is a clear difference between London bombings and non-London bombings, although the difference is not statistically significance. Results from Table 6.15 show that London bombings had more of a negative impact on stock returns than non-London bombings supporting the local bias hypothesis.

Table 6.15: The next day return for Blitz bombings on London and outside of London with the t-test for the returns the day after a major bombing in London against the returns the day after a major bombings outside of London. ***, **, *indicate significance at 1%, 5% and 10% respectively.

City	Date	Next Day Return	City	Date	Next day Return
London	7th Sep	-0.003125	**Coventry**	14th Nov	0.006998
	8th Sep	-0.003125	**Bristol**	25th Nov	0.004277
	9th Sep	-0.00470589	**Birmingham**	22nd+23rd Nov	0.004295
	27th Dec	-0.00284495	**Sheffield**	12th Dec	0.00
	29th Dec	-0.00284495	**Merseyside**	22nd Dec	0.001430
	16th Apr	0.00	**Manchester**	22nd +23rd Dec	0.001428
	19th Apr	-0.00149589	**Clydebank**	13th+14th Mar	0.004461
	10th May	-0.00294551	**Plymouth**	21st Apr	0.00
	Mean return	-0.00263590		**Mean return**	0.002861
t-test for two sample = 5.43***					

Table 6.16: ARs and CARs for the FT30 after major Blitz bombings. Panel A reports the London bombings while Panel B reports the non-London bombings. ***, **, * indicate significance at 1%, 5% and 10% respectively.

City	Date	AR	5-day CAR	10-day CAR	Days to rebound
Panel A: London Bombings					
London	7th Sep	0.42% (0.99)	-0.88% (-0.69)	0.24% (0.14)	18
	8th Sep	0.42% (0.99)	-0.88% (-0.69)	0.24% (0.14)	18
	9th Sep	-0.10% (-0.23)	-1.83% (-1.43)	-0.97% (-0.55)	10
	27th Dec	-0.69% (-1.60)	0.17% (0.14)	-0.25% (-0.14)	1
	29th Dec	-0.69% (-1.60)	0.17% (0.14)	-0.25% (-0.14)	1
	16th Apr	-0.43% (-1.01)	-1.27% (-0.99)	-0.62% (-0.35%	10
	19th Apr	0.03% (0.07)	0.78% (0.61)	0.10% (0.05)	0
	10th May	0.39% (0.91)	0.39% (0.30)	0.39% (0.22)	0
Means		-0.08%	-0.42%	-0.14%	-
Panel B: Non-London Bombings					
Coventry	14th Nov	-0.43% (-1.00)	-0.22% (-0.17)	-2.68% (-1.51)	40
Bristol	25th Nov	-0.67% (1.56)	-2.34%* (1.82)	-3.03%* (1.71)	1
Birmingham	22nd+23rd Nov	-0.21% (-0.50)	-2.36%* (-1.84)	-3.12* (-1.75)	1
Sheffield	12th Dec	0.32% (0.74)	2.04% (1.59)	3.50%** (1.97)	0
Merseyside	22nd Dec	1.28%*** (2.97)	-0.34% (-0.26)	0.79% (0.45)	0
Manchester	22nd +23rd Dec	0.71%* (1.64)	-1.53% (*1.19)	-0.77% (-0.43)	0
Clydebank	13th+14th Mar	0.23% (0.53)	0.07% (0.05)	-1.61% (-0.91)	0
Plymouth	21st Apr	-0.07% (-0.16)	-1.68% (-1.31)	-1.76% (-0.99)	4
Means		0.15%	-0.80%	-1.09%	-
Panel C: Two sample t-test					
-	-	-0.60	0.88	1.13	-

Like the previous two sections, the seasonality's are examined before the regression analysis to determine which of them are actually evident in the data. The seasonality's are examined from the beginning of the sample (1/7/1035) to the end of the Blitz period (12/5/1941). The results are documented in Table 6.17 and show that only the serial correlation up to lag 3 and the turn-of-the-month effect are evident in the data, thus these are the only seasonality's accounted for in the OLS regression, QR and GARCH(1,1) regression.

Table 6.17: Pre-regression results for the known market anomalies during the Blitz period. ***, **, * indicate significance at 1%, 5% and 10% respectively.

Monday Effect	January Effect	TOTM Effect	Tax Effect	Returns^{-1}	Returns^{-2}	Returns^{-3}	Returns^{-4}	Returns^{-5}
0.0346212 (0.66)	0.0177841 (0.24)	0.1454008*** (2.72)	0.0624134 (0.42)	0.2696754*** (10.39)	0.0833163*** (3.10)	-0.0541809** (-2.01)	-0.0182641 (-0.68)	0.0186721 (0.72)

The results of the regression analysis presented in Table 6.18 indicate that the London bombings have a negative impact on the FT30. The day after a London bombings generate a negative coefficient which is quite high and significant at 5%. Further, the day after a non-London bombing produces a positive coefficient which is insignificant. It is clear to see from the OLS regressions that the London bombings had a detrimental effect on the FT30, while the non-London bombings seem to have little or no impact on the FT30. By examining the confidence intervals it is clear that the London bombings coefficient does not fall within the non-London bombings confidence interval and vice-versa, indicating that the London and non-London bombings are different with 95% confidence and supporting the local bias hypothesis. The QR analysis shows that the day after a London bombing also generates a negative coefficient which is significant at 1%, whilst the day after a non-London bombing generates a positive coefficient. Thus high volatility and extreme values during the Blitz may have been skewing the London bombings coefficient and making the coefficients not as strong as they actually are. Again both London and non-London bombing coefficients are not within each other 95% confidence intervals, indicating they are significantly different. The QR results again support the idea of local bias and negative investor sentiment in extreme circumstances. A GARCH (1,1) model is also estimated to account for the possible time-varying volatility in stock returns. The results confirm the previous OLS regression and QR results with the London bombings generating a negative coefficient and non-London bombings generating a positive coefficient. However the London bombings coefficient are no longer significant at any level indicating that the previous OLS regression and QR results may have been significantly affected by the time-varying volatility property of returns. The results from Table 7 suggest that London bombings generated negative investor sentiment on stock returns while non-London bombings produced no negative investor sentiment although the results are not as strong when the GARCH(1,1) regression is estimated. Further, the coefficients of London and non-London bombings are not within the 95% confidence interval of the other indicating that the coefficients are significantly different. Thus although the

GARCH(1,1) regression supports the idea of local bias, the results are not as strong as with the OLS regression and QR.

Table 6.18: The OLS, Quantile and GARCH regression results from the major Blitz bombings. The value in parentheses is the corresponding t-statistic, while the column beside present the 95% confidence intervals. ***, **, * indicate significance at 1%, 5% and 10% respectively.

	OLS Regression			**Quantile Regression**			**GARCH(1,1)**		
Blitz Major Bombings	**Estimate**	**95% Conf. Interval**		**Estimate**	**95% Conf. Interval**		**Estimate**	**95% Conf. Interval**	
γ_0	0.00011 (0.33)	-0.00056	0.00078	0.00020 (0.66)	-0.00039	0.00078	-0.00014 (-0.46)	-0.00075	0.00047
R_{t-1}	0.38812*** (5.15)	0.23935	0.53687	0.35044*** (5.43)	0.22304	0.47784	0.27223*** (2.69)	0.07412	0.47033
R_{t-2}	0.15362* (1.91)	-0.00505	0.31229	0.18730*** (2.67)	0.04861	0.32599	0.11283 (1.23)	-0.06657	0.29222
R_{t-3}	-0.07861 (-1.05)	-0.22697	0.06976	-0.00205 (-0.03)	-0.13291	0.12881	-0.06328 (-0.71)	-0.23694	0.11037
TOTM	0.00039 (0.52)	-0.00110	0.00189	0.00025 (0.38)	-0.00104	0.00154	0.000519 (0.83)	-0.00071	0.00175
London Bombing	-0.00350** (-2.18)	-0.00667	-0.00033	-0.00407*** (-3.11)	-0.00665	-0.00148	-0.00280 (-1.25)	-0.00717	0.00157
Non-London Bombing	0.00181 (1.28)	-0.00097	0.00460	0.00021 (0.18)	-0.00213	0.00255	0.00192 (0.76)	-0.00302	0.00687
Constant	-	-	-	-	-	-	3.78e-6* (1.83)	-2.64e-7	7.83e-6
ARCH(1)	-	-	-	-	-	-	0.25599** (2.01)	0.00698	0.50500
GARCH(1)	-	-	-	-	-	-	0.49841** (2.53)	0.11243	0.88439

6.5.4. Blitz Conclusion

This section examines the period known as 'the Blitz' during WW2 in Britain and to determine the level of investor sentiment in the FT30. The Blitz period as a whole is found to not have a negative impact on stock returns as a whole when compared to samples before and after the event. Although even from a purely rational viewpoint the Blitz would have been expected to have had a substantial negative effect on stock prices, it is not evident at all in the data. However, when individual bombings were examined, the mean ARs and CARs for major bombings in London are negative while major bombings outside of London generate positive ARs and CARs. This suggests the local bias hypothesis, that is, the closer to the event the more the market in affected. The regression analysis further supports the local bias hypothesis and when extreme values are accounted for through a QR, the London bombings negative return is statistically significant. A further GARCH-regression is also estimated to account for the varying volatility in stock returns, which also supports the local bias hypothesis, although the strength of the negative effect of London bombings is reduced. This section can conclude that the Blitz period has a whole had no impact on the FT30, while the largest London bombings had a negative impact and non-London bombings had little or no impact.

6.6. Chapter Conclusion

Investor sentiment has been examined extensively in the literature although the majority of studies have examined seemingly insignificant and economically unimportant events. However, extreme events have not received the same level of attention and this chapter investigates one of the most extreme events in history, WW2. The WW2 period has not been examined in great detail in the literature and provides an opportunity to examine investor sentiment in stock returns during the most extreme of all circumstances, when investor's lives are at risk. Major positive and negative events, naval disasters and the period known as 'the Blitz', are studied to determine the level of investment sentiment during WW2.

The key conclusions from this chapter are;

(i) Negative events had a significant negative effect on next day returns in the FT30 for one day, while positive events had no significant impact on the FT30.

(ii) Break analysis reveals a number of significant break points in the data however the only major events found are the German entry into Paris and the attack on Pearl Harbour suggesting that these two events had the largest impact on the FT30.

(iii) Naval disaster results show that British ships sinking had a negative impact on the FT30 with carrier ships having a larger impact than battleships, although only carrier ships are significant. However, when the Courageous CV in excluded from our data, none of the results are significant suggesting that this one observation is driving the results.

(iv) The analysis of the Blitz shows that London bombings had a negative impact on the FT30 while non-London bombings had a positive impact, supporting the local bias hypothesis that closer to the stock market the event is, the more impact it has on the market itself.

It is important to note that the level of investor sentiment created by WW2 events is less than the sentiment found for many less important events. For example, Kamstra et al (2000) find strong evidence that daylight saving changes cause negative returns on stock markets, while Hirshleifer and Shumway (2003) find strong significant evidence that sunshine strongly effects stock returns. Further, Kaplanski and Levy (2010) find a transitory decline in the stock market is more than 60 times larger than the direct economic loss of the aircraft crashes. This could be due to the fact that trading was so low during the war period, or that investors did not realise the significance of the events. Either way, it is quite surprising to find little evidence of investor sentiment in such an extreme circumstance of lives being in danger.

Overall, this chapter shows that major negative events of WW2 had a significant impact on the FT30, while major positive events had no impact. This is in line with the literature which states that negative events have a stronger and more significant impact on stock returns than a corresponding positive event. Further, this chapter supports the local bias hypothesis. Only negative events that brought about a real threat of war coming to British shores were found using the exogenous break test while the fact that naval disasters had little impact on the FT30 could also be due to the fact that most of these sinkings occurred far away from Britain and had no direct impact to investors. Additionally, only London bombings during the Blitz generated a negative next day return while non-London bombings produced a positive next day return. Thus this chapter contributes to and extends the literature on investor sentiment in extreme circumstances while also supporting the local bias hypothesis.

Chapter 7 – Conclusion

7.1. Summary and Main Findings

This thesis examines whether the Adaptive Market Hypothesis (AMH) can explain the behaviour of stock returns over time better than the traditional Efficient Market Hypothesis (EMH) using long run data from the US, UK and Japanese markets represented by the DJIA, FT30 and TOPIX. Further, this thesis also examines the level of investor sentiment in the FT30 during the extreme period of World War Two.

Apart from the Introduction and Conclusion chapters, this thesis is structured around five main chapters, with four empirical chapters. Chapter Two begins by defining the EMH, its development over time, the main assumptions it relies on, as well as the various versions of it such as the martingales and random walk hypothesis. The main procedures to test for the EMH are also introduced, although each subsequent chapter provides a more detailed literature review of each procedure. The main stock market anomalies and technical analysis rules found in the literature are also presented, highlighting the conflict between the recent literature and the classical EMH. One model that aims to solve the conflict between inefficiencies in the market and the classic EMH, is the AMH. The AMH, suggested by Andrew Lo (2004), proposes that inefficiencies and the EMH can co-exist together in an intellectually consistent manner. A literature review in support of the AMH is conducted but due to the recent formulation of the hypothesis, is quite limited. Further, this chapter explains the classification of stock return behaviour which is proposed in this thesis. This classification allows the behaviour of stock returns to be categorized into five different types. The first type is market efficiency, where returns behave in a perfectly efficient manner throughout. The second type is moving towards market efficiency, where the returns have been behaving inefficiently but have moved to efficiency over time. The third type is a switch to efficiency/inefficiency, where returns have behaved inefficiently/efficiently but have reversed in behaviour rover time. The fourth type is the AMH, where returns have gone through at least three stages of efficiency/inefficiency over time. The fifth and final type is market inefficiency, where returns have behaved in an inefficiency manner throughout. This classification is applied in each of the three empirical chapters that examine the behaviour of returns over time. The last part of chapter two describes the stock markets examined in the thesis, with the calculation of the index of each also illustrated.

Chapter three examines the behaviour of stock returns over time using a battery of tests for independence incorporating conventional linear tests, as well as nonlinear tests. The first part of this chapter discusses the prior empirical studies conducted using these tests, showing that independence of stock returns was initially found but recently, more and more studies have found that stock returns are not independent. The data section shows that for each market the full sample and subsample returns do not conform to normality which is not surprising since this is a well known stylised fact for most financial time series data. The empirical results obtained in this chapter suggest the AMH is a more appropriate model for describing the behaviour of stock returns over time for all three markets according to the linear tests. The finding that the three unit root tests all suggest market efficiency is constant over time is not surprising since most stock market returns are stationary. When returns are filtered through an AR-model to remove all linear correlations, the three markets show evidence of constant and significant dependence over time, suggesting type 5 and market inefficiency. Returns are also filtered through an AR-GARCH filter to account for the heteroskedasticity in returns and strong evidence of the AMH is found. Thus this chapter shows strong evidence of the AMH for all three markets through linear and nonlinear tests for the independence of stock returns indicating that this model may a better description of the behaviour of stock returns than the classic EMH.

In chapter four, three of the most celebrated and successful calendar anomalies are examined to determine whether the AMH can describe their behaviour over time. The Monday effect, January effect and turn-of-the-month effect are all examined and the literature shows that the behaviour of these calendar anomalies may be changing over time since a number of recent studies find that their returns are decreasing. The empirical results from this chapter suggest that the Monday effect is not present in the FT30 at all, while the other anomalies in the three markets all decrease in magnitude after the publication of the seminal paper publicising that calendar anomaly. An analysis examining five-yearly subsamples analysis is conducted, showing that only three of the anomalies can be described by the AMH, with the switch-type describing two of the anomalies and constant market inefficiency describing four of the anomalies. Furthermore, using a simple trading strategy only the Monday effect in the DJIA, and the TOTM effect in the DJIA and FT30 can outperform the buy-and-hold strategy over the full sample. Studying the data after the seminal publication of each anomaly, only the Monday anomaly in the TOPIX as well as the TOTM anomaly in the FT30 and TOPIX can outperform the buy-and-hold strategy. All of the other anomalies cannot beat the buy-and-hold strategy. A “double or out” and “quadruple or out” trading strategies are also conducted so the trading strategy has a corresponding risk to that of the buy-and-hold strategy, with results being very similar but double in magnitude. Finally this chapter shows that when the TOTM days are eliminated from the January anomaly, the returns from the January anomaly turn from positive to negative, or from significant to insignificant, suggesting that the TOTM days are driving the success of the January anomaly. This chapter shows that the AMH is a more appropriate model for describing the behaviour of calendar anomalies over time than the EMH.

To further examine whether the AMH is a more appropriate model for describing the behaviour of stock returns than the EMH, the most popular technical analysis rule is examined in chapter five. A large number of prior studies indicate that the moving average rule does produce significant returns over time however the majority of the studies show that the rule does not generate superior returns to the buy-and-hold strategy after allowing for trading costs. The moving average rule is examined in this chapter to determine whether the seminal paper by BLL had a detrimental effect on the success of the rule and whether the AMH can describe the behaviour of the returns from this rule over time. The examination of the post BLL data for each market shows that the returns generated from the moving average rule have decreased since the publication of the paper, with DJIA returns turning negative, FT30 returns just remaining positive but no longer significant, and TOPIX returns magnitude falling although still significant. The five-yearly subsample analysis shows that the AMH can describe the behaviour of the moving average rule for five of the nine rules examined, with the remaining four suggesting a switch to inefficiency (which could be early stage AMH). The perfectly and imperfectly anticipated moving average rules are proposed in which the investor predicts the following days signal and trades on it today. The results show that these two predicting rules do produce positive and significant returns for the majority of moving average rules examined, thus suggesting that if investors can predict the following days signal the moving average rule does continue to be successful. Finally two simple trading strategies show that the moving average rule can outperform the buy-and-hold strategy for all the full samples of all the markets, however the results for post BLL data show mixed results for the DJIA and positive results for the FT30 and TOPIX. Further, when the simple trading strategies are implemented on the perfectly and imperfectly anticipated moving average rule, the two rules outperform the buy-and-hold strategy quite considerably, as well as the original moving average rule. This chapter shows that the moving average rule has decreased in power over time in its ability to create positive returns, however if investors can predict the signal on the following day, significant profits can be realised. This chapter also shows that the AMH can be used to describe the behaviour of the moving average rule in a number of markets better than the traditional EMH.

Chapter six is the final empirical chapter of this thesis and investigates the growing topic of investor sentiment. This chapter examines investor sentiment in extreme circumstances, World War Two in Britain through FT30 data. The literature on investor sentiment is vast, although the majority of studies examine sentiment for seemingly trivial and economically unimportant factors such as the amount of sunshine, the temperature and even sports results. Major positive and negative events, naval disasters as well as the largest bombings of the Blitz are examined. The empirical findings show that negative events had a significant negative effect on the FT30, however positive events did not have the corresponding effect. Further, although break analysis finds a number of significant break points, only two of the major events studied are found suggesting that the market did not react to these events. The naval disaster analysis shows that British sinkings had a negative impact on the FT30, with aircraft carrier ships sinking creating a lot more sentiment than battleship sinkings. However, when the Courageous carrier ship is taken out of the data, there is no sentiment, indicating that one outlier was driving the results. Finally the Blitz analysis shows that major London bombings had a negative impact on the FT30 while non-London bombings had a positive impact on the FT30, supporting the local bias hypothesis prescribed in the literature. Overall, this chapter shows there is some investor sentiment after major negative events of WW2 but little sentiment for major positive events. However there is little investor sentiment for major naval disasters although there is strong evidence of local bias from the bombings of the Blitz.

This thesis has investigated the AMH in some depth and whether it can explain the behaviour of stock returns through tests for independence, returns from calendar anomalies and returns from technical rules. Further it has examined investor sentiment in an extreme circumstance that have not been studied in great detail previously. The overall findings are that the AMH can describe the behaviour of stock returns in the DJIA, FT30 and TOPIX better than the traditional EMH through the previous testing procedures and that there is some evidence of investor sentiment in the FT30 during World War Two. This thesis represents a large extension of the knowledge of the AMH and investor sentiment in extreme circumstances. This thesis also provides a much more systematic and comprehensive study of the AMH than the previous literature. Significant limitations in the existing literature have been addressed and whilst the findings have important implications in terms of financial theory, they have wider significance. Specifically, to the large number of market practitioners who actively employ trading strategies to take advantage of the dependence between stock returns, calendar anomalies and technical rules on a day-to-day basis. It may well be that trading rules and calendar anomalies are likely to evolve over time and profits from them depend on market conditions, as stated by Andrew Lo (2004) for the AMH.

7.2. Limitations and Future Research

This thesis, like any other, has a number of limitations.

(i) The choice of five-yearly subsamples in the first three empirical chapters. Different sizes of subsamples could have been chosen, which could have produced different results. However with the data sets available and given the aim of this thesis to examine the AMH over time, the choice of five-yearly subsamples gave enough results to examine the behaviour over time while providing enough observations for the tests to produce reliable results. Many of the papers studying the AMH have used rolling sample windows, which have their own problems that are discussed in chapter two. Thus this thesis studies the AMH from a new perspective.

(ii) The length of the full sample periods. The sample periods for the different markets are not of the same length due to data availability. Each data period was chosen as the longest possible so as to gain an accurate description of how returns have behaved over time. If the data for all three markets data began in 1951 (when the TOPIX started), it would not give us any information about the DJIA and FT30 pre-1951 which would be less insightful than using the full sample periods available.

(iii) The lack of investor sentiment effects found during the WW2 period may be due to the market conditions that we are not able to observe such as low trading volume during. This is possibly the reason why there is very little investor sentiment in stock returns during this period, since many people were drafted to join the war effort, and those that were not probably had 'more important' things to do than trade on the stock market. However, this thesis has no access to the trading volume during World War Two so it is only with speculation that one can say that the results are due to the low volume of trading.

Future potential research on the AMH is potentially plentiful since it is a recently formed model and a number of testing procedures can be used to investigate it. The analysis of the markets through different sample periods, or the use of a rolling sample window could give further insights into the behaviour of stock market returns, but this relies on the availability of data. As more and more data becomes available, longer subsamples may be more fruitful to examine the AMH of these markets, although this may take a number of years. The AMH could also be examined through other markets, individual stocks, exchange rate markets, and bond markets. Further, comparing the evidence of the AMH in developed markets and developing markets (given data availability) may enable investors to predict when certain anomalies may increase/decline in power. One exciting area of future research is to examine during which market conditions certain market anomalies produce significant returns. For example if a period of time produces significantly strong returns in a market, is it characterised by high/low interest rates, bull/bear markets, high/low inflation etc. It then may be possible to predict in the future when certain anomalies will and will not be successful. Another interesting area for future research would be to study whether there were any linkages between the three markets studied in this thesis in regards to the calendar anomalies or any technical analysis rule. Does the rule in one country drive the results in another? This could be the case with the DJIA driving other markets. Also, a full examination of all known technical analysis rules and whether it is possible to predict the following days signal would be very worthwhile to examine whether investors have been doing this and gaining high returns when the original rule is declining in power. Furthermore, a full examination of all known calendar anomalies, technical analysis rules and their behaviour over time could reveal how anomalies and trading rules behave over time, and possibly give an indication about the behaviour of future anomalies.

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