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Three anomalies in finance

by

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ABSTRACT

This thesis is dedicated to the study of the broad subject of market anomalies. Within this framework, three specific finance problems are investigated in depth, namely: 1 – An event study focusing on the FTSE100 index changes which evidences structural change over time in this well known anomaly; 2 – The investigation of interim and final companies' results announcements as sources of extreme events in the company lifetime. 3 - The pricing of options and the effect of the underlying asset expected return on their valuation;

The first part studies the effect of UK companies being promoted or relegated from the FTSE100 index to the FTSE250 on the share price. The data sample consists of all the index promotions since the constitution of the index in 1984 until November 2004. It is split into four characteristic time periods of the lifetime of the FTSE100 index (1984-1989; 1990-1994; 1994-1999; 2000-2004) in an attempt to observe alterations in investor behaviour to index changes along time, and how these relate to the prevailing explanations in the academic literature. I find evidence for structural changes over time in the share behaviour upon promotion/relegation to the FTSE100 index. These findings show support for price-pressure hypothesis and permanent share price change depending on the time-window and time period under study. For index promotions, the results support mainly a permanent share price increase, which is not related to an increased traded volume and therefore is likely to be information-related. For relegations, support for a permanent share price decrease is weak and we find evidence for price-pressure within shorter time-windows that is associated with larger average daily traded volumes.

The second part of the thesis investigates companies' interim and final results announcements as possible sources of extreme events in the company return distribution. We find that on these dates even though there is no evident share return pattern either with evidence of an abnormal return on the event date or cumulative abnormal returns before or after the event, there is strong evidence of higher dispersion of the abnormal returns on the event date.

The third and fourth parts investigate the effect of the underlying asset return on the valuation of options. We first examine the problem theoretically by obtaining a closed form expression that relates the expected value of the call option with the Black-Scholes value. We then provide, in part four, empirical evidence of the effect of historical returns on the Black-Scholes implied volatilities (IVs). We show that our expression for the expected value of the call option can explain the empirical observations that show a strong relation between past returns and IVs. We conclude that the market uses underlying asset expectations to price options, which should not occur under the Black-Scholes conditions.

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Table 5.6: Regression statistics for Put options IV spread with historical returns of different time periods (2, 3, 6, 10, 20, 30-day periods). The regression equation is given by (5.1c). The moneyness of the options, log(S/X), ranges from deep out-of-the-money options to deep in-the-money options, as shown in table 2. Options with log(S/X) ranging between –0.01 and +0.01 are considered at the money options. N is the total sample size. The time to maturity of the options ranges from 20 days to 30 days. *, **, *** Denote at least 10%, 5% and 1% statistical significance levels, respectively.

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Chapter I

“Introduction”

1. Objective

The purpose of this thesis is to contribute to the advance of finance by researching different aspects of the functioning of financial markets. In particular throughout this thesis we propose to investigate different stock market anomalies which could give a better understanding of how the markets operate. We define an anomaly in broad sense as an effect that contradicts the well-established behaviour of an efficient market system. In chapter II we concentrate on an "anomaly" (promotions and relegations from stock market indexes) which is know to yield share price predictability leading to statistical arbitrage opportunities. By analysing share price effects around index promotions/relegations we will show evidence that the market tends to correct for so-called anomalies even if with a larger than expected time lag. In chapter III the "anomaly" is not empirical evidence of share price predictability but evidence of an anomalous dispersion on companies' earnings announcements. If news arrives to the market as Gaussian noise as assumed by most theories, then the evidence of extreme share price movements on particular well-known dates is an anomalous behaviour and could be used both for risk management purposes or arbitrage opportunities. Finally, the third anomaly we explore in chapters IV and V concerns the role of share price predictability in option pricing. Our argument lies upon the statement: if share returns are predictable, then they should have an impact on option prices. This statement however contradicts established option pricing theories as it is argued that higher returns are related to higher volatilities and taken into account in option valuation models. In an attempt to find empirical evidence on the previous argument we investigate the impact of past returns on option prices, finding that past returns do have an impact on option prices in the real market, which may help better understand the dynamics of the complex options market.

2. Overview

Market anomalies of all sorts have been widely reported in the academic literature by authors trying to find holes in the generally accepted efficient market hypothesis (EMH). Usually these anomalies either disappear a few years after they are reported as investors assimilate the public information or do not present profitable arbitrage opportunities after accounting for transaction costs and consequently the defenders of the EMH prevail. Nevertheless, for a given time period, the anomaly existed and could be exploited to make arbitrage profits. Furthermore, the way market intervenients act upon a particular market anomaly may cause side effects, which analysed with sufficient data may constitute another market imperfection by itself. In this thesis we provide an example of such an anomaly (share price effects occurring on index constituent changes) where agents trying to arbitrage the well known share-price effect away have in the process, exacerbated a longer-term effect.

The participation in the stock markets of agents with different investment strategies and performance objectives gives rise to a behaviour which could fall in the realm of complexity where processes are not random but are coupled giving rise to herding effects. These kind of human interactions give rise to a natural share return distributions which are not Gaussian as typically assumed in the academic media but with Paretian tails. This means that extreme events are more likely to occur than by assuming a Gaussian distribution for share returns. We present evidence of such behaviour by observing that abnormal returns for a sample of companies follow a power law instead of a Gaussian distribution. Furthermore, we observe that on a given event date (earnings announcements), the distribution is still Paretian but with larger dispersion. I suggest that such events may be in the origin of the leptokurtosis typically found in financial time series. I also find evidence of share price predictability following large price changes on the announcement date which goes against the EMH.

Finally, the predictability of share returns may have an impact on the pricing of options. If arbitrage opportunities exist then it is expected that the highly efficient options markets will have incorporated such information into the prices. For example, there is extensive evidence in the academic literature of the existence of market momentum. If so, then the options markets should react to past returns. This of course goes against the Black-Scholes assumptions. We do find however that option prices are dependant on past index prices which cannot be explained by changes in volatility. It is as if the options markets do not price options according to Black-Scholes but simply through supply and demand effects.

3. Structure of the thesis

The thesis is divided into three parts that focus on three problems in finance. The common factor to each of these problems is that they represent an evidence of market malfunction (market anomaly) where excess returns could be generated when adjusted for the risk. The first part provides a general overview of the thesis and how it fits into the advancement of research in finance. Chapter II is dedicated to examining a well-known market anomaly where arbitrage opportunities have been exploited by some agents (typically in the form of hedge funds). The aforementioned anomaly is the effect of rebalancing on the FTSE100[1] when a share is promoted/relegated to the index, which is included within a broader range of similar anomalies named event studies occurring on particular public information releases.

Chapter III is another event study. It investigates the impact of public interim or final results announcements of companies belonging to the FTSE100 and FTSE250 on the share price behaviour. Although earnings announcements have been extensively examined in the academic literature, the analysis of abnormal return dispersion on these dates has been overlooked. We find that there is no trend or apparent predictable pattern in share returns on the event date or within time windows before and after the event, which is in agreement with the efficient market hypothesis. However, when examining the dispersion of share return on the event date and on a typical day within the event window, we observe that the results announcements are high impact events on the company shares. Specifically, we find that there is a higher than normal incidence of extreme events on this date, and that a part of the leptokurtosis observed in financial time series could be explained if such events are taken into account. We consider this behaviour as a market anomaly as traditional market theories assume Gaussian distribution and arrival of continuous information to the market with equal impact on the share price (white noise). This research has

[1] In fact, as will be shown in chapter II, most academic literature investigating share price effects occurring on index rebalancing is focused on the S&P500 (the original papers on the subject are Harris and Gurel (1986) and Shleifer (1986) to more recent studies by Chen et al. (2004)). There also exists a large quantity of academic literature examining these effects on major international indices.

important implications as these and other such public announcements may explain a large portion of the typical leptokurtosis in the share return distribution.

Chapter IV examines the effect of the underlying asset return on option pricing. Traditional options pricing theories based on non-arbitrage arguments eliminate the underlying asset return from the valuation of options. By relaxing the assumption of perfect capital markets, options become non-redundant securities. We examine the implications on option valuation by obtaining a formula that relates the expected value of the call option (given different investors expectations of asset return) with the Black-Scholes price.

In Chapter V we provide empirical evidence from FTSE100 index options that options prices are related with past index returns, which is used as a proxy for expected index returns. We also show that option prices may be non-redundant due to supply and demand effects related investors over/under reaction to past index returns. We manage to fit the empirical evidence with a simple expectations model for option prices, as shown from the previous chapter IV. Part VI gives some concluding remarks to the thesis and insights to future pathways of research. The following sections provide a brief summary of each chapter.

Chapter II – The appearance and disappearance of a market anomaly: The case of FTSE100 index promotions and relegations.

In this part of the thesis the share price effects due to FTSE100 index constituent changes is investigated. The promotion/relegation of a share to/from a major stock index is well known as a singular event in the company lifetime and the effects associated with it have been widely reported for indexes around the world with main incidence on the study of the S&P500 index. By splitting the data sample into different time periods it is shown that the FTSE100 index anomaly changed structurally along the lifetime of the index. Recently, the excess returns that could be obtained by exploiting an arbitrage strategy have practically disappeared, which pays a great tribute to the way an efficient market operates. However, the study also shows evidence that the uncertainty of the share price on the index change date increased in recent years which could mean that a new anomaly is in the build which is more subtle than the previous one and more difficult to arbitrage away. We show that the index promotion/relegation of a company is likely to lie in the tails of the historical return distribution, this is, it is an extreme event in the life of the company. Furthermore, we show evidence of semi-strong form of market efficiency as the correction to the share price starts to occur several weeks before the public announcement is made.

Chapter III – Interim and final results announcements: sources of extreme events?

Following the work from part II, share price effects around companies' interim and final results announcement are examined. If the relegation or promotion of a share to a major index consists of a high impact event in the company lifetime, as seen in chapter II, then it is plausible that other singular dates could yield similar behaviours. Public interim and final results announcements are a perfect event to research as they occur frequently (twice a year for each company) and are in the public domain several months in advance. Consequently, the resulting large data sample provides a unique opportunity for reaching statistical significant results and test for market inefficiencies as the event is in the public domain. In our research two independent samples are used in order to check the robustness of our analysis (and avoid sample selection biases): the first sample consists of interim and final results announcements of companies that were at one point relegated from the FTSE100 market index while the second sample consists of companies that were promoted to the FTSE100. We then select all the events since 1985 until 2005 for each company in the sample. With this sample selection we also avoid survivorship bias, as some of the companies either were de-listed, were taken over or merged at some stage in the time period.

The results show no evidence of market inefficiency around the event date; either in terms of a statistical significant abnormal return on the event date or by means of pre and post event patterns. These findings are inline with previous academic research. However, by comparing the dispersion of abnormal returns on the event date with other days within the 25-day event window, it is observed that on the announcement date, there is an increase in the frequency of extreme events. In other words, there is evidence for higher share price volatility on the event date when compared with "normal" non-event dates. In fact the average rise in volatility on the announcement date is around 2.4 times the normal volatility. Our results show a high degree of statistical significance both through parametric and non-parametric tests. We also find evidence that the distribution of the magnitude of abnormal returns follows more closely power-law behaviour than a Gaussian behaviour. We observe that on the event date there is a significant increase in the scale parameter of the power-law distribution (of around 3 times), which provides further evidence of the high impact the announcement date has on the company share price. Finally, the results of the analysis of the samples show that the share price behaviour is very similar across samples as well as for different time periods and therefore, the results are robust.

The findings in this part of the thesis provide empirical evidence that company specific information events could constitute sources of extreme returns in the lifetime of a company. It appears that different events have a different impact on the share price, which goes against traditional market theories that assume a Gaussian distribution of share returns and constant volatility over time (information sources arrive continuously to the market). In this work, we show that the continuous information sources arriving to the market do not have all the same importance. High impact information sources, such as the one analysed in this chapter (public interim or final result announcement), may be partially responsible for the typical leptokurtosis that is observed in share return distributions. The predictability of such extreme events could be of extreme importance to portfolio managers or risk managers who desire to minimise the portfolio noise and control for unexpected losses, respectively.

Chapter IV – The hole in Black-Scholes.

Modern option pricing started in 1973 when Fischer Black, Myron Scholes and Robert C. Merton published their seminal papers showing a deterministic formula for the fair value of a European call option. Their deduction of the formula was based on the construction of a replicating or continuously hedged portfolio and the usage of

Ito's lemma for obtaining a second order approximation to the change in option value. For their formula to be valid they imposed a Gaussian share return distribution, a continuous time market, the possibility to borrow at the risk-free rate of interest and the assumption of perfect capital markets.

If the assumption of perfect markets is relaxed then different investors have different expectations of the underlying asset return and investors are not all risk-neutral but to a great extent, risk averse, this will have an impact on options prices. There is an extensive literature on the predictability of asset returns. If share returns are predictable to some extent, then should two options with the same historical volatility have different option prices if their expected returns are different? Alternatively, should option prices depend on expected future returns, as for instance due to market continuation effects? Even though these situations should not occur in perfect markets, it is possible that on specific occasions markets are not in equilibrium and consequently, options prices should depend on asset returns. In this chapter this question is analysed by deducing and expression that shows the relation between the expected value of a call option and the Black-Scholes value. We then estimate the implied discount rate implied by the Black-Scholes valuation and discuss its implications. In chapter V, the effect of share return on option values is also investigated empirically by using a dataset of FTSE100 index options from LIFFE, where empirical evidence supporting the previous hypothesis is shown.

Chapter V – The hole in Black-Scholes – Empirical evidence

In this chapter we present empirical evidence of a relation between historical returns and option prices. To investigate the effect of past returns on option prices, options implied volatilities are calculated using the Black-Scholes formula and compared with different measures of historical volatility. We find evidence that the spread between the volatility implied by the market and measured historically is strongly related with past returns for put options, while this correlation is weaker for call options. This behaviour could be caused by the action of supply and demand forces by originated by market intervenients buying portfolio insurance when index returns are negative. An alternative explanation could be the changes in investors' future expectations due when they analyse past index returns and their consequent action through buying or selling of put and call options. In summary, the results show empirical evidence that "market intervenients" price options taking into account past index returns, which is obviously not rational according to prevailing option pricing theories, which predict no such relation. In fact, in options pricing models based on non-arbitrage arguments, the return on the underlying asset is irrelevant by the construction of the risk-neutralised portfolio (martingale stochastic process). Our empirical evidence for the put options market shows this is not the case in real markets. Consequently, the discussion of the influence of the asset return on the valuation of options is relevant, as we can explain theoretically the empirical results observed in the market by assuming investors use historical returns as proxies for future returns.

Chapter VI – Conclusions.

In this chapter the implications and a general overview of the findings in this thesis are discussed and future pathways of research are proposed.

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Chapter II

"The appearance and disappearance of a market anomaly: The case of FTSE100 index promotions and relegations"

Abstract: In this chapter the effect of UK companies being promoted or relegated from the FTSE100 index on the share price is investigated. The data sample consists of all the index promotions since the constitution of the index in 1984 until November 2004. It is split into four characteristic time periods of the lifetime of the FTSE100 index (1984-1989; 1990-1994; 1995-1999; 2000-2004) in order to observe alterations in investor behaviour to index changes through time, and how these relate to the prevailing explanations in the academic literature.

We find evidence for structural changes over time in the share price behaviour when a company is promoted/relegated to/from the FTSE100 index. Our findings show support for price-pressure hypothesis or permanent share price change depending on the time-window and time period under study. For index promotions, the results support mainly a permanent share price increase, which is not related to an increased traded volume and therefore is likely to be information-related. For relegations, support for a permanent share price decrease is weak and we find evidence for price-pressure within shorter time-windows that is associated with larger average daily traded volumes. We show that this asymmetric behaviour between index promotions/relegations is enhanced with the presence of agents attempting to arbitrage the share price effects, which could be explained by imperfect substitutes for relegated shares. Finally, we identify the index change date as a possible source of extreme abnormal returns in the lifetime of the company.

1. Introduction

This chapter investigates share-price effects for stocks that have been promoted or relegated from the UK FTSE100 for the period 1984 until 2004. We split our data sample into four characteristic time periods which are analysed separately. The rationale behind this split is the possibility of structural change over time in share price behaviour around index changes. We investigate whether the well-documented arbitrage opportunities still exist given the growing presence of hedge funds and the availability of public information of arbitrage opportunities around index change dates.[1]

It is well established that changes to different international stock indices are associated with share-price behaviours which are inconsistent with the long-held assumption of perfect elasticity for stocks. If stocks were perfectly elastic securities with a horizontal demand curve, then non-informational events, such as the case of index composition changes, should not result in permanent wealth changes to the added/deleted stocks. Even if stocks were not perfectly elastic to demand shocks, the share-price effects of index rebalancing should be temporary in nature (price pressure) and not permanent. Most studies however, show that there is strong evidence for the proposition that demand curves for stocks slope downward. Furthermore, there is evidence that arbitrage profits can be made by trading around index changes. One such strategy is buying/selling shares that are promoted/relegated from a major stock index before the change date while maintaining market neutrality.

In this chapter, by analysing four different time periods namely (1984-1989; 1990-1994; 1995-1999 and 2000-2004)[2] our results show that the typical abnormal returns behaviour (for both promotions and relegations) around the event date changed over time. It is found that during the first time period 1984-1989, just after

[1] Hedge funds are investment companies that measure their performance in absolute terms instead of performance relative to benchmarks. Their scope varies from long/short equity strategies to statistical arbitrage. The term "arbitrage" used throughout this chapter refers to statistical arbitrage where there is a positive return expectation after costs when a large number of events occur.
[2] The rationale for analysing the promotions/relegations effect during these time periods is two fold: First it splits the sample into four equal time slots with a similar number of events in each and second, it allows the examination of characteristic periods such as the stock market boom period pre 2000 and the bursting of the bubble post 2000.

the index formation, there is lower abnormal volume on the index change date and we find no evidence of price pressure on the event date. However, during the time periods 1990-1994 and 1995-1999 there is respectively a significant 1.62% and 2.59% average abnormal return on the promotion date and -1.82% and -2.40% average abnormal return on the relegation date.[3] For the final time period (2000-2004) we show that the statistically significant positive/negative abnormal return on the promotion/relegation date almost disappears, even though the abnormal traded volume on the change date remains high.[4] While arbitrageurs have apparently removed the opportunities for playing the index rebalancing game based on the event date, their impact on the long-term pre and post event share price behaviour has also been significant. When analysing cumulative abnormal returns, we find that over the 2000-2004 period there is an increase in the asymmetric share price behaviour between promoted and relegated companies within a ±25 day window: While the relegated stocks show evidence of price reversals, the promoted stocks show evidence of a permanent wealth increase. However, when analysing a longer ±100 day window, we find that there is a permanent wealth effect for both promoted and relegated shares.

When comparing the long-term pre-event price decrease for relegated companies over the four time periods, our results show cumulative abnormal returns of (-8.0%, -15.0%, -12.4% and -28.4%). The large decline in the final 2000-2004

[3] The abnormal returns on the index change date have been reported for different stock indices. They are attributed to the increased demand caused by index tracking funds rebalancing their portfolios. Index tracking funds are widely accepted as the cheaper and most effective way to gain exposure to the stock markets. Malkiel (2003) shows that only 1/3 of actively managed funds manage to outperform market-tracking funds. Brealey (2000) estimates that the UK pension fund industry had about £134bn in index tracking assets by the year 2000, amounting to about 8.6% of the stock market capitalisation of UK-traded equities. Ever since the adverse market correction in late 2000 there has been a decline in passive fund management coupled with a higher demand for bonds and in parallel a surge of hedge funds, which has reduced considerably the amount of index tracking funds.

[4] We attribute the disappearance of the effect within the 2000-2004 period to the increased popularity of hedge funds and unpopularity of the stock market and index tracking funds due to the 2000 market crash. This is consistent with the conclusions of Record (2004) who, using data from JP Morgan, reported that in the 2001–2004 period the FTSE100 promotion/relegation effect had been arbitraged away due to the weight of hedge fund capital. Evidence of the growth of hedge funds is shown by the exponential growth of both the number of hedge funds and the assets under management (AUM) by hedge funds, see for example the Barclay Group or Henessee Group survey of hedge funds who show an increase in AUM from $130m in 1997 to $1.2Tn in 2006. Evidence for the decline in index tracking can be found by a keynote speech by John C. Bogle ex CEO of Vanguard Group one of the biggest providers of indexed mutual funds before the Financial Planning Association 2002 Forum in New York, April 25, 2002, who states that capital outflows from indexed funds occur after the bursting of bubbles when investors reassess their attitude towards risk.

period, is attributed to the effect of arbitrageurs exacerbating the effect by not being able to find suitable substitutes in order to implement a riskless arbitrage trade.[5] For promoted shares, the pre-event abnormal returns show permanent share price increase of (13.6%, 15.5%, 35.4%, and 11.6%) for time periods (1984-1989, 1990-1994, 1995-1999 and 2000-2004). The large share price increases observed during 1995-1999 are associated with the booming stock market and increasing popularity of index tracking funds during that period. The effect has to a great extent been arbitraged away in the recent period of 2000-2004.

When investigating abnormal volume around event dates we show that there is no evidence of a permanent change in volume before and after the index rebalancing. We do find extremely high abnormal volumes on the index change date which increased over time. During the periods 1990-1994, 1995-1999 and 2000-2004 average abnormal volumes on the promotion date increased from +89% to +398.6% and 312.5%, respectively. In addition, comparable results were found for index relegations (+85.6% increased to +236.8% and 200.7%, respectively).

This chapter contributes to the literature at several levels. First, we investigate a large sample of index changes, both promotions and relegations, for the UK FTSE100.[6] We obtain a reasonable-sized sample for both promotions and relegations which is large enough to analyse different time periods. Second, by splitting our data sample into four characteristic time periods, we observe a structural change in the share-price behaviour around index changes. We then discuss the share-price behaviour during the different time periods in context of the prevailing exiting theories. Third, we report that the FTSE100 effects have been arbitraged away in the later 2000-2004 time period. Finally, and most importantly, we show that during 2000-2004, the asymmetric share price response between index promotions and relegations, reported by Chen et al., (2004), has been exacerbated and not reduced by the presence of arbitrageurs.

The rest of this study is organised as follows: Section 2 gives a review of the relevant academic literature and prevailing theories explaining the share-price effects

[5] See Wurgler and Zhuravskaya (2002).

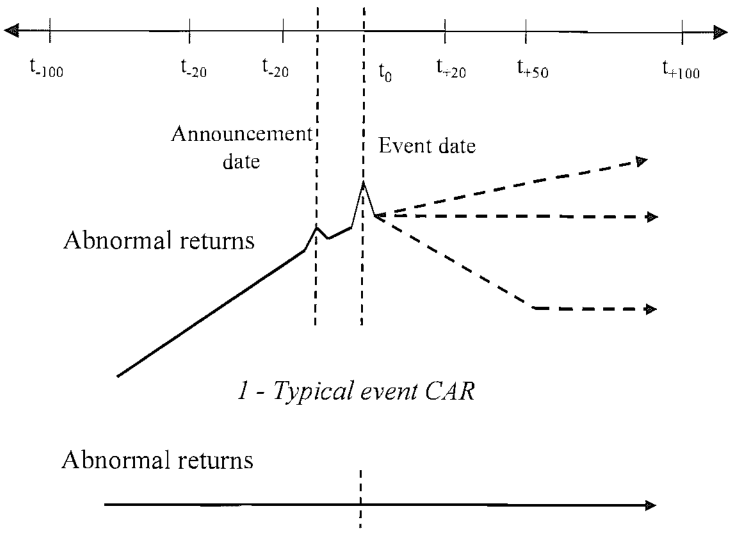
[6] The academic literature on FTSE100 constituent changes is scarce compared to available literature on the S&P500 index. Key studies on the FTSE are Brealey (2000), Mase (2002) and Gregoriou and Ioannidis (2006).

around index constituent changes. Section 3 explains the event study methodology used in the paper. The data sample is described in section 4. Section 5 shows the results of the analysis and is divided as follows: Parts A and B analyse abnormal returns for the promotions and relegations samples, respectively. Part C investigates abnormal volumes and part D investigates the existence of extreme abnormal returns on the event date. In section 6 we reconcile the empirical findings with prevailing academic literature and we draw conclusions in section 7.

2. Previous Research on index changes

When studying the impact of index promotions/relegations within a given time-window, extensive academic literature shows evidence of positive abnormal returns before the event date but generally evidence is mixed regarding abnormal returns after the event. The analysis of the data for different time periods also shows that on the day of the promotion, there is a statistically significant abnormal positive return followed by a negative return of similar magnitude in the day following the event. This behaviour suggests that apart from the portfolio rebalancing before the index change date, there is a large jump on the day of the event possibly due to a bulk purchase of the security. On the following day the share price is readjusted to correct for this jump. A similar behaviour is found in the literature for the announcement date of a share promoted/relegated to/from the S&P 500 index[7]. Figure 2.1 shows the typical behaviour observed when a share is promoted to a major index within a ±100-day window. In a perfect market, there should be no impact of index changes on the share price behaviour in both the long-term as on singular dates. This is, the market should have incorporated the information in the share price prior to the event and it should also be able to provide the liquidity for the extra demand on the event date so that no price pressure effects would be observed. Furthermore, even if the extra volume has an effect on the share price (imperfect market), index relegations and index promotions should exhibit a symmetric behaviour.

[7] For example see Harris and Gurel (1986), Shleifer (1986) or Jain (1997).



1 - Typical event CAR

2 – Event CAR in a perfect market

Figure 2.1: Top: Typical behaviour within the event window for a share promoted to a major index. Bottom: Expected behaviour in a perfect market. The event date refers to the day when a company is promoted/relegated from the index occurring at t_0.

Jain (1987) finds abnormal returns for firms added to other S&P indices even though index trackers do not track these indices. Harris and Gruel (1986) study the same phenomenon over a similar time frame, and find contradictory evidence that supports the price-pressure hypothesis, which requires the share price to revert post-event. Shleifer (1986) finds support for the imperfect substitutes hypothesis where the demand is not perfectly elastic and the price change is permanent. In all the studies, the authors examine the effect of inclusion into the S&P500 index due to the availability of a reasonably large data sample while data on relegations is scarcer due to confounding effects occurring upon relegation such as bankruptcies, spin-offs or de-listing due to a merger[8].

Other international indices have also been investigated for the reported market behaviour when an index change occurs. Such examples include Vespro (2001) for the French CAC40 and Belgium SBF120, Mase (2002) and Brealey (2000) for the UK FTSE100, Chung and Kryzanouski (1998) for the Canadian TSE300 and Biktimirov (2004) for the conversion of the Canadian TSE100 to the S&P/TSE 60,

[8] For index relegations see for example an early study from Goetzmann and Garry (1986) investigates share price effects when companies are delisted from the S&P500.

Chan and Howard (2002) investigate the Australian all ordinaries index, Liu (2000) for the Japanese NIKEI500, Chakrabarti et. al. (2005) study international MCSI indices, Duque and Madeira (2004) for the Euronext-Lisbon PSI20, among others. The effects seem to occur in all reported indices even though the empirical evidence of each study are split between support for the price-pressure hypothesis and support for a downward slopping demand curve depending on the time-period under study and the length of the event window (the different hypothesis tested within the academic literature are explained below). Nevertheless, all these studies support the existence of market microstructures that are known to affect the share price behaviour. One of the main drawbacks of several of these studies is the relatively small sample sizes used in some analysis, which questions the strength of some conclusions. The main hypothesis proposed within the academic literature to explain the index promotion/relegation effects are the summarized as follows:

Price pressure Hypothesis:

For stocks added to an index, this hypothesis predicts a temporary increase in the share price and trading volume due to index fund purchases of the security. Harris and Gurel (1986) find that the increase in trading volume is permanent but the increase in share price is reverted over time, for S&P 500 stocks. More recently, Elliot and Warr (2003) find further evidence of price pressure on the NYSE and Nasdaq analysing additions and deletions to S&P500 stocks. Similar results are obtained by Duque and Madeira (2004) for the Euronext Lisbon PSI20 index and also find evidence supporting the price pressure hypothesis. In contrast, Shleifer (1986), Beneish and Whaley (1996), Dhillon and Johnson (1991), Lynch and Mendenhall (1997) report that the wealth effect due to inclusion into the S&P 500 is permanent and attribute it to a downward sloping demand curve.[9]

[9] Empirical evidence of downward sloping demand curves has also been reported when analysing index weight adjustments as shown in Kaul et al., (2000). The argument is that in order to reduce tracking errors, fund managers adjust the portfolio weights accordingly and thereby create a permanent wealth effect.

Imperfect substitutes Hypothesis:

Under this hypothesis, stocks are characterised by a downward sloping rather than perfectly elastic (i.e. horizontal) demand curve.[10] This is due to the lower impact of arbitrageurs that are exposed to more risk when they cannot find a perfect substitute for the share in order to create a neutral position. In this case, they will be subject to higher arbitrage risk and therefore trade less aggressively, Scholes (1972) and Wurgler and Zhuravskaya (2002). In an efficient market, arbitrageurs would arbitrage any share mispricing away making the demand curve tend towards horizontal. The impact of arbitrageurs will depend on the arbitrage risk (the existence of perfect substitutes), their risk aversion and the volume under management by hedge funds (the number of arbitrageurs).

Information Hypothesis:

This hypothesis suggests that the Standard & Poors Corporation uses both public and non-public information when selecting stocks for inclusion or deletion from the S&P500 index. Since the inclusion of stocks is seen as good news, the share price should register a permanent rise on announcement of its inclusion to the index. Similarly, when a company is relegated from the index, there should be a permanent reduction in the share price reflecting the "bad information" this event implicitly conveys to the market. While Jain (1987) and Dhillon and Johnson (1991) find evidence to support the information hypothesis when analysing data on the S&P500 changes, Harris and Gurel (1986) do not find evidence to support it, as they observe that the effect is temporary (price pressure) due to index funds rebalancing their portfolios. Recently, Denis et al., (2003) shed some light on the subject by investigating earnings expectations of companies promoted to the S&P 500 index, finding that companies promoted to the S&P500 index experience increased EPS in the following years, which gives some support for the information hypothesis.

[10] Different theories have been proposed to explain the empirical evidence of a downward sloping demand curve namely: the *imperfect substitutes hypothesis* of Scholes (1972), the *information hypothesis, certification hypothesis* and *liquidity hypothesis.*

Certification Hypothesis:

It argues that the inclusion of a company to a top ranking market representing index, works as a certificate of the quality of the company and therefore once it is promoted/relegated from the index the company will attract a wider/narrower spectrum of investors, see Brooks et al., (2004) or Jacques (1988). This hypothesis is very similar in nature to the information hypothesis and difficult to distinguish form it. In both cases on inclusion/relegation, investors will require a lower/higher premium to invest in the company and therefore the data should show a permanent rise/decrease in the share price before and after the event.

Chen et al. (2004) propose an explanation to the share price effects around S&P500 constituent changes that is slightly different to the certification hypothesis. By analysing a large sample of promotion and relegation events they find evidence of asymmetric behaviour, that is, while index promotions show evidence of permanent share price increases post-event, relegated shares show evidence of share price reversal after the event. They argue that this asymmetric effect can be explained by investor awareness: They suggest investor awareness increases for promoted shares, but when shares are relegated investor awareness does not diminish as much.

Liquidity Hypothesis:

Amihud et al (1997) propose that liquidity costs increase the required rate of return on securities. This implies that the inclusion of a stock in the S&P 500 index decreases its transaction costs and liquidity risk and hence the stock price will have a permanent rise to reflect the lower expected return. Brennan and Subrahmanyam (1996) present empirical evidence supporting this hypothesis by finding that equity returns vary directly with illiquidity costs due to the direct and asymmetric information costs of transacting. If an addition to the S&P 500 leads to an improvement in the market quality, then at least part of the documented abnormal returns should be positively related to the decline in the effective spread, as well as a decline in the information costs of trading, Hegde and McDermott (2003).

3. Methodology

The calculation of abnormal returns can be performed by using different indexes or different market models that adjust for effects such as size (see Dimson and Marsh (1988)), value, or growth (multi index market models). In our study, as the window of the event is relatively small and all the firms are mid-large to large size stocks, there will be a relatively small size effect. Other multifactor models such as in Fama and French (1995), which include explanatory factors such as book to market or the P/E ratio could be used to calculate abnormal returns but are more cumbersome and require a larger variety of data that is sometimes unavailable. Consequently we adopt the single index market model, as the benchmark, which we believe, is suitable for the relatively short time window that is analysed. The event study methodology employed in this study is the same as described in Campbell, Lo and MacKinlay (1997).[11] The estimation window used to calculate the market model parameter estimates consists of the 100 trading days before and after the event date; this is based on a total sample of N_1=200 daily returns. The abnormal returns (AR) are calculated using the following formula:

$$AR_{j,t} = R_{j,t} - \hat{\alpha}_j - \hat{\beta}_j R_{m,t} \qquad (1)$$

AR_j – Abnormal return of company j.

j – index representing a given company.

$\hat{\beta}_j$ – estimate for the beta of company j.

R_m – Return of the market portfolio (FTSE all share)

t – Abnormal return date.

$\hat{\alpha}_j$ – Estimate of alpha coefficient for company j when using the market model.

The market model estimates for each company are calculated using OLS for the whole sample window (from t_{-100} to t_{100}). The regression residuals (abnormal

[11] See also Cable and Holland (1999a, 1999b, 2000) who give support for the usage of the market model for event studies. They also suggest that simple OLS regressions for sample size equal or greater than 60 are robust using OLS even though high kurtosis may be evidenced on the individual security level, Cable and Holland (2000).

returns), are assumed to be normally distributed, and iid. Consider the vector of event-window (N_2) abnormal returns $\mathbf{AR_i}$ = [$AR_{i,T1}$... $AR_{i,T2}$]' of size ($N_2 \leq N_1$x1) where the respective market return vector $\mathbf{Rm_i}$ = [$Rm_{i,T1}$... $Rm_{i,T2}$]' (N_2x1) with parameter estimates a$\hat{\alpha}_i$ and $\hat{\beta}_i$. Conditional of the market return over the event window, the abnormal returns will be jointly normally distributed with zero conditional mean E($\mathbf{AR}_i$ | $\mathbf{Rm}_i$)=0 and conditional variance matrix $\mathbf{V}_i$=E($\mathbf{AR}_i\mathbf{AR}_i'$ | $\mathbf{Rm}_i$). If the length of the estimation window is large enough then the sampling error of the parameter estimation tends to zero and the abnormal returns become independent and therefore inferences can be drawn on the sample abnormal returns assuming $\mathbf{AR}_i \sim N(0, \mathbf{V}_i)$ as in Campbell, Lo and MacKinlay (1997). Once this is established for a single abnormal return, we can aggregate abnormal returns both in time and cross-section and make inferences of the significance of those abnormal returns.

To study the effect of index changes on a given particular date (either announcement date, change date or others), the average returns are aggregated in cross-section for each day relative to the event date t_0 yielding the average abnormal return vector.[12]

$$\mathbf{AAR} = \langle \mathbf{AR} \rangle = \frac{1}{M}\sum_{i=1}^{M} \mathbf{AR}_i \quad \text{with;} \quad \mathrm{Var}(\langle \mathbf{AR} \rangle) = \frac{1}{M^2}\sum_{i=1}^{M} \mathbf{V}_i \,. \qquad (2)$$

Where M is the cross-sectional sample size (number of companies) and $\mathbf{AAR}$=[AR_{T1}...AR_{T2}]' is the average abnormal return vector of size (N_2x1), the length of the event time window. The variance of the abnormal returns will allow us to make inferences on the significance of the results. Another diagnostic statistic that will be used to test the significance of the abnormal returns is the binomial Zb test. This test is a nonparametric test that estimates the parameter significance by measuring the relation of positive to negative abnormal returns. As it is non-parametric, it has the advantage of being relatively insensitive to sample outliers. Theoretically, the proportion of negative and positive abnormal returns should be 0.5

[12] Index trackers follow stock market indexes with an objective to minimise tracking error. They have therefore some constraints on rebalancing the portfolio before the event date (e.g. on the announcement date) which could give rise to tracking errors.

(50%) if the market model is correct and no other confounding effects are included within the sample. The binomial distribution of positive (or negative) abnormal returns asymptotically tends towards a normal distribution when N is large enough, and therefore can be used in conjunction with the variance to test the significance of the abnormal returns. The binomial Zb test is given by:

$$Z_n = \frac{(NEG/N - p)}{[p(1-p)/N]^{1/2}}, \qquad (3)$$

where NEG (or POS) is the count of negative (or positive) abnormal returns at day *t* and N is the total sample size. The subscript n stands for "negative" but the same test would apply for positive returns with subscript p.

Next, we aggregate abnormal returns over different temporal windows the share price behaviour can be observed before and after its promotion/relegation to/from the FTSE100 index. The cumulative abnormal returns for a particular company, j, given a temporal window from t_m to t_n is:

$$CAR_j(t_m : t_n) = \sum_{i=m}^{n} AR_{j,i} \qquad (4)$$

And, when the sample is aggregated in cross-section, the average CAR is:

$$ACAR(t_m : t_n) = \langle CAR(t_m : t_n) \rangle = \frac{1}{M}\sum_{j=1}^{M} CAR_j(t_m : t_n) \qquad (5)$$

The time window selected to investigate the effects of the index promotions/relegations event was chosen in order to take into consideration that other confounding effects should be excluded from the analysis whenever possible, following the recommendations in McWilliams and Siegel (1997). On the other hand, as the effect studied in this paper has an announcement date, which can be two weeks before the actual event takes place; it is reasonable to study an extended time period before and after the event. This is done with awareness that this extended time period can be prone to confounding effects resulting from one or several of the numerous information sources relevant to the companies of the sample. Intraday effects and day-of-the-week-effects are ignored, as they are considered negligible in the context of this study.

The event study can be divided into two parts: A short window that consists ±10 working days relatively to the promotion/relegation date, where abnormal returns are examined. Secondly, an extended period, consisting of any time period within the ±100 working day window that studies the share price behaviour of market anticipation of the event and the possible price adjustment after the event takes place.

4. The data sample

According to FTSE regulations, the FTSE regional committee meets on the Wednesday after the first Friday in March, June, September and December to decide upon a promotion/relegation or changes in the reserve list. These decisions are then implemented on the next trading day following the expiry of the LIFFE futures and options contracts, which normally takes place on the third Friday of the same month, corresponding to 7 trading days after the public announcement. Furthermore, the FTSE100 reserve lists consisting of the 10 largest capitalisation FTSE250 companies that are in the pecking order to be selected for promotion to the FTSE100, also changes on the announcement date. Therefore, public information on the topmost shares in that list is available 3 months and 7 trading days before the next index change date. A similar situation occurs for the companies, which could be selected for relegation from the FTSE100.

The data sample consists of a list of companies that were upgraded/downgraded from the FTSE250 to the FTSE100 market index since the start of the index in January 1984 until December 2004. The sample can be divided into two subsets consisting of FTSE100 promotions and FTSE100 relegations. The first subset has 285 data points each of which corresponds to the date when a given company is incorporated into the FTSE100 index. The second subset is composed of 282 data points each of which corresponds to the date a given company is relegated from the FTSE100 to the FTSE250. The data for the promotions/relegations was obtained through the London

Business School FTSE100 index constituent database. After searching for data on share prices and dividends for each of the events, the total sample for promotions/reductions was reduced to 283 and 277 respectively due to data unavailability on Thomson Datastream.

The next step was to filter which data points will be analysed and which should be excluded. The first filtering mechanism required the use of only those companies for which we could obtain at least 100 data points before and after the event date so that the market model parameters could be computed for each case[13]. This selection process excludes: companies that merged, recent spin-offs and liquidated companies. Secondly, companies with missing data points were excluded from the analysed sample. After filtering, the total sample size was 223 and 226 for promotions and relegations respectively. Finally, the sample was split into four different time period within the 1984-2004 total sample period. Table 2.1 summarises the sample details with Panel A showing the promotions sample while panel B shows the relegations sample.

Table 2.1
Summary details of the promotion and relegation data samples. Items were removed either due to data unavailability over the evaluation period or confounding effects such as mergers or IPOs.

Panel A: Promotions sample

Time period	Total Sample	Filtered Sample	Removed Items
1984-1989	74	57	17
1990-1994	67	56	11
1995-1999	75	57	18
2000-2004	67	53	14
Totals	**283**	**223**	**60**

Panel B: Relegations sample

Time period	Total Sample	Filtered Sample	Removed Items
1984-1989	71	57	14
1990-1994	67	58	9
1995-1999	72	60	12
2000-2004	67	51	16
Totals	**277**	**226**	**51**

[13] The daily share prices for each company for the time period t_{-100} to t_{100} were obtained through Thomson Datastream (consisting of the 100 trading days before and after the event date, t_0). Finally, the market index used to estimate the abnormal returns was the FTSEALL, also obtained from Thomson Datastream.

5. Results

The data sample is divided into four time periods with similar sample size. The study of these four time periods will shed light on the changing market reaction to the apparent statistical arbitrage opportunity occurring when these promotion/relegation events take place. Moreover, the analysis of different time periods may show if there has been a reduction in the event-date abnormal return over time. With the growing popularity of sophisticated investors (such as hedge funds or sophisticated investment strategies), which generate abnormal returns by exploiting market inefficiencies such as the index promotion/relegation event, their action of arbitraging the effect may result in a change in the characteristics of abnormal returns in our event study. The four periods that are analysed are 1984-1989, 1990-1994, 1995-1999 and 2000-2004. Historically, these periods represent typical time windows in the lifetime of the FTSE100 UK stock market index. The first period is characterised by the start of the FTSE100 index and it is expected that the effect of promotions/relegations of the index is small due to the small number of index tracking funds under management. The nineties are characterised by strong bullish conditions for the stock market with an ever increasing amount of assets under management most of which are invested in tracker funds.[14] Finally after the 2000 market crash, with investors fleeing equity markets to the bond markets and the emergence of alternative investment management offered by hedge funds, it is interesting to analyse the impact these had on the promotion/relegation arbitrage opportunities.

A. Index promotions

Analysis of abnormal returns around event date:

Table 2.2 shows the results of the analysis of the share price changes for a small window around the promotion date. The first column represents the date relative to day zero, when the index change takes effect. The shaded area shows the window that is of more interest to analyse. The AAR is the cross-sectional average of

[14] See Brealey (2000).

abnormal returns of the companies in the sample at the relative date to the event. The last two columns are statistical significance tests namely the binomial nonparametric Zb test and the standard t test. As the binomial test is non-parametric it is a useful measure in conjunction with the t test since is gives an idea of the power of the abnormal return which does not depend on the size of the abnormal event and therefore filters for sample outliers.

The results show that in the early period of 1984-1989 (the FTSE100 index started January 1984) there is no apparent abnormal return on the day of the event or the previous day. However, from 1990-1994 there is a statistically significant price abnormal return of about +1.6%** on the promotion date but no negative reaction the following day.[15] In the period 1995-1999, there is a statistically significant abnormal return of 2.6%** on the event date and a negative return of –1.5%** the following day. This result is comparable with the findings in Brealey (2000) for the period March 1994 to April 1999. He found no significant abnormal return around the announcement date but found an abnormal return of +1.7%** on the promotion date and –1.1%* on the following day. The differences between the results lies in the fact that in his study Brealey (2000) defines an abnormal return by subtracting the return on the FTSE All Share for the same day while we use the single index market model. Also, the samples are slightly different as our sample consisted of 57 data points for the 1995-1999 period while Brealey used only 36 from his selection criteria for March 1994 to April 1999. However, both show similar share price behaviour around the event date. Finally, in the later period (2000-2004) the abnormal return on the event date seems to have been somewhat arbitraged away but the negative abnormal return on the following day was –1.8%** and statistically significant.

[15] * Denotes statistical significance level of 5%. ** Denotes statistical significance at 1%.

Table 2.2
Average abnormal returns across the time window around the promotion date. The table reports the average abnormal returns, AAR, aggregated across the cross-section of companies within each sample for each day within the event window. The standard deviation of the abnormal returns and t-statistics are also reported. Furthermore, non-parametric binomial Zb test is performed, which tests if the percentage of positive abnormal returns number is significantly different than 50%. Panels A, B, C and D show the results for different time periods of the promotions sample, namely 1984-1989, 1990-1994, 1995-1999, 2000-2004 respectively. N is the total number of events within each subsample. ΔT represents the date relative to the event day, t0. For example, ΔT=0 refers to the event date while ΔT=-1 refers to the previous date. * Denotes statistical significance at the 5% level. ** Denotes statistical significance at 1%.

	Panel A			**Panel B**			**Panel C**			**Panel D**		
Period:	1984-1989			1990-1994			1995-1999			2000-2004		
N	57			56			57			53		
ΔT	AAR, %	Zb	t-stat	AAR, %	Zb	t-stat	AAR, %	Zb	t-stat	AAR, %	Zb	t-stat
10	0.05	-0.66	0.31	0.06	-0.92	0.34	-0.98	-2.52	-1.89	-0.14	-0.69	-0.47
9	-0.14	-0.66	-0.84	-0.24	-0.39	-1.42	-0.96	-2.52	-2.37	0.29	0.69	1.34
8	0.12	-0.13	0.40	0.17	0.39	0.62	-0.31	-1.46	-1.03	0.40	0.69	1.06
7	-0.10	-1.99	-0.54	-0.50	-1.44	-2.64	0.27	1.99	0.71	-0.24	-1.24	-0.79
6	-0.06	-0.66	-0.30	0.15	0.39	1.14	-0.02	-1.72	-0.05	0.55	0.69	2.17
5	-0.33	-1.72	-1.84	-0.19	-1.97	-1.04	0.14	-1.99	0.41	0.40	0.41	1.57
4	-0.33*	-1.99	-2.15	-0.39*	-1.71	-1.98	-0.36	-2.78	-0.91	0.08	0.14	0.27
3	-0.17	-0.66	-0.84	-0.11	-0.13	-0.52	-1.40**	-3.31	-3.63	0.27	-0.96	0.79
2	-0.34	-2.78	-1.63	-0.73*	-2.49	-3.05	-2.02**	-4.11	-3.66	0.54	0.41	1.11
1	-0.18	-1.19	-0.97	-0.39	-1.71	-1.59	-1.54**	-2.78	-2.99	-1.81**	-4.53	-4.42
0	0.39	-1.72	1.59	1.62**	3.81	4.95	2.59**	4.64	4.05	0.78	1.51	2.20
-1	0.06	-0.40	0.40	0.58	1.18	2.75	0.18	1.99	0.27	0.17	0.14	0.47
-2	0.12	0.40	0.46	0.25	-0.13	1.40	-0.76	-3.05	-1.57	-0.31	-0.96	-1.00
-3	0.52	0.40	1.87	-0.21	-1.18	-1.32	0.30	0.93	0.80	0.10	0.96	0.36
-4	-0.08	-3.05	-0.52	-0.33*	-2.76	-2.05	-0.47	-0.40	-1.20	-0.59*	-2.34	-2.13
-5	0.39	-0.40	2.08	-0.28	-1.71	-1.48	0.04	0.93	0.11	-0.22	-0.41	-0.90
-6	0.43	1.46	2.23	0.51*	1.97	2.58	0.19	2.25	0.47	0.13	-0.14	0.30
-7	-0.31	-1.46	-1.52	0.22	0.39	1.21	0.08	-0.93	0.22	-0.47	-2.06	-1.11
-8	0.48	0.66	1.94	0.72	1.71	2.90	0.01	0.93	0.02	-0.16	0.41	-0.43
-9	-0.02	0.40	-0.11	0.40*	2.76	2.21	0.36	0.13	0.69	0.26	0.96	1.13
-10	0.02	-1.46	0.11	0.26	1.71	1.55	0.41	0.13	1.02	0.01	-0.14	0.04

The average daily abnormal returns relative to the event date are shown in graphical format in figures 2.2a) to 2.2d). They provide a visual summary of the results listed in table 2.2. The striking aspects of this analysis are the inexistence of price pressure effects around the event date in the early period of 1984-1989. As the FTSE100 index started in January 1984, it seems natural that with lower volumes of index tracking funds, there should be no noticeable price-pressure effects around the event date. With the popularity of the stock market and of index tracking funds as preferred investment vehicles in the 90s, there started to exist a noticeable abnormal positive return on the change date and the respective correction on the following day. Since 2000, the analysis suggests that there is an attempt at correction of the effect by the market. The market correction on the day t_1 is more pronounced even exceeding the positive abnormal return on the event date, which is reduced. This provides evidence consistent with the hypothesis of agents attempting to arbitrage the effect away.

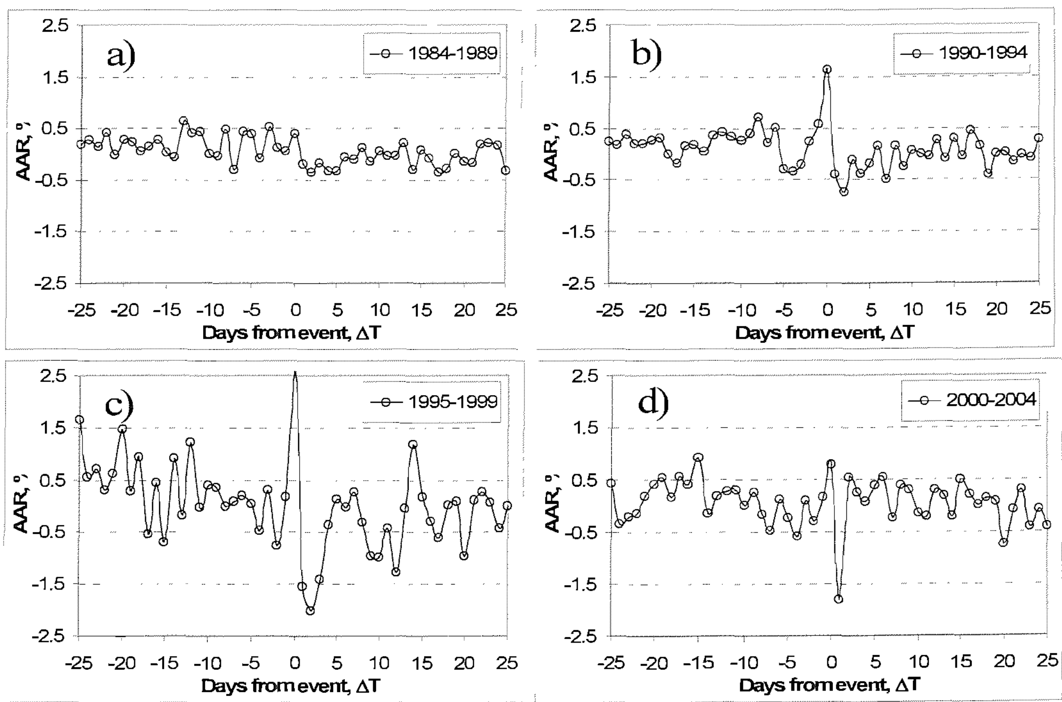


Figure 2.2: Daily average abnormal returns relatively to the FTSE100 promotion date for different time periods. a) 1984-1989; b) 1990-1994; c) 1995-1999; d) 2000-2004. ΔT refers to the date relative to the promotion day.

Next, to test for the existence of statistical arbitrage opportunities mentioned previously, we investigate the difference of abnormal returns on the day of the event and the following date. We assume that short-selling is possible and that the bid-ask spread is included in the transaction costs.

Analysis of t_1-t_0 event:

The objective of this analysis is to test whether an arbitrage opportunity exists around the date a share is included in the FTSE 100 index, and if it is still profitable once transaction costs are taken into consideration. For this test we subtract the AAR on the day of the event from the AAR on day t_1, that is, $AAR(t_0)$-$AAR(t_1)$ for the different time periods. This is equivalent to buying (or short-selling)[16] a share and short-selling (or buying) the respective offsetting position in the index, on the day t_{-1} and then, closing the positions on day t_0 by selling the share and buying the respective position in the index. Furthermore, we then analyse the strategy by assuming costs of 0%, 0.5%, and 0.75% for each leg of the strategy (which includes the bid-ask spread, information costs and stamp duty).[17] The total number of transactions is 2 (from opening a position until it is closed) and therefore the total costs for the arbitrage strategy are respectively 0%, 1% and 1.5%. We assume transaction costs in the index are negligible. To test the significance of the results we use the percentage of positive returns and the respective binomial Zb test. The results are shown on table 2.3.

[16] In general stocks large enough to be considered for entry/exit to the FTSE100 should be relatively easy to short.

[17] The justification for these transaction costs are based on typical bid-ask spreads, transaction costs and the 0.5% stamp duty on buying UK stocks. Institutional investors who are members of the London Stock Exchange have the stamp duty costs wavered. The transaction cost levels of 0%, 0.5% and 0.75% per leg of the strategy, would account for different cost levels depending of the circumstances of each investor. To implement the strategy the arbitrageur would buy the shares and sell the index on the day previous to the company promotions and invert the positions on the following day.

Table 2.3
Analysis of the FTSE100 promotions arbitrage trading strategy for different transaction costs. We consider the total transaction costs for the implementation of the arbitrage strategy of 0%, 1% and 1.5%, which correspond to panels A, B and C, respectively. These costs result from buying shares on day t-1, and short-selling on day t0. The different cost levels provide indicators to which extent arbitrage opportunities exist. * and ** denote statistical significance at 5% and 1%, respectively.

	Panel A No transaction costs			**Panel B** 1% transaction costs			**Panel C** 1.5% transaction costs		
Time period	AAR, %	% Pos	Zp	AAR, %	% Pos	Zp	AAR, %	% Pos	Zp
1984-1989	0.57	52.6	0.40	-0.42	29.8	-3.05	-0.92	22.8	-4.11
1990-1994	2.02**	75.0	3.74	1.02	62.5	1.87	0.52	50.0	0.00
1995-1999	4.13**	89.5	5.96	3.13**	82.5	4.90	2.63**	71.9	3.31
2000-2004	2.59**	83.0	4.81	1.59**	71.7	3.16	1.09*	64.2	2.06

Consistent with our previous analysis of average daily abnormal returns, during 1984-1989 there seems to be no significant effect even when transaction costs are neglected. During 1990-1994, the effect is small and only statistically significant when transaction costs are not included. In fact once transaction costs are included, the percentage of positive returns is reduced from 75% to 62.5% and finally to 50%. During 1995-1999 the results of the analysis suggest that statistical arbitrage opportunities did in fact seem to exist even when transaction costs are included as shown by the binomial Z test (statistical significance to at least 1%). The average performance from the arbitrage strategy was (4.13%, 3.13%, 2.63%) when transaction costs of (0, 1%, 1.5%) are included. More recently, during 2000-2004, the average return from the strategy was 2.59% (no costs) but when transaction costs of 1.5% were included, it reduced to 1.09% but significant only to 5% (only 64.2% positive returns).

Analysis of cumulative returns:

To investigate the market behaviour upon a share promotion to the FTSE100 index over a larger time window we aggregate the daily abnormal returns over time. The main features previous authors have observed, while researching changes to the S&P500 are the medium or long-term pre-event window, the window between the announcement date and the event date (promotion date) and the medium or long term post-event windows. The main purpose of the analysis of these time windows is to investigate: 1) if the market adjusts to the event before the announcement date, which would evidence semi-strong form of market efficiency; 2) if there is any market adjustment prior to the event date – which could be either due to the price-pressure, information, certification or liquidity hypothesis; 3) if the abnormal returns are reversed after the event date or if they are permanent – which would support the price-pressure hypothesis and provide evidence to reject the others. We therefore calculate the average cumulative abnormal returns time windows (t_{+7}- t_0), (t_{+20}- t_0), (t_{+50}- t_0), (t_{+100}- t_0) after the event date and (t_{-100}- t_0), (t_{-50}- t_0), (t_{-20}- t_0), (t_{-7}- t_0). The t test is used to test if the cumulative returns during the time period are significantly different to zero. Furthermore, we analyse the (t_{-100}- t_{+100}), (t_{-50}- t_{50}), (t_{-20}- t_{20}), (t_{-7}- t_7) time windows to investigate if there is a correction to the share price before and after the event within different windows. The t test is used again to infer if these results are significantly different than zero. If so, the price-pressure hypothesis within that particular time window will be excluded. The results of the analysis of cumulative returns over the different time windows are shown in table 2.4.

The results show that the market does in fact appear to react to information on a share promotion to the index a long time before either the event date or public announcement take place. This provides evidence of semi-strong form of market efficiency where some agents act upon information on a share promotion to the FTSE100 index approximately 3 months before the actual event takes place. This coincides with the fact that the FTSE100 constituents are re-evaluated every 3 months. Hence an explanation for the market anticipation of index changes is that once the index is rebuilt, agents start betting on the next possible candidates for promotion/relegation occurring in 3 months time.[18]

[18] Record (2004), reports that hedge funds managers have been actively trading shares within the FTSE100 reserve list with expectations of an eventual promotion.

Table 2.4

Analysis of time-aggregated cumulative abnormal returns for the FTSE100 promotions sample for different time periods within the event window. Panels A, B, C and D show the results for the time periods 1984-1989, 1990-1994, 1995-1999 and 2000-2004, respectively. The average cumulative abnormal returns (ACAR) are obtained by aggregating the average abnormal returns (AAR) across different time windows. Δ represents the different time windows investigated. For example, the period t-20:t0 investigates any market reaction pre-event while t0:t+20 investigates post-event CARs. The t-statistics of the CARs are reported in the third column of each Panel.

	Panel A			**Panel B**			**Panel C**			**Panel D**		
	1984-1989			1990-1994			1995-1999			2000-2004		
ΔT	ACAR, %	σ, %	t-stat	ACAR, %	σ, %	t-stat	ACAR, %	σ, %	t-stat	ACAR, %	σ, %	t-stat
t0 - t-100	13.64**	2.33	5.84	15.49**	1.92	8.08	35.38**	4.19	8.44	11.57**	3.38	3.43
t0 - t-70	11.95**	2.09	5.71	12.84**	1.62	7.93	26.55**	3.69	7.19	10.52**	2.69	3.92
t0 - t-50	9.18**	1.79	5.13	10.40**	1.36	7.65	19.62**	3.20	6.13	8.59**	2.22	3.87
t0 - t-20	4.48**	1.20	3.73	5.65**	0.92	6.17	6.81**	2.22	3.07	3.35	1.52	2.20
t0 - t-7	1.52*	0.60	2.53	2.36**	0.59	4.02	2.16	1.35	1.60	-0.40	0.97	-0.41
t7 - t0	-1.13*	0.56	-2.01	-0.53	0.63	-0.84	-2.33	1.29	-1.80	0.57	0.97	0.59
t20 - t0	-2.02	0.97	-2.08	0.04	0.91	0.05	-6.65**	2.05	-3.24	1.38	1.40	0.98
t50 - t0	-0.72	1.49	-0.49	-0.90	1.30	-0.70	-7.53*	2.96	-2.54	0.48	2.14	0.22
t100 - t0	-1.65	2.12	-0.78	-0.13	1.84	-0.07	-6.41	4.13	-1.55	1.04	3.31	0.31
t-7 - t+7	0.01	0.78	0.01	0.21	0.80	0.26	-2.76	1.75	-1.58	-0.62	1.32	-0.46
t-20 - t+20	2.07	1.52	1.36	4.07**	1.25	3.27	-2.44	2.95	-0.83	3.95	2.04	1.94
t-50 - t+50	8.07**	2.32	3.48	7.88**	1.85	4.26	9.50*	4.32	2.20	8.28**	3.01	2.75
t-100 - t+100	11.59**	3.14	3.69	13.74**	2.63	5.22	26.37**	5.85	4.51	11.82*	4.68	2.53

*Significant at 5%

**Significant at 1%

In summary, our findings give support to the hypothesis that shares promoted to the FTSE100 index suffer a permanent share price increase, which occurs before the promotion date as indicated in table 2.4. We also find that the abnormal share price increase is caused by information effects and not due to a permanent increase in traded volume (liquidity). This is corroborated by the analysis of the volume data (that is investigated in section C), which shows that the main source of abnormal volume occurs on the index change day and no significant abnormal volumes are found on the time window before (or after) the event or announcement date. The results show that cumulative returns after the event date tend to be negative but with low statistical significance. The exception is the 1995-1999 sample, which shows a price recovery within a 20-day window on each side of the event date providing some support for the price-pressure hypothesis during this period. This exception could possibly be explained by the huge popularity of index trackers and the booming stock market during that period[19] that exacerbated the price-pressure due to higher volumes involved. Figure 2.3 shows these results for the different time periods.

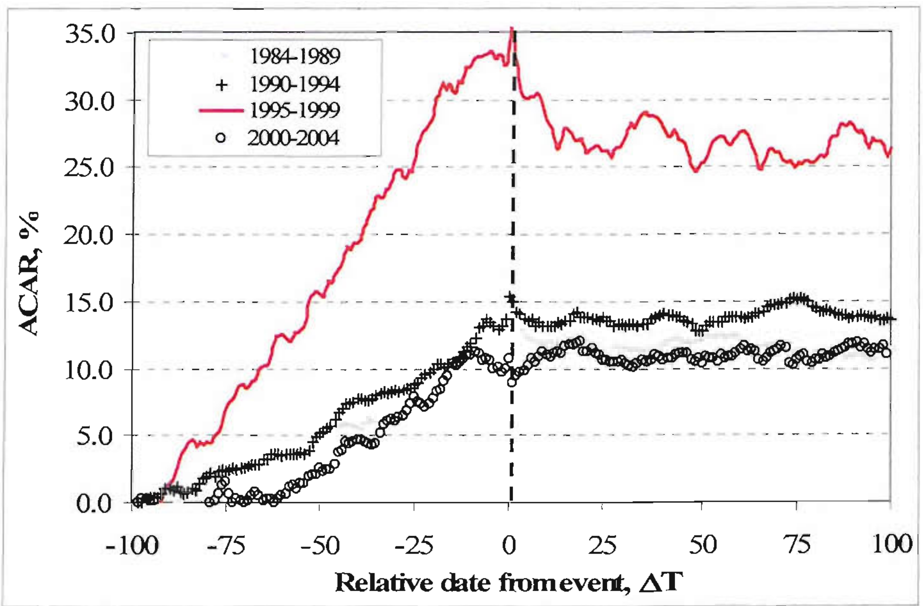


Figure 2.3: average cumulative abnormal returns for shares promoted to the FTSE100 index over different time periods. The vertical line corresponds to the reference (event) date.

[19] The FTSE100 index raised approximately 110% from the beginning of 1995 until the end of 1999.

All the time periods evidence a similar pattern supporting the hypothesis that the share price behaviour before it is included within the index and after is different. There appears to exist a permanent abnormal share price rise that is not adjusted for after the event date, which means that the effect is permanent and therefore could be explained either by the information hypothesis or certification hypothesis or liquidity hypothesis. Additionally, if we analyse the first time period (1984-1989), characterised by the FTSE100 index launch, it is noticeable from the absence of a significant effect on the index change date that this period is less prone to price pressure effects. Nevertheless, the permanent average cumulative abnormal share price increase of approximately 12% during this period evidences the positive impact of the company promotion to the FTSE100 index on its share price. The only period showing evidence of price-pressure is 1995-1999 within a ±20-day window from the index change date, although a permanent share price increase is observed for a larger window. Therefore, even though there is strong evidence for a permanent ex-post increase in share price when a company is promoted to the FTSE100, the 1995-1999 period shows a distinct behaviour with conflicting evidence: On one side there is evidence of share price recovery within a 25-day window giving support to the price-pressure hypothesis; on the other side, there is also evidence of a permanent abnormal share price rise within a larger time window, as shown in table 2.4.

B. Index relegations

Analysis of abnormal returns around event date:

The results shown in this section refer to a similar analysis than that made in section A where index promotions were investigated. Table 2.5 and figure 2.4 show the results of the analysis of the share price changes for a small time window around the index relegation date. In table 2.5, the first column represents the date relative to day zero, when the index change has taken effect. The shaded area shows the window that is of more interest to analyse. The AAR is the cross-sectional average of abnormal returns of the companies in the sample at a given date relatively to the index change. The last two columns are statistical significance tests, namely the binomial nonparametric Zb test and the standard t test.

As with the promotion sample the results from analysing the relegations sample show that in the early period of 1984-1989 there is no apparent abnormal return on the day of the event or the previous day. From 1990-1994 there is a statistically significant price abnormal return of -1.82%** on the relegation date and a positive recovery of +1.38%* on the following day.[20] In the period 1995-1999, the effect was more pronounced with a statistically significant abnormal return of -2.4%** on the event date and a positive return of +1.78%** the following day. This compares with minus 1.7%** and 1.4%** for the relegation date and following date respectively, obtained by Brealey (2000) for the time period from March 1994 to April 1999. The differences between the results lie in the method used to calculate abnormal return, the sample selection and the slightly different time period as discussed in the previous section. Finally, in the later period of 2000-2004 the abnormal return on the event date seems to have been arbitraged away both on the day of the event and the following day, where the abnormal returns have low statistical significance.

The striking aspects of this analysis are the lack of price pressure effects around the event date in the early period of 1984-1989 that, as mentioned previously when investigating the promotions sample, is related to the low index tracking volumes at the start of the FTSE100 index. With the popularity of the stock market and of index tracking funds as preferred investment vehicles in the 90s, a noticeable abnormal positive return on the change date and the respective correction on the following day emerged. Since 2000, the analysis suggests that there is an attempt at correction of the effect by the market, providing empirical evidence consistent with the hypothesis of agents attempting to arbitrage the effect away.

[20] * Denotes statistical significance level of 5%. ** Denotes statistical significance at 1%.

Table 2.5
Average abnormal returns across the time window around the relegation date. The table reports the average abnormal returns, AAR, aggregated across the cross-section of companies within each sample for each day within the event window. The standard deviation of the abnormal returns and t-statistics are also reported. Furthermore, non-parametric binomial Zb test is performed, which tests if the percentage of positive abnormal returns number is significantly different than 50%. Panels A, B, C and D show the results for different time periods of the relegations sample, namely 1984-1989, 1990-1994, 1995-1999, 2000-2004 respectively. N is the total number of events within each subsample. ΔT represents the date relative to the event day, t0. For example, ΔT=0 represents the event date while ΔT=-1 refers to the previous date. * Denotes statistical significance at the 5% level. ** Denotes statistical significance at 1%.

	Panel A			**Panel B**			**Panel C**			**Panel D**		
Period:	1984-1989			1990-1994			1995-1999			2000-2004		
N	57			56			57			53		
ΔT	AAR, %	Zb	t-stat	AAR, %	Zb	t-stat	AAR, %	Zb	t-stat	AAR, %	Zb	t-stat
10	0.62	0.13	1.94	0.85	2.10	2.11	0.46	2.07	1.31	0.62	-0.70	0.97
9	0.28	0.13	1.12	0.13	0.26	0.44	0.38	0.77	1.63	0.78	-0.14	0.87
8	0.21	2.25	0.95	-0.15	-0.79	-0.33	-0.32	0.00	-1.12	2.00	1.54	1.94
7	0.23	0.13	1.16	-0.42	-0.26	-1.31	0.41	1.03	1.58	-1.61	-0.70	-2.38
6	0.17	-0.13	0.93	0.43	1.84	1.62	0.23	1.03	1.05	-0.64	-0.70	-1.16
5	-0.02	-0.40	-0.05	0.44	1.31	1.38	0.41	2.32	1.58	-0.85	-0.98	-1.35
4	0.31	1.46	1.05	-0.29	1.05	-0.85	0.97**	3.10	2.99	-0.96	0.98	-0.99
3	-0.27	-0.13	-1.58	-0.25	2.63	-0.36	0.25	-0.77	0.88	-1.60	-1.82	-2.56
2	-0.02	-0.93	-0.14	0.88	1.05	2.09	1.18	0.52	2.82	-0.56	-0.70	-0.84
1	-0.08	0.66	-0.26	1.38*	2.89	2.53	1.78**	3.36	2.74	0.59	1.54	0.92
0	0.02	1.19	0.14	-1.82**	-3.41	-3.67	-2.40**	-3.87	-3.92	-1.16	-1.26	-1.96
-1	-0.20	-0.13	-0.87	-0.40	-0.53	-1.15	0.36	-0.26	0.81	-0.60	-1.26	-1.34
-2	0.28	0.93	1.17	0.24	-1.31	0.70	0.81	-0.77	1.71	-0.08	-0.98	-0.16
-3	-0.05	-0.13	-0.17	0.03	-0.53	0.10	0.00	-0.77	0.00	-0.37	-1.26	-0.56
-4	0.29	1.46	1.33	-0.17	0.79	-0.57	0.26	-0.77	0.71	-1.42*	-2.10	-2.45
-5	0.02	-0.40	0.10	0.19	2.89	0.55	-0.21	0.00	-0.50	0.29	0.98	0.66
-6	-0.26	-1.99	-1.22	-0.08	-0.79	-0.35	0.03	1.29	0.10	-0.61	-1.54	-1.35
-7	0.08	0.40	0.25	-0.63	-1.84	-1.36	-1.12*	-2.07	-3.32	0.54	0.42	0.85
-8	-0.84	-1.72	-1.73	0.45	-1.58	1.16	-0.79*	-2.32	-2.23	0.32	0.70	0.43
-9	-0.02	-0.13	-0.10	-0.08	-0.79	-0.31	-0.61*	-2.07	-2.05	-0.34	0.14	-0.36
-10	-0.35	-1.46	-1.81	-0.21	-2.89	-0.63	-0.23	-2.84	-0.67	1.38	1.54	1.94

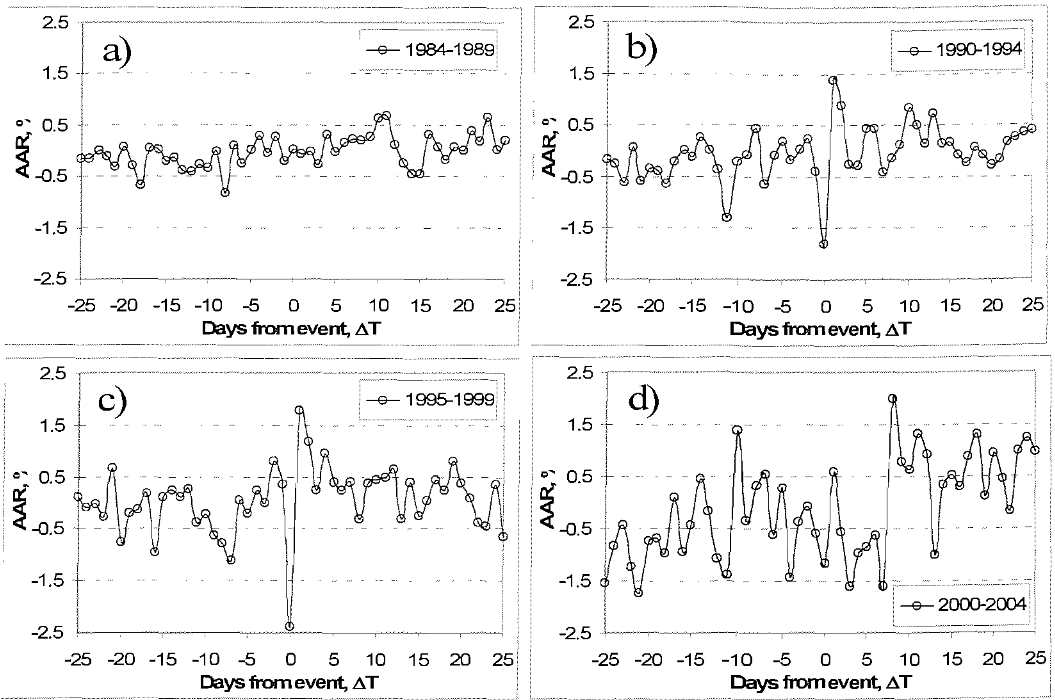


Figure 2.4: Daily average abnormal returns relatively to the FTSE100 relegation date for different time periods. a) 1984-1989; b) 1990-1994; c) 1995-1999; d) 2000-2004. ΔT refers to the date relative to the relegation day.

As with our previous analysis for the promotion sample, we test for the existence of statistical arbitrage opportunities mentioned previously by testing the difference of abnormal returns on the day of the event and the following date. We assume that short-selling is possible and that the bid-ask spread is included in the transaction costs.

Analysis of t_1-t_0 event:

This analysis tests whether there exists an arbitrage opportunity around the date a share is relegated from the FTSE 100 index, and if it is still profitable once transaction costs are included. For this purpose we subtract the AAR on the day of the event from the AAR on day t_1, this is, $AAR(t_1)-AAR(t_0)$ for the different time periods. This is equivalent to short-selling the share (and buying the index) on the day before the share is included in the index and then buying it at the end of day t_0 (and short-selling the index) and holding it until the end of that day. Furthermore, we analyse the impact of transaction costs of (0%, 0.5%, and 0.75% for each leg) on the performance of the strategy. As the total number of transaction legs is 2, from opening a position until it is closed, the total costs for each case are respectively 0%, 1% and 1.5%. The percentage of positive returns and the respective binomial Zb test are used to test the statistical significance of the results. Table 2.6 shows the results of the analysis.

Table 2.6
Analysis of the FTSE100 relegations arbitrage trading strategy for different transaction costs. We consider the total transaction costs for the implementation of the arbitrage strategy of 0%, 1% and 1.5%, which correspond to panels A, B and C, respectively. These costs result from short-selling shares on day t-1, and buying on day t0. The different cost levels provide indicators to which extent arbitrage opportunities exist. * and ** denote statistical significance at 5% and 1%, respectively.

	Panel A			**Panel B**			**Panel C**		
	No transaction costs			1% transaction costs			1.5% transaction costs		
t_1-t_0	AAR, %	% Pos	Zp	AAR, %	% Pos	Zp	AAR, %	% Pos	Zp
1984-1989	-0.10	49.1	-0.13	-1.10	26.3	-3.58	-1.60	15.8	-5.17
1990-1994	3.20**	74.1	3.68	2.20*	65.5	2.36	1.70	60.3	1.58
1995-1999	4.18**	75.0	3.87	3.18**	66.7	2.58	2.68*	63.3	2.07
2000-2004	1.75	62.7	1.82	0.75	52.9	0.42	0.25	52.9	0.42

Consistent with our previous analysis of average daily abnormal returns, during 1984-1989 there seems to be no significant effect even when transaction costs are not included. During 1990-1994, the average returns from this strategy would be 3.2% but once transaction costs of 1% are included, they are reduced to 2.2% and with a statistical significance of only 5%. With transaction costs of 1.5%, the results are no longer statistically significant, with only about 60% of positive returns being achieved. Similar results were obtained for the 1995-1999 period: the analysis suggests that 75% of statistical arbitrage opportunities only existed when transaction costs were not included. Once transaction costs were included, the statistical significance of the strategy returns was reduced to the 5% level. The average performance from the arbitrage strategy was (4.18%, 3.18%, 2.68%) when transaction costs of (0, 1%, 1.5%) are included. More recently, during 2000-2004, the average return from the strategy was 1.75% (no costs) but not statistically significant. Once costs are included the strategy becomes even less likely to yield arbitrage opportunities. This result is in line with the one obtained for the promotion sample where it appears that in recent periods, the effect has been arbitraged away to a certain extent, reflecting the efficiency of the market. In would be interesting to study if the arbitrage activity is related to the reference to literature on the subject or by the increased volume of capital allocated to hedge funds.

Analysis of cumulative returns:

As with the promotions sample, we calculate the average cumulative abnormal returns time windows (t_{+7}- t_0), (t_{+20}- t_0), (t_{+50}- t_0), (t_{+100}- t_0) after the event date and (t_{-100}- t_0), (t_{-50}- t_0), (t_{-20}- t_0), (t_{-7}- t_0). The t test is used to test if the cumulative returns during the time period are significantly different to zero. We also investigate the (t_{-100}- t_{+100}), (t_{-50}- t_{50}), (t_{-20}- t_{20}), (t_{-7}- t_7) time windows to infer if there is a permanent correction to the share price before and after the event within different windows. The t test is used to infer if these results are significantly different to zero.[21] The results of the analysis of cumulative returns over the different time windows are shown in table 2.7.

The results show that the market appears to react to share relegation from the FTSE100 index a long time before the change date or even the date when the public announcement takes place. This provides further evidence of semi-strong form market efficiency (in similarity with the results obtained previously for the promotions sample) where some agents act upon information on the reserve list 3 months prior to the actual relegation event. Our findings give support to the hypothesis that the relegation from the index does signal the market with negative information. A significant difference from the promotions sample is that the relegation sample shows stronger evidence supporting a price reversal. For example, the permanent long-term share-price decrease due to the index relegation (t_{-100}-t_{+100}) is (–7.11%*, -8.9%*, -3.8% and –21.67%*) for the respective time periods of (1984-1989, 1990-1994, 1995-1999 and 2000-2004). The cumulative abnormal returns only show significance at the 5% level, which is lower than that obtained when analysing the FTSE promotions sample. Another characteristic is the apparent price reversal for

[21] As an illustration, if the value of the t-statistic is greater than 1.96 then it would indicate a permanent wealth increase with a confidence of 95%. In such a scenario the price-pressure hypothesis can be excluded (within the particular time window).

(t_{-20}-t_{+20}) or (t_{-50}-t_{+50}) time windows in all the periods analysed except (2000-2004).[22] The increase of the effect of index relegation in the later 2000-2004 time period is also consistent with the presence of other market players such as hedge funds that act upon the information. These informed agents would sell the stock before the index change and buy it after, exacerbating the relegation effect. However, their intervention on the event date, as shown by the t_1-t_0 analysis, reduced the abnormal share price drop on the relegation date. Figure 2.5 gives a visual illustration of the cumulative abnormal returns for different time periods. The x-axis refers to the date relative to the announcement day (company relegation) while the y-axis denotes the average cumulative abnormal returns. All periods seems to exhibit a common pattern prior to relegation whereby there stock prices fall relative to the index with a small recovery post event date.

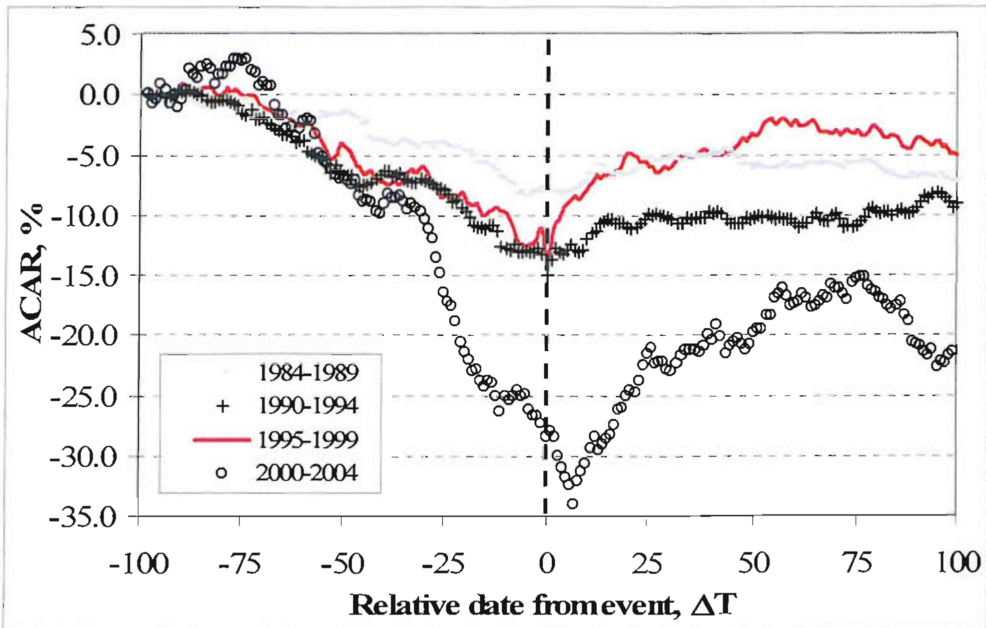


Figure 2.5: Average cumulative abnormal returns for shares relegated from the FTSE100 index over different time periods. The vertical line corresponds to the reference (event) date.

[22] Our empirical results are in-line with the findings of Chen et al. (2004). We show evidence of asymmetric share price behaviour around index constituent changes. Promoted shares are subject to a permanent share price increase while relegated shares tend to see share price reversals post event. One possible explanation could be the one proposed by Chen et al. (2004) who argue that the effect could be caused by asymmetry in investor awareness.

Table 2.7

Analysis of time-aggregated cumulative abnormal returns for the FTSE100 relegations sample for different time periods within the event window. Panels A, B, C and D show the results for the time periods 1984-1989, 1990-1994, 1995-1999 and 2000-2004, respectively. The average cumulative abnormal returns (ACAR) are obtained by aggregating the average abnormal returns (AAR) across different time windows. ΔT represents the different time windows investigated. For example, the period t-20:t0 investigates any market reaction pre-event while t0:t+20 investigates post-event CARs. The t-statistics of the CARs are reported in the third column of each Panel.

	Panel A 1984-1989			**Panel B** 1990-1994			**Panel C** 1995-1999			**Panel D** 2000-2004		
ΔT	ACAR, %	σ, %	t-stat	ACAR, %	σ, %	t-stat	ACAR, %	σ, %	t-stat	ACAR, %	σ, %	t-stat
t_0 - t_{-100}	-8.04**	2.63	-3.06	-15.00**	2.75	-5.45	-12.40**	3.23	-3.84	-28.39**	5.42	-5.24
t_0 - t_{-70}	-6.43*	2.38	-2.70	-12.97**	2.45	-5.29	-12.74**	2.82	-4.53	-29.14**	4.68	-6.22
t_0 - t_{-50}	-6.61**	2.02	-3.27	-8.64**	2.10	-4.12	-9.44**	2.41	-3.92	-21.44**	4.12	-5.20
t_0 - t_{-20}	-3.23**	1.16	-2.78	-5.62**	1.49	-3.78	-5.42**	1.63	-3.33	-7.86**	2.90	-2.71
t_0 - t_{-7}	0.20	0.68	0.29	-2.63*	1.03	-2.56	-2.27	1.20	-1.89	-3.41*	1.54	-2.21
t_7 - t_0	0.34	0.65	0.52	0.37	1.26	0.29	2.82*	1.16	2.44	-6.79**	1.93	-3.52
t_{20} - t_0	1.38	1.17	1.18	2.28	1.67	1.37	6.24**	1.63	3.82	2.24	3.38	0.66
t_{50} - t_0	2.14	1.67	1.28	2.98	2.20	1.36	7.80**	2.36	3.30	7.55	4.50	1.68
t_{100} - t_0	0.95	2.23	0.43	4.19	2.83	1.48	6.21*	3.16	1.97	5.56	6.01	0.92
t_{-7} - t_{+7}	0.51	0.93	0.55	-0.45	1.55	-0.29	2.94	1.55	1.90	-9.04**	2.40	-3.78
t_{-20} - t_{+20}	-1.87	1.64	-1.14	-1.53	2.18	-0.70	3.22	2.22	1.45	-4.46	4.41	-1.01
t_{-50} - t_{+50}	-4.48	2.62	-1.71	-3.84	3.00	-1.28	0.76	3.32	0.23	-12.74*	6.07	-2.10
t_{-100} - t_{+100}	-7.11*	3.44	-2.06	-8.90*	3.91	-2.30	-3.80	4.48	-0.85	-21.67**	8.07	-2.69

*Significant at 5%

**Significant at 1%

All the time periods seem to exhibit a share price recovery after the relegation date. However, there also exist arguments supporting a permanent abnormal share price reduction even though as we have seen in table 2.7, this reduction has low statistical significance. One particularity of figure 2.5 is the apparent continuation of the negative abnormal returns after the event date in the 2000-2004 sample peaking 7 days after the relegation date. Only then the share price starts to recover with positive abnormal returns in the next 75 days. We cannot find a convincing argument to explain this share price behaviour that is unique to this study. Another particularity observed when comparing the promotions and relegations samples results is that for the 2000-2004 time period, even though agents seem to have arbitraged some of the abnormal returns on the event date. However, when analysing the cumulative abnormal returns for the 2000-2004 period, the promotions sample shows a lower permanent share price increase when compared to previous time periods but when analysing the relegations sample, the behaviour is quite distinct showing an increase in the magnitude cumulative abnormal share price drop. This asymmetric behaviour provides support to the imperfect substitutes hypothesis (Black 1972) where agents cannot find suitable replicating portfolios to exploit the arbitrage opportunities, and consequently exacerbate the share price effect instead of reducing it.

C. Volume data

Analysis of volume data can provide some further clarification on the abnormal returns found when a share is promoted to or relegated from the FTSE100 index. Namely, the share price effects for the promotions' and relegations' samples can be tested for changes in the share liquidity both on the event date and within different post-event windows. Previous academic research on testing for the liquidity hypothesis includes Hegde and McDermott (2003) who investigate liquidity effects of share additions' to the S&P500 index. Our methodology for the analysis of the volume data is similar to that used by Chakrabarti et al. (2005) who investigated promotions and relegations of companies to/from international indices.

The methodology employed to investigate the abnormal share volume around the index change date is similar to that used previously in the analysis of abnormal returns. To measure an abnormal volume, $\varepsilon_{V,t}$, we simply compare the volume, V_t, at given day t with the average volume, $\overline{V}$, across a 100-day window (-50 days from event to +50 days after). This is,

$$\varepsilon_{V,t} = \frac{V_t - \overline{V}}{\overline{V}} \quad \text{with} \quad \overline{V} = \sum_{t=-50}^{50} V_t / N$$

While calculating the average volume, the data on the index change date is not included since it is a sample outlier that will bias the average volume upwards. Volume, V_t, is defined as the traded volume on day t divided by the market capitalization of the company on that day. Once the abnormal volumes are computed, we aggregate them across the cross-section of securities in the data sample to yield the average abnormal volume, AAV. Additionally, to investigate the temporal share volume behavior around the event date, the cumulative average abnormal volumes CAAV are calculated by aggregating the AAV across different time windows. Similarly to the abnormal returns' analysis, the non-parametric binomial Zb test and the standard parametric t test are used to make statistical inferences on the results. The results for the average abnormal volumes around the event date for both index promotions and relegations are shown in table 2.8.[23]

[23] Due to data limitations in Thomson Datastream, we only had volume data going back to 1989 and therefore could not investigate the period 1984-1989.

Table 2.8
Analysis of average abnormal volumes for the FTSE100 promotions and relegations samples across the event window. Panels A and B show the results for promotions and relegations samples, respectively. The time period in the data sample ranged from January 1989 to December 2004. The average average abnormal volumes (AAV) are obtained by aggregating abnormal volumes (AV) cross-sectionaly across the sample of securities. ΔT represents the date relative to the event date. For example, ΔT=-1 indicates the day before the event while ΔT=+1 the day after. The t-statistics are reported in the fourth column of each Panel and the non-parametric binomial Zb test is shown in the third column.

	Panel A FTSE100 promotions January 1989 - December 2004				**Panel B** FTSE100 relegations January 1989 - December 2004			
ΔT	AAV, %	% high vol	Zb	t-stat	AAV, %	% high vol	Zb	t-stat
15	29.83	42.94	-1.88	1.85	-2.53	34.13	-4.10	-0.30
14	8.28	46.93	-0.82	1.47	-5.52	33.33	-4.36	-0.91
13	7.42	42.70	-1.95	1.14	-2.89	32.16	-4.66	-0.30
12	3.19	38.89	-2.98	0.54	-9.77	35.29	-3.83	-1.76
11	-15.30	30.49	-5.00	-3.07	-20.19	22.52	-6.75	-3.40
10	0.25	36.53	-3.48	0.03	-21.99	27.22	-5.73	-3.55
9	-9.98	36.57	-3.55	-1.86	-8.09	33.73	-4.19	-1.25
8	16.28	37.71	-3.25	1.18	-6.23	30.77	-5.00	-0.73
7	-5.98	37.87	-3.15	-0.82	-18.01	28.93	-5.31	-3.19
6	-12.34	29.63	-5.19	-2.13	-5.91	28.76	-5.25	-0.76
5	27.98	39.64	-2.69	0.96	-3.38	31.06	-4.81	-0.39
4	5.79	43.02	-1.83	0.95	12.29	42.33	-1.96	1.51
3	6.72	43.10	-1.82	0.81	12.41	35.93	-3.64	1.10
2	23.48	50.00	0.00	2.83	19.47	43.60	-1.68	2.58
1	63.08**	69.23	5.19	6.64	41.12^	54.02	1.06	3.90
0	283.45**	87.93	10.01	5.55	182.49**	85.19	8.96	8.01
-1	27.93^	51.11	0.30	3.81	39.36^	52.63	0.69	3.84
-2	7.85	45.51	-1.20	1.51	21.70	48.55	-0.38	2.54
-3	9.57	41.99	-2.16	1.46	11.59	39.66	-2.73	1.67
-4	-15.69	30.41	-5.12	-3.20	-2.53	30.06	-5.09	-0.35
-5	23.48	43.86	-1.61	1.36	11.21	45.06	-1.26	1.30
-6	31.32	48.07	-0.52	2.53	6.77	40.80	-2.43	1.07
-7	8.44	45.60	-1.19	1.43	24.08	45.40	-1.21	2.93
-8	12.62	44.44	-1.49	1.84	19.41	45.98	-1.06	2.67
-9	-11.36	33.33	-4.47	-2.13	-8.75	32.76	-4.55	-1.46
-10	-4.47	30.39	-5.28	-0.59	13.42	41.95	-2.12	1.09
-11	3.56	36.11	-3.73	0.49	11.62	42.53	-1.97	1.83
-12	12.45	35.20	-3.96	1.28	13.23	38.95	-2.90	1.48
-13	-3.59	33.52	-4.37	-0.55	-1.01	34.50	-4.05	-0.16
-14	-15.49	30.71	-4.56	-2.55	-3.98	35.34	-3.38	-0.54
-15	13.34	30.00	-5.37	0.70	0.98	32.37	-4.64	0.11

**Statistically significant at 1%
^Statistical significance using parametric t test but does not hold with binomial Z_b test

The main characteristic evidenced by these results is the high abnormal volume on the event date. For the promotions sample the average abnormal volume was 283% with Zb=10.0 of positive abnormal volumes across the sample, while for the relegations sample the average abnormal volume was 182% (Zb=8.0). A noticeable aspect of these results is the low significance in both t statistics and Zb of any abnormal volume around the announcement date (t_{-7}, t_{-8}). This can be explained if the market already knows this information beforehand, which is consistent with our previous findings (in section A) when analysing the abnormal share returns. Investors seem to have already assimilated the public information on the FTSE reserve list by tracking the respective company behaviour over time. Figures 2.6a) and 2.6b) show the binomial Zb statistics for different dates relative to the index change for the promotions' sample and relegations' sample, respectively. These figures illustrate that only the days around the index change date present abnormal volume with statistical significance.

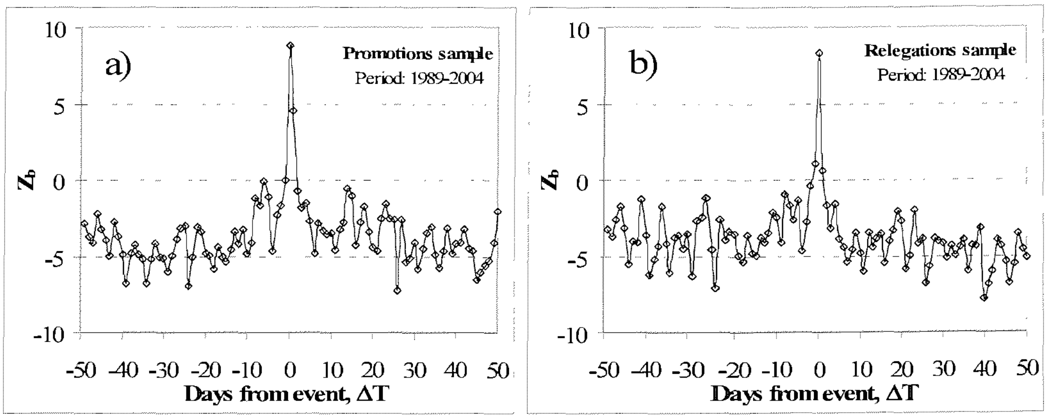


Figure 2.6: Binomial Zb test for abnormal volume across the sample time window. a) Promotions data sample from 1989 to 2004. b) Relegations data sample from 1989 to 2004.

Cumulative abnormal volumes:

In this section, the cumulative abnormal volumes are examined for different windows before and after the event date, as in Chakrabarti et al. (2005). This analysis is aimed at investigating if the abnormal share volume over a time window is consistent with the share return behaviour for index promotions or relegations. With this information we can test whether the cumulative share returns are price-pressure induced by higher volumes or alternatively "information" based. We can also test if the permanent share price change is met with a respective permanent rise in average share volume when a share is promoted to the FTSE100 index. We examine the time windows (t_{-50} : t_{-1}), (t_{-25} : t_{-1}), and (t_{-10} : t_{-1}) before the event date and (t_{+1} : t_{+10}), (t_{+1} :

t_{+25}) and (t_{+1} : t_{+50}) after the event date to study if the cumulative abnormal volumes are higher before or after the event and within which time window. Table 2.9 shows the daily average of the cumulative abnormal volumes within each window.

Table 2.9

Analysis of time-aggregated cumulative abnormal volumes for the FTSE100 promotions/relegations samples. Panels A and B show the results for the promotions and relegations samples, respectively. The average cumulative abnormal volumes (ACAV) are obtained by aggregating the average abnormal volumes (AAV) across different time windows. ΔT represents the different time windows investigated. For example, the period t-20:t0 investigates any market reaction pre-event while t0:t+20 investigates post-event ACAVs.

	Panel A	**Panel B**
	FTSE100 Promotions	FTSE100 Relegations
ΔT	ACAV, % (daily)	ACAV, % (daily)
(t_{-50} - t_{-1})	0.04	3.91
(t_{-25} - t_{-1})	2.04	5.50
(t_{-10} - t_{-1})	8.95	13.66
(t_{+1} - t_{+10})	13.08	4.42
(t_{+1} - t_{+25})	9.39	4.39
(t_{+1} - t_{+50})	-0.12	-4.12
(t_{-50} - t_{-10})	-2.25	1.82
(t_{+10} - t_{+50})	-3.38	-6.74
(t_{-10} - t_{+10})[+]	11.01	9.04

[+] Excludes event date, t_0

By comparing the time windows (t_{-10} - t_{+10}) with (t_{-50} - t_{-10}) and (t_{+10}-t_{+50}) it is apparent that the average daily abnormal share volume is significantly higher during the 10 trading days preceding the index change date to 10 days after, for both the promotions and relegations samples. Therefore, if the market is not perfectly elastic, price-pressure effects due to abnormal trading volumes should be more noticeable during this time window.

The results in table 2.9 also show that there is no evidence to support the hypothesis that there is a permanent increase in traded volume before and after the promotion of a share to the FTSE100 index. Hence, the results suggest that the permanent share price increase we previously observed is information related and not due to abnormal traded volumes post-event. These results support the information or certification hypothesis but provide evidence that contradict with the liquidity hypothesis. In fact, if increased liquidity is associated with increased volume, then our data finds evidence to reject it. However, with the data we have, we cannot reject the liquidity hypothesis because the bid-ask spread might be reduced due to information bias of belonging to the FTSE100 index. Additionally, evidence from table 2.9, shows that the relegation of a share from the FTSE100 index appears to lead to lower traded volumes. The average daily abnormal volume within the (t_{-50}-t_{-1}) window was +3.91% while for the post-relegation time window (t_{+1}-t_{+50}) it was –4.12%. As we have previously shown when investigating the abnormal share returns, there is no strong evidence for a permanent share price reduction after its relegation from the FTSE100 index. We conclude that the reduction in traded volume does not lead to a permanent decrease in share price.

Abnormal volumes for different time periods:

The average share volume behavior around the event date has been investigated for the whole data sample. We have observed that the most significant source of abnormal volume is on the index change date. To support our hypothesis that tracker funds' or other agents volumes have increased since 1984 we now investigate how the average abnormal volume on this date changes through time. We find that the AAV for 1990-1994 is about 85%-90% for both the promotions and relegations samples with the binomial Zb test showing statistical significance at the 5% level at least. The results of the study are shown in table 2.10. When comparing it with 1995-1999 however, we find that the abnormal volume increased to 398% for index promotions and 237% for index relegations, indicating a significantly higher volume of index rebalancing. An intriguing point is the higher abnormal volume when a share is promoted to the index than when it is relegated. Perhaps this could be explained by the high abnormal volume accruing before the share is relegated from the index (t_{-50}-t_{-1}), which means that index trackers or other investors are already acting upon possible future entrants or exists from the FTSE100. Finally, for 2000-2004, the average abnormal volumes continued to be high (313% for promotions and 201% for relegations) and with strong statistical significance.

Table 2.10
Abnormal volumes on the FTSE100 index change date for different time periods. Panels A and B show the results for the promotions and relegations samples, respectively. The table shows the average abnormal volume (AAV) across the sample of securities, on the event date, t0. The percentage of positive abnormal volumes on the event date is also shown, in conjunction with the respective non-parametric binomial Zb test. The last column shows the standard t-statistic.

	Panel A				**Panel B**			
	FTSE 100 promotions				FTSE 100 relegations			
Period	AAV, %	% pos	Zb	t-stat	AAV, %	% pos	Zb	t-stat
1990-1994	88.97	75.56	3.43	3.78	85.59	66.67	2.24	3.59
1995-1999	397.61	81.36	4.82	2.95	236.84	89.09	5.80	4.91
2000-2004	312.53	94.20	7.34	5.66	200.66	90.16	6.27	5.36

D. Extreme events

Singular events such as the promotion or relegation of a share from an index or other events that have an information impact on the share are likely to have a return that breaks the normal market model correlation, this is, the return on the event date might be uncorrelated with the share β. To test this hypothesis we compare the magnitude of the abnormal return on a given day with a measure of the historic abnormal return dispersion (standard deviation or 50% point). We then count the number of "extreme" occurrences and compare it with the theoretical probability of occurrence using the nonparametric binomial Zb test. As a definition of extreme returns we use three different methodologies in order to obtain a more robust analysis namely, the 50% point (x_{50}), one standard deviation (x_{σ}) and two standard deviations ($x_{2\sigma}$) of the distribution of abnormal share returns.[24]

We start by calculating the abnormal daily returns in a similar manner as in section B, based on 200 daily returns and daily return on the FTSE all-share (100 trading days before and after the event). The abnormal return distribution parameters are then calculated using these 200 data points (including the abnormal return on the event date). It should be noted that the calculated sample standard deviation, which includes the event date, biases the standard deviation upwards overstating the

[24] Similar definitions for extreme events are used in Pritmani and Singal (2001) who investigate share price predictability following extreme share price movements. Other authors such as Cox and Peterson (1994) use absolute returns instead of relative returns as a definition of an extreme event (such as a 10% jump in share price). We believe the first definition is the appropriate one as it is measured relative to the volatility of each individual stock.

volatility. Even though the expected abnormal returns across the time window should be zero, when comparing the abnormal return on a given day with the sample standard deviation, we adjust it for any constant bias by subtracting the average abnormal return. Finally, to test if there is consistently an extreme return during the event window, we compare the share dispersion for the number of companies in the data sample. An extreme event occurs when $\left|AR_{i,t} - \overline{AR}_{i,t=[-100:+100]}\right| > x_{50,\sigma,2\sigma}$ and the count of extreme events (EXTREMES) across the sample cross-section for a given day with the event window is given by:

$$EXTREMES = \sum_i a \qquad \text{where} \qquad a = \begin{cases} 1 & \text{if}\left(\left|AR_{i,t} - \overline{AR}_{i,t=[-100:+100]}\right| > x_{50,\sigma,2\sigma}\right) \\ 0 & \text{if}\left(\left|AR_{i,t} - \overline{AR}_{i,t=[-100:+100]}\right| \leq x_{50,\sigma,2\sigma}\right) \end{cases}$$

Three measures of dispersion are used: 50% point of the normal distribution (x_{50}), one standard deviation point ($P(x_\sigma)=68.3\%$) and two standard deviations ($P(x_{2\sigma})=95.4\%$). To test the significance of each of the measures for extreme events, the binomial Zb test is used with p=0.5, (1-0.683) and (1-0.954), respectively:

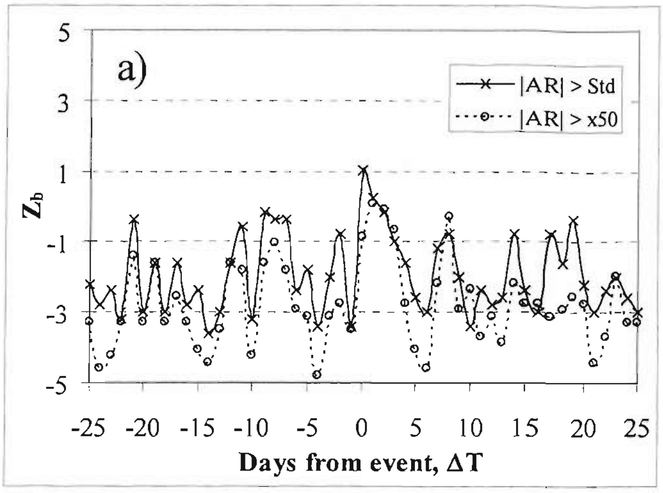
$$Z_b = \frac{(EXTREMES / N - p)}{[p(1-p)/N]^{1/2}}$$

The results of the analysis of extreme returns for the promotions sample are shown in table 2.11. The data sample was split into two time periods in similarity with the analysis of abnormal volume on the event date. The first time period, 1984-1994 is characterised by lower abnormal transaction volumes while the more recent time period 1995-2004 had by higher abnormal volumes on the date the FTSE100 index change is effective. In tables 2.11 and 2.12, p refers to the theoretical probability of occurrence of an extreme abnormal return above the respective distribution point x_{50}, x_σ or $x_{2\sigma}$. The table shows the percentage of extreme returns (% Ext) and respective binomial Zb test, for different dates relative to the event date. The different distribution points are used in order to capture extreme returns at different threshold levels, which provide a better understanding of the nature of these extremes. It should be noted, however, that since the data samples are approximately N=110, and the theoretical probability of an extreme abnormal return above 2σ is only 4.55%, corresponding to a total number of events of only 5, the power of this test may be questionable.

The results in table 2.11 provide evidence that the promotion of a company to the FTSE100 index is likely to be an extreme event during the event window, this is, the abnormal return around the event date lies in the tails of the probability distribution. Table 2.11 also shows that the extreme abnormal returns are more significant for the 1995-2004 time period that for the earlier 1984-1994 time period. The exception is the percentage of extreme abnormal returns during 1984-1994 above x=2σ on the event date, t_0, which is 17.7%. The x=50% point is has lower significance in terms of identifying extreme events because is lies much closer to the centre of the probability distribution, this is the impact of extremes on the 50% point of the distribution will be quite low. As we mentioned previously, x=2σ has a very low probability and therefore for our sample size the test may not be significant, this is, the results may simply be spurious. We believe x=σ is the best measure of an extreme event for the size of our sample because is a trade off between probability of occurrence and the sensitivity of the probability distribution to a change in σ. Figure 2.7 shows the binomial Zb test for extreme events across the time window under study.

Table 2.11
Analysis of extreme abnormal returns for companies promoted to the FTSE100 index. Panel A corresponds to events occurring within the time period 1995-2004 while Panel refers to the 1984-1994 time period. The analysis of extreme events consists in measuring the probability of an abnormal return with magnitude greater than a given measure of dispersion (% Ext). Three measures of dispersion are used: the 50% points of the distribution (|AR|>x_{50}), one standard deviation (|AR|>σ) and two standard deviations (|AR|>2σ). p refer to the theoretical probabilities of occurrence. ΔT is the date relative to the event day. The binomial Zb test is included to test for the significance of the results.

	Panel A Time period: 1995-2004 Sample size: N=110						Panel B Time period: 1984-1994 Sample size: N=113					
	x=50%		x=σ		x=2σ		x=50%		x=σ		x=2σ	
Theoretical	p=50%		p=31.73%		p=4.55%		p=50%		p=31.73%		p=4.55%	
ΔT	% Ext	Zb	% Ext	Zb	% Ext	Zb	% Ext	Zb	% Ext	Zb	% Ext	Zb
5	33.64	-3.43	18.18	-3.05	3.64	-0.46	30.97	-4.05	20.35	-2.60	3.54	-0.52
4	36.36	-2.86	23.64	-1.82	2.73	-0.92	37.17	-2.73	24.78	-1.59	4.42	-0.06
3	41.82	-1.72	28.18	-0.80	6.36	0.91	46.90	-0.66	27.43	-0.98	6.19	0.84
2	40.00	-2.10	30.00	-0.39	10.91	3.20	49.56	-0.09	30.97	-0.17	8.85	2.19
1	65.45	3.24	50.91	4.32	11.82	3.66	50.44	0.09	32.74	0.23	9.73	2.64
0	53.64	0.76	43.64	2.68	9.09	2.29	46.02	-0.85	36.28	1.04	17.70	6.71
-1	55.45	1.14	40.91	2.07	14.55	5.03	33.63	-3.48	16.81	-3.41	6.19	0.84
-2	49.09	-0.19	31.82	0.02	7.27	1.37	37.17	-2.73	28.32	-0.78	6.19	0.84
-3	38.18	-2.48	22.73	-2.03	3.64	-0.46	35.40	-3.10	23.01	-1.99	7.08	1.29
-4	45.45	-0.95	29.09	-0.59	4.55	0.00	27.43	-4.80	16.81	-3.41	1.77	-1.42
-5	35.45	-3.05	20.00	-2.64	1.82	-1.37	35.40	-3.10	23.89	-1.79	4.42	-0.06



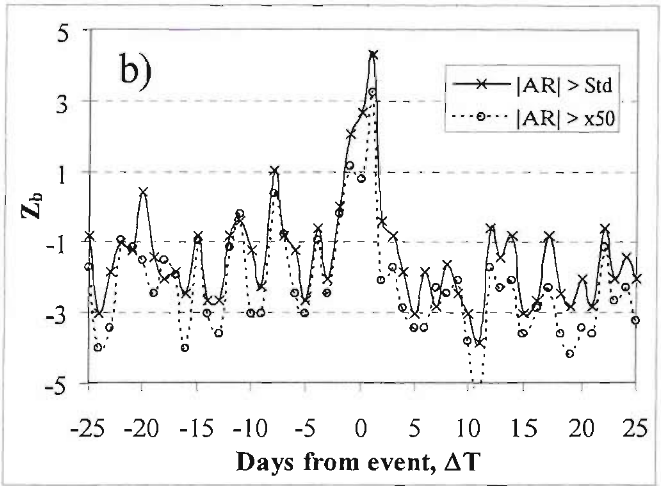


Figure 2.7: Binomial Zb test for extreme abnormal returns on the event date for shares promoted to the FTSE100 index. a) refers to the 1984-1994 time period. b) refers to the 1995-2004 time period. The binomial Zb test was performed for different measures of dispersion, namely one standard deviation (σ) and the 50% points of the distribution (x50).

It can clearly be observed that there is evidence for extreme abnormal returns around the event date for the 1995-2004 period. We believe that the difference from the 1984-1994 period is associated with higher abnormal volumes in the later period, as we investigated previously in section C. Next, the relegations sample is analysed. Table 2.12 shows the results for the analysis of extreme abnormal returns around the relegation date for two different time periods.

Table 2.12

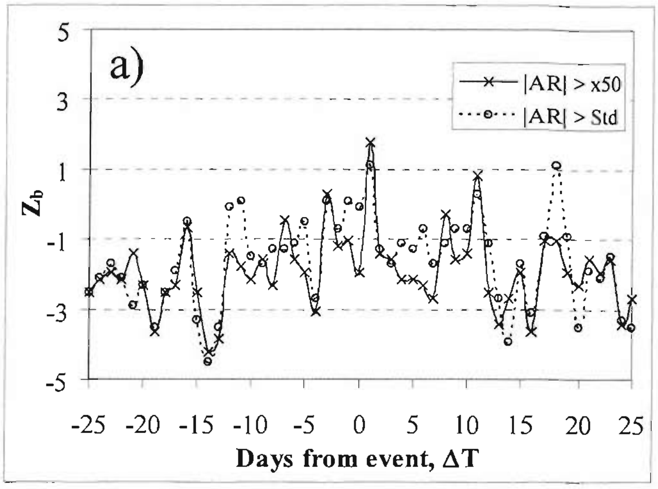
Analysis of extreme abnormal returns for companies relegated from the FTSE100 index. Panel A corresponds to events occurring within the time period 1995-2004 while Panel refers to the 1984-1994 time period. The analysis of extreme events consists in measuring the probability of an abnormal return with magnitude greater than a given measure of dispersion (% Ext). Three measures of dispersion are used: the 50% points of the distribution (|AR|>x50), one standard deviation (|AR|>σ) and two standard deviations (|AR|>2σ). p refer to the theoretical probabilities of occurrence. ΔT is the date relative to the event day. The binomial Zb test is included to test for the significance of the results.

	Panel A Time period: 1995-2004 Sample size: N=111						Panel B Time period: 1984-1994 Sample size: N=115					
	x=50%		x=σ		x=2σ		x=50%		x=σ		x=2σ	
Theoretical	p=50%		p=31.73%		p=4.55%		p=50%		p=31.73%		p=4.55%	
ΔT	% Ext	Z_b	% Ext	Z_b	% Ext	Z_b	% Ext	Z_b	% Ext	Z_b	% Ext	Z_b
5	39.64	-2.18	24.32	-1.68	6.31	0.89	40.00	-2.14	26.09	-1.30	4.35	-0.10
4	54.95	1.04	27.03	-1.06	9.01	2.25	40.00	-2.14	26.96	-1.10	8.70	2.13
3	40.54	-1.99	30.63	-0.25	7.21	1.34	42.61	-1.59	24.35	-1.70	4.35	-0.10
2	44.14	-1.23	32.43	0.16	9.91	2.71	43.48	-1.40	26.09	-1.30	7.83	1.69
1	53.15	0.66	45.95	3.22	13.51	4.53	58.26	1.77	36.52	1.10	15.65	5.71
0	61.26	2.37	45.05	3.01	17.12	6.35	40.87	-1.96	31.30	-0.10	12.17	3.92
-1	42.34	-1.61	27.93	-0.86	5.41	0.43	45.22	-1.03	32.17	0.10	7.83	1.69
-2	46.85	-0.66	29.73	-0.45	10.81	3.17	44.35	-1.21	28.70	-0.70	6.96	1.24
-3	38.74	-2.37	27.03	-1.06	6.31	0.89	51.30	0.28	32.17	0.10	9.57	2.58
-4	44.14	-1.23	30.63	-0.25	8.11	1.80	35.65	-3.08	20.00	-2.70	5.22	0.34
-5	45.95	-0.85	27.03	-1.06	6.31	0.89	40.87	-1.96	29.57	-0.50	7.83	1.69

These results show evidence that the relegation of a company from the FTSE100 index is likely to be an extreme occurrence within the event window, similar to a company promotion to the index. They also show that extreme abnormal returns are more significant for the later 1995-2004 time period than for the earlier period of 1984-1994. On the event date for the 1995-2004 period, the binomial Zb test for the absolute abnormal returns above x_{50} is 2.37^{*} while above x_{σ} it is 3.01^{**} and for $x_{2\sigma}$ it is 6.35^{**} which provides statistical evidence supporting that, on the relegation date, the correlation between the market index and the company returns might be broken.[25] As this effect is not so noticeable within the 1984-1994 period, we believe that the main cause of correlation breakage is the extreme abnormal volume on the relegation date, which is exacerbated in the later 1995-2004 period. Table 2.12 also shows that on day t_1 there is also evidence of extreme abnormal returns that is also expected due to the typical positive share price reaction on the day following the share relegation (as we have observed in section B). Figure 2.8 shows the binomial Zb test for extreme abnormal returns across the time window under study, for the relegations sample.

As with the promotions sample, when examining the relegations sample it can clearly be observed that there is evidence for extreme abnormal returns around the event date for the 1995-2004 period. There is no evidence of extreme events elsewhere within the event window, as for example the announcement date, which is consistent with our findings when examining abnormal returns for both FTSE100 relegations and promotions. The promotion or relegation of a company to/from the FTSE100 index is likely to be an extreme event in the life of that company, where the share return on the index change date might break the usual correlation with the market index. In absolute terms the magnitude of the share return is also likely to fall in the tails of the share return distribution. This raises the question of whether other event studies might bring some insight to the sources of the characteristic leptokurtosis in the return probability distribution. By relating these results with the study of abnormal volume around the event date, we also conclude that these extreme returns are associated with higher traded volumes instead of a fundamental change in the asset value due to new information.

[25] * and ** refer to 5% and 1% significance levels, respectively.



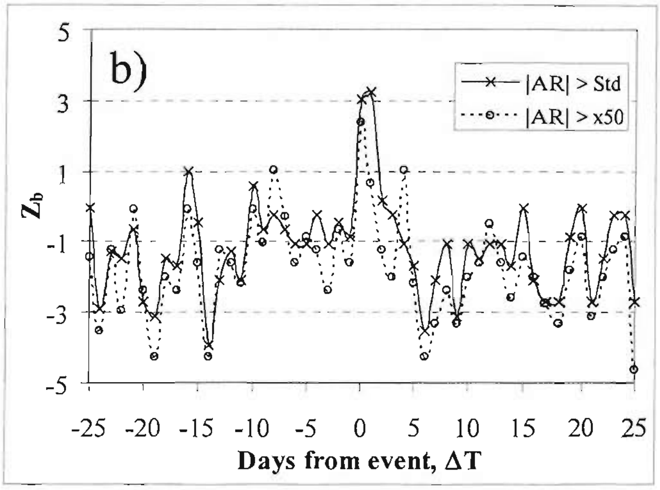


Figure 2.8: Binomial Zb test for extreme abnormal returns on the event date for shares relegated from the FTSE100 index. a) refers to the 1984-1994 time period. b) refers to the 1995-2004 time period. The binomial Zb test was performed for different measures of dispersion, namely one standard deviation (σ) and the 50% points of the distribution (x50).

6. Reconciliation of the evidence with the various hypotheses

Price pressure:

Our study does not eliminate the price pressure hypothesis. Both promotions and relegations samples show evidence of price-pressure for shorter time windows (t_{-20} : t_{20}) and for different time periods. However, empirical evidence in general supports a permanent share price change associated with index promotions/relegations when analysing larger time windows (t_{-100} : t_{100}). When analysing volume data, it is observed that closer to the event date average daily trading volumes are higher, which provides further evidence of price-pressure for shorter time windows.

Imperfect substitutes:

Our study shows evidence of the effect of arbitrageurs acting upon the index change event. If the later time period of 2000-2004 is characterised by higher arbitraging activity, it's effect on the share price behaviour around FTSE100 relegations and promotions seems to enhance their asymmetric nature (as illustrated by figure 2.3 and figure 2.5). This may indicate the existence of imperfect substitutes and therefore in the case of index promotions, the effect is reduced while in the case of index relegations, it is exacerbated. It could be argued that to counteract the share price increase before a share is promoted to the FTSE100, arbitrageurs would start to adjust its price beforehand, eventually making the effect disappear. However in the case of relegations, this behaviour would indeed exacerbate the share decline as arbitrageurs would start selling the share before the relegation date. This situation is clearly observed in figure 2, which provides evidence for the imperfect substitute hypothesis for relegated shares; that is, it shows that the impact of increased arbitrage volume on the anomalous share price behaviour is exacerbated and not eliminated.

Certification and Information:

Our analysis cannot distinguish between these two hypotheses, as the one performed by Denis et al. (2003) who investigate future EPS of companies promoted to the S&P500. Our results do support the existence of a permanent share price increase/decrease when investigating larger time windows (t_{-100} : t_{100}) for index promotions/relegations. For promotions we also show that the increase is not associated with higher abnormal volumes but instead, it is information related and that it starts about 65 trading days before the announcement date based on public information on the index reserve list. For index relegations the price adjustment also appears to begin 65 trading days before the announcement date but contrary to the case of index promotions, it is associated with lower traded volumes post-event. In this case it is inconclusive if the share price decrease is volume related or due to the information hypothesis.

Liquidity:

We find no evidence of a permanent increase in traded volume associated with a share promotion to the FTSE100 index but we do find some evidence supporting decreased trading volumes associated with share relegation. This test however does not eliminate the liquidity hypothesis as increased share liquidity may be information-related and the Amihud et al. (1997) methodology should be used to test this hypothesis.

7. Conclusions

Empirical evidence from this study shows that promotion or relegation of a company to/from the FTSE 100 index is a special event in the lifetime of a company. We show that in the past simple trading strategies of buying/selling a company that was promoted/relegated from the index on the day before the index change took place and then inverting the positions on the following date would yield positive abnormal returns. These profit opportunities appear to have been noticed by agents who arbitraged the effect away (at least partially), as shown by Record (2004). This evidence is consistent with the growth of hedge funds and the decline in popularity of index tracking funds after the stock market crash of 2000, which altered the nature of the agents acting upon the FTSE 100 index changes. This can be interpreted as evidence for market efficiency, by showing the way the stock market assimilates known anomalies and adjusts for them over time. Our results show that the learning process is quite slow, and not immediate as would be expected in highly efficient stock markets. Finally, contrary to other studies performed on the S&P 500; Jain (1987), Dhillon and Johnson (1991), Lynch and Mendenhall (1997), we do not find any significant abnormal returns or volumes around the announcement date for both the cases when a share is promoted to or relegated from the FTSE100 index. Our findings are consistent with the Brealey (2000) study of promotions/deletions from the FTSE100 for the time period from March 1994 to June 1999. For the FTSE100 it seems that investors have already assimilated the information of a share being promoted or relegated from the index before the announcement date.

When investigating cumulative abnormal returns our findings are mixed. On the one hand, there seems to be asymmetric share price behaviour when comparing index promotions with index relegations, which is in agreement with the findings in Chen et al. (2004). Empirical evidence for the promotion of a company to the FTSE 100 is associated with a permanent rise in the share price when looking at a longer ($t_{-50} : t_{50}$) time window.[26] On the other hand, our results are not conclusive of a permanent share price decrease when a share is relegated from the index. Instead, we find some support for a permanent share price change depending on the time period analysed, and some support for the price pressure hypothesis within shorter event windows ($t_{-20} : t_{20}$). Furthermore, from investigating the volume data we conclude that this behaviour is not supported by higher/lower trading volumes but instead, it is likely to be information-related. Our findings show that when a company is promoted to the FTSE100 it experiences similar average daily volume on the 50 trading days preceding the event date and after the event date, and therefore, there is no evidence for a permanent increase in the share liquidity in terms of volume. When a company is relegated from the index, there is evidence of a decrease in liquidity by lower average daily traded volumes post-event. Additionally, we also find that the pre-event share price increase/reduction when a company is promoted/relegated has its origin approximately 60-70 trading days from the event date suggesting semi-strong form market efficiency. However, it should be noted that public information on reserve lists for the FTSE100 are published on the announcement date for index changes, which occurs quarterly; this is approximately every 65 trading days.

[26] It should be noted that it is not trivial to establish causality between share promotion to an index and the permanent wealth increase. It is also plausible to consider that a permanent share price increase would lead to a company's promotion to the FTSE100. However, our empirical data favours the first relationship. The reason is that if a given share is experiencing a period of positive abnormal returns, then there is no reason these abnormal returns should stop once the company is promoted to the FTSE100. It is more plausible that the effect of information of the promotion of the company to the index leads to a period of abnormal returns pre-promotion and no abnormal returns post-event, as shown by our results.

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Chapter III

"Interim and final results announcements: Sources of extreme events."

Abstract: In this chapter I investigate the abnormal share return dispersion occurring when companies announce their interim or final earnings. I find strong evidence supporting that on the event date, there is an abnormal dispersion of share returns and that those public announcements are sources for extreme events. This study therefore offers a step forward in identifying sources for the leptokurtosis found traditionally in time series stock market returns. The data sample is comprised of interim and full year results for mid to large capitalisation UK companies. In similarity with the extensive literature published on this subject, I find no evidence of market inefficiency around the event date, or straightforward arbitrage opportunities on the event date. However, information of the abnormal dispersion found on the event date could be of great importance to risk managers as it can be used to provide them with an early warning on possible extreme events.

1. Introduction

Traditionally, financial markets practitioners assume that share returns follow a random walk with a noise term with a given probability distribution. Most stochastic processes assume a Gaussian distribution for the noise term but empirical evidence within the academic literature suggests that this might be misleading. There is extensive evidence of leptokurtosis in the distribution of share (or index) returns, which means that the probability of share returns lying in the tails of the distribution have a higher weight than the one predicted by the normal distribution. Mandlebrot proposes a stable Paretian hypothesis for stock market returns instead of the traditional normal distribution, (see Mandlebrot 1963, Fama 1963 and Fama 1965). Fama tests his model (Fama 1965) and finds that in fact the stable Pareto distribution with $\alpha<2$ provides a better fit than the Gaussian distribution for most the companies in his study. If indeed the market returns are Paretian then large price jumps can occur frequently and in these occasions, the variance can tend towards infinity (there is a discontinuity) meaning that the variance may be an inadequate measure of dispersion.

Since Mandlebrot (1963) and Fama (1965) seminal papers, many authors have been dedicated to fitting different distributions to different stock market time series. Praetz (1972) and Kon (1984) and Longin (1996) use different large-tail distributions to fit the stock market data while more recently Longin (2005) uses extreme value theory[1]. These papers are quite sophisticated and find good fits for the share price distributions of their samples but do not search for the nature of the extended tails. Jondeau and Rockinger (2003) investigates the differences in left and right tails using tails index estimates for a stock market data sample across several countries. He finds no significant difference between left and right tails. Gettinby et al. (2004) analyse the extreme return distribution in the UK stock market from 1975 to 2000 by using a number of distributions namely, Gumbel, Frechet, Weibull, Generalised Pareto and Generalised Extreme Value, to fit the empirical data. Even though they manage to fit each distribution to the actual share-return distributions successfully; they do not investigate the sources of the extreme events.

[1] Also see Jansen and de Vries (1991) and for an excellent review see Mandelbrot (2001).

Recently, Ryan and Taffler (2004) investigated the effect of firm specific news on the share price. Their study is a comprehensive analysis of the impact of different information releases on the companies' share price and abnormal traded volume. They begin by calculating the frequency of occurrence of a large price change due to each event and then they measure the magnitude of those events. Their sample consists of all the extreme events for a sample of around 215 UK firms from 1/1/1994 to 31/12/1995. The definition they use for an extreme event is an abnormal return with magnitude larger than twice the standard deviation for that firm. They find that around 65% of the extreme returns occur on public information releases and therefore are a main driving force for price changes.

In this chapter we provide further insight into the nature of these discontinuities, which we will call extreme events throughout this chapter. It is plausible that a general model for share returns could be based on information releases, which have more or less impact on the share price. High impact events are less common but yield extreme returns while the rest of the "low impact" information will provide a normal background noise. In this case it might be possible that the high impact events are responsible for most of the extreme events. We test this hypothesis in this chapter by analysing a sample of interim and final results announcements by UK mid-large capitalisation companies. We use an event study methodology to compute abnormal returns in order to isolate the event specific effect. We find that even though there is no significant change in the share price on the event date neither a significant pattern for the cumulative abnormal returns pre and post event, the event date is a high impact event in the lifetime of the company, that is, it is an extreme event. This finding could go towards explaining the nature of the Pareto distribution that appears in stock market returns. Such events might be sources of discontinuity due to high impact information releases as the interim and final results announcements investigated in this study.

This chapter makes a number of contributions to the literature: First, our work differs from the analysis of Ryan and Taffler (2004) as we investigate the share price behaviour around interim and final results announcements in greater detail. While they select a sample of extreme events and analyse the informational releases responsible for such events, we investigate a large data sample concerning one specific event (interim and final results announcements). We then use different dispersion measures to define an extreme event occurrence and show evidence for an increased abnormal return dispersion on the event date. Additionally, we use a larger sample size and perform robustness tests across different samples as well as through several time periods. Our results show that around 36% probability of occurrence of an extreme abnormal return, with magnitude greater than 2σ, on the event date, when compared with a theoretical value of 4.8% that is observed across the remaining of the event window. These results show higher impact than the 17% found by Ryan and Taffler (2004) for interim and preliminary company results. We also find that the average jump in the dispersion of abnormal returns on the event date is 2.3 times (this is, a 130% increase), which represents a substantial increase.

Second, we extend our analysis to the cumulative abnormal returns conditional upon an extreme event on the announcement date by investigating the share price ex-post behaviour after an extreme occurrence. Similar studies have been presented in the literature: Cox and Peterson (1994) study stock returns following one-day 10% or more price declines and find evidence of price reversal on the three days following the event. However they find no evidence of a negative correlation between the abnormal returns on the decline date and subsequent three-day returns, which is inconsistent with market overreaction. They also find that the bid-ask bounce accounts for a large part of the price reversal. One of the problems of their study is the definition of extreme event as an absolute value of a 10% drop, while a more realistic measure should take into account the firm volatility (which would reduce the size effect). In our analysis the extreme event is defined as an abnormal return that is n times larger than the company standard deviation across the event window. Bremer and Sweeney (1991) investigate the share price reversal after large 10-day decreases and find that the reversal lasts for a period of 2 days only. More recently, Pritmani and Singal (2001) investigated the return predictability following large price changes and information releases. They find that large price changes accompanied by a public announcement show price continuation while those that are not associated with new information do not. They also find evidence of price reversals when a large price change is not information related and an increase in traded volume. Additionally, applying trading rules based on their analysis on out of sample data they show arbitrage possibilities yielding positive abnormal returns after including transaction costs.

The stock market reaction to both expected and unexpected informational announcements has been investigated in the academic literature at different levels. Mitchell and Mulherin (1994) found no evidence of a relation between information releases and stock prices at an aggregate level[2]. At the company level, Roll (1988) finds a weak relation between public information releases and returns for large capitalisation stocks. However, when the information events are split into different categories, some patterns have been observed namely the price continuation after earnings announcements observed by Bernard and Thomas (1989). They find that good news events are followed by 60-day cumulative abnormal returns (CAR) of around 2% while bad news events are followed by CARs of minus 2%. Michaely et al. (1995) find 60-day CARs of 1.8% and -4.6% when initiating or omitting dividends respectively. Dhillon and Johnson (1994) study 2-day returns after dividend increase (decrease) announcements and find abnormal returns of approximately +1% (-2%) with high statistical significance. Ikenberry et al. (1995) find evidence of share price under-reaction to share repurchase announcements. Womack (1996) analyses the informational value of brokerage analysts' recommendations on a sample of 1573 events on 822 US companies. He finds that brokerage firms apparently do have market timing and stock picking ability as his results show an average +2.4% post event drift for buy recommendations and -9.1% drift for sell recommendations. The positive drift is short lived while the negative drift extends for six months post announcement. Other authors focus on the relation between abnormal traded volume and abnormal returns for particular events. They attempt to identify if abnormal returns are caused by the information surprise or by price-pressure due to higher volume. Chan and Lakonishok (1995) investigate the

[2] More recently, Kothari et al. (2006) investigate the stock markets reaction to aggregate earnings news and find no evidence of any post-earnings drift. They find that market returns are unrelated to past earnings on the aggregate level and that returns are negatively correlated with current earnings.

price-pressure around large institutional trades while Bamber (1986) analyses the price-volume relation on annual earnings releases. Krinsky and Lee (1996) and Venkatesh and Chiang (1986) investigate the effect of earnings and dividend announcements on the bid-ask spread but find no significant relation.

Another line of research tries to find linkage between the investors overreaction (underreaction) to news and stock momentum. Scott et al. (2003) argue that investors underreact to information events and share price momentum is a side effect of this underreation. Their results are consistent with a seminal study by Chan et al. (1996) who state that a significant part of the momentum effect can be explained as investors' delayed reaction to news. There exists also an extensive literature on earnings surprises to analysts' estimates that attempt to find a link between earnings expectations and actual announced earnings. A recent study by Burgstahler and Eames (2006) find evidence that companies earnings are managed in order to avoid negative surprises in relation to expectation, which corroborates previous established literature. Skinner and Sloan (2002) provide evidence that inferior returns by growth stocks relative to value stocks are related to overoptimistic expectations of future actual earnings.

Structure of this chapter:

This chapter starts with a short introduction on the context of the work and relevant academic literature. In section 2 the event study methodology used in this work is described. Next in section 3 we describe the data sample used for the event study. Section 4 presents the data analysis results of this paper. This part is split into different aspects of the event study namely: A. Study of the abnormal returns across the event window. It investigates for significant abnormal returns around the announcement date due to the arrival of new information by aggregating the sample of abnormal returns in cross-section. Part B, the cumulative abnormal returns for different pre and post event date time periods are analysed. Part C investigates the occurrence of extreme events across the event window. This study is the main breakthrough presented in the paper. We find evidence that those companies' interim and final announcement date are extreme events in the investigated time window. In part D we test the robustness of our results by splitting the data sample into different time periods. In part E we investigate the post event cumulative abnormal returns conditional upon the occurrence of an extreme event on the announcement date. We find evidence of over-reaction on the event date followed by subsequent price reversal over a 15-day period. Finally, a summary and conclusions are provided in section 5.

2. Methodology

In this chapter we perform a typical event study around the earnings announcement dates to investigate if there are any observable share price patterns (pre or post event). For this effect, the methodology used is identical to the one described in the methodology section of chapter II based closely on the methodology provided in Campbell, Lo and Mackinlay (1997). Please refer to that section for the full description of the method as well as relevant references. We use the single index model to obtain share abnormal returns (AR) and then aggregate these cross-sectionaly to obtain average abnormal returns (AAR) and then temporally obtaining cumulative average abnormal returns (CAAR).

3. The data sample

The data sample consists of interim and final earnings and dividend public announcements for a list of companies that were upgraded/downgraded from the FTSE250 to the FTSE100 market index since January 1984 until November 2004.[3] For each of the companies, we obtain the dividend history and share price from 1984 until November 2004. The data sample includes recent spin-offs and companies that were delisted due to merger, insolvency or takeover and therefore survivorship bias should be small. Another characteristic of the data sample is that all the companies

[3] Note that the sample of stocks used for this study was the same as the sample used in the previous chapter when the share price effects around index promotions relegations was investigated. The rationale for using this sample is explained below.

lie within the threshold of blue chip large cap stocks and mid cap FTSE250 stocks and consequently the size effect[4] should be small.[5]

The sample was divided into two subsets consisting of FTSE100 promotions and FTSE100 relegations. The data for the promotions/relegations was obtained through the London Business School FTSE100 index constituent database. After searching Thomson Datastream for available data on share prices and dividends for each of the events, the total number of companies promoted/relegated from the FTSE100 was 283 and 277 respectively. Next, we filtered the sample so that we used only companies for which we could obtain at least 100 daily returns before and after the event date so that the market model parameters could be computed for each case. Companies with missing data points were excluded from the analysed sample. The final sample was composed of 219 relegated companies and 223 promoted companies for which we obtained respectively 4989 and 5140 interim and final results announcements. Share price and dividend information was obtained for the 100 days before and after each public announcement. Finally, the market index used to estimate the abnormal returns was the FTSEALL (all share index for UK stocks), also obtained from Thomson Datastream. Table 3.1 summarises the sample details with Panel A showing the promotions sample while panel B shows the relegations sample.

Table 3.1

Summary details of the interim and final earnings announcements data samples. Panel A refers to the promotions sample while Panel B to the relegations sample. Companies refer to the number of companies in each data sample. Dividend increase(decrease) corresponds to earnings announcements associated with an increased(decreased) company dividend.

Panel A		Panel B	
Promotions sample		Relegations sample	
Companies	*223*	***Companies***	*219*
Events		**Events**	
Dividend Increase	4658	Dividend Increase	4505
Dividend Decrease	482	Dividend Decrease	484
Total sample	5140	Total sample	4989

[4] See Dimson and Marsh (1986) for further information.

[5] The sample selection is important in order to ensure that the analysis is unbiased. By selecting companies based on promotion/relegation from the FTSE100 index, we hopefully reduce survivorship bias as the sample includes dead companies. We also analyse relegated and promoted companies separately, in order to eliminate the case of sample selection bias.

Div. Increase is the number of public announcements showing an increase in the dividend payout while Div. Decrease is the number of events where the dividend was decreased. It can be observed that in both the relegations and promotions samples, dividends are generally not reduced. This is in agreement with literature on dividend policy that dividend cuts are viewed as negative news and signs of a struggling company and management will avoid raising capital by retaining earnings.[6] Table 3.1 shows that only around 10.5% of the announcements in our sample were followed by a dividend reduction and that there is no significant difference between the relegated and the promotions sample sizes.

To control for changes in the share price behaviour over time we also split the sample into four time periods namely: 1983-1989, 1990-1994, 1995-1999 and 2000-2004.[7] As the Div. Decrease sample sizes are relatively small, analysis of changes over time was only performed using the Div. Increase samples[8]. Table 3.2 shows the distribution of the events over time.

Table 3.2

Distribution of the sample of events over different time periods. Panel A refers to the promotions sample, that is, interim and final earnings announcements for companies promoted to the FTSE100 index. Panel B refers to the relegations sample. Both samples refer to events associated to an increased or maintained dividend.

Panel A Promotions sample (Div. Increase)				
Time period	**1983-1989**	**1990-1994**	**1995-1999**	**2000-2004**
Sample size	1403	1087	1192	976

Panel B Relegations sample (Div. Increase)				
Time period	**1983-1989**	**1990-1994**	**1995-1999**	**2000-2004**
Sample size	1737	1040	1040	688

[6] See for instance Frankfurter and Wood (2003) for a review on dividend policy.

[7] The choice of the time windows in this chapter follows the same reasoning from that of chapter 2: It split the data into equal periods in time (with roughly equal sample sizes) in order to analyse the robustness of the results over different market conditions.

[8] The dividend decrease sample is used, however, in sections 4.A, 4.B and 4.C where the abnormal returns, cumulative abnormal returns and extreme events around the event window are investigated, respectively.

Additionally, Figure 3.1 shows the monthly distribution of the interim and final results announcement across the year for both the total data sample (promotions plus relegations). Usually, the interim and final announcements split the year in half, which means that months with a low number of events should have a match in 6 months time. That is, if April has a few events, then October should have a low event count as well, the same occurs with high event counts for March and September, and so on (see Figure 3.1). The differences are due to missing data, events occurring close to the beginning or end of the month. Our samples show higher incidence of events in March, September and November and a low incidence in January, April and October.

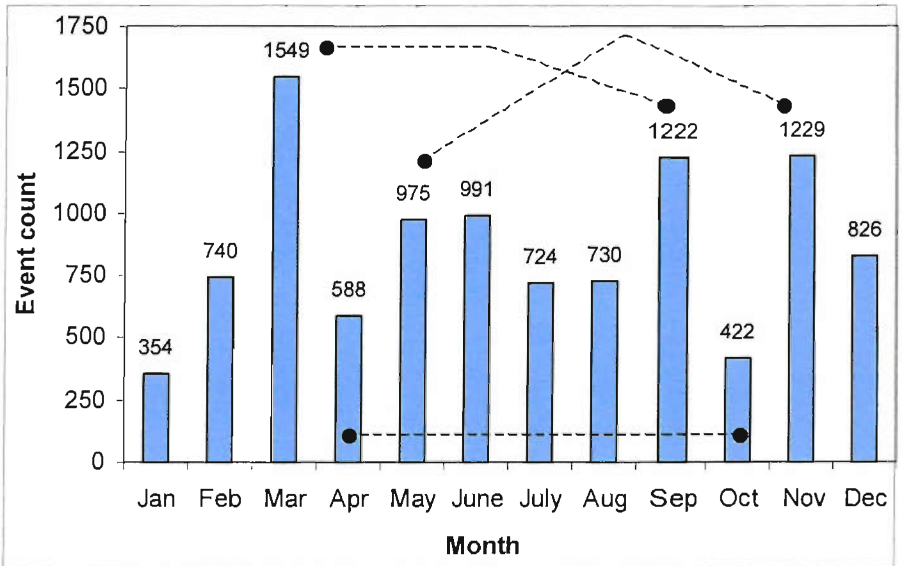

Figure 3.1: Monthly distribution of the total sample of interim and final earnings announcements across the year. These earnings announcements are usually separated by six months and therefore months with low incidence of events are cyclical. This is, April is related to October, November with May, and March with September, as shown above.

4. Results

The analysis of the data sample is split into several sections aimed at investigating different characteristics of the share price behaviour around the event date. Firstly, in section A the standard study of abnormal returns within the event window is performed. The main purpose is to investigate if there is evidence of price-pressure on the event date. Theoretically there should exist no such effect, as the market should already have assimilated the information by public releases of the financial analysts or brokerage firms. Next, in section B, the cumulative abnormal returns within the event window are analysed. Section C investigates the dispersion of abnormal returns within the event window and in particular, the frequency of occurrence of extreme events on the event date. We find with some surprise that interim and final results announcements are events with high impact on the share price, this is, they can be considered extreme events in the investigated time-window of the company. We perform both parametric and non-parametric tests, which provide strong evidence supporting our findings. In section D, we perform the tests for extreme events for different time periods and different samples, in order to investigate the robustness of the results. Finally, section E investigates the share price effects after the announcement date conditional on the occurrence of an extreme event. We find evidence for a price reversal following an extreme abnormal return on the event date. The price reversal occurs over a 5 to 15-day period.

A. Abnormal returns

Firstly, the usual analysis of abnormal returns within a ±10-day time window is performed. Abnormal returns for each data point in the sample are obtained by using a single index market model with parameters estimated from daily share returns over a ±100-day time window. The market proxy used for the model was the FTSE All share index. The abnormal returns are then aggregated cross-sectionaly in order to obtain the average abnormal return for a given date, t_n, relatively to the event date, t_0. Both the promotions sample and the Relegations sample are analysed independently and compared in order to check the consistency of the results. Theoretically, both samples should yield similar results if there is no significant information bias due to a company being relegated or promoted to the FTSE100 index[9]. The sources of this

[9] There exists an extensive literature dedicated to investigating share price effects when a company is promoted/relegated from a given market index. Most studies in the academic literature are aimed at the S&P500 index (see Dhillon and Johnson (1991) and Denis et al. (2003) for good reviews on the subject). Other studies include Chakrabarti et al. (2005) who provide a good analysis of such effects on international indices and Brealey (2000) studies the case of promotions/relegations to/from the UK FTSE100. For more details, refer to chapter 2.

possible bias could be due to informational effects (higher scrutiny for a FTSE100 listed company), due to a certification effect (golden seal for belonging to the FTSE100), liquidity effect (higher liquidity due to wider number of agents tracking the company) or simply due to spurious selection bias.

On the event date (interim or final results public announcement), companies also publish the next interim or final dividend payout and it is usual for the share to go ex-dividend shortly after. This provides a unique opportunity for investigating any changes in the share price behaviour resulting from a change in dividend policy. The dividend controversy is a widely discussed issue in finance (see Frankfurter and Wood (2003)). Even though Modigliani and Miller (1961) in their seminal work argue that the dividend payout is irrelevant for the company, the well-known fact is that companies have reluctance to cutting dividends and would raise capital by all other means before retaining more earnings (as shown in Table 3.1). One of the explanations for this behaviour suggested within the academic literature is that investors perceive a cut in dividends as bad news and therefore the share price would come under pressure. To analyse differences in the share price behaviour when companies reduce or increase their dividends, the respective data samples (within the promotions and relegations data samples) were examined. By comparing samples of dividend increases and dividend decreases, the effect of the dividend information can be analysed as a robustness check for the finding on the event date. In rational markets, there should be no significant difference in the share price behaviour within these two samples, both on the event date, as in the cumulative abnormal returns post-event. Comparing these sub-samples will provide a further robustness test for our results.

Table 3.3 shows the aggregated abnormal returns and respective statistics, within the ±10-day time window, for announcements where the company dividend is increased. On the left the promotions sample is analysed and on the right, the relegations sample.

Table 3.3

Average abnormal returns across the event window for both the promotions and relegations samples whose dividends were increased or maintained. The table reports the average abnormal returns, AAR, aggregated across the cross-section of companies within each sample for each day within the event window. The standard deviation of the abnormal returns and t-statistics are also reported. Furthermore, non-parametric tests are performed by using % Pos, the percentage of positive abnormal returns and the respective binomial Zb test which tests if that number is significantly different than 50%. Panel A shows the results for the promotions sample while Panel B shows the results for the relegations sample. N is the total number of sample events. ΔT represents the date relative to the event day, t_0 For example, ΔT=0 represents the event date while ΔT=–1 refers to the previous date.

Panel A						**Panel B**					
Promotions sample - Dividend increase						Relegations sample - Dividend increase					
N= 4658						N= 4505					
ΔT	AAR, %	std, %	t-stat	% Pos	Zb	ΔT	AAR, %	std, %	t-stat	% Pos	Zb
-10	0.012	0.026	0.471	0.476	-3.282	-10	0.024	0.023	1.014	0.479	-2.756
-9	-0.013	0.023	-0.559	0.471	-4.015	-9	-0.019	0.023	-0.839	0.463	-4.932
-8	-0.078	0.025	-3.127	0.467	-4.571	-8	-0.080	0.025	-3.262	0.467	-4.395
-7	-0.038	0.023	-1.650	0.465	-4.806	-7	-0.046	0.023	-1.994	0.465	-4.723
-6	0.045	0.023	1.913	0.489	-1.465	-6	0.071	0.024	2.948	0.493	-0.879
-5	-0.026	0.024	-1.050	0.471	-3.897	-5	-0.032	0.024	-1.330	0.474	-3.501
-4	0.013	0.025	0.526	0.475	-3.399	-4	0.008	0.025	0.327	0.476	-3.203
-3	0.014	0.026	0.528	0.479	-2.901	-3	-0.002	0.026	-0.069	0.475	-3.382
-2	0.052	0.025	2.051	0.489	-1.436	-2	0.016	0.025	0.622	0.479	-2.786
-1	0.103	0.034	3.034	0.508	1.114	-1	0.075	0.034	2.223	0.497	-0.372
0	0.328*	0.061	5.344	0.532	4.308	0	0.306*	0.062	4.932	0.532	4.276
1	0.070	0.030	2.364	0.497	-0.352	1	0.026	0.030	0.879	0.486	-1.862
2	0.026	0.025	1.038	0.489	-1.465	2	0.034	0.027	1.270	0.494	-0.819
3	0.120	0.024	4.895	0.511	1.524	3	0.111	0.025	4.504	0.508	1.117
4	0.064	0.025	2.527	0.490	-1.407	4	0.037	0.025	1.504	0.484	-2.101
5	0.044	0.023	1.931	0.485	-2.051	5	0.032	0.023	1.391	0.484	-2.131
6	-0.014	0.023	-0.634	0.463	-5.040	6	0.002	0.023	0.103	0.471	-3.918
7	-0.024	0.022	-1.065	0.468	-4.337	7	-0.014	0.023	-0.613	0.474	-3.531
8	0.020	0.023	0.853	0.473	-3.634	8	0.053	0.023	2.273	0.483	-2.250
9	0.014	0.025	0.555	0.465	-4.835	9	0.030	0.025	1.189	0.476	-3.233
10	0.035	0.024	1.481	0.480	-2.696	10	0.036	0.023	1.541	0.482	-2.429

*Statistical significance to 1% level with both t-stat and non-parametric Zb test

To test the significance of the abnormal returns, both the standard t-test and non-parametric binomial Zb test are performed. When analysing the results in Table 3.3 it is observed that there is an average abnormal return of 0.33% and 0.31% for the promotions and relegations sample, respectively. However, even though these returns are statistically significant (with t-stat of 5.3 and 4.9 and binomial Zb tests of 4.3 and 4.3, respectively), they are not economically significant if transaction costs are taken into account. Next, we repeat the analysis for announcements where the dividend was reduced. The results are shown in Table 3.4.

Table 3.4

Average abnormal returns across the event window for both the promotions and relegations samples whose dividends were decreased. The table reports the average abnormal returns, AAR, aggregated across the cross-section of companies within each sample for each day within the event window. The standard deviation of the abnormal returns and t-statistics are also reported. Furthermore, non-parametric tests are performed by using % Pos, the percentage of positive abnormal returns and the respective binomial Zb test which tests if that number is significantly different than 50%. Panel A shows the results for the promotions sample while Panel B shows the results for the relegations sample. N is the total number of sample events. ΔT represents the date relative to the event day, t_0. For example, ΔT=0 represents the event date while ΔT=–1 refers to the previous date.

Panel A						Panel B					
Promotions sample - Dividend decrease						Relegations sample - Dividend decrease					
N= 482						N= 484					
ΔT	AAR, %	std, %	t-stat	% Pos	Zb	ΔT	AAR, %	std, %	t-stat	% Pos	Zb
-10	0.147	0.107	1.378	0.517	0.729	-10	0.316	0.155	2.041	0.517	0.727
-9	0.045	0.121	0.377	0.502	0.091	-9	0.163	0.125	1.311	0.519	0.818
-8	-0.213	0.122	-1.739	0.436	-2.824	-8	-0.243	0.130	-1.875	0.440	-2.636
-7	-0.170	0.117	-1.454	0.421	-3.462	-7	-0.113	0.126	-0.894	0.424	-3.364
-6	-0.079	0.100	-0.791	0.442	-2.551	-6	0.004	0.108	0.034	0.477	-1.000
-5	0.077	0.116	0.659	0.517	0.729	-5	0.023	0.124	0.186	0.498	-0.091
-4	0.157	0.108	1.452	0.521	0.911	-4	0.065	0.124	0.523	0.500	0.000
-3	-0.040	0.129	-0.313	0.481	-0.820	-3	-0.081	0.122	-0.660	0.486	-0.636
-2	-0.012	0.128	-0.091	0.450	-2.186	-2	0.176	0.129	1.362	0.486	-0.636
-1	0.458	0.174	2.628	0.529	1.275	-1	0.367	0.188	1.955	0.529	1.273
0	-0.262	0.324	-0.807	0.508	0.364	0	-0.483	0.358	-1.350	0.500	0.000
1	0.280	0.132	2.120	0.521	0.911	1	0.282	0.131	2.155	0.527	1.182
2	-0.063	0.123	-0.508	0.508	0.364	2	-0.134	0.123	-1.088	0.508	0.364
3	0.085	0.137	0.619	0.492	-0.364	3	0.027	0.176	0.156	0.490	-0.455
4	0.030	0.122	0.243	0.490	-0.455	4	-0.081	0.124	-0.653	0.483	-0.727
5	0.007	0.103	0.066	0.477	-1.002	5	0.070	0.114	0.613	0.477	-1.000
6	-0.006	0.126	-0.050	0.490	-0.455	6	-0.025	0.128	-0.193	0.473	-1.182
7	0.330	0.148	2.224	0.488	-0.547	7	0.339	0.149	2.275	0.479	-0.909
8	-0.010	0.113	-0.090	0.488	-0.547	8	0.003	0.127	0.025	0.469	-1.364
9	-0.027	0.109	-0.244	0.448	-2.277	9	-0.013	0.109	-0.119	0.465	-1.545
10	-0.127	0.183	-0.695	0.483	-0.729	10	-0.036	0.182	-0.195	0.488	-0.545

The results in Table 3.4 show that there is a negative average abnormal return on the event date of -0.26% and -0.48% for the promotions and relegations sample respectively. These returns have no statistical significance as they show low values for the both the parametric t-test nonparametric binomial Zb test for the event date. When comparing the results in Table 3.4 to those of Table 3.3, it is observed that the standard deviation of the average abnormal returns is significantly higher for the dividend decrease sample. This fact is mainly due to the significantly smaller sample sizes of the dividend decrease sample. When comparing the share price behaviour around the event date for companies whose dividend increased to those with a reduced dividend we find that there is no evidence of arbitrage opportunities, which means that the market has already incorporated this information. In the following section we analyse cumulative abnormal returns before and after the event date.

B. Cumulative average abnormal returns

By analysing cumulative average abnormal returns (CAAR) over different time periods within the event window, we can test for the efficiency of the stock market. If there is evidence of a share price adjustment before the event date, then the market shows evidence of semi-strong form efficiency while post-event cumulative abnormal returns would point towards market under/over reaction to the event and the respective correction. In the previous section we observed no significant abnormal return on the event date and therefore the main question that we address is whether there is evidence of return predictability pre or post event. We analyse pre event periods ranging from t_{-20} and t_{-7} to t_0 and post event periods from t_0 to t_{+7} and t_{+20}. These time periods correspond to relatively short time windows in order to avoid the influence of other confounding effects. Table 3.5 shows the results of the analysis. Panel A1 refers to the promotions sample with dividend decreases and panel A2 refers to dividend increases. Panel B1 and B2 relates respectively to dividend decreases and dividend increases of the relegations sample.

Table 3.5

Cumulative abnormal returns for different time periods within the event window. Panel A1 and Panel A2 show the results for the promotions samples (dividend decrease and dividend increase/maintained, respectively). Panel B1 and Panel B2 show the results for the relegations samples (dividend decrease and dividend increase/maintained, respectively). The cumulative average abnormal returns (CAAR) are obtained by aggregating the average abnormal returns (AAR) across different time windows. Δ represents the different time windows investigated. For example, the period t-20:t0 investigates any market reaction pre-event while t0:t+20 investigates post-event CARs. The t-statistics of the CARs are reported in the third column of each Panel. ** and *** denote statistical significance at a two-sided 5% or 1% levels, respectively.

Panel A1			**Panel A2**		
Promotions sample - dividend decreases			Promotions sample - dividend increases		
ΔT	CAAR, %	t-stat	ΔT	CAAR, %	t-stat
t-20: t0	0.36	0.61	t-20: t0	0.79***	6.27
t-7:t0	0.07	0.15	t-7:t0	0.64***	6.90
t0:t+7	0.39	0.83	t0:t+7	0.16	1.81
t0:t+20	0.78	1.26	t0:t+20	0.15	1.25
t-7: t+7	0.46	0.80	t-7: t+7	0.80***	7.06
t-20: t+20	1.14	1.40	t-20: t+20	0.94***	5.74

Panel B1			**Panel B2**		
Relegations sample - dividend decreases			Relegations sample - dividend increases		
ΔT	CAAR, %	t-stat	ΔT	CAAR, %	t-stat
t-20: t0	0.02	0.03	t-20: t0	0.83***	6.62
t-7:t0	-0.34	-0.68	t-7:t0	0.55***	5.91
t0:t+7	0.44	0.87	t0:t+7	0.09	0.99
t0:t+20	1.40**	2.15	t0:t+20	0.13	1.11
t-7: t+7	0.10	0.16	t-7: t+7	0.64***	5.60
t-20: t+20	1.41	1.63	t-20: t+20	0.96***	5.89

From panels A1 and B1 we find that there is some evidence of pre or post event cumulative abnormal returns. Panels A2 and B2 show that for both the promotions and the relegations samples, there is a statistically significant positive CAAR of 0.79% and 0.83%, over a t_{-20} to t_0 period, respectively. These results show that: 1) Our analysis is robust over independent data samples; 2) The cumulative abnormal returns in the pre event period of t_{-20} to t_0 are statistically significant but have a small economic impact. Similar results are found for the t_{-20} to t_{+20} time window with CAAR of 0.94% and 0.96% for the promotion and relegations sample, respectively. Most of these CAARs are however due to the pre-event period and there is no evidence of post-event correction to the pre-event CAARs.

These results are in agreement with the assumption that markets are efficient in pricing securities around earnings announcements. As shown by table 3.3 to 3.5, the market has already absorbed the information contained in the interim and final results when the company dividend is decreased. For dividend increases or sample size is significantly larger and therefore it is easier to find statistical significance of a possible pattern. It is however very weak in terms of economic significance. In summary, our analysis shows weak evidence of return predictability around companies' interim and final results announcements which would not be profitable if transaction costs were included.

C. Extreme returns

The analysis of abnormal returns on singular public information announcements such as earnings, dividends, mergers, spin-offs, share repurchases, index promotions/relegations among others have been widely covered in the academic literature. In this section we aim to investigate the share price dispersion on the event date, or more concretely, we would like to test the hypothesis if interim or final results announcements are extreme events in the company lifetime. The method used to test this hypothesis is based on non-parametric tests to count events where the abnormal return for a given share is greater than given measurements of the share return dispersion. The measures we use are characteristic points of the share return distribution, namely the 50% points, the standard deviation and two standard deviations. In fact, if σ_k is the standard deviation of abnormal returns within the ±50 day event window for a given company announcement k, and $AR_k(t_j)$ is the abnormal return of share k on day t_j, then we count the number of occurrences such that $|AR_k(t_j)| > \sigma_k$ and then compare those occurrences with the theoretical values assuming a Gaussian share price distribution. As was already mentioned, the measures of dispersion we used was the $x_{50\%}$ (50% points) with a theoretical probability of $p_{th}=0.5$, σ with $p_{th}=0.465$ and 2σ with $p_{th}=0.048$. Finally, we test the significance of the probability of the occurrence of an extreme event by using the binomial Zb test for each day with the event window under study. The results of this analysis for the relegations sample are shown in Table 3.6.

Table 3.6

Extreme abnormal return statistics for the relegations sample using different definitions of dispersion: Left: 50% points. Middle: 1σ (63.5%). Right: 2σ (95.2%). The table reports non-parametric tests for analysing extreme occurences across the event window. These tests consist on counting the number of abnormal returns with magnitude greater than standard dispersion measures such as the 50% points of the distribution (x_{50}), one standard deviation (σ) and two standard deviations (2σ). The probability of occurences are then obtained by dividing these by the number of events (N). p_{th} denotes the theoretical probability of occurence of such events assuming a Gaussian distribution. Zb is the non-parametric binomial test which is used to investigate if the measured probabilities are significantly different to the theoretical values. The shaded area shows the statistics for the event date, t_0.

	N=4505			N=4505			N=4505		
ΔT	p(|x|>x_{50})	p_{th}	Zb	p(|x|>σ)	p_{th}	Zb	p(|x|>2σ)	p_{th}	Zb
-14	0.387	0.5	-15.36	0.232	0.465	-31.33	0.045	0.048	-0.75
-13	0.367	0.5	-18.10	0.224	0.465	-32.44	0.047	0.048	-0.26
-12	0.385	0.5	-15.66	0.232	0.465	-31.30	0.040	0.048	-2.43
-11	0.397	0.5	-14.02	0.236	0.465	-30.85	0.045	0.048	-0.89
-10	0.388	0.5	-15.30	0.232	0.465	-31.36	0.048	0.048	0.09
-9	0.410	0.5	-12.35	0.240	0.465	-30.26	0.047	0.048	-0.26
-8	0.418	0.5	-11.31	0.260	0.465	-27.54	0.056	0.048	2.46
-7	0.400	0.5	-13.66	0.248	0.465	-29.15	0.053	0.048	1.77
-6	0.402	0.5	-13.42	0.236	0.465	-30.74	0.051	0.048	1.07
-5	0.429	0.5	-9.76	0.261	0.465	-27.39	0.050	0.048	0.79
-4	0.414	0.5	-11.73	0.259	0.465	-27.72	0.060	0.048	3.79
-3	0.430	0.5	-9.61	0.269	0.465	-26.31	0.061	0.048	4.14
-2	0.440	0.5	-8.33	0.281	0.465	-24.76	0.062	0.048	4.42
-1	0.562	0.5	8.03	0.412	0.465	-7.05	0.149	0.048	31.97
0	0.734	0.5	30.97	0.619	0.465	20.76	0.361	0.048	98.33
1	0.469	0.5	-4.48	0.306	0.465	-21.42	0.085	0.048	11.84
2	0.435	0.5	-9.01	0.271	0.465	-26.08	0.070	0.048	6.87
3	0.425	0.5	-10.38	0.266	0.465	-26.70	0.061	0.048	4.00
4	0.404	0.5	-13.16	0.249	0.465	-29.00	0.054	0.048	1.98
5	0.400	0.5	-13.60	0.250	0.465	-28.91	0.050	0.048	0.65
6	0.384	0.5	-15.75	0.231	0.465	-31.51	0.049	0.048	0.37
7	0.377	0.5	-16.79	0.223	0.465	-32.53	0.042	0.048	-1.73
8	0.384	0.5	-15.78	0.228	0.465	-31.93	0.043	0.048	-1.52
9	0.400	0.5	-13.72	0.241	0.465	-30.14	0.044	0.048	-1.17
10	0.392	0.5	-14.73	0.234	0.465	-31.03	0.051	0.048	1.07
11	0.387	0.5	-15.36	0.236	0.465	-30.79	0.051	0.048	0.86
12	0.388	0.5	-15.24	0.227	0.465	-32.05	0.046	0.048	-0.47
13	0.392	0.5	-14.76	0.232	0.465	-31.30	0.046	0.048	-0.68
14	0.410	0.5	-12.38	0.242	0.465	-30.02	0.051	0.048	1.00

The results in Table 3.6 show that for all measures of dispersion of the share abnormal return, on the event date, the probability of the occurrence of an abnormal return greater than each of the measures of dispersion is significantly higher than the theoretical value. In other words, the probability of the occurrence of an abnormal return greater than $x_{50\%}$ is p=73.4% compared to p_{th}=50% with a high Zb statistic of 30.97. The probability of an abnormal return greater than σ_k is p=61.9% compared to p_{th}=46.5% with Zb=20.76. Finally, and most importantly, the probability of the occurrence of abnormal returns greater than 2σ is p=36.1% compared to a theoretical value of p_{th}=4.8% with Zb=98.3. The most striking evidence that the public announcement of companies interim or final results is likely to be an extreme event in the lifetime of the company is the high probability of occurrence of an abnormal return greater than 2σ. Next, we perform the same analysis on the promotions sample, which corresponds to a control sample to provide robustness to our analysis (reduces selection bias as previously discussed). The results for the promotions sample are shown in Table 3.7.[10]

[10] We also performed an analysis of abnormal dispersion using the mean absolute deviation (MAD) of the residuals as a proxy for the sample dispersion. That is, we use y(t) = MAD(t) across the cross-section of companies. The results we obtain provide further support to our finding of an abnormal dispersion on the event date. We find that the average jump in the magnitude of the abnormal returns is 2.45 and 2.60 for the div. increase and div. decrease samples, respectively with a high t-statistic of around 4.9. These results are shown in appendix A1.

Table 3.7

Extreme abnormal return statistics for the promotions sample using different definitions of dispersion: Left: 50% points. Middle: 1σ (63.5%). Right: 2σ (95.2%). The table reports non-parametric tests for analysing extreme occurences across the event window. These tests consist on counting the number of abnormal returns with magnitude greater than standard dispersion measures such as the 50% points of the distribution (x_{50}), one standard deviation (σ) and two standard deviations (2σ). The probability of occurences are then obtained by dividing these by the number of events (N). p_{th} denotes the theoretical probability of occurence of such events assuming a Gaussian distribution. Zb is the non-parametric binomial test which is used to investigate if the measured probabilities are significantly different to the theoretical values. The shaded area shows the statistics for the event date, t_0.

	N=4505			N=4505			N=4505		
ΔT	$p(\lvert x\rvert>x_{50})$	p_{th}	Zb	$p(\lvert x\rvert>\sigma)$	p_{th}	Zb	$p(\lvert x\rvert>2\sigma)$	p_{th}	Zb
-14	0.381	0.5	-16.29	0.231	0.465	-32.05	0.042	0.048	-1.93
-13	0.359	0.5	-19.28	0.222	0.465	-33.26	0.045	0.048	-0.76
-12	0.388	0.5	-15.33	0.237	0.465	-31.17	0.039	0.048	-2.68
-11	0.397	0.5	-14.10	0.237	0.465	-31.14	0.048	0.048	0.07
-10	0.387	0.5	-15.38	0.232	0.465	-31.82	0.047	0.048	-0.28
-9	0.409	0.5	-12.45	0.245	0.465	-30.08	0.052	0.048	1.30
-8	0.415	0.5	-11.66	0.259	0.465	-28.17	0.058	0.048	3.16
-7	0.395	0.5	-14.39	0.249	0.465	-29.52	0.054	0.048	2.13
-6	0.391	0.5	-14.83	0.235	0.465	-31.46	0.054	0.048	1.92
-5	0.438	0.5	-8.50	0.266	0.465	-27.20	0.056	0.048	2.54
-4	0.417	0.5	-11.31	0.266	0.465	-27.26	0.058	0.048	3.30
-3	0.423	0.5	-10.52	0.267	0.465	-27.06	0.061	0.048	4.12
-2	0.440	0.5	-8.21	0.281	0.465	-25.15	0.065	0.048	5.43
-1	0.564	0.5	8.67	0.417	0.465	-6.49	0.149	0.048	32.52
0	0.729	0.5	31.21	0.622	0.465	21.56	0.360	0.048	100.19
1	0.468	0.5	-4.42	0.310	0.465	-21.24	0.090	0.048	13.48
2	0.422	0.5	-10.61	0.269	0.465	-26.76	0.065	0.048	5.50
3	0.418	0.5	-11.25	0.268	0.465	-26.97	0.059	0.048	3.50
4	0.402	0.5	-13.42	0.249	0.465	-29.47	0.055	0.048	2.47
5	0.398	0.5	-13.98	0.251	0.465	-29.26	0.048	0.048	0.07
6	0.390	0.5	-15.00	0.233	0.465	-31.73	0.049	0.048	0.41
7	0.374	0.5	-17.17	0.229	0.465	-32.23	0.043	0.048	-1.65
8	0.377	0.5	-16.73	0.225	0.465	-32.76	0.042	0.048	-1.72
9	0.402	0.5	-13.39	0.236	0.465	-31.29	0.043	0.048	-1.52
10	0.386	0.5	-15.56	0.236	0.465	-31.29	0.052	0.048	1.37
11	0.387	0.5	-15.44	0.238	0.465	-31.02	0.050	0.048	0.89
12	0.384	0.5	-15.77	0.228	0.465	-32.46	0.048	0.048	0.07
13	0.381	0.5	-16.23	0.225	0.465	-32.76	0.046	0.048	-0.48
14	0.406	0.5	-12.81	0.244	0.465	-30.20	0.051	0.048	1.17

The results shown in this Table 3.7 are very similar to those for the relegations sample in Table 3.6, which provides robustness to the analysis to sample biases. For the 50% points the probability of and extreme occurrence is $p(|AR_k(t_0)|>x_{50\%})$ = 72.9% with p_{th}=50% and Zb=31.2. For occurrences greater than σ we have $p(|AR_k(t_0)|>\sigma_k)$ = 62.2% with p_{th}=46.5% and Zb=21.56. Finally, for extreme abnormal returns greater than 2σ we have $p(|AR_k(t_0)|>2\sigma_k)$ = 36% with p_{th}=4.8% and

Zb=100.2. We find that around 36% probability of occurrence of an extreme abnormal return, with magnitude greater than 2σ, on the event date, when compared with the 17% found by Ryan and Taffler (2004) for interim and preliminary company results. The difference in the returns may lie in the calculation method for an abnormal return or the sample selection as they use FTSE 350 companies' extreme events from 1 January 1994 to 31 December 1995. Of those, they find that 17% of the sample extreme events were related to earnings announcements information events.

The large sizes of the relegations and promotions samples allow us to investigate the increase in volatility on the event date by performing a test that compares the standard error of the abnormal returns on day t_j aggregated cross-sectionaly with the standard error on the event date, t_0. For each day t_j relative to the event date, the cross-section sample of events is the same, and therefore, the average standard error for a given day t_j should be the same across the event window. However, according to the extreme events results obtained previously (Table 3.6 and Table 3.7), we should find a significant increase of the dispersion of the residuals on the event date. To test for an increase in the abnormal return dispersion on the event date, we calculate the average and dispersion of the standard error of the residuals for the ±25-day event window and perform the usual t-test for the significance of the results. If y_j is the standard error for the cross-sectionaly aggregated abnormal returns of the data sample on day t_j, then we calculate:

$$\langle y \rangle = \frac{1}{M}\sum_{j=-25}^{25} y(t_j) \qquad \text{and} \qquad se(y) = \frac{1}{M-1}\left(\sum_{j=-25}^{25}\left(y(t_j)-\langle y \rangle\right)^2\right)^{1/2}$$

and the t statistic for day t_j is given by

$$t-\text{stat}(t_j) = \frac{y(t_j)-\langle y \rangle}{se(y)} \sim N(0,1)$$

M is the number of points across the event window. It should be noted that as we include the event date when estimating the sample statistics across the time window, these estimates will be biased upwards due to the higher volatility observed around the announcement date. This means that if there is a statistically significant increase in volatility on the event date, then the significance of the results are underestimated by the sample bias. However, we are aware of this bias and will analyse the results with it in mind. Table 3.8 shows the results of the analysis of the dispersion of the abnormal returns within a ±10 day event window.

Table 3.8

Analysis of the abnormal volatility within the event window. To test for an increase in the abnormal return dispersion on the event date, we calculate the average and dispersion of the standard error of the residuals for the ±25-day event window and perform the standard t-test for the significance of the results. y(t) is the standard error for the cross-sectionaly aggregated abnormal returns of the data sample on day t and t-stat is the respective t statistic. <y> represents the average of y(t) across the ±25-day event window and se(y) its standard error. y(t)/<y> gives the increase(decrease) in y on day t relative to its average across the event window. The shaded area illustrates the event date, which shows evidence of a significant increase in dispersion of abnormal returns. *** Denotes statistical significance at least at the 1% level

	Dividend increase sample *N=9162*			Dividend decrease sample N=965		
	<y>	*se(y)*		*<y>*	*se(y)*	
	1.753	*0.490*		*2.923*	*0.987*	
ΔT	y(t)	t-stat	y(t)/<y>	y(t)	t-stat	y(t)/<y>
-10	1.673	-0.164	0.954	2.919	-0.004	0.999
-9	1.562	-0.390	0.891	2.694	-0.232	0.922
-8	1.675	-0.159	0.956	2.764	-0.161	0.946
-7	1.562	-0.390	0.891	2.673	-0.253	0.914
-6	1.609	-0.294	0.918	2.296	-0.635	0.786
-5	1.637	-0.236	0.934	2.644	-0.282	0.905
-4	1.719	-0.069	0.981	2.550	-0.378	0.873
-3	1.749	-0.009	0.997	2.757	-0.168	0.943
-2	1.699	-0.110	0.969	2.830	-0.094	0.968
-1	2.284	1.083	1.303	3.964	1.056	1.356
0	4.166***	4.923	2.376	7.504***	4.644	2.567
1	2.019	0.542	1.152	2.874	-0.049	0.983
2	1.755	0.004	1.001	2.704	-0.222	0.925
3	1.655	-0.200	0.944	3.463	0.548	1.185
4	1.691	-0.127	0.964	2.705	-0.220	0.926
5	1.560	-0.394	0.890	2.385	-0.545	0.816
6	1.542	-0.430	0.880	2.795	-0.130	0.956
7	1.515	-0.486	0.864	3.252	0.334	1.113
8	1.575	-0.364	0.898	2.643	-0.284	0.904
9	1.701	-0.106	0.970	2.404	-0.526	0.823
10	1.596	-0.320	0.910	4.012	1.104	1.373

The results provide further support to the evidence found when performing the non-parametric tests for extreme events on the event date. Even though there is no significant abnormal return of the event date, there is a significant increase in the dispersion of the abnormal returns. This is valid for both the case when the dividend is increased as well as when a dividend decrease is announced. The average jump in the abnormal returns dispersion on the event date is 2.38 and 2.57 times for the div. increase and div decrease samples respectively. The difference is very small and may be due simply to the smaller size of the dividend decrease sample. In any case, the magnitude of the jump in "volatility" on the event date is substantial. Additionally the t statistic shows a high level of significance providing further support to our findings. To give an idea of the statistical significance of the volatility jump on the event date, Figure 3.2 shows the t statistic across the event window for both the investigated samples. Even though the sample sizes differ quite substantially, their t tests show a very similar pattern across the event window. It is clearly observed that on the event date the volatility increase has a very high level of statistical significance. Economically it means that on this event date, abnormal returns have much higher fluctuations than on any other day even though on average there is no statistically significant average abnormal return.

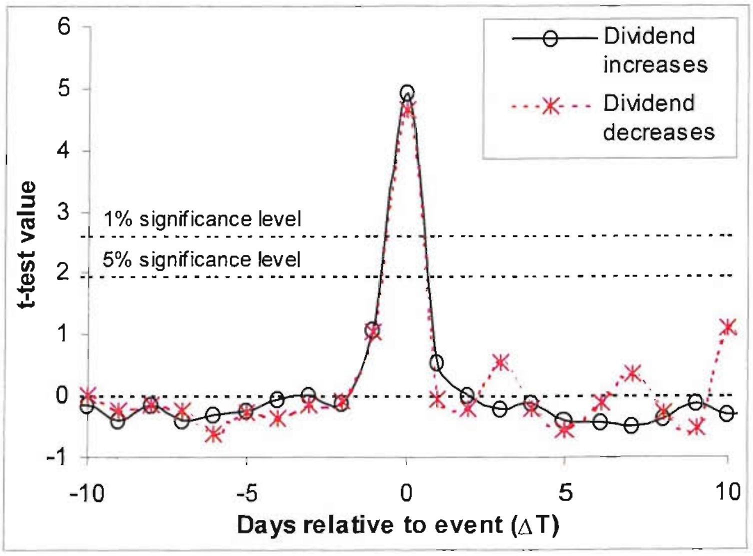

Figure 3.2: t-statistic showing the level of significance of the abnormal return dispersion across the event window. The peak observed on day t_0 is evidence of the abnormal dispersion on the event date showing very high statistical significance. Doted line corresponds to the dividend decrease sample while solid line to the dividend increase(maintain) sample.

Even though these empirical tests show a higher volatility on the event date when compared to other days within the event window, it can be argued that the previous tests are not meaningful for non-Gaussian distributions. They do however; provide strong evidence for the existence of higher incidences of extremes on the announcement date (consistent with different definitions of an extreme event). There is wide evidence that stock market prices follow a Paretian power-law distribution as shown in Mandlebrot (1963) and Gabaix et al (2003). These suggest an 'universal' probability distribution for the magnitude of the return over a given time scale:

$$P(|AR_t| > x) \sim x^{-\xi}$$

Which means that there is a linear relation between the magnitude of the daily abnormal return and the logarithm of the probability of occurrence of that event. The parameter ξ represents the scale parameter, which is equivalent to the volatility measure in Gaussian statistics. The smaller ξ is, the greater is the probability of occurrence of returns with larger magnitudes. Conversely, the greater ξ is, the lower the probability of occurrence of returns with large magnitudes. By plotting the probability of occurrence of an event with magnitude greater than $x>0$ versus the magnitude of that event, we should obtain a linear relation. The slope of that line is related to the parameter ξ. Therefore comparing the slope of the linear relation for the event date with other days within the event window, one might observe evidence of higher volatility on the event date. Figure 3.3 shows the empirical probability distribution for our sample of abnormal returns. It shows clearly that there is an increase in volatility on the event date, t_0, compared to day t_5. The figure on the right shows the power-law behaviour when plotting the logarithm of the probability of occurrence of an abnormal return versus the magnitude of that occurrence (for both positive and negative events). On the event date, the slope of the distribution is much lower than for t_5, in other words, the probability of extreme occurrences is much higher.

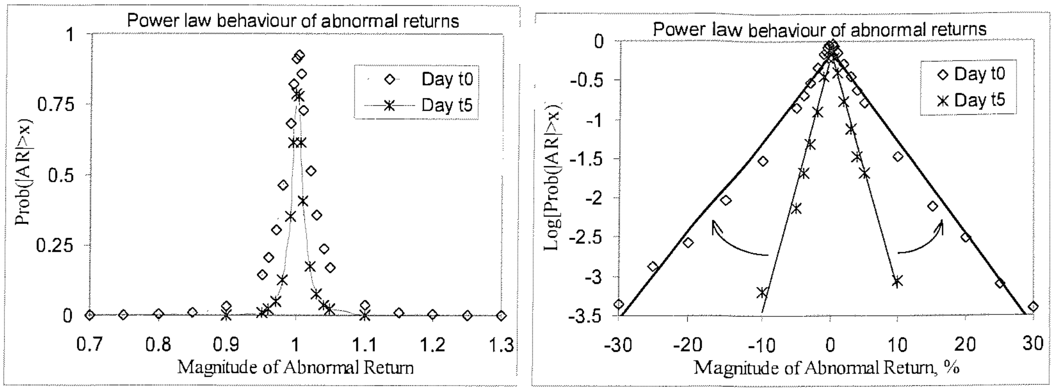

Figure 3.3: Probability distribution of the magnitude of the abnormal return for the event date (t_0) and an arbitrary non-event date (t_5). The distribution was measured using the sample consisting of all events of both the promotions and relegations samples (increased dividend). Left: Shows the measured probability distribution in linear scale. Right: Logarithm of the probability illustrates the power law behaviour. The straight lines refer to linear regression fits to left and right tails.

To quantify the change in the slope of the power-law distribution for the event date when compared to the non-event date we regressed Log(P(|AR|>x)) with the magnitude of the abnormal returns (both positive and negative). The results are shown in Table 3.9.

Table 3.9

Regression statistics showing the difference in power-law behaviour between the event date, t_0, and an arbitrary 'normal day' within the event window, t_5. The OLS regression investigates the relation between magnitude of the abnormal return with the logarithm of the probability of occurrence of such an abnormal return. A linear relation provides evidence of the Power law distribution of the sample of residuals (abnormal returns). The slope of the regression corresponds to the scale parameter, ξ, of the power law distribution, which is a non-Gaussian measure of dispersion. Negative tails correspond to negative abnormal returns while positive tails refer to positive abnormal returns. NT refers to negative tails while PT refers to the positive tail.

	Slope	se	t	intercept	se	t	R2	F
				'Normal day' (t_5)				
NT	0.321	0.024	13.399	-0.205	0.106	-1.943	0.968	179.53
PT	-0.293	0.013	-22.773	-0.147	0.057	-2.590	0.989	518.62
				Event day (t_0)				
NT	0.113	0.004	25.462	-0.167	0.061	-2.716	0.985	648.31
PT	-0.118	0.004	-29.611	-0.110	0.055	-1.994	0.989	876.78

The results show a high degree of statistical significance for the linear relation between Log(P(|AR|>x)) and the magnitude of the abnormal returns. However, a power-law relationship does implies that the intercept of regression should be zero while the results show that this does not hold. This may be attributed to the fact that for low abnormal returns, the distribution behaves like more like a Gaussian while the power-law relationship is more suitable for the tails of the distribution. Nevertheless, the regression shows a high explanatory power through a high F statistic and R^2 close to 1. When comparing the slope of the regression for a normal day within the event window and the announcement date we find evidence for increased frequency higher magnitude abnormal returns on the event date. The slope of the regression changed from –0.302 (day t_0) to –0.118 (day t_5) for negative abnormal returns which indicates that the probability of occurrence of a negative return of magnitude x is about 3 times higher on the event date than on day t_5. This compares with an average volatility increase of approximately 2.4 times shown previously in Table 3.8 using Gaussian statistics.

In summary, in this section we presented evidence supporting the occurrence of an extreme abnormal return on the date a company has its interim or final results announcements. Our results give raise to a discussion on how to identify sources of extreme abnormal returns, typically observed in financial time series. It is possible that the presence of leptokurtosis in the share return distribution may be partially explained by public announcements and other singular informational events. It appears that the particular event of this study has a high impact on the company share price and could be considered an extreme event on the lifetime of the company. It is conceivable that this event may trigger a transition from a low to high volatility period for the share, and therefore might be used in conjunction with a jump diffusion to model to price options. Another application of this knowledge could be in value at risk models to predict shortfalls of capital or in portfolio management where the fund managers want to be aware of high volatility events in order to speculate/hedge against such occurrences. Finally, it is also possible that by studying other such events, with higher or lower impact on the company/index share price, one could isolate the main sources of extreme events.

D. Behaviour over different time periods

To test the robustness of our findings across different time intervals we split each of the data samples into four periods namely: 1983-1989, 1990-1994, 1995-1999 and

2000-2004. We only perform this analysis using the dividend increase sample due to the large number of data points available[11]. Theoretically we would expect no significant change in the behaviour around the event date over time and, similar results for both the promotions and relegations samples. Table 3.10 shows the results of this analysis for the promotions and relegations samples. On the top section we have the extreme return non-parametric statistics for $|AR_j(t_0)|>\sigma_j$, while on bottom of the table the abnormal return statistics on the event date are shown. The abnormal return statistics on the event date include the aggregate abnormal return, the standard error of the residuals and the respective t-test for the significance of the abnormal returns. The non-parametric extreme event statistics show the sample size, N, the number of events above or below one standard error of the abnormal return distribution across the ±50-day event window. With these values the probability of an event $|AR_j(t_0)|>\sigma_j$ is computed and compared with the theoretical value, p_{th}, assuming a Gaussian distribution of abnormal returns and the binomial Zb test is used to test the significance of the results. Finally, the ratio of positive to negative events is also calculated. The quantity x represents $AR_j(t_0)$.

[11] Results for the div. decrease sample are available on request from the authors. The analysis we conducted of this sample shows similar behaviour to the promotions samples. However the statistical significance of some results is weak due to the small sample size (as expected).

Table 3.10

Abnormal return and extreme event statistics on the event date across different time periods. Panel A: Promotions sample; Panel B: Relegations sample. The table reports non-parametric extreme event statistics for $|AR|>\sigma$ as well as parametric abnormal return statistics for different time periods namely (1983-1989; 1990-1994; 1995-1999 and 2000-2004). N is the sample size for each of the analysed time period. $p(|x|>\sigma)$ is the probability of an abnormal return with magnitude greater than one standard deviation of the abnormal returns across the event window. p_{th} is the theoretical probability of such an occurrence which is 46.5%. The binomial Zb test reports the significance of the measured probability being different to the theoretical value. $p(|x|>\sigma)/p_{th}$ represents the ratio of measured probability to theoretical prediction, assuming Gaussian statistics. Abnormal return statistics show the average abnormal return (AAR) aggregated cross-sectionally, standard error (σ) and respective t-statistic (t-stat). N refers to the size of each sample.

	Panel A Promotions sample, day t_0				**Panel B** Relegations sample, day t_0			
Period:	1983-1989	1990-1994	1995-1999	2000-2004	1983-1989	1990-1994	1995-1999	2000-2004
	Extreme event statistics ($|AR|>\sigma_i$)				*Extreme event statistics ($|AR|>\sigma_i$)*			
N(x>+σ)	452	410	378	370	540	396	356	262
N(x<−σ)	415	265	366	243	509	250	313	163
N	1403	1087	1192	976	1737	1040	1040	688
p(|x|>σ)	0.62	0.62	0.62	0.63	0.60	0.62	0.64	0.62
p_{th}	0.465	0.465	0.465	0.465	0.465	0.465	0.465	0.465
Zb	11.503	10.324	11.032	10.227	11.625	10.110	11.540	8.043
p(|x|>σ)/p_{th}	1.330	1.336	1.343	1.351	1.299	1.336	1.384	1.329
	Abnormal return statistics				*Abnormal return statistics*			
AAR, %	0.199	0.337	0.215	0.643	0.102	0.358	0.278	0.783
σ, %	0.099	0.108	0.112	0.179	0.087	0.111	0.124	0.228
t-stat	2.002	3.117	1.923	3.602	1.176	3.220	2.236	3.433
N	1403	1087	1192	976	1737	1040	1040	688

When analysing the results in Table 3.10 we conclude that our study of extreme events on the earnings announcement date is robust across samples as well as across different time periods. Namely, probability of an extreme event is $p(|x|>\sigma)\approx 62\%$ compared to the theoretical value of $p_{th}=46.5\%$ for all the sub-sample periods with the binomial Zb test showing a very high level of statistical significance. Furthermore, when analysing the aggregated abnormal returns, it can be observed that they are similar for each time period of the relegations and promotions samples. It is also interesting to observe that for the 2000-2004 period, the AAR is around 0.7% compared with the overall average of 0.3%. These average abnormal returns are in general significantly different than zero given the relatively high values of the t-test. However, the average abnormal returns do not have high economic impact except for the 2000-2004 period. As there are no significant differences over time as well as across samples, these tests give some further strength to the robustness of our results.

E. Abnormal returns after an extreme event

Recently, Pritmani and Singal (2001), investigated cumulative share returns for a sample of extreme share price movements. They studied a large sample of extreme events of stocks listed in the New York Stock Exchange (NYSE) between 1990 to 1992 and analysed the share price behaviour after those dates. They split their sample into different kind of company events such as analyst reports, earnings announcements and finally, information unrelated events. For earnings announcements they found evidence of share price continuation over the 20-day period post event.

In this part we analyse share price abnormal returns conditional upon an extreme event on the public announcement date for the whole data sample (consisting of 4505 plus 4658 data points of the relegations and promotions samples respectively). As a definition of extreme event we chose absolute share abnormal returns above 3 times the share standard error, this is, $|AR_{t=0,k}|>3\sigma_k$, where k is the event index and σ_k is calculated for a ±50-day window, including the event date, in similarity with Pritmani and Singal (2001). For each extreme event satisfying the previous condition we compute the future cumulative abnormal share returns for: 1, 5, 10, 15 days after the event date. It should be noted that the return 1-day after the event date corresponds simply to the next day abnormal return. If the market overreacted to the new information on the public release date, then we would expect some kind of correction post event. Figure 3.4 shows the relation between the extreme events on the event date and the subsequent 15-day cumulative abnormal returns.

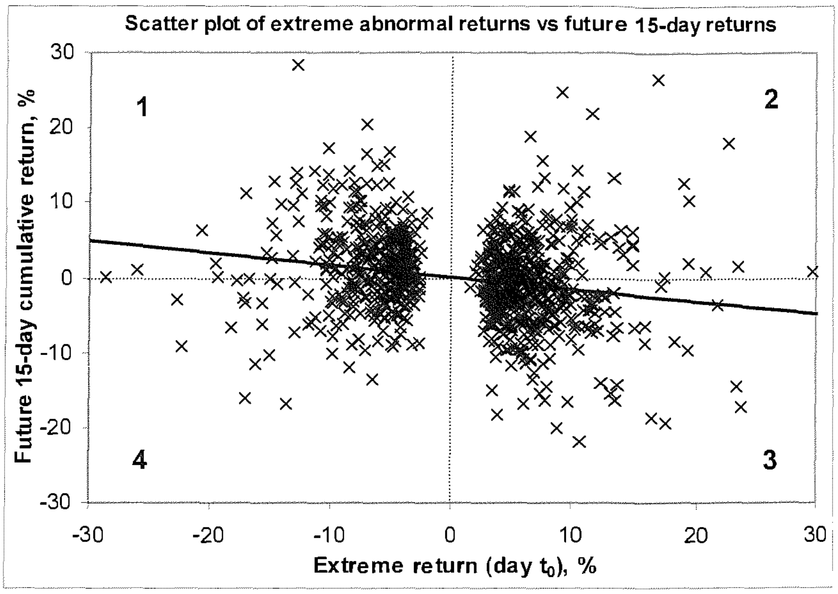

Figure 3.4: Scatter plot showing the relation between extreme abnormal return on the event date and subsequent 15-day cumulative returns. The abnormal return on the event date (t_0) is defined as an extreme event when its magnitude is greater than 3 times the normal standard deviation, this is when $|AR(t_0)_i|>3\sigma_i$. Points lying in the 1st and 3rd quarters are indication of share price reversal post event while points lying in the 2nd and 4th quarters indicate continuation. The sample consists of the whole dividend increase sample for both promotions and relegations with a size of 943 events.

A simple method to formally investigate for a relation between the extreme event and future corrections is to perform an ordinary least squares regression (OLS) of the future returns as a function of the extreme event return. The results of this analysis for future cumulative abnormal returns of different time periods are shown in Table 3.11. These results show no significant relation between the extreme event and the share return on the following day. However, when analysing the 5-day cumulative returns, we found a significant negative relation between the Extreme return on day t_0 and the future cumulative returns. The regression coefficient was –0.063 significant to at least 99% level. The intercept coefficient was not significantly different to zero, as should be expected, and the F statistic of 25.5 for the regression shows a high statistical significance. When regressing the 10-day and 15-day future abnormal returns with the extreme event returns, we found that the relation was stronger and the statistical significance of the regression coefficients increased. In particular, for the 15-day case, the regression coefficient was –0.161 with a t statistic of –6.7, which shows a strong statistical significance. Our results are in disagreement with the findings of Pritmani and Singal (2001) for US stocks during the 1990 to 1992 period. While we find evidence for share price reversal after the extreme event, the findings in their paper show support for price continuation. These differences may be due to sample selection, the period under examination, or the different definitions of an extreme event.

Table 3.11

OLS regression statistics for the relation between the extreme abnormal return on the event date and subsequent future cumulative returns. The sample size is N=943. The extreme event on the announcement date is defined as any company experiencing an abnormal return greater than 3 times the standard deviation across the ±50-day event window. Cumulative abnormal returns are measured for the 1-day, 5-day, 10-day and 15-day periods after the event date. Regression statistics are reported in the table: m is the slope coefficient, sem is the standard error and tm the respective t-statistic. b denotes the regression intercept with seb the standard error and tb the t-statistic. The F-statistic is also reported in the final column. *** Denotes statistical significance at the 1% level or higher.

Period	*m*	*sem*	*tm*	*b*	*seb*	*tb*	*R2*	*F*
1-day	0.000	0.008	0.009	0.043	0.066	0.655	0.000	0.000
5-day	-0.063***	0.017	-3.818	0.149	0.132	1.128	0.015	14.576
10-day	-0.099***	0.019	-5.171	0.132	0.154	0.862	0.028	26.739
15-day	-0.161***	0.024	-6.671	0.244	0.193	1.263	0.045	44.497

To support the results shown in Table 3.11, we performed a non-parametric analysis of the relation between extreme events and subsequent future returns. This analysis is performed by simply counting the number of data points lying in the 1st or 3rd quarter of the graph in Figure 3.4 and the data points lying within the 2nd and 4th quarters. The correlation coefficient can be easily obtained as well as the binomial Zb test for analysing the significance of the relation. The results are shown in Table 3.12. When comparing these results with the respective OLS regressions, we find that the results are in agreement and therefore we have stronger evidence of the return predictability shown in Table 3.12.

Table 3.12

Non-parametric correlation tests for the relation between the extreme abnormal return on the event date and subsequent future cumulative returns. The sample size is N=943. The extreme event on the announcement date is defined as any company experiencing an abnormal return greater than 3 times the standard deviation across the ±50-day event window. Cumulative abnormal returns are measured for the 1-day, 5-day, 10-day and 15-day periods after the event date.

Period	1-day	5-day	10-day	15-day
N_1=Qrt(1+3)	503	516	545	581
N_2=Qrt(2+4)	440	427	398	362
N	943	943	943	943
Slope=$(N_2-N_1)/N$	-0.067	-0.094	-0.156	-0.232
Zb	2.052	2.898	4.787	7.132

These results provide further evidence that there is in fact a share price reversal following an extreme abnormal return (defined as $|AR_{t=0,k}|>3\sigma_k$) on the event date. The statistical significance of this reversal is stronger the longer the time period (5 to 15 days post event) but is not significant for the day following the event. The non-parametric correlation between the extreme event sign and the subsequent sign of the cumulative returns is negative indicating reversal. For the next day abnormal returns, the significance of the binomial test Zb=2.1 is low whether for the 5-day cumulative returns, a significantly higher number of points fall in the 1^{st} and 3^{rd} quarters compared to the 2^{nd} and 4^{th} quarters. The highest statistical significance is observed for the case of 15-day cumulative returns with Zb=7.1 and a probability of lying in the 1^{st} and 3^{rd} quarters of p_{1+3}=61.46%.

This study opens possibilities for further research such as testing the reversal strength for different magnitudes of the extreme event (based on different definitions for the extremes, based either on absolute magnitudes or relative to each share volatility) or by analysing longer time windows. Additionally, the magnitude of the extreme events could be related with the volume of traded shares in similarity to the analysis in Bamber (1986) and Chan and Lakonishok (1995) or with the changes in the bid-ask spread as in Krinsky and Lee (1996) and Venkatesh and Chiang (1986).

5. Conclusions

Event studies on public informational releases have been extensively analysed in the literature in an attempt to find patterns, which violate the efficient market hypothesis and yield profitable arbitrage opportunities. Most studies focus on abnormal returns around the event date or cumulative returns in different time periods and generally find that the market is "well behaved" to the arrival of earnings information (see for example Aharony and Swary (1980)). In this study, we find higher than normal dispersion on the event date, when investigating the dispersion of abnormal returns. However, when simply analysing abnormal returns around companies' interim and final results announcement dates our results corroborate previous studies: We find no statistically significant abnormal returns on the announcement date nor do we find evidence of any pre or post event return predictability.

Even though this particular event shows no evidence of being different from any other within the event window, when investigating the dispersion of abnormal returns, we find higher than normal dispersion on the event date. Our results show that there is a 2.37 times increase in the average residuals (magnitude of the abnormal returns) on the event date when comparing with the remaining event window. The results display a high level of statistical significance. When performing non-parametric tests, we find that, for a given company, the probability of the occurrence of an abnormal return with magnitude above 2σ is 36.0% compared to a theoretical value of 4.8% and comparing to around 17% obtained by Ryan and Taffler (2004). These results have a high statistical significance due to the large sample sizes under investigation. Similar evidence is found when estimating the probability of abnormal returns with magnitude greater than σ is 62.4% compared to a theoretical value of 46.4%. We find that our results are robust across different samples as well as different time periods. These findings provide some insight into the nature of extreme events in the typical share return distribution found in financial time series. In fact, the companies' interim or final results announcement date appears to be a source of extreme events for the company, in other words, we can say that these events have a high impact on the share returns. This opens the possibility for the identification of other such events such as analysts' estimates, earnings announcements, broker upgrades/downgrades, share repurchase announcements, interest rate changes, index promotions/relegations, among others, as sources of extreme returns. It can be argued that these events are potentially the origin of the Paretian-like distribution found in share returns (Mandlebrot (1963), Fama (1965)).

Furthermore, in similarity with previous studies such as Pritmani and Singal (2001), we find evidence return predictability conditional upon the occurrence of an extreme event on the announcement date. We define the extreme event relatively to the abnormal return volatility specific to each firm, which we chose to be 3σ (3 times the ±25 day daily volatility). Our results show that after an extreme event, there is evidence of share price reversal in the 5 to 15 days following the event. These results contradict those found by Pritmani and Singal (2001) for a sample of NYSE stocks during the 1990 to 1992 period where they find evidence for share price continuation. When analysing the abnormal returns on the day following an extreme event, we find no correlation. These results suggest that when abnormal returns above 3σ occur, they are likely to be caused by over-reaction that is then followed by a correction. Future studies could focus on analysing how this correlation changes with changes in the magnitude of the extreme events (eg 2σ, 3σ, 4σ etc). Additionally, the relation between abnormal volume and the respective extreme events could be investigated as in Bamber (1986) or Blume et al. (1994) and Ryan and Taffler (2004).

The findings in this chapter might have implications towards the methodologies employed to manage risk in general and market risk in particular. The results in this chapter show that to some extend large share price changes can be predicted which might have implications for diversification and risk minimization in portfolio management, this is, the knowledge of possible large share price decreases on given dates can provide an effective tool for the managers to reduce portfolio volatility (see Silvapulle and Granger (2001)). Ultimately by mapping the whole universe of events and their impact on different assets classes, an event-driven risk management system could be achieved. Obviously, further research is required in events that have an impact on share prices. Namely, the analysis of the impact of other type of news announcements such as analyst reports, interest rate changes, macroeconomic announcements, credit rating upgrades/downgrades, index promotions/relegations, broker recommendations, among others. This type of analysis could also be extended to other asset classes such as companies' credit default swaps (CDSs) or bond and FX markets. The results in this chapter could also be applied in jump diffusion stochastic models (used to price options) where there is a stochastic probability of an extreme occurrence. Our results suggest that the extreme occurrences could, to some extent be predicted increasing the predictive power of the model.

An additional line of research is the possibility that such high impact events may trigger periods of higher share price volatility, from the extensive evidence of volatility autocorrelation and mean reversion (see for example Poon and Granger (2003) for an excellent review on volatility forecasting methods). Such issues should be addressed as they might have implications in the validity of certain market models based upon the assumption of constant Gaussian noise such as the capital asset pricing model or other multifactor models.

VI. Appendix A1

Table A3.1

Analysis of the abnormal volatility within the event window. To test for an increase in the abnormal return dispersion on the event date, we calculate the average and dispersion of the mean average deviation (MAD) of the residuals for the ±25-day event window and perform the standard t-test for the significance of the results. y(t) is the MAD for the cross-sectionaly aggregated abnormal returns of the data sample on day t and t-stat is the respective t statistic. <y> represents the average of y(t) across the ±25-day event window and se(y) its standard error. y(t)/<y> gives increase(decrease) in y on day t relative to its average across the event window. The shaded area illustrates the event date, which shows evidence of a significant increase in dispersion of abnormal returns.

	Dividend increase sample *N=9162*			Dividend decrease sample N=965		
	<y>	*se(MAD)*	*N=9162*	*<MAD>*	*se(MAD)*	*N=965*
	1.150	*0.340*		*1.771*	*0.582*	
ΔT	y(t)=MAD(t)	t-test	y(t)/<y>	y(t)=MAD(t)	t-test	y(t)/<y>
-10	1.034	-0.340	0.900	1.641	-0.224	0.927
-9	1.056	-0.274	0.919	1.564	-0.355	0.883
-8	1.081	-0.201	0.941	1.670	-0.173	0.943
-7	1.052	-0.288	0.915	1.654	-0.200	0.934
-6	1.065	-0.250	0.926	1.582	-0.324	0.894
-5	1.107	-0.124	0.963	1.715	-0.096	0.969
-4	1.109	-0.118	0.965	1.628	-0.245	0.920
-3	1.133	-0.049	0.986	1.708	-0.108	0.964
-2	1.157	0.021	1.006	1.781	0.018	1.006
-1	1.579	1.264	1.374	2.508	1.266	1.416
0	2.817***	4.906	2.451	4.600***	4.860	2.598
1	1.300	0.444	1.131	1.953	0.313	1.103
2	1.159	0.027	1.008	1.794	0.041	1.013
3	1.116	-0.100	0.971	1.761	-0.017	0.994
4	1.100	-0.146	0.957	1.674	-0.167	0.945
5	1.063	-0.256	0.924	1.543	-0.391	0.871
6	1.028	-0.357	0.895	1.695	-0.129	0.957
7	1.000	-0.441	0.870	1.754	-0.028	0.991
8	1.015	-0.397	0.883	1.498	-0.469	0.846
9	1.051	-0.291	0.914	1.489	-0.485	0.841
10	1.057	-0.274	0.919	1.823	0.090	1.030

***Significant at least at the 1% level

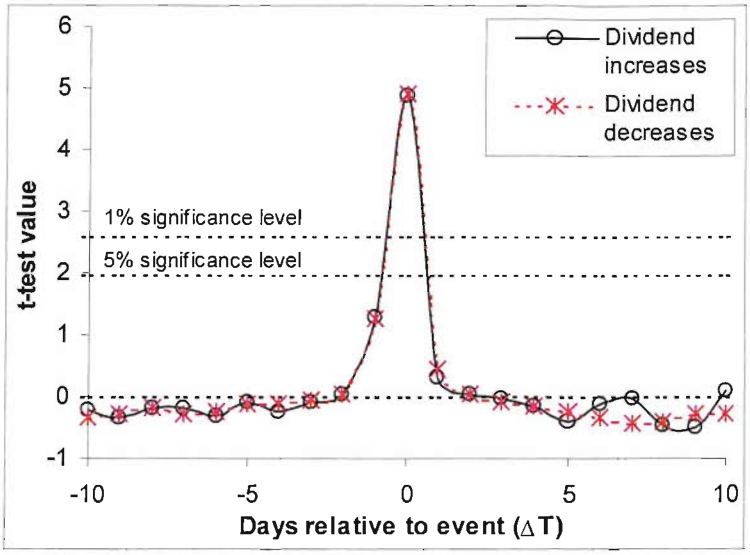

Figure A3.1: t-statistic showing the level of significance of the abnormal return dispersion across the event window. The peak observed on day t_0 is evidence of the abnormal dispersion on the event date showing very high statistical significance. Doted line corresponds to the dividend decrease sample while solid line to the dividend increase(maintain) sample.

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Chapter IV

"The Hole in Black-Scholes"

Abstract: In this chapter the effect of return on options prices is examined. Traditional option pricing models, which are based on non-arbitrage arguments, eliminate the expected return of the underlying asset from the equation. However, in real markets (imperfect markets), return predictability over certain time periods could be possible and consequently arbitrage opportunities in the options markets might occur. We examine the implications of return predictability on the Black-Scholes calculation of options prices by deducing a formula that relates the Black-Scholes value of a call option to the expected value of the call option at maturity. We then estimate the discount rate implied by the Black-Scholes price and discuss its implications.

1. Introduction

In his paper "How to use the Holes in Black-Scholes", Fischer Black (1988) reflects: *"If you are bullish on the stock, you may buy shares or call options, but you won't change your estimate of the option's value. A higher expected return on the stock means a higher expected return on the option, but it doesn't affect the option's value for a given stock price".*

Consider the following extreme example: if we have two different call options with identical prices of the underlying shares, identical exercise price and the same time to maturity they would have the same value even though one of the companies' shares are expected to increase in value more rapidly. If financial markets were perfect, then such a situation could not exist. Arbitrageurs would sell the shares with the lower expected return and buy those with the higher expected return until the two were identical. In reality, markets are not perfect. In particular, investors will possess different information sets and it is upon these that they form their subjective assessments of expected asset returns and volatilities. This subjective information will then be used to design strategies. Thus the apparent anomaly identified by Black provides a useful basis for choosing a portfolio of options. In the Black-Scholes equation the only parameter that requires empirical estimation is the volatility of the underlying share. However, in order to take advantage of Black's anomaly we also require an estimate of the expected returns of the underlying asset. The aim of this chapter is to explore the technical implications of this insight.

This study is organised as follows: Section 2 places this chapter into context by reviewing option valuation using the Binomial approach and the more general risk-neutral valuation. This introduction will prove extremely useful for relating both these approaches with the role of the expected return of the underlying asset. In section 3 we find a relation between both these approaches by deriving an expression that relates the Binomial value with the expected value of the call option. This relation provides an insight into the nature of binomial option valuation that is based upon the construction of a hedged or replicating portfolio. In particular, when examining this relation, the role of the expected return of the underlying asset on the option valuation is clarified. In section 4 we discuss some implications namely: the adjusted discount rate implicitly used by Black-Scholes to discount the expected call value to present date and the hole in Black-Scholes are discussed. Some conclusions are drawn in section 5.

The Black-Scholes approach for pricing an European call option is based on the construction of a riskless (delta-hedged) portfolio and the use of Ito's lemma to obtain the value of the call option (see Black and Scholes (1973) and Merton (1976)). The popularity of this approach is due to the fact that it enables an analytic expression for the value of the call option and therefore it is computationally fast and easy to implement. The key parameter for the accurate pricing of options using Black-Scholes is the underlying asset volatility. Another approach that is traditionally used to value European call options is risk neutral valuation where the expected value of the call option is calculated as if investors were risk-neutral and then discounted using the risk-free rate of interest. In our opinion this practice, which is common among professionals in the financial area, should be clarified and some warnings are raised. For that purpose, using the binomial approach we obtain an explicit relation between the expected value of the call option and the value obtained using the binomial or Black-Scholes methodology. This relation shows that both these methodologies are equivalent when the return on the underlying asset is the risk-free rate of interest. When the expected return on the underlying asset does not coincide with the risk-free rate, then the adjusted discount rate should be used so that both these valuations are equivalent. However, in some particular market situations when the expected return on company shares is predicted as well as the volatility, this information can be used when pricing options on those shares. It only seems natural the insight that, if the shares of two companies have similar volatilities but different expected returns, then the options on these shares should be necessarily different. The "hole in Black-Scholes" described by Black (1988) is exemplified by the following hypothetical situation: If we have two shares that are identical in every aspect but have different expected returns, is it reasonable to assume that both will have the same call price as predicted by the Black-Scholes formula? One answer is that the market should compensate for this unbalance by setting a higher implied volatility on one of the shares, which is equivalent to saying that one option will in fact be more expensive than the other and therefore the information on the expected return on the market could provide further information for valuing the options. On the other side, the other situation that might occur, even tough unlikely, is that the volatilities of the options might adjust in order to compensate for the difference in expected returns.

2. Binomial and Risk-neutral Option Valuation

A. The Binomial Method

The binomial method for calculating the value of a European call option was first proposed by Cox et al (1979). It relies on reducing the possible movements of the share price to two scenarios, which consist in an upper movement with return u and probability of occurrence q, and a downward movement with return d and probability 1-q. Therefore, the share price at a future time follows a path with movements consisting in binomial random draws. For example, if the initial share price is S_0 the share price at time N is S_N, can consist of any path described by $S_N=S_0u^jd^{N-j}$, where j is a random draw of the number of upward movements during the period. One of the main motivations for Cox et al (1979) developing the binomial approach was to simplify the complex mathematics behind option pricing models (namely, involving stochastic processes and Ito's lemma) to a simple binomial process. This method, where two possible states of the world are allowed is intuitive, easy to understand and bring to light in an understandable fashion the underlying economics behind option valuation. If the Black-Scholes paper became famous for achieving an analytic expression for pricing options, the binomial method helped to understand and propagate the principles behind option pricing, in particular the construction of the replicating or hedged portfolio. The value of the call option is calculated using expectations of each state of the world and no arbitrage considerations. Figure 4.1 describes the evolution of the share price and option-replicating portfolio for two periods. The initial share price can take two possible paths at time t_1: either up to S_0u or down to a taking a value of S_0d. C_u is the value of the call option at time t_1 when share price has gone up to S_0u while C_d is the value of the call option at time t_1 when share price has dropped to S_0d.

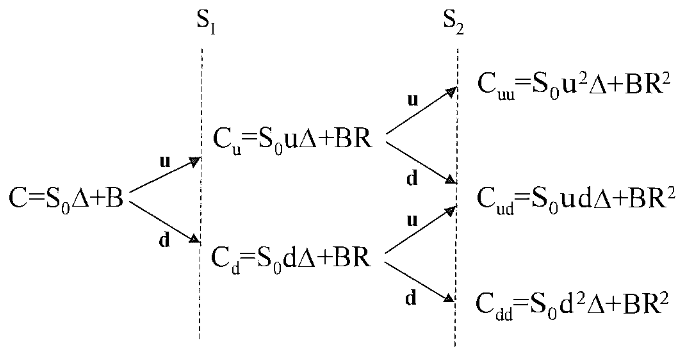

Figure 4.1: portfolio replicating the value of the call option used in a two-step binomial approximation.

The unknown parameter here is C, the present value of the option. Cox et al (1979) propose the creation of a portfolio that replicates the payoff of the call option that consists of Δ shares bought and borrowing B at the risk-free rate of interest. R is the risk free rate during the period $\Delta t=(t_{n+1}-t_n)$, this is, $R=(1 + r_f\Delta t)$. Δ and B are calculated so that the portfolio has the same payoff as the call option. Under these circumstances, the value of the call option must be the same as the value of the portfolio. Figure 4.1 illustrates how the value of the call option can be calculated for a two-step binomial approximation. The derivation undertaken by Cox to determine a general expression for a N-step approximation is shown in appendix 1. The general expression obtained by Cox et al. (1979) for the value of the call option is:

$$C_N = \frac{1}{(R)^N}\sum_{i=0}^{N} C_i^N k_1^{N-i} k_2^i \max(S_0 u^{N-i} d^i - X, 0) \qquad (4.1)$$

where

$$k_1 = \frac{R-d}{u-d} \text{ and } k_2 = \frac{u-R}{u-d} \text{ and } k_1 + k_2 = 1 \text{ and } R = 1 + r_f dt$$

In their paper, Cox et al. (1979) go a step further by achieving a Black-Scholes type expression for the value of the call option using the binomial approach. Consider an integer number, **a**, such that for i<**a**, the option is worthless, this is, $S_0u^{N-a}d^a>X$. In this case, the value of the call option can be written as:

$$C_N = \frac{1}{(R)^N}\sum_{i=a}^{N} C_i^N k_1^{N-i} k_2^i (S_0 u^{N-i} d^i - X) \Leftrightarrow$$
$$C_N = \frac{1}{(R)^N}\sum_{i=a}^{N} C_i^N k_1^{N-i} k_2^i S_0 u^{N-i} d^i - \frac{1}{(R)^N}\sum_{i=a}^{N} C_i^N k_1^{N-i} k_2^i X \quad (4.2)$$

Finally, after few manipulations this expression can be written in a format that resembles the Black-Scholes pricing formula shown in equation (4.1).

$$C_N = S_0 \sum_{i=a}^{N} C_i^N \left(\frac{uk_1}{R}\right)^{N-i} \left(\frac{dk_2}{R}\right)^{i} - \frac{X}{(R)^N}\sum_{i=a}^{N} C_i^N k_1{}^{N-i} k_2{}^{i} \quad (4.3)$$

In the extreme case where N tends to infinity, the binomial probability distribution tends towards a Normal distribution and Cox and Rubinstein show that the Black-Scholes formula can be derived from equation (4.3). While the Black-Scholes pricing formula is obtained for a continuous lognormal distribution of share returns, the Binomial method is based on discrete steps. The main advantage of the Black-Scholes formula is that it is analytic and easy to implement and with low computational requirements. The binomial approach is discrete and the option value can be calculated iteratively instead of using equation (4.3), which provides an increased flexibility to include term structure effects or discrete events (such as dividend or earnings announcements, share repurchases, stock splits or others) in the valuation process.

B. Risk neutral valuation

Let's now revisit the risk-neutral approach to option valuation in context of the binomial method. As we already mentioned risk-neutral option valuation is a general method with fewer restrictions than the Black-Scholes or binomial methods due to fewer assumptions being imposed. A significant difference with this approach is that it does not rely on the construction of a hedged portfolio to calculate the value of the call option. The principle here is that the price the investor should pay for the option corresponds to the expected value at a given future time so that no arbitrage opportunities occur. The problem that emerges from this situation is the selection of the discount rate to bring the expected value to the present day and the estimation of the future share price probability distribution.

The payoff of a call option is given by:

$$C(T) = \max(S(T) - X, 0)$$

S(T) - Share price at time T
X – Exercise price

The expected value of the call option at expiry can be obtained readily if the probability distribution, p(S(T)), at expiry is known. The expected value of the call option is written as:

$$E(C(T)) = \int_0^\infty p(S) \cdot \max(S - X, 0) dS = \int_X^\infty S p(S) dS - X \int_X^\infty p(S) dS \qquad (4.4)$$

The first integral has a lower limit of zero because the share price being always greater than zero due to the limited liability that the shareholders are entitled to. The integration is performed over all the share prices possibilities. In fact, the lower limit for the integral shown in equation (4.4) is the exercise price, X, of the option because the value of the call option is zero if S<X. Hence equation (4.4) can be interpreted as the difference between the expected share price if S>X and the strike price multiplied by the probability of exercise of the option. One of the problems of using this approach is that the share price future probability distribution is not known. One of the assumptions is that is commonly imposed to expression (4.4) is that the share price is log-normally distributed. Under this assumption, the Black-Scholes formula for the call option is obtained by discounting E(C(T)) at the risk-free rate of interest.

One method for obtaining the future share price distribution at time t is by using the binomial distribution as proposed by Cox and Rubinstein. If the share price follows a binomial process where after one time period it can either rise by **u** with probability **q** or fall by **d** with probability **1-q** as shown in figure 4.2:

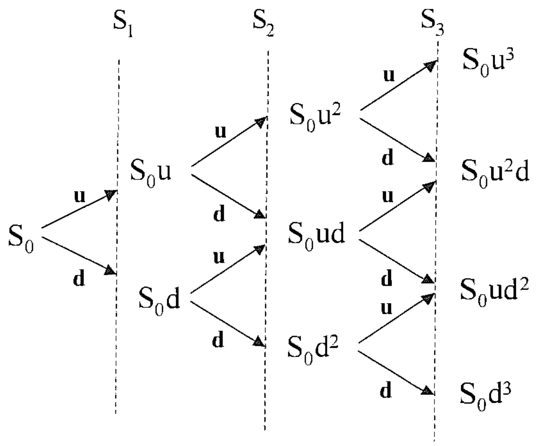

Figure 4.2: Possible share price movements for a three-step binomial approach.

The probability distribution of the share price can be obtained by using a Monte Carlo simulation where S_n is computed N times by random draws of j. Each draw of the number of upward movements in the share price, j, can be obtained by generating a random number R[0,1] and then multiplying by the number of steps (or time periods), N. The number of downward movements is given by N-j. It should also be noticed that the expected value for j is Nq=N/2 when using the parameterisation suggested by Jarrow & Rudd (1983) where q=1/2 and $u = \exp\left(\rho dt + \sigma\sqrt{dt}\right)$ and $d = \exp\left(\rho dt - \sigma\sqrt{dt}\right)$. To implement the expected value of the call option in practice, even though it is the most powerful technique, Monte Carlo simulations require large computational times in order to give good accuracy, particularly when a large number of steps are used. When the effects of dividends, stochastic volatility, varying interest rates are ignored and the simplest binomial approach is considered where **u** and **d** are the possible upward and downward movements in the share price respectively, the probability distribution can be easily be calculated for a time period $N\Delta t$ as $C_k^N/2^N$ for a share price of $S_0 d^k u^{N-k}$. The expected value of the call option at time $N\Delta t$ can then be written as:

$$E(C_N) = \sum_{h=0}^{N} p_h C_h = \sum_{h=0}^{N} \frac{C_h^N}{2^N} \max(S_0 u^{N-h} d^h - X, 0) \qquad (4.5)$$

It should be noted that $C_h^N = \dfrac{N!}{h!(N-h)!}$ in expression (4.5) represents the combinations of h in N and should not be confused with the option price for a given state of the world, C_h. $E(C_N)$ is the expected value of the call option for N binomial steps. Now, to obtain the present value, the problem that arises is the selection of the discount rate. In a risk-neutral world, the discount rate is the risk-free rate of interest. As we have already discussed in the previous section, Black-Scholes show that by constructing a hedged portfolio, the share price returns can be removed from the value of the share price and therefore, the actual discount rate is the risk-free rate independently of the risk preferences of the investor (risk takers, risk neutral or risk averse). The present value of the call option discounted at the risk-free rate of interest is:

$$C(0) = \frac{1}{(R)^N} \sum_{h=0}^{N} \frac{C_h^N}{2^N} \max(S_0 u_1^{N-h} d_1^h - X, 0) \qquad (4.6)$$

Note that in this expression, $\mathbf{u}_1$ and $\mathbf{d}_1$ are calculated by substituting the rate of return by the risk free rate of interest ($\rho = r_f$) in **u** and **d**.

3. Relation between the Binomial and risk-neutral valuation

An alternative method to calculating the value of a European call option using the binomial approach involves creating a hedged portfolio, which consists on Δ shares bought and one call option written. If the portfolio is riskless, then the values at any state of the world are the same and the portfolio earns the riskless rate of interest during each time period, $R=1+r_f\Delta t$. Figure 4.3 shows the hedged portfolio over two periods of time.

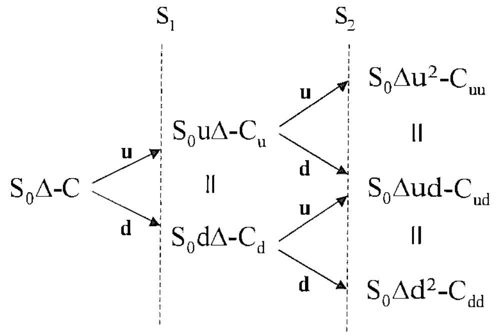

Figure 4.3: Hedged portfolio for calculating the call option value using the binomial approach.

$$\Delta S_0 u - C_u = \Delta S_0 d - C_d \Leftrightarrow \Delta = \frac{C_u - C_d}{S_0(u-d)} \tag{4.7}$$

the hedged portfolio earns the risk-free rate of interest during that period:

$$(S_0\Delta - C)R = S_0\Delta d - C_d \Leftrightarrow C = \frac{\Delta S_0(R-d)+C_d}{R} = \frac{\Delta S_0(R-u)+C_u}{R}$$

A more convenient way of writing the value of the call option is by adding both values (calculated using C_d and using C_u). Even though both of them are the same, by construction, it will be shown that the result is a closed form expression, which has significant insight into the implications of the assumptions undertaken by using the hedged portfolio. Consequently, we can write the value of the call option, C, as

$$2C = \frac{\Delta S_0(R-d)+C_d}{R} + \frac{\Delta S_0(R-u)+C_u}{R} \Rightarrow C = \Delta S_0\left(1-\frac{u+d}{2R}\right)+\frac{C_u+C_d}{2R} \tag{14.8}$$

Substituting Δ into the previous expression and denominating k=(u+d)/2R, we can write the value of the call option for 1 step approximation (note that the we will change the denomination of C to C_1 that has a meaning "option value for 1-step approximation"):

$$C_1 = (C_u - C_d)\frac{1-k}{u-d} + \frac{C_u + C_d}{2R} \qquad (4.9)$$

C_u and C_d can be calculated in the same way from the values of C_{ud} , C_{uu} and C_{dd} at time 2. Finally, a general expression for N steps can be obtained by repeating this process and recurring to some algebra manipulation. The full derivation of the general expression for an N-step approximation to the price of the option using this alternative binomial approach is given in appendix 2. The approximated value of the call option calculated using N steps of the hedged portfolio is written as:

$$C_N = \sum_{i=0}^{N}\left[C_i^N \frac{m^i}{(2R)^{N-i}}\left(\sum_{j=0}^{N-i} C_j^{N-i} \sum_{h=0}^{i} C_h^i (-1)^h \max(S_0 u^{N-j-h} d^{j+h} - X, 0)\right)\right] \qquad (4.10)$$

$$\text{where } m = \frac{1-k}{u-d} = \frac{1-\frac{u+d}{2R}}{u-d} \quad \text{and} \quad C_p^n = \frac{n!}{p!(n-p)!}$$

This expression is different to the formula published by Cox, Ross and Rubinstein (1979) because they used an option-replicating portfolio instead of a hedged portfolio to reach their general expression. Their expression for calculating the value of the call option after N steps is quite simple as it consists in a modified binomial where u and d are modified accordingly to accommodate for the effect of changes in B and Δ, after each iteration. The expression shown in this paper looks quite complicated but provides a very important insight into the effect of the process of delta hedging on the calculation of the value of the call option. It shows explicitly the relation between the expected value of the call option and the present value of the call option when using the hedged portfolio (Black-Scholes or Binomial). By separating the first term in equation (4.10) where i=0 from the remaining terms we obtain:

$$C_N = \sum_{h=0}^{N} \frac{C_h^N \max(S_0 u^{N-h} d^h - X, 0)}{(2R)^N} + \sum_{i=1}^{N}\left[C_i^N \frac{m^i}{(2R)^{N-i}}\left(\sum_{j=0}^{N-i} C_j^{N-i} \sum_{h=0}^{i} C_h^i (-1)^h \max(S_0 u^{N-j-h} d^{j+h} - X, 0)\right)\right] \qquad (4.11)$$

The first term in equation (4.11) does not depend on m, and represents the expected value of the call option discounted to the present value using the risk-free rate of interest. To make it clearer, let's write the first term as follows:

$$\frac{1}{(R)^N}\sum_{h=0}^{N}\frac{C_h^N}{2^N}\max(S_0u^{N-h}d^h - X,0) = \frac{1}{(R)^N}\sum_{h=0}^{N}p_hC_h = \frac{1}{(R)^N}E(C_N) \qquad (4.12)$$

where p_h is the probability of occurrence of an option value of C_h. Once more, it should be noted that C_h represents the value of the call option for a given state of the world with probability of occurrence p_h, and should not be confused with $C_h^N = \frac{N!}{h!(N-h)!}$, which stands for combinations of h in N. Expression (4.12) makes the previous argument explicit. The second term in C_N, where i>1, represents a correction due to the construction of the hedged portfolio. This represents a small increment or decrement to the expected value of the call option, which is related to the expected return on the company shares. For the particular case where the expected return during the period is the same as the risk-free rate of interest, is works out that m=0 and therefore the value of the call option given by the risk-neutral valuation is exactly the same as the value given by the binomial approach. Let's analyse in a bit more detail the effect of the share return on the value of the call option. Remembering that u, d and q were parameterised according to the one suggested by Jarrow and Rudd (1983), we can write:

$$u = \exp\left(\rho dt + \sigma\sqrt{dt}\right) \approx 1 + \rho dt + \sigma\sqrt{dt}$$
$$d = \exp\left(\rho dt - \sigma\sqrt{dt}\right) \approx 1 + \rho dt - \sigma\sqrt{dt}$$
$$m = \frac{1-k}{u-d} = \frac{1 - \frac{u+d}{2R}}{u-d} \approx \left(1 - \frac{1+\rho dt}{1+r_f dt}\right) / \left(2\sigma\sqrt{dt}\right)$$

in order to achieve m=0, we need that u+d=2R. By substituting the values we obtain the following requirement:

$$u + d = 2R \quad \Leftrightarrow \quad R = 1 + r_f dt = 1 + \rho dt \quad \Leftrightarrow \quad r_f = \rho$$

Since we know that in the Binomial (and Black-Scholes) pricing model the expected return is eliminated from the equation, the value of the call option does not vary for shares with different expected returns. In this sense, the terms where $m \neq 0$ in equation (4.11) are a correction to the expected value of the call option such that the present value of the call option remains independent of the expected return of the underlying asset. Equation (4.11) therefore provides an insight to the nature of option valuation using when using the binomial or Black-Scholes models.

4. Implications

A. Expected value and Black-Scholes value.

Does the expected return of the underlying asset play a role on option valuation? The Black-Scholes pricing formula is cited by many authors to be the end of a story that started with Bachelier in 1900.[1] They derived a formula that gives the fair value for a European call option based on the construction of either a replicating portfolio or riskless hedge, and the problem was deemed to be solved. Since then, the aim of most studies was to determine accurately the correct input parameters for the Black-Scholes formula, namely, the estimation of the volatility.[2] Some authors however question the use of a hedged portfolio to value options due to the hidden parameters, which apparently are taken out of option valuation, Heston (1993). Equation (4.12), which is based on the construction of a hedged portfolio, is equivalent to the Black-Scholes and binomial approaches. It shows explicitly the correction needed to add/subtract from these models in order to have the expected value of the call option,

[1] In Bachelier, L. *Theory of Speculation* (translation of 1900 French edition), in Cootner (1964), pp. 17-78.

[2] There exists an extensive literature on volatility forecasting which attempts to assess the advantages/drawbacks of different methods for estimating volatility. See for example Poon and Granger (2003) for a review of the different methods for forecasting volatility and see ap Gwilym and Buckle (1999), Canina and Figlewski (1993), Lamoureux and Lastrapes (1993) and Andersen and Bollerslev (1998) for empirical investigations of the different methods. An interesting fact that is common to all these studies is that market observed volatilities, implied by the Black-Scholes formula tend to consistently overestimate future volatility.

which is the fair value of the call option at time T (typically, at maturity). To analyse the impact of the expected return of the share price on the expected value of a European call option, numerical simulations were performed based on equation (4.11), which gives the call value based on the construction of a hedged portfolio using the binomial approach. Equation (4.11) also relates explicitly the expected value of the call option with the value obtained by the binomial approach (or Black-Scholes). The nature of this relation is going to be analysed by varying the expected return on the share while keeping all the other simulations parameters constant. This is equivalent to changing **m** in equation (4.11). As it was already mentioned previously, if the expected return is different to the risk-free rate then $\mathbf{m} \neq 0$. The terms in equation (4.11) that depend on **m** represent difference between the expected value of the call option discounted at the risk-free rate and the Black-Scholes value (if N is sufficiently large). The parameters used in the numerical simulations are shown in table 4.1.

Expected return, ρ	–10% to +10%
Volatility, σ	10%
Risk free rate, rf	2%
Time to maturity (days), T	100
Share price, S_0	\$50
Strike price, X	\$50
Binomial steps used	160

Table 4.1 – Parameters used in the simulation.

The results of the numerical simulations are shown in figure 4.4. On the left the value of an European call option is shown for different values of the expected return on the share. The red line represents the call value obtained by discounting the expected value of the call option to the present date using the risk-free rate of interest, which is in fact equation (4.12). The black line represents the value of the call option calculated using the binomial approach, which is in fact equation (4.11). As expected, the value of the call option using the binomial approach (hedged) is independent of the expected return on the share price. Figure 4.4 (right) shows only the correction to the expected value of the call option obtained by equation (4.12) required to obtain the same value for the call option independently of the expected return on the share. It is striking to notice from figure 4.4 that if the expected return on the share price is greater than the risk-free rate of interest, $\rho > r_f$, then the expected value of the call option is greater than the Black-Scholes calculated value (the option is cheap). This is equivalent to stating that the required discount rate to bring the expected value of the call option to present value must be greater than the risk-free rate of interest. On the other side, if the expected return is lower than the riskless rate of interest, $\rho < r_f$, then value of the expected value of the call option is lower than the value calculated using the binomial approach (hedged), which is equivalent to saying that the required discount rate must be lower than the risk-free rate of interest. Furthermore, the correction to the value of the call, f(m), also depends on the volatility of the asset. The value of the parameter **m** is inversely proportional to the volatility of the underlying asset. As $m \approx \left(\frac{(r_f - \rho)dt}{1 + r_f dt} \right) / \left(2\sigma\sqrt{dt} \right)$, the absolute correction to the expected value of the call option discounted at the risk-free rate of interest will be greater for assets with lower the volatilities. In the extreme case of $\sigma \rightarrow 0$ then **m** tends towards infinite for a fixed expected return, $\rho \neq r_f$.

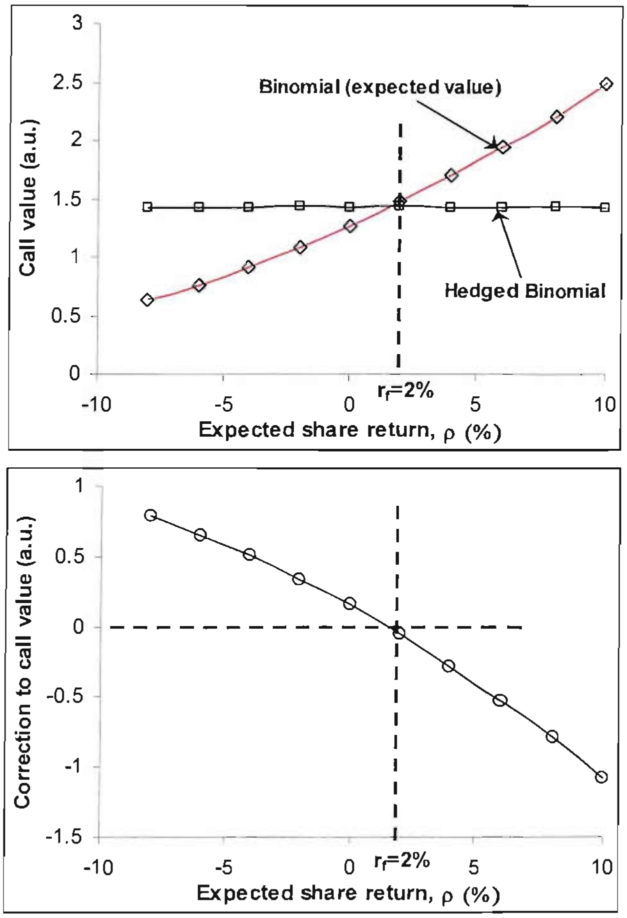

Figure 4.4: ***Top***: Value of the call option calculated using the binomial approach and expected value discounted at the risk-free rate. ***Bottom***: Difference between the binomial and expected value of the call option for different expected share returns.

In summary, these results give a clear example of one of the problems associated to the Black-Scholes approach (or other approaches that rely on arbitrage considerations). In my opinion, the Black-Scholes formula is not the end of the story when calculating the fair value of options, as it does not take into account the expected return on the share. The Black-Scholes valuation may be suitable for the market as a whole but may fail for individual securities where the risk-return relationship is not priced according to the risk-return implied by using the Black-Scholes stochastic process. The results shown in figure 4.4 are for a particular case of an option with relatively small time to maturity and low volatility. For higher values of volatility and time to maturity, the impact of the expected return of the underlying asset may be more severe and cannot be neglected.

B. Discount rate

Another pertinent question is: What discount rate should be used for discounting the expected value of the call option so that the value given by Black-Scholes is obtained? To analyse this question, let's re-write equation (4.11) that gives the present value of a call option calculated using the binomial approach and the construction of a hedged portfolio in the following form:

$$C_N(0) = \frac{1}{(R)^N} E(C_N) + f(m) = \frac{1}{(1+\rho dt)^N} E(C_N) \qquad (4.13)$$

where f(m) is a function of the expected return on the share price, ρ, that takes a zero value when the expected return is the same as the risk-free rate of interest, this is, if $\rho = r_f$ => m=0 and consequently f(m)=0. Furthermore, f(m) is the correction to the binomial pricing formula so that the value of the call option is the same as the expected value of the call option discounted at the risk-free rate. What is needed here is to translate this correction in the call value to a required discount rate that achieves the same purposes. Therefore, we need to find the discount rate, ρ_c, such that:

$$C_N(0) = \frac{1}{(1+r_f dt)^N} E(C_N) + f(m) = \frac{1}{(1+\rho_c dt)^N} E(C_N) \qquad (4.14)$$

After few manipulations we find the following relation:

$$\frac{f(m)}{E(C_N)} = \frac{1}{(1+\rho_c dt)^N} - \frac{1}{(1+r_f dt)^N}$$

Finally, as the number of steps increases, the rates of return above converge towards the continuously compounded rates, which are more convenient to use. Remembering therefore that the time to maturity, T, is related to the number of steps used in the binomial approach N and the time period, dt corresponding the binomial step by T=Ndt, we can write the previous equation as:

$$\exp\left[(r_f - \rho_c)Ndt\right] = 1 + \frac{f(m)}{E(C_N)}\exp(r_f Ndt)$$

By taking the natural logarithm of both sides and then rearranging we get:

$$\rho_c - r_f = -\log_e\left(1 + \frac{f(m)}{E(C_N)}\exp(r_f Ndt)\right)/Ndt \qquad (4.15)$$

Equation (4.15) gives the difference between the risk-free rate of interest and the required discount rate so that the expected value of the call option is the same as the binomial (or Black-Scholes) value. To illustrate the significance of the choice of the discount rate once the expected value of the call option is calculated, the correction to the risk-free rate of interest needed to make the present value of the call option the same as the value obtained using the binomial approach (or Black-Scholes) was calculated using the same parameters as shown in table 4.1. The results of the simulations are shown in figure 4.5, which plots the difference between the risk-free rate of interest and the required discount rate while varying the expected return on the shares. It is observed that the higher the expected return, the higher the discount rate as the call option is more valuable than calculated using Black-Scholes. On the other side, if the expected return on the shares is lower than r_f, then the correction to the discount rate is negative, which means that the required discount rate to bring the expected call value to present value is lower than r_f. Finally, as expected, if the expected return of the shares is the same as the risk-free rate, then m=0 in equation (4.11) and hence, the correction to the discount rate is zero. It should also be noticed that this figure is complementary to figures 4.4, which shows the difference between the Black-Scholes value of the call option and the risk-neutral discounted expected call value.

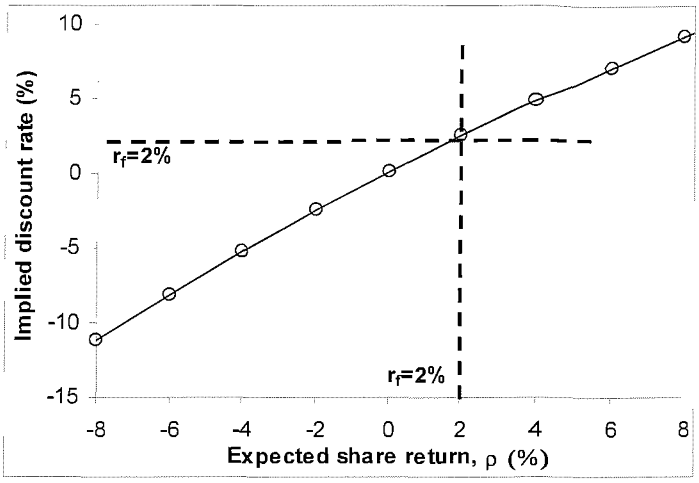

Figure 4.5: Discount rate implied by the Black-Scholes formula while varying the expected return on the shares.

Resuming, figure 4.5 illustrates clearly the answer posed by our question. To obtain the Black-Scholes value of the call option, the discount rate must be corrected in relation to the risk-free rate when the expected return on the shares is varied. Only in the particular case where $\rho=r_f$, the correction is zero, or in other words, r_f is the correct discount rate. Therefore, caution has to be applied when stating that the proper discount rate is the risk-free rate of interest when valuing a call option using the risk-neutral approach. For example, it is obvious from Figure 4.5 that when $\rho<r_f$, the implied discount rate is negative, which means that the present value of the call option is higher than it's future expected payoff.

C. The hole in Black-Scholes?

In the Black-Scholes or Binomial world, the construction of a hedged portfolio eliminates the expected return of the underlying asset form the valuation of the call option and uses the reference risk-free rate and volatility to price the option. Information on the expected return of the underlying asset is irrelevant and in efficient markets this information should be therefore totally incorporated into the implied volatility. This gives rise to a puzzle, which was discussed by Fisher Black in his paper on the holes in Black-Scholes, Black (1988): If we consider two different shares which are identical in every aspect except the expected return on the shares, then according to the Black-Scholes pricing model, a call option written on these shares will have the same premium. Of course, in CAPM equilibrium, this kind of situation should not occur as every asset must lie on the security market line, which is the same as saying that there is a linear risk return relation between the share return and the volatility. But if they do occur, then the expected values for the call options will differ and consequently intuitively it seems reasonable that two options on underlying assets with the same volatilities but different expected returns over a given period should necessarily be different. However, according to the Black-Scholes/binomial pricing formulas, both these options have the same value because the expected return on the underlying asset is irrelevant.

Nevertheless, there is the possibility of the occurrence of market inefficiencies where the risk-return relationship is violated (that is, some assets may not be represented on the CAPM securities market line). Although market imperfections might exist, many believe that stock markets are still efficient as those situations might only be temporary and not predictable, and additionally, they might not be profitable after transaction costs are taken into account. There is an extensive literature on market anomalies and the predictability of stock returns, which shows that these imperfections do exist. Among the published anomalies we find seasonal effects as the January effect, the excess returns of: momentum strategies (see Rouwenhorst (1998) for international evidence); strategies related to market overreaction or underreaction to specific events such as dividend announcements, earnings (De bondt and Thaler (1985), Ikenberry (1995), Aharony and Swary (1980), Petit (1972)); strategies related to the fundamental financial ratios such as the discussion of value versus growth (see Fama and French (1995 and 1998) or Dimson et al. (2003)) where there seems that excess returns can be achieved by selecting stocks with low P/E ratios, high dividend yields or high book-to-market-ratios. (See Fama (1998) for a survey). Pritmani et al (2001) report return predictability following large share price jumps (falls or rises). Other authors look at insider trading or analyst forecasts to predict excess-return generating strategies. All of this literature suggests that option prices can deviate from their fundamental Black-Scholes values due to anomalies in underlying assets' risk-return relationship. What is this effect on the pricing of options and how can they be accurately valued since option valuation does not take into account share returns? It seems likely that to address this problem options should be evaluated using both the expected return on the underlying asset as well as its volatility.

D. A possible test for the "hole" in Black-Scholes

Ingersoll (1987) shows that the CAPM is a sufficient condition for the Black-Scholes differential equation to be valid. He also shows that the risk premium on the call option, $x_c=(\rho_c-r_f)$, is related to the risk premium on the stock, $x=(\rho-r_f)$, by $x_c=x\sigma_c/\sigma$, where σ_c and σ are the volatilities of the call option and underlying asset respectively. In other words, the Sharpe ratios of the underlying asset and the call option must be the same. This result is valid for any derivatives, which follow the same stochastic process as the Black-Scholes stochastic process. It also provides an insight into the answer to Blacks' "hole in Black-Scholes". If one can predict the expected return on the asset, as well as the volatility of the asset, one can calculate the expected return on the call option, as previously shown, and finally verify the validity of the previous relation where the only unknown variable is the volatility of the call option, σ_c. So, for two shares with the same volatilities but different expected returns, the volatility of the options must be such that both the Sharpe ratios are equal. Alternatively, the adjustment may occur by "supply and demand market forces" giving different input implied volatilities to the call options with different expected returns of the underlying assets even though their historical volatilities are the same. However, this market adjustment may not occur and arbitrage opportunities will exist, as mentioned by Black (1988).

Furthermore, from the Black-Scholes option pricing formula, Ingersoll (1987) derives the relation between the volatility of the option and the underlying asset as $\sigma_c=\sigma SC_S/C$, where S is the share price, C is the option price and $C_S=dC/dS$ is the instantaneous option delta. As delta does not depend on the expected return of the underlying asset, there should be no "market adjustment" for the expected return of the option if the market is using the Black-Scholes formula to price the option. Then, the volatility of the call option only depends on delta (that is related to the leverage of the option), and the volatility of the underlying asset, which means that the ratio of the risk premium of the option and the stock is given by $x_c/x=C_SS/C$. This suggests that a test for the "hole in Black-Scholes", (the effect of the underlying asset return on the valuation of options) would be to analyse the relationship between the volatilities of the option and underlying asset with the relation between the option and asset returns over the same period. This relationship could then be compared with the theoretical relation between the volatilities of the underlying asset and its call option.

The focus upon volatility engendered by the Black/Scholes approach also has important implications for empirical work. Neglect of the process generating the asset return implies that there is a high likelihood that the model will be misspecified. This in turn means that volatility estimates will be biased. As the Black-Scholes formula for the value of the call option does not depend on the return of the underlying asset, the estimate of volatility will inevitably include information about the underlying asset return such as interest rate expectations, specific future events and other relevant "noise" sources. The estimation of volatility consequently remains an art form disguised as a science.

5. Conclusion

In this chapter we compared option pricing methods based on the construction of hedged portfolios, namely the Black-Scholes and Binomial approaches, with a less restrictive method which is based on the knowledge of the future probability distribution for the share price. To compare both these valuation methods, the binomial approach was used together with the construction of a hedged portfolio to give a novel expression that provides insight into the fundamental differences between these two approaches. The expression obtained provides an explicit relation between the expected value of the call option and the Black-Scholes valuation and their relation with the expected return of the underlying asset. When the expected return of the underlying asset is different from the risk-free rate, then the expected return of the call option has to be discounted using an adjusted discount rate to achieve the same Black-Scholes present value. As for the hole in Black-Scholes described originally by Black (1988), even though the Black-Scholes formula does not depend on the expected return of the underlying asset, the market may adjust for it by means of either an increased implied volatility or an increased option volatility, so that the Sharpe ratio of the underlying asset and the option are the same. An interesting study is to see if this relation holds and if so, how the market adjusts for information on expected return.

In chapter V we provide empirical evidence that gives some support to our argument. Namely, we show that there is an asymmetric behaviour between put options' implied volatilities and call options implied volatilities conditional upon previous price momentum. These results imply that investors are pricing put and call options differently, and we show that this can be explained by using equation (4.6) while assuming that past short-term returns are a predictor for expected returns.

Appendix 1:

Derivation of the binomial pricing formula

Let's analyse the calculation of the call option step by step:

Step 1: Construct the portfolio to replicate the payoff of the call option.

$$\begin{cases} C_u = S_0 u\Delta + BR \\ C_d = S_0 d\Delta + BR \end{cases} \Rightarrow \begin{cases} \Delta = \dfrac{C_u - C_d}{S_0(u-d)} \\ B = \dfrac{uC_d - dC_u}{R(u-d)} \end{cases} \tag{A1}$$

Step 2: Calculate the value of the call option, which must be same as the value of the replicating portfolio:

$$C = \Delta S_0 + B = \frac{(R-d)C_u + (u-R)C_d}{(u-d)R} \tag{A2}$$

Now the values for C_u and C_d need to be calculated through the next iteration. It can be easily shown by using a similar method as described previously, this is, by creating a replicating portfolio for both the possible scenarios. Note that the number of shares bought, Δ, and the amount borrowed at the risk-free rate, B, are adjusted after each step. Then let's repeat the process for the possible scenarios at time 2:

Step1: Construct the portfolio to replicate the payoff of the call option.

$$\begin{cases} C_u = \Delta_1 S_0 u + B_1 = \dfrac{(R-d)C_{uu} + (u-R)C_{ud}}{(u-d)R} \\ C_d = \Delta_2 S_0 d + B_2 = \dfrac{(R-d)C_{du} + (u-R)C_{dd}}{(u-d)R} \end{cases} \tag{A3}$$

with

$$\begin{cases} \Delta_1 = \dfrac{C_{uu} - C_{ud}}{S_0 u(u-d)}; B_1 = \dfrac{uC_{ud} - dC_{uu}}{(u-d)R} \\ \Delta_2 = \dfrac{C_{du} - C_{dd}}{S_0 d(u-d)}; B_2 = \dfrac{uC_{dd} - dC_{du}}{(u-d)R} \end{cases} \quad \text{(A4)}$$

Step 2: Calculate the value of the call options C_u and C_d, which must be same as the value of the replicating portfolios. By substituting (A4) into (A3) we obtain a better approximation (two-step approximation) for the value of the call option.

$$C_2 = \frac{(R-d)^2 C_{uu} + 2(u-R)(R-d)C_{ud} + (u-R)^2 C_{dd}}{(u-d)^2 (R)^2} \quad \text{(A5)}$$

It can easily be noticed that a pattern emerges. A general expression was obtained by Cox and Rubinstein by repeating this process over N iterations such that the value of the call option is:

$$C_N = \frac{1}{(R)^N} \sum_{i=0}^{N} C_i^N k_1^{N-i} k_2^i \max(S_0 u^{N-i} d^i - X, 0) \quad \text{(A6)}$$

where

$$k_1 = \frac{R-d}{u-d} \text{ and } k_2 = \frac{u-R}{u-d} \text{ and } k_1 + k_2 = 1 \text{ and } R = 1 + r_f dt$$

Appendix 2:

Derivation of the alternative binomial pricing formula:

$$\Delta S_0 u - C_u = \Delta S_0 d - C_d \Leftrightarrow \Delta = \frac{C_u - C_d}{S_0 (u-d)} \quad \text{(A7)}$$

the hedged portfolio earns the risk-free rate of interest during that period:

$$(S_0 \Delta - C)R = S_0 \Delta d - C_d \Leftrightarrow C = \frac{\Delta S_0 (R-d) + C_d}{R} = \frac{\Delta S_0 (R-u) + C_u}{R}$$

A more convenient way for writing the value of the call option is by adding both values (calculated using C_d and using C_u). Even though both of them are the same, by construction, it will be shown that the result is a closed form expression, which has significant insight into the implications of the assumptions undertaken by using the hedged portfolio. Consequently, we can write the value of the call option, C, as

$$2C = \frac{\Delta S_0(R-d)+C_d}{R} + \frac{\Delta S_0(R-u)+C_u}{R} \Rightarrow C = \Delta S_0\left(1-\frac{u+d}{2R}\right)+\frac{C_u+C_d}{2R} \quad \text{(A8)}$$

Substituting Δ into the previous expression and denominating k=(u+d)/2R, we can write the value of the call option for 1 step approximation (note that the we will change the denomination of C to C_1 that has a meaning "option value for one-step approximation"):

$$C_1 = (C_u - C_d)\frac{1-k}{u-d} + \frac{C_u + C_d}{2R} \qquad \text{(A9)}$$

C_u and C_d can be calculated in the same way from the values of C_{ud} , C_{uu} and C_{dd} at time 2:

$$\begin{aligned} C_u &= \Delta_1 S_0 u(1-k) + \frac{C_{uu}+C_{ud}}{2R} = \frac{(1-k)}{(u-d)}(C_{uu}-C_{ud}) + \frac{C_{uu}+C_{ud}}{2R} \\ C_d &= \Delta_2 S_0 d(1-k) + \frac{C_{ud}+C_{dd}}{2R} = \frac{(1-k)}{(u-d)}(C_{ud}-C_{dd}) + \frac{C_{ud}+C_{dd}}{2R} \end{aligned} \qquad \text{(A10)}$$

where $\Delta_1 = \dfrac{C_{uu}-C_{ud}}{S_0 u(u-d)}; \Delta_2 = \dfrac{C_{ud}-C_{dd}}{S_0 d(u-d)}$

the value of the call option for two step approximation can hence be calculated as:

$$C_2 = \frac{C_{uu} + 2C_{ud} + C_{dd}}{(2R)^2} + 2\frac{(1-k)}{(u-d)}\frac{C_{uu} - C_{dd}}{2R} + \frac{(1-k)^2}{(u-d)^2}(C_{uu} - 2C_{ud} + C_{dd})$$

(A11)

C_{uu}, C_{dd} and C_{ud} can be calculated in the same way from the values of C_{udd} , C_{uud} , C_{uuu} , C_{ddd} at time 3:

$$C_{uu} = \Delta_1 S_0 u^2(1-k) + \frac{C_{uuu} + C_{uud}}{2R} = \frac{(1-k)}{(u-d)}(C_{uuu} - C_{uud}) + \frac{C_{uuu} + C_{uud}}{2R}$$

$$C_{ud} = \Delta_2 S_0 ud(1-k) + \frac{C_{uud} + C_{udd}}{2R} = \frac{(1-k)}{(u-d)}(C_{uud} - C_{udd}) + \frac{C_{uud} + C_{udd}}{2R}$$

$$C_{dd} = \Delta_3 S_0 d^2(1-k) + \frac{C_{udd} + C_{ddd}}{2R} = \frac{(1-k)}{(u-d)}(C_{udd} - C_{ddd}) + \frac{C_{udd} + C_{ddd}}{2R}$$

(A12)

where $\Delta_1 = \frac{C_{uuu} - C_{uud}}{S_0 u^2(u-d)}; \Delta_2 = \frac{C_{uud} - C_{udd}}{S_0 ud(u-d)}; \Delta_3 = \frac{C_{udd} - C_{ddd}}{S_0 d^2(u-d)}$

the value of the call option for two step approximation can hence be calculated as:

$$C_3 = \frac{1}{(2R)^3}(C_{uuu} + 3C_{uud} + 3C_{udd} + C_{ddd}) + 3\frac{m^1}{(2R)^2}(C_{uuu} + C_{uud} - C_{udd} - C_{ddd}) +$$
$$+ 3\frac{m^2}{(2R)^1}(C_{uuu} - C_{uud} - C_{udd} + C_{ddd}) + m^3(C_{uuu} - 3C_{uud} + 3C_{udd} - C_{ddd})$$

(A13)

A pattern seems to emerge. To simplify the previous expression, let's write it using matrices:

$$C_3 = \begin{bmatrix} C_{uuu} \\ C_{uud} \\ C_{udd} \\ C_{ddd} \end{bmatrix} \begin{bmatrix} 1 & 3 & 3 & 1 \\ 3 & 3 & -3 & -3 \\ 3 & -3 & -3 & 3 \\ 1 & -3 & 3 & -1 \end{bmatrix} \begin{bmatrix} \frac{1}{(2R)^3} & \frac{m^1}{(2R)^2} & \frac{m^2}{(2R)^1} & m^3 \end{bmatrix} \qquad \text{(A14)}$$

Finally in order to make it easier to deduce a general expression that can explain the different approximation steps, let's repeat the process for the 4th step.

$$\begin{aligned}
C_{uuu} &= \Delta_1 S_0 u^3(1-k)+\frac{C_{uuuu}+C_{uuud}}{2R}=\frac{(1-k)}{(u-d)}(C_{uuuu}-C_{uuud})+\frac{C_{uuuu}+C_{uuud}}{2R}\\
C_{uud} &= \Delta_2 S_0 u^2 d(1-k)+\frac{C_{uuud}+C_{uudd}}{2R}=\frac{(1-k)}{(u-d)}(C_{uuud}-C_{uudd})+\frac{C_{uuud}+C_{uudd}}{2R}\\
C_{udd} &= \Delta_3 S_0 u d^2(1-k)+\frac{C_{uudd}+C_{uddd}}{2R}=\frac{(1-k)}{(u-d)}(C_{uudd}-C_{uddd})+\frac{C_{uudd}+C_{uddd}}{2R}\\
C_{ddd} &= \Delta_4 S_0 d^3(1-k)+\frac{C_{uddd}+C_{dddd}}{2R}=\frac{(1-k)}{(u-d)}(C_{uddd}-C_{dddd})+\frac{C_{uddd}+C_{dddd}}{2R}
\end{aligned} \qquad \text{(A15)}$$

where $\Delta_1=\frac{C_{uuuu}-C_{uuud}}{S_0u^3(u-d)};\Delta_2=\frac{C_{uuud}-C_{uudd}}{S_0u^2d(u-d)};\Delta_3=\frac{C_{uudd}-C_{uddd}}{S_0ud^2(u-d)};\Delta_4=\frac{C_{uddd}-C_{dddd}}{S_0d^3(u-d)}$

By substituting (A15) into A(14), the value for the call option using a 4-step approximation can be written in matrix form as:

$$C_4=\begin{bmatrix}C_{uuuu}\\C_{uuud}\\C_{uudd}\\C_{uddd}\\C_{dddd}\end{bmatrix}\begin{bmatrix}1&4&6&4&1\\-4&-8&0&8&4\\6&0&-12&0&6\\-4&8&0&-8&4\\1&-4&6&-4&1\end{bmatrix}\begin{bmatrix}\frac{1}{(2R)^4}&\frac{m}{(2R)^3}&\frac{m^2}{(2R)^2}&\frac{m^3}{(2R)^1}&m^4\end{bmatrix}$$

(A16)

Finally, a general expression for N steps can be obtained by repeating this process and recurring to some algebra manipulation. The approximated value of the call option calculated using N steps of the hedged portfolio can be written as:

$$C_N=\sum_{i=0}^{N}\left[C_i^N\frac{m^i}{(2R)^{N-i}}\left(\sum_{j=0}^{N-i}C_j^{N-i}\sum_{h=0}^{i}C_h^i(-1)^h\max(S_0u^{N-j-h}d^{j+h}-X,0)\right)\right] \qquad \text{(A17)}$$

with $m=\frac{1-k}{u-d}=\frac{1-\frac{u+d}{2R}}{u-d}$ and $C_p^n=\frac{n!}{p!(n-p)!}$

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Chapter V

"Empirical evidence of the impact of past returns on option prices"

Abstract: In this chapter we present evidence of a relation between historical FTSE100 index returns and option prices. Our results show evidence of the existence of a strong negative correlation between past index returns and the put option volatility spread. They also show weaker evidence of a positive correlation between past index returns and the call option volatility spread. One explanation could be supply and demand price-pressure effects caused by agents buying portfolio insurance when index returns are negative. The study examines market data for FTSE100 option prices from 1993-1997. In order to investigate the effect of past returns on option prices, options implied volatilities are calculated and compared with different measures of historical volatility. It is shown that the spread between the volatility implied by the market and measured historically is strongly related with past returns in the case of put options while this correlation is weaker for call options. In our analysis we control for the time to maturity and moneyness of the options by grouping the option prices into different categories. In summary, this study provides evidence that agents price options taking into account past index returns, which is obviously not rational according to prevailing option pricing theories.

1. Introduction

Prevailing options pricing models, such as the Black-Scholes or the binomial models assume martingale stochastic process for the underlying asset return[1], no transaction costs, perfect capital markets and the existence of a risk-free asset. Under these assumptions, options can be priced by replicating the options payoffs or by creating a hedged portfolio that disallows arbitrage possibilities. However, in real markets, some of these assumptions do not hold. Transaction costs in the options markets are considerable due to both the large bid-ask spreads and the brokerage costs, which mean that the construction of replicating or hedged portfolios is not possible. Furthermore, when the perfect markets assumption is relaxed, it becomes difficult to create hedged portfolios or replicate the option payoffs. Under these circumstances, option prices can deviate from their fundamentals by showing different implied volatilities for puts and calls as shown by Kaushik et al. (2004). In their paper, they show that to some extent the prices of puts and calls of the same time to maturity and strike price, behave independently being determined by supply and demand and no arbitrage considerations when markets are imperfect. Factors that affect the supply and demand of put or call options could include investors' perception of the market direction[2] as well as volatility or the price-pressure of insurance buying when stocks prices are falling. Past stock returns could also play a role when pricing options in real markets as investors often use past stock returns of predictors for future returns (momentum hypothesis) and consequently act upon this information by either hedging (buying portfolio insurance) or speculating on the share price direction. Consequently, if real market considerations are taken into account, empirical evidence on the options market could show a relation between past market returns

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[1] See Black and Scholes (1973), Merton (1976) for the original works on non-arbitrage option pricing models based on a hedged or replicating portfolio. See Cox et al. (1979) for the binomial pricing model, which is a discrete version of Black and Merton pricing continuous time option pricing theory.

[2] There exists an extensive literature on market imperfections due to singular events or share price momentum, all of which could be sources for changing the perception of options investors. See for example Harris and Gurel (1986), Scholes (1972) and Shleifer (1986) for price and volume effects occurring when companies are added into the S&P500 index. There is also evidence of share return predictability after extreme events has been found by Pritmani and Singal (2001), while evidence of momentum has been found by numerous authors, see Chan et al. (1996) or Rouwenhorst (1998). Further examples can be found in the literature on behavioural finance where evidence exists of share price over/under reaction certain to informational events (see De Bondt and Thaler (1985)).

and option prices, contrary to the underlying assumptions of prevailing option pricing models.

Further evidence of an inconsistent behaviour in the options markets include Bakshi et al. (2000) who perform and empirical analysis of S&P500 options to test if some properties common to all one-dimensional diffusion option models hold. They find inconsistencies in the dynamics of real options markets with standard pricing models (such as Black-Scholes). In particular, they show that put and call prices often go up or down together in both intraday and interday samples and therefore concluding that options are non-redundant securities; Figlewski (1989) shows that put and call options can deviate from equilibrium prices if market imperfections such as volatility estimation errors, transaction costs, indivisibilities and non-continuous rebalancing are considered. An early study by Stein (1989) shows empirical evidence of overreaction of long-term puts and calls relative to short-term options when volatility jumps in the S&P100 index occur. This empirical evidence could be related to supply and demand pressure from insurance buyers who drive up option prices in times of crisis.

In addition to the previous literature, which attempts to find inconsistencies in the behaviour of option markets, there is an extensive body of literature focusing on volatility forecasting by testing different historical volatility forecasts against those implied by the options markets. Empirical research performed by Canina and Figlewski (1993) supports Figlewski's (1989) conclusions by finding evidence that implied volatility, as calculated by standard using Black-Scholes, has no correlation with 60-day historical volatility and is a poor predictor of future volatility. These results are supported by empirical findings by Lamoureux and Lastrapes (1993) who compare implied volatilities with historical volatility measures finding that the later perform better in 8 of 10 US equity options that they examined. More recent studies from Fleming (1998) and Christensen and Prabhala (1998) find evidence in the opposite direction: implied forecasts are more informative than daily returns when forecasting equity volatility even though they tend to be biased positively (overestimate future volatility). However, with the recent advent of high frequency data collection and storage, new evidence is arising that may challenge once again these beliefs. Andersen and Bollerslev (1998) (for FX markets) and Andersen et al. (2001) (for equity markets) show that regression methods using daily volatility estimates give low R^2 because squared returns are noisy estimates of volatility. They show that by using intraday returns a low noise daily volatility estimate can be constructed. They then find significant improvements in the forecasting performance of ARCH models. Blair et al. (2001) confirm those results for the S&P100 index and compare the performance of the high-frequency forecasts of daily volatility with the implied ones finding that even though the high-frequency forecasts do provide an improvement in forecasting volatility relatively to the low-frequency daily forecast, implied volatilities still have superior forecasting power. A more recent study from Martens and Zein (2004) finds further evidence that confirms the results from Blair et al. (2001). By analysing three different markets (S&P500, YEN/USD and Light, Sweet Crude Oil) they find that implied volatilities provide superior forecasts compared to both low-frequency and high-frequency daily GARCH(1,1) forecasts.

In this chapter we test for the existence of a relation between option prices and past market returns. The focus of this study is not to try to access the information content of implied volatilities but to observe the behaviour of stock index put and call options markets relative to past index returns. Our study is in the same context of a recent work by Kaushik et al. (2004) who show empirical evidence on this subject by investigating violations to the put-call parity relation as a function of 60-day S&P100 index (OEX) past returns. In their study, they match pairs of puts and call transactions from S&P100 index options in order to perform non-parametric tests on the put-call parity violations. They also relate the implied volatility spread of put and call pairs with historical 60-day returns finding evidence for a relation between past returns and option prices supporting the momentum hypothesis. Their results show that negative past returns put pressure on put option prices due to portfolio insurance buying while positive returns creates pressure on call option prices due to investors expectations of positive index momentum. Our study differs from Kaushik et al (2004) as we test the relation between past returns and put and call options implied volatility (IV) spreads independently. We define the implied volatility spread for each option as the difference between the IV calculated using BS adjusted for dividends and a measure of realised historical volatility. This definition avoids biases arising from changes in market volatility over time. We then regress the put and call options' implied volatility spreads with different past stock returns time periods while controlling for historical volatility (using both simple equally weighted historical volatility and an exponentially weighted moving average volatility (EWMA) measurement).[3]

We find that the shorter the time period of measurement of the past return, the greater the impact is found on option prices. In particular, put options prices are under significantly higher pressure for 2-3 day price falls/rises than for 20-30 day negative past returns. Our results show a strong negative correlation between past returns and the IV spread for put options and consequently when previous index prices increase, put option IV decrease and when index prices decrease, IVs increase. However, in the case of call options the evidence is mixed even though predominantly show evidence of a positive or no correlation between past index returns and call option IV spreads. We also investigate the IV spread correlation with past returns as a function of the moneyness of the options. For put options we find that negative/positive past returns create higher pressure on out of the money options than on in the money options. As for call options, we also identify as similar trend as we observe positive correlation between past returns and IV spreads for out of the money options while for in the money options we find a negative correlations, which suggests that market prices are dictated by the pressure on the put options. Finally, we analyse how the options IV spreads behave as a function of the time to maturity (from 10 to 200 days). We find that there are no significant changes in the term structure of the options IV spread. Therefore, the impact of past returns on options prices is consistent across different maturity ranges and is not only a local anomaly.

Our work contributes to the available literature in the following ways: First we introduce the use of the implied volatility spread which measures the difference between the options implied volatility and an historical measure. We believe there is a case for using such measures as volatility changes considerably over time, which could introduce errors when comparing options over different time periods.

[3] Refer to section 3 for details of the construction of the volatility estimates.

Additionally, using the IV spread, we can monitor the behaviour of both put and call options against a common consistent volatility measure. The choice of the reference volatility measure is a question we have not addressed here and could be subject for further research. We use low-frequency measures for historical volatility as the benchmark but high-frequency GARCH estimates could be equivalently utilised. Second, our results shed some further light into the dynamics of option prices in real markets. The strong negative relation between put options' IV spreads and past FTSE100 index returns goes against standard options pricing models. Third, we find evidence of a distinct behaviour for put options and call option prices, which lead us to question if options are in fact redundant securities.[4] Finally, we show that by using a parsimonious model for pricing options (shown in chapter IV), which is based on calculating the expected value of the options using past returns as a proxy for future returns, we are able to explain the options' behaviour.

The chapter is structured as follows. Section 2 describes the data sample. Section 3 describes the methodology we used in calculating the IV spreads and the empirical tests we performed relate these with past returns. Section 4 presents the results of the empirical regressions for both put and call options. In section 5 we investigate how our results change with the options term structure. In section 6 we fit some data sub-samples with a parsimonious approximated theoretical model for options prices. Finally, in section 7 we draw some conclusions.

2. The data sample

The data originates from a CD containing a database of FTSE100 index European-style options contracts traded at LIFFE (London International Financial Futures and Options Exchange) from 4-1-1993 to 18-12-1997. The data is comprised of transactions tick data for put and call options of different maturities and strike prices

[4] In similarity to previous authors who also question if options are redundant securities. For example, Figlewski (1989) shows that put and call options can deviate from equilibrium prices if market imperfections such as volatility estimation errors, transaction costs, indivisibilities and non-continuous rebalancing are considered. Kaushik et al. (2004) also find empirical evidence of put-call parity relation violations as a function of past returns which questions again if the market in fact prices options using standard arbitrage based models.

for both American-style and European-style contracts. For our study we use the European options data, which is the less liquid contract but is more suitable for our empirical investigation, as implied volatilities can be computed easily using the Black-Scholes formula directly without any approximation. The sample comprises of a total of 104687 put and call options trades. In order to obtain comparable option prices, we split the data into different slots according to the moneyness and time to maturity. Most previous studies focus on OEX options (options on the S&P100), which have much higher liquidity than FTSE100 index options. However, with our data sample we are able to observe some statistically significant results especially in the put options behaviour. The database fields consist of: the delivery date, transaction time and date, time to maturity, strike price, transaction value, option type (call/put) and index value. We exclude options with times to maturity lower than 10 days due to the lack of observations and the volatile nature of these options. As a proxy for the risk-free rate of interest we use the 3-month Treasury bill yield across the sample period obtained from the Bank of England. The CD also contains the value of the underlying FTSE100 index at the time of the transaction which is used to calculate the options implied volatility. We obtain the dividend yield on the FTSE100 index from Thomson Datastream. Table 5.1 shows the distribution of the options transactions over time. We observe that from 1993 to 1997 there has been a monotonic increase in the number of transactions in the sample. Therefore, most of the sample refers to the year of 1997 that has a heavier weight on the observations.

Table 5.1
Description of the number of options transactions by type and year in the LIFFE FTSE100 index options database. The number of transactions increases significantly in 1997 and therefore our analysis is biased temporally to 1997. Nevertheless this fact does not invalidate our research as we are relating past stock prices with put and call options' IV spreads, which should be insensitive to the analysed time period.

Time Period:	**1993**	**1994**	**1995**	**1996**	**1997**	**Total**
Puts	4740	6179	9383	11302	19434	51038
Calls	5765	6745	9608	11814	19707	53639
Total	10505	12924	18991	23116	39141	104677

3. Methodology

The aim of our study is to test if actual option prices are affected by historical returns on the FTSE100 index. In order to test this hypothesis we regress the implied volatility spread against past returns of different time periods while controlling for different measures of historical volatility. The implied volatility spread (ΔIV) is the difference between the call (or put) options' IV calculated using the Black-Scholes formula corrected for the dividend yield of the FTSE100 index and a reference historical volatility. We believe there is a case for using the implied volatility spread as volatility changes considerably over time, which could introduce errors when comparing options over different time periods. Additionally, using the ΔIV, we can monitor the behaviour of both put and call options against a common consistent volatility measure. The choice of the reference volatility measure is a question we have not addressed here and could be subject for further research. We use low-frequency measures for historical volatility as the benchmark but high-frequency GARCH estimates could be equivalently utilised.

We use two different measures for the reference volatility in order to test the robustness of our results. One measure is an exponentially weighted historical volatility estimate with a persistence parameter of $\lambda=0.94$. This imposes a heavy weight on very short term past returns and low weight on past returns older than about 20 days. The second measure of historical volatility is the standard 22-day equally weighted volatility. The analysis of a relative implied volatility or IV spread ensures that our results are not due simply to higher (or lower) index volatility at a given point in time. It is reasonable to observe that if we simply analysed options IV, the analysis could not distinguish between the impacts of past returns from the impact of changes in the underlying assets' volatility. After obtaining the IV spreads we regress them against past index returns of different time periods namely, 2, 3, 6, 10, 20, 30 day periods. In the process we also regress the two measures of historical volatility in order to control our results for changes in volatility. Equations (5.1) and (5.2) summarise the methodology we used to test the hypothesis. Equation (5.1) shows the regression equation with variables HRet (historical return of period t), $HVol_{22d}$ (22-day historical volatility) and $HVol_{EWMA}$ (EWMA historical volatility with a persistence parameter of $\lambda=0.94$). ε is the standard white noise term.

$$\Delta IV = (IV_{BS} - HVol_{22d}) = \alpha + \beta_1 HRet(\tau) + \beta_2 HVol_{22d} + \varepsilon \qquad (5.1a)$$

$$\Delta IV = (IV_{BS} - HVol_{22d}) = \alpha + \beta_1 HRet(\tau) + \beta_2 HVol_{EWMA} + \varepsilon \qquad (5.1b)$$

$$\Delta IV = (IV_{BS} - HVol_{22d}) = \alpha + \beta_1 HRet(\tau) + \varepsilon \qquad (5.1c)$$

Historical volatility measures:[5]

1 – Simple 22-day equally-weighted historical volatility, $HVol_{22d}$:

If r_t are the log-return time series and R the average return then the simple historical volatility estimate, $\hat{\sigma}_t$ is calculated as:

$$HVol_{22d} = \hat{\sigma}_t = \left[\frac{1}{N-1}\sum_{i=1}^{N}(r_{t-i} - R)^2\right]^{1/2} \qquad \text{with} \qquad N = 22 \qquad (5.2a)$$

2 – Exponentially weighted historical volatility with λ=0.94, $HVol_{EWMA}$:

If r_t are the log-return time series then the exponentially weighted volatility estimate, $\hat{\sigma}_t$ is calculated iteratively as:

$$\hat{\sigma}_t^2 = (1-\lambda)r_t^2 + \lambda\hat{\sigma}_{t-1}^2$$

By recursively replacing $\hat{\sigma}_{t-1}$ in the previous equation, we get

$$HVol_{EWMA} = \hat{\sigma}_t = \left[(1-\lambda)\sum_{i=1}^{N}\lambda^{i-1}r_{t-i}^2\right]^{1/2} \qquad \text{with} \qquad \lambda = 0.94 \qquad (5.2b)$$

The persistence parameter of 0.94 corresponds roughly to a decay parameter of $\tau = 1/(1-\lambda) \approx 16.7$ days. The truncation of equation (5.2b) will give rise to an error in the volatility estimate which depends of the number of days used in the volatility estimate, N, and the decay factor. In our case, for a persistence parameter of 0.94 using N=50 days will yield a small error in the volatility estimate.

[5] See for instance Jorion (2002) pages 186-196 for a simplified explanation of volatility estimation or Poon and Granger (2003) for a review of volatility models used within the academic literature.

Organisation of the data:

For the results of the regressions in equations (5.1) to be meaningful, we need to compare options with identical characteristics. For this purpose we split the options data into bins according to their term structure and moneyness. We analyse options with 20 to 30 trading days to maturity in most of this study. Then we analyse briefly the robustness of our results when considering options with a range of maturities. We find there is no significant difference in our results that would justify a full analysis of options of each maturity range individually and that our results hold across the options term structure. The options data are also split into bins of moneyness. The definition for the option moneyness is $\log_e(S/X)$ where S is the FTSE100 index value and X is the option strike price. For call options negative values of $\log_e(S/X)$ are related to out of the money options while for put options the inverse is true. We use 10 bins of options moneyness as shown in table 5.2.

Table 5.2
Ranges of options moneyness into which the data sample is split. Each column corresponds to a bin of option moneyness which is used in the data analysis. At the money options are the two central bins where log(S/X)=[-0.01, 0] or log(S/X)=[0, +0.01]

	log(S/X)									
From	**-0.10**	**-0.05**	**-0.03**	**-0.02**	**-0.01**	**0.00**	**0.01**	**0.02**	**0.03**	**0.05**
to	**-0.05**	**-0.03**	**-0.02**	**-0.01**	**0.00**	**0.01**	**0.02**	**0.03**	**0.05**	**0.10**

4. Results

A. The relation between past returns and the IV spread

In this section we analyse the relation between put and call option prices on past index returns. We use options with time to maturity (TTM) of 20 to 30 trading days that are at the money with Log(S/X) ranging from –0.01 to 0. That is, we select options with a strike price that is slightly higher than the underlying index value. We consider however that these options are at the money options due to $S \approx X$. Finally, we perform the multivariate regressions of equations (5.1) by considering both 3-day past returns and 20day past returns. We use the 22-day historical volatility ($HVOL_{22d}$) as the reference volatility in order to calculate the IV spread for both put and call options. Table 5.3 shows the results of the multivariate regression analysis for a 3-day past index return. To test for the robustness of any statistical correlation between past index returns and IV spreads, we reduce the number of regression variables to observe the effect on the historical return coefficient (HRet).

Table 5.3
Multivariate regression analysis according to equations (5.1). The historical return variable corresponds to a 3-day period previous to the option transaction date. The implied volatility spread (ΔIV) is calculated as the difference between the Black-Scholes IV adjusted for dividends, and the 22-day historical volatility as in equation (5.2a). *, **, *** Denote at least 10%, 5% and 1% statistical significance levels, respectively.

Panel A Put options Log(S/X): [-0.01, 0] , TTM (20-30d) N=790 ; Past return period: 3days					**Panel B** Call options Log(S/X): [-0.01, 0] , TTM (20-30d) N=662 ; Past return period: 3days				
	EWMA	**HRet**	**HVol**	**Const**		**EWMA**	**HRet**	**HVol**	**Const**
Coef.		-1.12***	0.38***	-0.006	**Coef.**		0.17	0.18***	-0.00219
t		-10.826	8.409	-1.096	**t**		1.398	3.828	-0.404
F	90.48	**df**	787		**F**	9.22	**df**	659	
p-value	4.28E-36	**R2**	0.19		**p-value**	0.00	**R2**	0.03	
Coef.	0.36***	-1.12***		-0.004	**Coef.**	0.16***	0.14		0.000945
t	12.582	-11.360		-1.068	**t**	4.828	1.220		0.250
F	139.90	**df**	787		**F**	13.57	**df**	659	
p-value	1.03E-52	**R2**	0.26		**p-value**	0.00	**R2**	0.04	
Coef.		-1.09***		0.039***	**Coef.**		0.23*		0.018***
t		-10.064		24.339	**t**		1.925		12.011
F	101.28	**df**	788		**F**	3.71	**df**	660	
p-value	1.7E-22	**R2**	0.11		**p-value**	0.05	**R2**	0.01	

The results in table 5.3 indicate that for put options, the IV spread correlation with 3-day past returns is highly significant even when controlling for different measures of historical volatility. It is observed that HRet regression coefficient is negative (-1.1) denoting that there is a positive pressure on put options IV due to recent market falls and a negative pressure on recent market rises, which cannot be explained by increases in volatility. We also observe that when including historical volatility measures HVol or EWMA, the statistical significance of HRet is reduced slightly but it still remains highly significant. Both the historical volatility measures are also highly significant factors explaining most of the bias in the regressions (intersect coefficient α). This is, when either EWMA or HVol are included it is observed that α=0. Finally, of both the historical volatility measures, it appears that EWMA has the highest explanatory power, having a higher t statistic and achieving the highest the F statistic for the regression.

For call options, we don't find such a strong correlation between the IV spread of the call options and 3-day past returns. Additionally, any weak statistical significance in the HRet coefficient is eliminated when additional explanatory variables are included. It appears the EWMA is the variable that better explains the calls' IV spread and past returns have weak explanatory power. We conclude that contrary to the evidence found for put options, past returns do not explain the IV spread for call options.

Next, the same analysis is performed for the relation between IV spread and 20-day past returns. The results of the multivariate regressions are shown in table 5.4.

Table 5.4

Multivariate regression analysis according to equations (5.1). The historical return variable corresponds to a 20-day period previous to the option transaction date. The implied volatility spread (ΔIV) is calculated as the difference between the Black-Scholes IV adjusted for dividends, and the 22-day historical volatility as in equation (5.2a). *, **, *** Denote at least 10%, 5% and 1% statistical significance levels respectively.

Panel A Put options Log(S/X): [-0.01, 0] , TTM (20-30d) N=785 ; Past return period: 20days					**Panel B** Call options Log(S/X): [-0.01, 0] , TTM (20-30d) N=662 ; Past return period: 20days				
	EWMA	**HRet**	**HVol**	**Const**		**EWMA**	**HRet**	**HVol**	**Const**
Coef.		-0.75***	0.18***	0.023***	**Coef.**		-0.054	0.185***	-0.001
t		-17.705	4.259	4.275	**t**		-1.000	3.876	-0.203
F	195.71	**df**	782		**F**	8.73	**df**	659	
p-value	1.23E-69	**R2**	0.33		**p-value**	0.00	**R2**	0.03	
Coef.	0.20***	-0.70***		0.019***	**Coef.**	0.16***	-0.027		0.002
t	7.393	-16.317		5.016	**t**	4.836	-0.499		0.379
F	222.48	**df**	782		**F**	12.93	**df**	659	
p-value	3.25E-77	**R2**	0.36		**p-value**	0.00	**R2**	0.04	
Coef.		-0.81***		0.044***	**Coef.**		-0.083		0.02***
t		-19.521		30.747	**t**		-1.545		12.109
F	365.27	**df**	783		**F**	2.39	**df**	660	
p-value	4E-67	**R2**	0.32		**p-value**	0.12	**R2**	0.00	

In similarity to the results in table 5.3, the results in table 5.4 indicate that for put options, the IV spread correlation with 20-day past index returns is highly significant even when controlling for different measures of historical volatility. It is observed that HRet regression coefficient is negative (-0.7) denoting that there is a positive pressure on put options IV due to recent market falls and a negative pressure on recent market rises, which cannot be explained by increases in volatility. Both the EWMA and HVol volatility measures have a strong explanatory power for the regression with the EWMA providing more information. A striking difference for the results for 20-day past returns compared to the 3-day returns is that in the later case, EWMA or HVol explained the bias in volatility spread by eliminating a from the regression. In the case of 20-day past returns, HVol and EWMA do not remove completely the bias, explaining approximately 50% of the regression a. The remaining component is still highly significant.

For call options, we find that 20-day past returns variable (HRet) has no significance in explaining the IV spread of the call options. Additionally, any weak statistical significance in the HRet coefficient is eliminated when including additional explanatory variables such as EWMA or HVol. It is also interesting to compare the 3th regression in each table where only variable HRet is regressed (corresponding to equation 5.1c). In these cases, the regression constant gives the average bias in the IV relatively to the 22-day historical volatility measure, for at the money options. We can observe that the bias is highly significant and takes a non-zero value of around 2% for call options and 4% for put options. This is in agreement with common knowledge that 1) there is an average premium on put and call options relatively to the volatility of the underlying asset 2) that premium is higher for put options than for call options.[6]

[6] This bias is well documented in the literature. See for example ap Gwilym and Buckle (1999) who document the bias for a sample FTSE100 index options, which is similar to the one used in this investigation. For further references on the more widely researched S&P100 index options, see Canina and Figlweski (1993), Fleming (1998), Christensen and Prabhala (1998). Perhaps the most illustrative examination of the IV bias is an investigation by Green and Figlewski (1999) where they sold portfolios of fairly priced options using historical volatility measures which resulted in large losses over an extended period. They concluded that the evidence for the observed IVs premiums is well justified as options sellers would have not been paid by the risk they were taking while selling the options. Their finding also showed that the losses were greater when selling put options than call options which justifies the higher premium paid for put options in the market.

The results in tables 5.3 and 5.4 provide evidence of different behaviour patterns for put and call option prices. Put options prices are negatively correlated with historical returns of different time periods with highly significant regression coefficients. Call options do not show the same behaviour as put options as HRet seems to be an insignificant variable when regressing the calls' IV spread. This distinct behaviour between put and call option prices is not predicted by any non-arbitrage option pricing models and is an anomalous market behaviour. It is clear that if put options are negatively correlated with past returns while call options are not, there will be occasions where put and call options prices move in the same direction as shown by Bakshi et al (2000), and consequently, there will be violations to the put-call parity relation which are dependant on past index returns, as observed by Kaushik et al (2004) for the S&P100 (OEX) options. Our empirical results for options on the FTSE100 index show however that what drives this anomalous behaviour is the market pressure on the put options. Call options IVs are a balance between arbitrage opportunities if put options' IVs drift too far from call option IVs and the market pressure on call options if past returns are positive, due to investors' positive expectations for the index. We also observe that put option prices are much more sensitive to short-term (3-day) past returns than to longer-term (20-day) price falls (or rises). In fact, the HRet regression coefficient was about –1.1 for 3-day past returns while only around -0.7 for 20-day past returns. This is indication of extra pressure on put options due to investors buying insurance at above market prices when short-term drops in the index are observed.

The second feature of our empirical observations is that the implied volatility spreads ΔIV are biased positively, which is in agreement with previous studies. We find that when using 3-day past returns (HRet) and a historical volatility factor (either HVol or EWMA) we eliminate the bias completely (as seen in table 5.3). This is not the case when using 20-day historical returns and EWMA or HVol where the bias is only partially explained by these factors. We believe this fact brings some insight into the nature of the IV spread bias observed in options markets. Perhaps a portion of the bias can be accounted for by changes in volatility regime and short-term market movements.

Next we investigate the IV spread behaviour for different moneyness and historical past return time periods.

B. IV spread dependence on option moneyness and historical return period

In this section we will characterise the relation between the IV spread of both put and call options with past returns across different options moneyness and past return periods. In order to test the robustness of the results we characterise the IV spread where calculated as IV minus the EWMA historical volatility ($HVol_{EWMA}$). As a robustness check, we performed the same analysis for the IV spread calculated using the simple 22-day historical index volatility ($HVol_{22d}$) obtaining very similar results. We perform single factor regressions according to equation (5.1c). As we have seen previously this is a reasonable assumption for put options where the high statistical significance of HRet is independent of the other variables and where HRet has a very high regression explanatory power. For call options this assumption does not hold, as the statistical significance of HRet is low. It is nevertheless an interesting exercise to investigate if the low significance of HRet is the same for all option moneynesses and for a range past return time periods. The results in table 5.5 show the regression statistics for the put options IV spread ($IV-HVol_{EWMA}$).

These results provide further evidence of the strong negative correlation between past FTSE100 index returns and put option IV spreads independent of the option moneyness. There is however, a noticeable trend in the impact of past returns on the put options IV spread as the options moneyness is increased: The negative correlation coefficient decreases as put options moneyness is decreases. This means, that in-the-money put options are less affected by past index returns than out-of-the-money options. There is also a similar trend as the past return period is increased: The longer the past index return time period, the lower is the impact on put option IVs. As we have previously mentioned, this behavior indicates that there is a higher impact of short-term index movements on put prices than longer-term movements.

Table 5.5

Regression statistics for Put options IV spread with historical returns of different time periods (2, 3, 6, 10, 20, 30-day periods). The regression equation is given by (5.1c). The moneyness of the options, log(S/X), ranges from deep out-of-the-money options to deep in-the-money options, as shown in table 5.2. Options with log(S/X) ranging between –0.01 and +0.01 are considered at the money options. N is the total sample size. The time to maturity of the options ranges from 20 days to 30 days. *, **, *** Denote at least 10%, 5% and 1% statistical significance levels, respectively.

	In the money				**← Moneyness →**				**Out of the money**	
log(S/X)	-0.10	-0.05	-0.03	-0.02	-0.01	0.00	0.01	0.02	0.03	0.05
	-0.05	-0.03	-0.02	-0.01	0.00	0.01	0.02	0.03	0.05	0.10
					Puts 2d					
β1	-0.61***	-1.12***	-1.42***	-1.33***	-1.29***	-1.38***	-1.57***	-1.59***	-1.69***	-1.73***
t(β1)	-4.04	-7.98	-9.39	-8.66	-9.26	-8.50	-8.69	-6.15	-9.30	-8.75
α	0.07	0.05	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.05
t(α)	43.49	32.82	24.43	22.92	23.53	18.43	17.72	13.06	18.02	17.83
N	1537	1041	685	697	790	844	470	370	390	372
R2	0.01	0.06	0.11	0.10	0.10	0.08	0.14	0.09	0.18	0.17
					Puts 3d					
β1	-0.65***	-1.07***	-1.31***	-1.24***	-1.09***	-1.22***	-1.47***	-1.50***	-1.51***	-1.63***
t(β1)	-5.27	-9.71	-10.88	-10.24	-10.04	-9.65	-10.44	-7.23	-10.84	-10.72
α	0.07	0.05	0.05	0.04	0.04	0.04	0.04	0.05	0.05	0.05
t(α)	43.70	33.72	25.54	23.61	23.98	18.90	18.67	13.79	19.12	19.10
N	1537	1041	685	697	790	844	470	370	390	372
R2	0.02	0.08	0.15	0.13	0.11	0.10	0.19	0.12	0.23	0.24
					Puts 6d					
β1	-0.50***	-0.75***	-0.80***	-0.86***	-0.74***	-0.77***	-1.00***	-1.14***	-1.06***	-1.13***
t(β1)	-5.86	-9.65	-9.40	-10.19	-10.18	-8.41	-10.34	-7.93	-10.93	-10.57
α	0.07	0.05	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.05
t(α)	43.98	33.78	24.33	23.55	23.89	18.14	18.15	13.58	18.43	18.22
N	1537	1041	685	697	790	844	470	370	390	372
R2	0.02	0.08	0.11	0.13	0.12	0.08	0.19	0.15	0.24	0.23
					Puts 10d					
β1	-0.25***	-0.56***	-0.69***	-0.66***	-0.57***	-0.61***	-0.84***	-0.96***	-0.88***	-0.88***
t(β1)	-3.67	-9.23	-10.87	-10.21	-10.20	-8.91	-12.09	-9.30	-12.50	-11.29
α	0.07	0.05	0.04	0.04	0.04	0.03	0.04	0.05	0.04	0.05
t(α)	43.08	33.58	24.97	23.35	23.55	18.08	18.43	13.25	18.26	18.26
N	1537	1041	685	697	790	844	470	370	390	372
R2	0.01	0.08	0.15	0.13	0.12	0.09	0.24	0.19	0.29	0.26
					Puts 20d					
β1	-0.14***	-0.39***	-0.54***	-0.52***	-0.58***	-0.62***	-0.70***	-0.78***	-0.76***	-0.73***
t(β1)	-2.56	-8.42	-10.00	-9.54	-12.57	-10.80	-11.66	-8.71	-12.81	-11.43
α	0.07	0.05	0.05	0.05	0.04	0.04	0.05	0.05	0.05	0.05
t(α)	42.17	33.00	25.41	24.04	25.99	19.92	19.60	14.36	19.89	19.38
N	1537	1041	685	697	790	844	470	370	390	372
R2	0.00	0.06	0.13	0.12	0.17	0.12	0.23	0.17	0.30	0.26
					Puts 30d					
β1	-0.22***	-0.30***	-0.46***	-0.50***	-0.54***	-0.46***	-0.62***	-0.69***	-0.64***	-0.55***
t(β1)	-4.37	-6.81	-9.13	-9.59	-12.08	-8.37	-10.12	-7.71	-10.09	-8.40
α	0.07	0.06	0.05	0.05	0.04	0.04	0.05	0.06	0.05	0.05
t(α)	43.48	33.63	26.15	25.50	26.37	20.25	20.54	15.56	20.21	18.41
N	1537	1041	685	697	790	844	470	370	390	372
R2	0.01	0.04	0.11	0.12	0.16	0.08	0.18	0.14	0.21	0.16

Table 5.6

Regression statistics for Put options IV spread with historical returns of different time periods (2, 3, 6, 10, 20, 30-day periods). The regression equation is given by (5.1c). The moneyness of the options, log(S/X), ranges from deep out-of-the-money options to deep in-the-money options, as shown in table 5.2. Options with log(S/X) ranging between –0.01 and +0.01 are considered at the money options. N is the total sample size. The time to maturity of the options ranges from 20 days to 30 days. *, **, *** Denote at least 10%, 5% and 1% statistical significance levels, respectively.

	In the money				**← Moneyness →**					**Out of the money**
log(S/X)	-0.10 -0.05	-0.05 -0.03	-0.03 -0.02	-0.02 -0.01	-0.01 0.00	0.00 0.01	0.01 0.02	0.02 0.03	0.03 0.05	0.05 0.10
					Calls 2d					
β1	-1.26*	0.03	-0.14	-0.33	-0.19	-0.50**	-0.04	-0.67**	-0.41**	-0.50*
t(β1)	-1.68	0.06	-0.47	-1.44	-1.06	-2.49	-0.14	-2.35	-2.16	-1.88
α	0.07	0.05	0.04	0.03	0.02	0.02	0.03	0.03	0.02	0.04
t(α)	7.97	8.06	10.43	11.60	13.05	8.92	9.27	10.17	13.44	12.18
N	191	286	297	390	662	1009	743	841	1324	665
R2	0.01	0.00	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01
					Calls 3d					
β1	-0.56	0.45	-0.17	-0.03	0.04	-0.44***	0.01	-0.61***	-0.30**	0.13
t(β1)	-0.95	1.03	-0.74	-0.19	0.32	-2.72	0.05	-2.82	-1.99	0.63
α	0.07	0.05	0.04	0.03	0.02	0.02	0.03	0.03	0.02	0.04
t(α)	7.63	7.59	10.80	11.20	12.79	9.02	9.32	10.42	13.42	11.62
N	191	286	297	390	662	1009	743	841	1324	665
R2	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00
					Calls 6d					
β1	-0.31	0.09	0.32**	0.19	0.02	0.00	0.29**	-0.04	-0.28***	0.25*
t(β1)	-0.80	0.27	2.07	1.60	0.17	0.01	2.06	-0.27	-2.74	1.68
α	0.07	0.05	0.03	0.03	0.02	0.02	0.02	0.03	0.03	0.04
t(α)	7.79	7.83	10.05	10.87	12.85	8.31	8.88	9.64	13.69	11.74
N	191	286	297	390	662	1009	743	841	1324	665
R2	0.00	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.00
					Calls 10d					
β1	-0.37	0.30	0.26*	0.15	0.11	0.09	0.20*	0.10	-0.27***	0.23*
t(β1)	-1.08	1.15	1.94	1.54	1.33	0.96	1.68	0.83	-3.11	1.77
α	0.07	0.05	0.03	0.03	0.02	0.02	0.02	0.03	0.03	0.04
t(α)	7.91	7.18	9.41	10.87	12.16	8.04	8.91	9.49	13.85	11.61
N	191	286	297	390	662	1009	743	841	1324	665
R2	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00
					Calls 20d					
β1	-0.41	0.34*	0.32***	0.10	0.10*	0.08	0.33***	0.32***	-0.04	-0.21**
t(β1)	-1.56	1.66	3.14	1.23	1.64	1.15	3.81	3.53	-0.62	-2.03
α	0.08	0.04	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.04
t(α)	7.54	5.65	7.98	9.79	10.95	7.43	7.33	7.78	12.50	12.22
N	191	286	297	390	662	1009	743	841	1324	665
R2	0.01	0.01	0.03	0.00	0.00	0.00	0.02	0.01	0.00	0.01
					Calls 30d					
β1	-0.24	0.41**	0.27***	0.11	0.13***	0.09	0.16**	0.27***	0.04	-0.03
t(β1)	-1.03	2.20	3.27	1.74	2.88	1.44	2.06	3.38	0.73	-0.38
α	0.07	0.04	0.02	0.02	0.02	0.01	0.02	0.02	0.02	0.03
t(α)	6.87	4.61	6.82	9.15	9.84	7.17	7.76	7.26	9.62	12.41
N	191	286	297	390	662	1009	743	841	1324	665
R2	0.01	0.02	0.03	0.01	0.01	0.00	0.01	0.01	0.00	0.00

Table 5.6 shows the regressions for the call options. The results shown in table 5.6 illustrate the mixed behavior for relation between the IV spread of call options and past index returns. In general the relation between past returns and the IVs of call options is not statistically significant. However, the results show that there are some specific call options where the HRet coefficient is positive and significant, namely with in or out-of-the-money options when using 20 or 30-day past return periods. There is also some evidence that with in or out-of-the-money options, the HRet coefficient is negative and significant for short-term past return periods of 2 to 3 days. The explanation to this behavior might be that when short-term past returns are considered, call IVs follow the strong negative correlation of put options (in order to avoid violations to the put-call parity), while for longer-term past returns, the call prices are dictated mainly by investors expectations of future index autocorrelation, as suggested by Kaushik et al. (2004). Figures 5.1a) and 5.1b) show the regression HRet coefficient (β_1) for past return time periods ranging from 2 days to 30 days for put and call options, respectively.

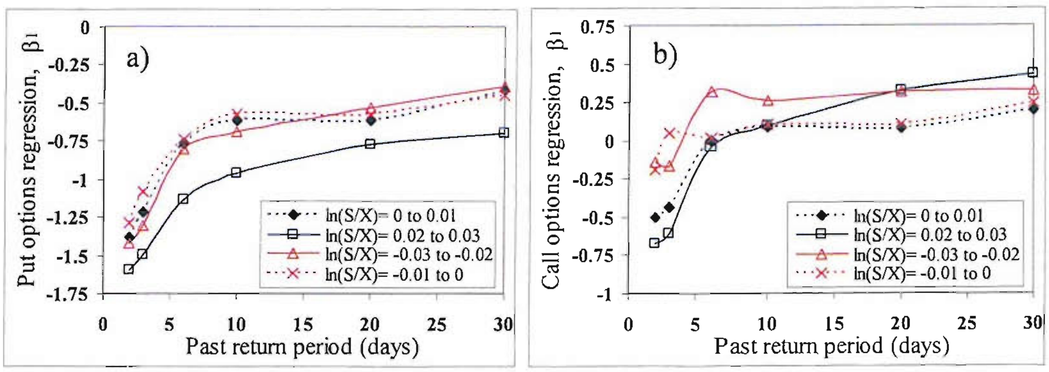

Figure 5.1: Relation of the HRet regression coefficient (β_1) with the past return time period of the HRet variable. a) Put options IV spread regressions. b) Call options IV spread regressions.

When analysing the variation of β_1 as the index past return period is increased, it is observed that the longer the time period, the lower the impact on the IV spread of put options. Figure 5.1a) shows that at-the-money put options, with log(S/X)≈0, β_1 varies from around –1.3 for 2-3 day past returns to –0.75 for 6-day past returns, which means that there is a high pressure on put options from short-term index falls (rises) while the effect of longer term trends is of lower impact but nevertheless with high statistical significance, as observed in table 5.5. Call options have a different behaviour as β_1 is not statistically significant different to zero. However, there seems to exist a general trend in figure 5.1b) where β_1 is negative for short-term (2-3 day) past returns while positive for longer-term past returns.

It is also interesting to investigate how β_1 varies as a function of the option moneyness. For this purpose we focus mainly on put options, as the results for call options are generally not significant. Figure 5.2 shows the put options' regression HRet coefficient (β_1) as a function of the option moneyness for past return time periods ranging from 2 days to 30 days. There is also evidence of a trend in the regression coefficient β_1 as the option moneyness is changed: As the put options moneyness is changed from out-of-the-money (log(S/X)>0) to in-the-money (log(S/X)<0), the regression coefficient β_1 increases, this is, out-of-the-money put options are more sensitive to changes in past returns than in-the-money put options. This effect may be due to the higher elasticity of the out-of-the-money options (higher leverage to the underlying asset) which enhances any dependence of the put options IV with past index returns.

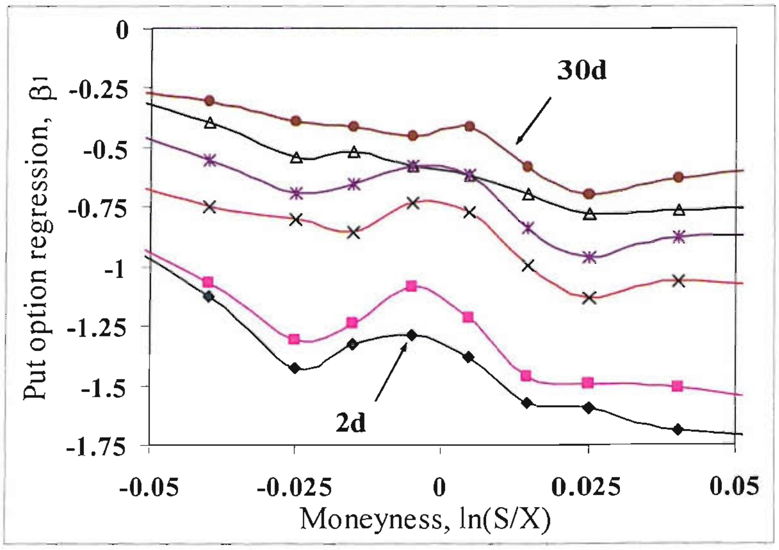

Figure 5.2: Variation of put options' HRet regression coefficient (β_1) with the options moneyness for different past return time periods of the HRet variable.

Finally, we investigate how the regression parameter α varies with the options moneyness. α is the IV spread regressions intersect, which corresponds to approximately the options' average IV bias relative to the EWMA historical volatility when past index returns are zero. It is not expected therefore, for α to vary significantly as the historical return time period is varied, as shown in tables 5.5 and 5.6. However, it is expected that α is related to the IV smile that typically appears in options chains in the market.[7] It is also expected that the IV spread should be biased positively for both put and call options due to the well-known premium that option sellers' demand. It is also common knowledge in the marketplace that put options carry a higher premium than call options due mainly to pressure on put options by portfolio insurance buyers.[8] Figure 5.3 shows the regression α for put and call options as a function of the options moneyness. We observe the typical implied volatility smile for call options where out-of-the-money options IV spreads are highest while at-the-money spreads are minimum. IV spreads for put options generally follow those of call options but with a premium of around 2% to 3%. We find that this premium is observed for different measures of volatility and our results also confirm that put options generally carry higher premiums than call options (of the same moneyness and time to maturity).

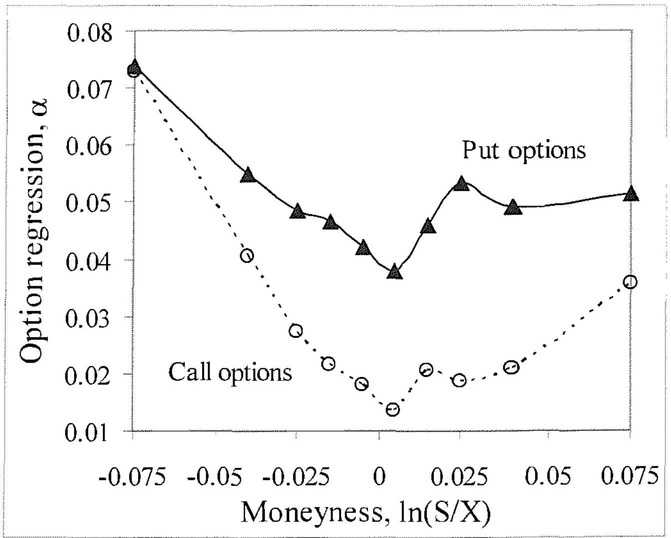

Figure 5.3: Variation of Put and Call options' regression intersect (α) as a function of the options moneyness.

[7] See for example Chiras and Manaster (1978) and MacBeth and Mervillle (1979) for early works showing the implied volatility smile typically observed in stock options markets.

[8] There exists an extensive body of academic literature across several markets that show that implied options volatilities are biased positively. Refer to footnote 6 for further details.

C. Options term structure

This section examines the robustness of our analysis across a range of options maturities. For that purpose we perform the single factor regressions for at-the-money options and a past return time period of 3 days, while varying the time to maturity (TTM) of the options. We split the options term structure in five different maturity bins, namely 10-20, 20-30, 30-40 and >40 days to maturity. As options with longer TTMs are less liquid and consequently have smaller sample sizes, we include all options with TTM greater than 40 days in the same bin. Table 5.7 shows the regression statistics results for put and call options across for the different maturities.

Table 5.7

Options IV spread regression statistics across the term structure. The regression equation is given by (5.1c). The moneyness of the options, log(S/X), ranges 0.01 to 0 (at-the-money). N is the sample size. TTM refers to the options time to maturity. Past return period of HRet variable used in the regressions was 3 days. *, **, *** Denote at least 10%, 5% and 1% statistical significance levels, respectively.

Panel A Put options Log(S/X)=[-0.01,0] Past return period: 3d;					**Panel B** Call options Log(S/X)=[-0.01,0] Past return period: 3d;				
TTM	10 20	20 30	30 40	>40	TTM	10 20	20 30	30 40	>40
β1	-1.07***	-1.09***	-1.21***	-0.80***	β1	0.33**	0.045	-0.05	0.34*
t(β1)	-11.43	-10.04	-9.23	-8.12	t(β1)	2.21	0.32	-0.19	1.79
α	0.038***	0.039***	0.048***	0.045***	α	0.022***	0.022***	0.025***	0.026***
t(α)	28.32	23.98	22.88	31.56	t(α)	10.44	12.79	6.88	10.96
N	1135	790	554	1048	N	718	662	346	813
F	130.71	100.85	85.14	65.92	F	4.87	0.10	0.04	3.22
dF	1133	788	552	1046	dF	716	660	344	811
p-value	1.0E-28	2.1E-22	5.9E-19	1.3E-15	p-value	0.028	0.748	0.848	0.073
R2	0.10	0.11	0.13	0.06	R2	0.01	0.00	0.00	0.00

The results in table 5.7 show that there is a consistent behaviour in the relation between put options prices and past returns across the term structure. There is a negative correlation between put options' IV spread with past returns. Furthermore, we performed similar experiments using different historical index return periods with similar outcomes, which provide additional robustness to our findings. We also observed a consistency in the low correlation between call options IV spreads with past returns by observing β_1 coefficients with low statistical significance. All α estimates have high statistical significance indicating the average bias in options IVs relative to the EWMA measure of historical volatility. The results in Table 5.7 show that the average options IV bias increases with the options time to maturity, which should generally be true due to option writers demanding a premium given uncertainty in volatility over time.

5. Fitting the empirical evidence

In order to fit the empirical evidence in section 4, we use the integral approach to compute the expected value of the options at maturity. The model is general and does not assume no-arbitrage restrictions and therefore, put and call option prices may deviate from their equilibrium prices. Consequently, violations to the put-call parity relation might occur if the underlying asset drift is large enough. Equation (5.3) shows the formula used to compute the expected value of the call options at maturity which was previously discussed in chapter IV (section 2.B). p(S) is the share price probability distribution which may take any form in order to account for extremes, stochastic volatility, dividends and other factors. We simply use the lognormal distribution for the share price (the same as in Black-Scholes), adjusted for dividends and with a drift rate (expected return) that differs from the riskless rate of interest. In order to fit our empirical data we adjust the drift rate until the correlation between IV spread and the past index return is obtained.

$$E(C(T)) = \int_{S>X}^{\infty} p(S(t))(S(t) - X)dS = \int_{S>X}^{\infty} S(t)p(S(t))dS - X\int_{S>X}^{\infty} p(S(t))dS \qquad (5.3)$$

Traditional non-arbitrage option pricing models do not encompass that there might be a relation between index returns with option prices. These models use a risk neutralised stochastic process for the underlying asset such that the return on the asset is the riskless rate of interest, rf. Under the Black-Scholes assumption, the index prices follow a log-normal distribution (and therefore index returns follow a normal distribution) given by $dS/S = \rho dt + \sigma dz$, where dz is a stochastic variable defined by a Wiener process with zero drift such that $dz = \varepsilon\sqrt{dt}$ and ε is a normally distributed stochastic variable $\varepsilon \sim N(0,1)$. With the construction of a continuously hedged portfolio, Black and Scholes (1973) obtain the well-known pricing formula, which is proved to be independent of the drift parameter ρ (see discussion in chapter IV). It is then possible to show that by using a lognormal distribution for p(S)[9], equation (5.3) reduces to the Black-Scholes formula if the drift parameter is the risk-free rate of interest and if E(C(t)) is then discounted to the present value by using the risk-free rate of interest. In reality, as the expected growth rate for the underlying asset changes, so does the required discount rate for the expected value of the call option. Under Black-Scholes, it works out that one change offsets the other such that the present value of the option does not depend on the return of the underlying asset and consequently the world can be treated as risk neutral (see chapter IV for more details).

To fit the empirical data, we calculate the forward value of the call (put) option using different assumptions for the rate of return of the underlying asset. We then discount the value of the option at the risk-free rate of interest. This estimate for present value of the option overestimates its true value due to the discount rate for a risky security being always greater than the risk-free rate of interest. Nevertheless, as the time to maturity of the call (put) options under examination is 20-30 days, the discount factor over the average 25-day period will be insignificant. In our simulations we use the following parameters to compute the expected value of the options: log(S/X)=-0.005, rf=0.05, σ=0.125 and TTM=25. To obtain a proxy drift parameter, we assume the market perceives the 3-day or 20-day historical returns as estimates for the market return over a given future time period. We then vary this time period iteratively until we optimise the IV spread relation given by the empirical data regressions. This procedure is equivalent to varying the degree of autocorrelation perceived in the Put (Call) options market. The theoretical IV spread is calculated as the IV calculated from the option price obtained by using the stated model minus the volatility used in the model. The market bias is introduced as an offset to the model IV. We fit the relation between put options IV spread for 3-day and 20-day historical

[9] We assume the future probability distribution given by the Black-Scholes stochastic process dS=ρSdt+σSdz that defines a log-normal distribution such that if φ(μ,,σ) is a normal distribution with mean μ and standard deviation σ, then $\ln(S(T)) \sim \phi\left[\ln(S(0)) + \left(\mu - \sigma^2/2\right)T, \sigma\sqrt{T}\right]$. See Hull (2000) – chapters 12 and 13 or Cox et al. (1979).

index returns. As we have seen from table 5.5, the regression coefficient β_1 was –1.09 for 3-day past returns and β_1=-0.58 for 20-day past returns. Our simulations show that the put option market perceives 3-day FTSE100 index rises (falls) as an indication of the index price movement over the next 100 trading days. Similarly, 20-day index rises (falls) are an indication of index returns over the following 200 trading days.

Table 5.8 shows put options' IV spread regressions with index historical returns of 3-day and 20-day time periods (Panel A), as well as, the IV spread regressions of our model results for different assumptions of the future index drift (Panel B). For example, in panel B a 100-day future price continuation assumes that the index returns observed in the past 3-day (20-day) time period is the same for the next 100 days. This is, if the index has dropped 5% in the past 3 days (or 20 days), then the market will assume a 5% drift over the future 100 days. The regressions are performed over the simulation results and consequently show a very high R^2 value, indicating an almost linear relation between past returns and the IV spread of put options calculated using our theoretical model. The results are easy to comprehend as the model simply calculates the expected value of the put option for different assumptions of the future index return and then discounts these values at a constant rate (which we chose to be the risk-free rate of interest). Hence, for positive future returns, the expected value of put options is smaller than for an assumption of negative future returns. The regressions results in panel B indicate that this relation is approximately linear for the parameters used in the model simulations, (the R^2 of the linear regression to the theoretical values is close to 1). When varying the future drift rate, which in our case we obtain by changing the evaluation period from 100 to 200 days, we obtain curve slopes, which explain the different β_1 coefficients shown in table 5.5 for the put options' IV spread regression with past returns of different time periods (2d, 3d 6d etc). Hence, it can be observed in table 5.8, that the relation between the IV spread and 3-day (20-day) historical returns can be explained by simply considering a future drift corresponding to the past return over a 100-day (200-day) time period in the simulation model. It should be noticed that standard non-arbitrage option pricing theories do not predict any relation between past returns and options prices.

Our evidence suggests that the market does not price put options according to the Black-Scholes model but instead is subject to overreactions to past returns due possibly to price-pressure caused by simple supply and demand. We also show that by using a simple model of calculating the expected value of the options with different drift parameters we can explain put options market behaviour by assuming that the market is using past index returns as a proxy for future returns of the underlying asset. Our results provide empirical evidence of the impact of expected returns on option prices for our particular sample giving support to the arguments presented in chapter IV regarding "the hole in Black-Scholes" initially identified by Black (1988).

Furthermore, we show that supply and demand effects due to short-term index falls (rises) have higher impact on put option prices than due to longer-term index falls (rises). There is an overreaction of put option prices to short-term index changes while the long-term index changes have an effect on investors' expectations and risk-preferences consequently skewing the expected index probability distribution.

Table 5.8

Panel A shows Put options' IV spread regressions with index historical returns of 3-day and 20-day time periods. Panel B shows the put options' IV spread regressions resulting from the linearisation of the simulation results for different assumptions of the future index drift. Note: A 100-day future period in the model simulations represents an assumption that future expected returns are distributed along a 100-day time frame. Hence, a 3-day return of 0.03 (3%) corresponds to a future daily drift of 0.03/3/100 (or 0.01%). The impact of shorter past return valuation periods is therefore lower than that of longer time periods.

Panel A

Empirical data

HRet period:	3d	20d
Regression statistics		
β_1	-1.088	-0.578
$t(\beta)$	-10.042	-12.575
α	0.039	0.042
$t(\alpha)$	23.977	25.986
F	100.9	158.1
df	788	788
P	2.1E-22	3.5E-33
R2	0.113	0.167

Panel B

Simulation results

Future period:	100d	125d	150d	175d	200d
Regression statistics					
β_1	-1.129	-0.904	-0.753	-0.645	-0.565
$t(\beta)$	-97.233	-97.233	-97.233	-97.233	-97.233
α	0.045	0.045	0.045	0.045	0.045
$t(\alpha)$	68.512	68.512	68.512	68.512	68.512
F	9454.3	9454.3	9454.3	9454.3	9454.3
df	98	98	98	98	98
P	2.8E-99	2.8E-99	2.8E-99	2.8E-99	2.8E-99
R2	0.990	0.990	0.990	0.990	0.990

Figure 5.4 shows the scatter plot of the put options IV spread as a function of the historical return and the respective linear regression and model fit. The data for the put options' IV spread correspond to 790 data points from our data sample during the period of 1993 to 1997, for at-the-money options with $\log(S/X) \in [-0.01,0]$ and $TTM \in [20,30]$ days. Figure 5.4a) shows the IV spread for 3-day past index returns which assumes a 100-day future drift period for the historical returns. Figure 5.4b) corresponds to 20-day past index returns and the respective model fit and assumes a 200-day future drift period for the historical returns. It is observed that the model fit relates closely to the linear regression of the market data. The regression noise is due to a multitude of factors namely the differences in the options moneyness, differences in TTM, differences in market conditions (e.g. different market volatilities) at the time of each data period and finally all the usual noise sources caused by market intervenients. Nevertheless, it is quite remarkable that there exists a strong relation of the IV spread of put options and past returns and that it can be explained simply by using equation (5.3) while assuming that past index returns are a proxy for future index returns.

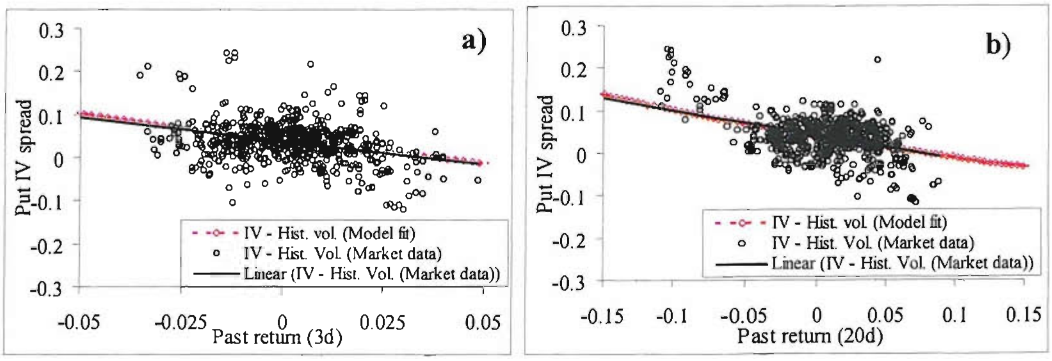

Figure 5.4: Scatter plot of the put options IV spread as a function of the historical return and the respective linear regression and model fit. The data for the put options' IV spread correspond to 790 data points from our data sample during the period of 1993 to 1997, for at-the-money options with $\log(S/X) \in [-0.01,0]$ and $TTM \in [20,30]$ days. a) IV spreads for 3-day past index returns, which assumes a 100-day future drift period for the historical returns. b) Corresponds to 20-day past index returns and the respective model fit and assumes a 200-day future drift period for the historical returns.

6. Conclusions

Our results provide further evidence of the existence of "anomalous" dynamics in options markets in addition to the work of Kaushik (2004), Bakshi (2000) and Canina and Figlewski (1993). Traditional models that are based on non-arbitrage arguments such as the Black-Scholes model cannot explain the existence of a relation between past returns and option prices. In fact, one of the main characteristics of the Black-Scholes pricing formula is the elimination of the expected underlying return (the drift) from the equation. We show however that options dynamics in real markets are not so well behaved. We find a strong negative correlation between put options IV spreads and historical returns that yields regression coefficients with high statistical significance. We also observe that our empirical results vary with the historical return time period: short-term historical returns have a higher impact on put option prices than longer-term historical returns. We are able to explain this relation qualitatively if we consider supply and demand effects together with investors' behaviour to different future expectations and short-term overreaction and herding. If investors perceive that past index returns are a guide for future returns, they panic-buy/sell put options as portfolio insurance in the short-term or buy put options on speculation of index momentum. These different reactions, through supply and demand, explain the put options IV spread behaviour observed in Figure 5.1. Additionally, we are able to explain this behaviour by using a simple and general non-arbitrage expectation model for options prices. We simply compute the future value of the call option using different assumptions for the drift parameter and then discount this value at the risk-free rate. The drift parameter represents agents' expectations of future returns and is fitted in order to explain the empirical data through changing the time period of price continuation. The lower the time period, the more aggressively investors are pricing the put options. We find that for short-term price changes (3-day), the investors perceive price continuation over the next 100-day period while for longer-term index changes (20-day) investors perceive price continuation distributed over a longer 200-day period. These findings are in line with the qualitative explanation that investors over-react through pressure on put option prices to shorter-term index increases (falls).

When analysing the call options market, we found weak evidence of a consistent relation between call options IV spreads and historical index returns. The evidence suggests that call options display mixed responses to past returns: Sometimes, they show a positive IV spread correlation with past returns, which denotes the market expectations of index price continuation. However, in other occasions, the empirical evidence shows a negative relation between call options' IV spreads and past returns suggesting that call options implied volatilities follow put option prices in order to avoid violations to the put-call parity relation. This mixed response is responsible for the weak evidence of the dependence of call option prices on past returns. Our findings are consistent with those of Bakshi et al. (2000) who find that call options prices sometimes move in the opposite direction of the underlying asset. For example as we have shown in tables 5.5 and 5.6, for short-term market falls, the call options IV may follow the put options IV and therefore in some occasions even though the underlying asset falls, the call option price will be the same or even increase. The evidence is also consistent with the results shown by Kaushik et al. (2004) who find a correlation between past returns and the number of violations to the put-call parity relation. From our evidence, as put option prices deviate significantly from their fundamentals as a response to past returns and call option prices do not, violations to the put-call parity will have a relation with past returns. We believe however that this behaviour is originated in the put options market which displays significant correlation to past index returns, perhaps due to price-pressure caused by portfolio insurance buyers and/or changes in investors' expectations of future index prices or skewness in the distribution of index returns.

Our results have several implications to the literature on option pricing. We find empirical evidence that shows imperfections in the options market and raises the question if options really are redundant securities as prevalent theories make believe. We show that the behaviour of put options and call options is very distinct with put options IV displaying a significant correlation with past returns while call options seem to have little correlation with past returns. This distinct behaviour leads to possible violations in the put-call parity relation and to the conclusion that options are non-redundant securities and their prices can deviate from the fundamental values. We also illustrate that either by price-pressure effects or by market expectations of future momentum acting through supply and demand, past returns play a role in the market prices of options. Traditional non-arbitrage models do not predict such a relationship. The low forecasting power between option IVs and realised future volatility shown in the extensive academic literature[10] suggest that there are other factors at hand other than the estimation of volatility as an input for the Black-Scholes formula. Perhaps a realistic option-pricing model should account for the future directionality of market returns based on historical returns, this is, it should account for different investors' expectations at different time periods. Our results in tables 5.3 and 5.4 seem to support this statement as we found that the bias in the IV spread could be at least partially explained using a short-term measure of historical returns and a historical measure of volatility.

Our empirical results of the FTSE100 index options market suggest that past returns could play a role in explaining implied volatilities through supply and demand effects. One of the main shortcomings of our analysis is that the market for FTSE100 index options of European type for the period under analysis is not the most liquid market. It would be interesting to analyse a more liquid market such as options on the S&P500 index for a more recent time period. Furthermore, we base our measurement for the implied volatility spread of a low-frequency (daily) measure of historical volatility. It would therefore be interesting to test our results using less noisy measures that include high-frequency corrections (see references in footnote 10 or Poon and Granger (2003) for an excellent review of volatility estimation and forecasting).

[10] Early research by Canina and Figlewski (1993) shows that implied volatilities are poor forecasts of future realised volatility. Since then, a vast body of academic literature focuses on the forecasting of volatility based on both historical measures of volatility and implied volatility. Recent academic research focuses on empirical evidence of high-frequency estimates of historical volatility which can reduce the noise in daily volatility measures found by Andersen and Bollerslev (1998) for FX markets. Since then several authors have shown that high-frequency corrections to daily volatility improve the forecasting power of the different historical volatility models in different markets (for example, Andersen et al. (2001), Blair et al. (2001), Martens and Zein (2004)). In a recent study, Martens and Zein (2004) went to the extent of comparing implied and historical forecasts of volatility by analysing three different markets (equity index, FX and commodities), finding that implied volatilities provide superior forecasts compared to both low-frequency and high-frequency daily GARCH(1,1) forecasts.

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Chapter VI

“Conclusions”

1. Conclusions

In this thesis we proposed to investigate stock market anomalies. We define an anomaly in broad sense as an effect that contradicts the well-established behaviour of an efficient market system. For example, an anomaly could be a share price effect that would yield predictability in asset returns and could originate statistical arbitrage opportunities. In search for so called anomalies, we also gain some insight into the functioning of financial markets. This thesis gives several contributions in explaining different aspects of the functioning of financial markets. Throughout the thesis, empirical evidence is found that sometimes contradicts well established theories.

In chapter II, we find evidence that contradicts the EMH by simply performing arbitrage around the promotion or relegation date of a company to the FTSE100 index. However, we also observed evidence of structural change over time where recently agents arbitraged the aforementioned anomaly away. These empirical results give support for the workings of an efficient market where eventually, once the anomaly has been documented, agents (typically hedge funds) have intervened towards exploiting it and eventually, arbitraging it away. The fact that the anomaly "survived" for a period of approximately 10 years is impressive when considering the amount of capital invested in financial market research by the large financial corporations. As hedge funds increased in popularity, they have managed an ever increasing amount of capital which has put under pressure most of the straightforward arbitrage opportunities. The natural evolution of such funds must be therefore to exploit new and more sophisticated anomalies, in more liquid markets.

The effects investigated in chapters III and V could be examples of such opportunities. Furthermore, the effects studied in these chapters could have applications in the reverse of arbitrage, that is, in hedging the risk. The knowledge provided in chapter III that extreme events occur more frequently on earnings announcements dates could be used to devise risk warning systems where the risk exposure is hedged prior to the event and unhedged after. This would yield long-term investment portfolios with lower volatility and consequently higher Sharpe ratio.

The information provided by chapter V could also be useful when hedging against market risk using options. For example, to hedge long stock positions using put options, it is preferable to by the puts after market rises relatively to market falls. We showed that historical returns as a proxy for investors' expected returns is a statistical significant factor in explaining options implied volatilities. The distinct behaviour of put and call options suggests that this effect is difficult to explain in the framework of volatility estimation and is likely to be related to supply and demand effects and the liquidity of the underlying market. Next a summary of the main conclusions of each chapter is provided.

A. Chapter II

In Chapter II share price and volume effects when companies are promoted/relegated from the UK FTSE100 share index are investigated. Previous research on index changes has focused mainly on the US S&P500 share index but the share price effects described in those papers have been confirmed by authors investigating international indices. Our analysis fills in the gap in the UK academic literature on index changes. Furthermore, by splitting our sample into characteristic time periods we provide a contribution to the literature in methodological terms. We find evidence of structural change over time in the share price behaviour around index changes. Over different time periods, we find a mixture of results that can be explained using the different hypotheses described within the academic literature depending on period analysed. To some extent the effect of agents (in the figure of hedge funds) have acted upon the index change event by either arbitraging the share price effects or exacerbating it in an asymmetric manner for index promotions and relegations. With some surprise we notice that arbitrage opportunities on the index change date have been arbitraged away to a large extent, which provides some comfort on the efficiency of the market and how it continuously acts towards the correction of anomalies.

We also identify that the index change date is a source of extreme events in the lifetime of the share, that is, on the event date, we find that the probability of occurrence of an abnormal return that lays towards the tails of the share return distribution. For example, the occurrence of abnormal returns with magnitude greater than 2σ (two times the share return standard deviation) is significantly higher than the theoretical value on the event date. This finding opens possibilities towards the existence of other such events related to other singularities (periodic public information releases).

B. Chapter III

Event studies on public informational releases have been extensively analysed in the literature in an attempt to find patterns, which violate the efficient market hypothesis and yield profitable arbitrage opportunities. Most studies focus on abnormal returns around the event date or cumulative returns in different time periods and generally find that the market is "well behaved" to the arrival of new information. As previously shown in chapter II, there are occasions when profitable arbitrage opportunities exist, even if just for a brief period of time.

In Chapter III we investigate share price effects around interim and final earnings announcements for UK equities. By using an event study methodology, we investigate possible pre or post event trends or evidence of significant average abnormal returns on the event date. When simply analysing abnormal returns around companies' interim and final results announcement dates our results corroborate previous studies: We find no statistically significant abnormal returns on the announcement date nor do we find evidence of any pre or post event return predictability. However, when investigating the dispersion of the abnormal returns, we find higher than normal dispersion on the event date. Our results show that, while using Gaussian statistics, there is a 2.37 times increase in the average residuals (magnitude of the abnormal returns) on the event date when comparing with the remaining event window (this is, when compared with a non-event date). The results display a high level of statistical significance. When using Paretian statistics we find that there is a 3 times increase in the dispersion of abnormal returns on the event date, compared to a non-event day. We also perform non-parametric tests by comparing the theoretical probability of occurrence of abnormal returns with magnitude greater than a given measure of dispersion (typically 1σ or 2σ, where the standard deviation for each security is calculated across the event window). We find that, for a given company, the probability of the occurrence of an abnormal return with magnitude above 2σ is 32% compared to a theoretical value of 4.8%. The binomial Zb tests show high level of significance which means that the empirical results are different than the theoretical ones with a high probability. These results have a high statistical significance due to the large sample sizes under investigation. Similar evidence is found when estimating the probability of abnormal returns with magnitude greater than σ is 62.4% compared to a theoretical value of 46.4%. We find that our results are robust across different samples as well as different time periods.

The findings in chapter III provide some insight into the nature of extreme events in the typical share return distribution found in financial time series. The companies' interim or final results announcement date appears to be a source of extreme events in the company lifetime. This evidence is an anomaly in the sense that traditional theories for stock prices assume background noise has a Gaussian distribution due to the continuous arrival of information to the market. Our evidence shows that some information has higher impact than normal background noise, such as companies' earnings announcements. This opens the possibility for the identification of other such events such as analysts' estimates, earnings announcements, broker upgrades/downgrades, share repurchase announcements, interest rate changes, index promotions/relegations, among others, as sources of extreme returns, see Ryan and Taffler (2004). It can be argued that these events are potentially the main sources of the Paretian-like distribution found in share returns (Mandlebrot (1963), Fama (1965)).

Another aspect of our research on share price effects surrounding earnings announcements concerns the possible predictability of returns conditional upon the occurrence of an extreme event on the announcement date. In similarity with previous studies such as Pritmani and Singal (2001), we find evidence return predictability conditional upon the occurrence of an extreme event on the announcement date. We define the extreme event relatively to the abnormal return volatility specific to each firm, which we chose to be 3σ (3 times the ±25 day daily volatility). Our results show that after an extreme event, there is a share price reversal in the 5 to 15 days following the announcement date. When analysing the abnormal returns on the day following an extreme event, we find no correlation. These results suggest that when abnormal returns above 3σ occur, they are likely to be caused by over-reaction that is then followed by a correction. Future studies could focus on analysing how this correlation changes with changes in the magnitude of the extreme events (eg 2σ, 3σ, 4σ etc). Furthermore, the relation between abnormal volume and the respective extreme events could be investigated as in Bamber (1986) or Blume et al. (1994).

C. Chapter IV

In his paper "How to use the Holes in Black-Scholes", Fischer Black (1988) reflects: "*If you are bullish on the stock, you may buy shares or call options, but you won't change your estimate of the option's value. A higher expected return on the stock means a higher expected return on the option, but it doesn't affect the option's value for a given stock price*".

In chapter IV we have compared option pricing methods based on the construction of hedged portfolios, namely the Black-Scholes and Binomial approaches, with a less restrictive method which is based on the knowledge of the future probability distribution for the share price. To compare both these valuation methods, the binomial approach was used together with the construction of a hedged portfolio to give a novel expression that provides insight into the fundamental differences between these two approaches. The expression obtained provides an explicit relation between the expected value of the call option and the Black-Scholes valuation and their relation with the expected return of the underlying asset. In theory, in a perfect market, investor expectations of future share returns should be fully incorporated into option and stock prices. In practice however, different implied volatility smiles are observed in the market at different times reflecting investors' expectations through supply and demand. By analysing the expected value of the call option instead of the risk-neutralised value, we believe some of the smile could be explained. We use this approach in chapter V to fit empirical observations of the dependence options implied volatilities with past returns (which are used sometimes as a proxy for future returns).

D. Chapter V

The empirical analysis in chapter V of a sample of European FTSE100 index options provides further evidence of the existence of "anomalous" dynamics in options markets. Traditional models that are based on non-arbitrage arguments such as the famous Black-Scholes model cannot explain the existence of a relation between past returns and option prices as shown in chapter IV. In fact, one of the main characteristics of the Black-Scholes pricing formula is the elimination of the expected share return (the drift) from the equation. We show however, that there is a strong negative correlation between put options IV spreads and historical returns that yields regression coefficients with high statistical significance. We also observe that our empirical results vary with the historical return time period: short-term historical returns have a higher impact on put option prices than longer-term historical returns. We are able to explain this relation qualitatively if we consider supply and demand effects together with investors' behaviour to different future expectations and short-term overreaction and herding. If investors perceive that past index returns are a guide for future returns, they panic-buy/sell put options as portfolio insurance in the short-term or buy put options on expectations of index price continuation.

When analysing the call options market, we found weak evidence of a consistent relation between call options IV spreads and historical index returns. The evidence suggests that call options display mixed responses to past returns: Sometimes, they show a positive IV spread correlation with past returns, which denotes the market expectations of index price continuation. However, in other occasions, the empirical evidence shows a negative relation between call options IV spreads and past returns which imply that call options implied volatilities follow put options prices in order to avoid violations to the put-call parity relation. This mixed response is responsible for the weak evidence of the dependence of call option prices on past returns. Our findings are consistent with those of Bakshi et al (2000) who find that call options prices sometimes move in the opposite direction of the underlying asset. For example, for short-term market falls, the call options IV may follow the put options IV and therefore in some occasions even though the underlying asset falls, the call option price will be the same or even increase. The evidence s also consistent with the results shown by Kaushik et al. (2004) who finds a correlation between past returns and the number of violations to the put-call parity relation. From our evidence, as put option prices deviate significantly from their fundamentals as a response to past returns and call option prices do not, violations to the put-call parity will have a relation with past returns. We believe however that this behaviour is originated in the put options market which displays significant correlation to past index returns, perhaps due to price-pressure caused by portfolio protection buyers and/or changes in investors expectations of future index prices or skewness in the distribution of index returns.

We are able to explain this behaviour by using a simple and general non-arbitrage expectation model for options prices as described in chapter IV. We simply compute the future value of the call/put option using different assumptions for the drift parameter and then discount this value at the risk-free rate. The drift parameter represents agents' expectations of future returns and is fitted in order to explain the empirical data through changing the time period of price continuation. The lower the time period, the more aggressively investors are pricing the put options. We find that for short-term price changes (3-day), the investors perceive price continuation over the next 100-day period while for longer-term index changes (20-day) investors perceive price continuation distributed over a longer 200-day period. These findings are in line with the qualitative explanation that investors over-react through pressure on put option prices to shorter-term index increases (falls).

2. Future research pathways

This thesis provides an in depth empirical analysis of characteristic market behaviours. Inevitability, in the search of deeper understanding of a particular topic, the deeper one goes, the less one knows, or in other words, the search of knowledge often opens more questions than it gives answers. This thesis is no exception. Consequently, here I suggest possible future research pathways:

A. Chapter II

The analysis performed in chapter II showed evidence of structural change over time for the share price behaviour of companies promoted or relegated to the FTSE100 index. Further research could encompass a similar analysis for other market indexes. With the recent popularity of exchange traded funds (ETFs) it is possible that companies promoted/relegated from other indexes show similar behaviours.

Additionally the question of causality of the effect remains unanswered: Is the share price behaviour of promoted/relegated companies around index changes due to relegation/promotion or the reason for promotion/relegation? It is difficult to untangle the cause from the effect. One avenue of enquiry could be by examining the behaviour of companies that belong to the FTSE100 reserve list and consequently are liable for promotion/relegation in the next quarterly index review meeting.

B. Chapter III

In chapter III the analysis of dispersion of abnormal returns on company earnings announcements showed interesting results. Firstly, the abnormal dispersion of abnormal returns found on the event date led to the conclusion that certain information arriving to the market has higher impact than other and, that some information announcements are known in advance. Consequently, an obvious extension of the research in chapter III would be to examine the impact of other information release dates such as index changes, interest rate committee meetings, analyst/broker recommendations, among others. Similarly, the research provided in chapter III focused on UK companies but the methodology could be employed in other international markets as well as different securities (bonds, fx rates etc). Another obvious extension of the work would be to investigate the relation between the magnitude of the abnormal return and abnormal volume on event and non-event dates. Such research could provide insights into the existence of herding behaviour on the event date. Finally, with all the research in place, it would be possible to devise risk management systems with built in event driven risk warning systems.

These systems could provide risk managers or fund managers a tool for monitoring expected jumps in net asset value.

During this chapter there were other questions which appeared once the anomalous dispersion was found, namely:

1) Is it possible that these singular events could be sources of changes in future volatility? This is, once an extreme event occurs do companies suffer from higher/lower share price volatility post event? The answer to this question could be a step forwards in implementing the jump diffusion stochastic process which is used to price options. Practitioners assume volatility will switch to a different regime during the option lifetime. The problem is that until now it is not possible to determine when or if there will indeed be a switch in the volatility behaviour.

2) Why is there a Paretian distribution for abnormal share returns both on an event and non-event day? The answer to this question passes by analysing herding and the type of agents who follow the companies. For example, Paretian distribution has been obtained through simulations by simply assuming a percentage of momentum driven investors and a percentage of contrarian or fundamental driven investors.

C. Chapters IV and V

In chapter IV we laid down arguments that suggested that option prices could be dependent, under certain circumstances, of past returns of the underlying asset. This type of behaviour can not be explained by non-arbitrage option pricing models such as the Black-Scholes model. In chapter V we tried to verify if the option prices in the real market make use of the expected returns of the underlying asset. For that purpose we employed historical returns as a proxy for investors' expected returns. Our empirical results of the FTSE100 index options market suggest that past returns could play a role in explaining implied volatilities through supply and demand effects. We relied on the implied volatility spread defined as the difference between the option IV subtracted by a low-frequency (daily) measure of historical volatility. In light of the recent advances in volatility forecasting and measurement (see Poon and Granger (2003) for an excellent review) it would be interesting to test our results using less noisy measures that include high-frequency corrections. Additionally, different volatility measures such as ARCH/GARCH could be employed as a benchmark for historical volatility in the IV spread.

An obvious extension of our research would be to investigate a market with higher liquidity and greater temporal history than the sample used in our study. For example it would be interesting to analyse a more liquid market such as options on the S&P500 index and for a more recent time period. Perhaps the effects we observed in the FTSE 100 index options were exacerbated by the lack of liquidity in that particular market.

Finally, an additional line of enquiry would be the use of technical momentum indicators instead of the simple historical returns as a proxy for expected returns. It is possible that investors that make use of such indicators could act upon them in a more systematic fashion than simple historical returns.

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