THE MOMENTUM EFFECT ON THE LONDON STOCK EXCHANGE

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'...the future of security prices is never predictable'

Benjamin Graham, 2003, p. 24

ABSTRACT

This study intends to investigate the momentum effect, which states that shares which performed the best (worst) over the previous three to twelve months continue to perform well (poorly) over the subsequent three to twelve months. Evidence suggests that a strategy that buys previous winner shares and sells short past loser stocks can generate abnormal profitability of about 1 per cent per month (Jegadeesh and Titman, 1993). Although momentum payoffs tend to persist when share returns in international markets are employed (e.g., Griffin et al., 2003, Rouwenhorst, 1998), a significant number of studies have debated the potential explanation of the momentum effect without reaching a consensus.

Using data from the London Stock Exchange from January 1975 to October 2001, this thesis investigates some factors that influence the magnitude of continuation gains that have not been previously identified. I examine the relationship between momentum profitability and the stock market trading mechanism and is motivated by recent changes to the trading systems that have taken place on the London Stock Exchange. Since 1975 the London stock market has employed three different trading systems: a floor based system, a computerised dealer system called SEAQ and the automated auction system SETS. I find that after the introduction of the computerised dealer system SEAQ momentum profits are higher than when the floor based system operated. I also document that companies trading on the SETS auction system display greater momentum profitability than shares trading on SEAQ. Results are robust to the use of different samples and alternative risk adjustments.

I investigate the role of volatility in influencing momentum profits. Shares with high volatility display wide spread out returns and therefore, potential higher magnitude momentum profitability. Given that shares displayed higher volatility traded on the post-Big Bang period (Tonks and Webb, 1991) and on the SETS system (Chelley-Steeley, 2003), I examine whether the different levels of momentum profitability achieved in alternative stock market structures arises from volatility. I find that momentum profits are strongly influenced by volatility, but the finding that the organisation of a stock market influences the momentum profits holds even after considering differences in volatility.

I examine whether the magnitude of momentum profitability varies following bull and bear markets. Momentum profits stem from the winner shares in bull markets and from the loser stocks in bear markets. I report that momentum profits are stronger following bear markets, showing a sign of mean reversion in the UK stock market.

Overall, this study contradicts the model of Hong and Stein (1999) that the momentum effect arises from the gradual expansion of information among investors and the model of Daniel et al. (1998) that the momentum effect stems from the investors' overconfidence that increases following the arrival of confirming news. This study also indicates that a significant portion of momentum profits stem from the magnitude of volatility.

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Chapter 1

INTRODUCTION

1.1 MOTIVATION

The theory of market efficiency constitutes one of the most interesting fields in finance. It states that share prices reflect all available information and investors cannot develop trading rules that earn systematic profits above transaction cost. Until the-mid 1970s, most evidence appeared to support the concept of market efficiency. However, from this point onwards, numerous papers have debated the validity of stock market efficiency. On the one hand, more and more findings have demonstrated that investors can achieve returns those expected given the level of risk involved. On the other hand, supporters of market efficiency have argued that alternative investment strategies are not convincing.

The momentum effect is one of several stock market anomalies that have contradicted market efficiency. In the momentum effect, shares that have achieved the highest (lowest) performance over the previous three to twelve months continue to perform well (disappointingly) over the following three to twelve months (Jegadeesh and Titman, 1993). Stated differently, momentum strategies suggest that investors should buy stocks with the best performances over the past medium period and sell short securities with the worst returns over the prior medium-term horizon.

The motivation to investigate the momentum effect stems from the significance of the findings in the field. Following momentum strategies, traders seem able to generate significant profits. Academic studies (e.g., Rouwenhorst, 1998; Liu et al.,

1999) report that the market-adjusted profitability of these strategies is approximately 1 per cent per month. This abnormal performance persists in the majority of out-of-sample tests, in different data sets and in different time periods. Momentum profits continued in the 1990s US market at the same magnitude as in previous periods (Jegadeesh and Titman, 1993, 2001b). Momentum profits are present in 12 developed European markets (Rouwenhorst, 1998), in 29 out of 37 international markets (Griffin et al., 2003), in 17 out of 20 emerging stock exchanges (Rouwenhorst, 1999) and in Asian markets with the exception of Japan and Korea (Chui et al., 2000). Consistent with Griffin et al. (2003), the average monthly momentum profits are 1.63 per cent in Africa, 0.78 per cent in America (excluding the US market), 0.32 per cent in Asia, 0.77 per cent in Europe and 0.49 per cent over the whole world.

Momentum strategies also appear to work in practical investment settings, since professional practitioners tend to employ momentum strategies for selecting stocks. Grinblatt et al. (1995) examine 274 mutual funds and report that 77 per cent of the managers use the momentum investment tool. Brozynski et al. (2003), using a survey to collect data, state that the momentum strategy is a very widely used investing tool among fund managers in Germany. Riley (1999) reports that the winner fund manager in Standard and Poor's Micropal award in 1999 stated that he frequently followed continuation investment strategies.

Extending the investigation beyond share returns, the momentum effect tends to persist even using industries and international stock index returns. Countries and industries that demonstrate the best (lowest) performance over the previous three to twelve months remain the winner (loser) countries and industries over the subsequent three to twelve months. For example, Moskowitz and Grinblatt (1999) report that the industry returns exhibit continuation effects, and Chan et al. (2000), employing 23 international markets, as well as Bhojraj and Swaminathan (2001), using 38 international countries and 16 developed countries, find that the international stock index returns demonstrate that momentum strategies can be profitable.

Explanations of the momentum effect seem to vary from study to study, since alternative explanations are not supported by different data sets and methodologies. For example, Moskowitz and Grinblatt (1999) report that an industry factor can explain the momentum profits. However, Chordia and Shivakumar (2002), excluding Nasdaq stocks from Moskowitz's and Grinblatt's sample and examining an alternative breakdown for defining winners and losers, argue that in these circumstances, the industry factor cannot explain the continuation profitability. The opposite findings that emerge using different data sets indicate the requirement for further empirical investigation into the rationale behind this anomaly. Over the last few years, an increasing number of papers attempt to explain the momentum effect including papers from the behavioural finance literature (e.g., Barberis et al., 1998).

Momentum profitability also appears to be more robust than other stock market anomalies. The three-factor model that controls for market returns, firm size and book-to-market values can explain a large number of anomalies such as the long-term overreaction effect, but not the momentum effect (Fama and French, 1996).

Fama (1998) doubts the robustness of the behavioural anomalies, but he accepts that the momentum anomaly remains an 'open puzzle'.

In addition, using UK data, very little attention has been focused on the momentum effect. Liu et al. (1999) is the first investigation, which employs UK returns, and examines the continuation effect. They find that the momentum effect is present for their sample of firms; abnormal profits persist after controlling for risk defined by the CAPM and the three-factor model. They examine further the momentum profits generated in alternative size, book-to-market and cash earnings to price sub-sample portfolios. Other UK studies investigate the momentum hypothesis are those by Hon and Tonks (2003) and Hou et al. (2003). Definitely, more investigation in the field could and should be undertaken.

These findings in favour of the momentum anomaly indicate a requirement for further investigation in the field.

1.2 OBJECTIVES AND FINDINGS

The focus of this thesis is to investigate factors that influence the magnitude of continuation profits. Researchers have proposed alternative factors that are associated with the momentum effect, but findings are not unanimously supported by different data sets and methodologies. This study intends to examine some factors that have not been previously identified.

I examine the relationship between momentum profitability and the stock market trading mechanism and is motivated by recent changes to the trading systems that have taken place on the London Stock Exchange. Since 1975 the London stock market has employed three different trading systems: a floor based system, a computerised dealer system called SEAQ and the automated auction system SETS. The level of transparency and operational efficiency that each system provides exerts an important influence on the diffusion of information. Since behavioural finance argues that the diffusion rate of information exerts a major influence over momentum we examine whether the magnitude of momentum profits are related to the type of stock market trading system. I find that after the introduction of the computerised dealer system SEAQ momentum profits are higher than when the floor based system operated. I also find that companies trading on the SETS auction system display greater momentum profitability than shares trading on SEAQ. Results are robust to the use of different samples and alternative risk adjustments.

I investigate the role of volatility in influencing momentum profits. Shares with high volatility display wide spread out returns and therefore, potential higher magnitude momentum profitability. Given that shares displayed higher volatility traded on the post-Big Bang period (Tonks and Webb, 1991) and on the SETS system (Chelley-Steeley, 2003), I examine whether the different levels of momentum profitability achieved in alternative stock market structures arises from volatility. I find that momentum profits are strongly influenced by volatility, but the finding that the organisation of a stock market influences the momentum profits holds even after considering differences in volatility.

I examine whether the magnitude of momentum profitability varies following bull and bear markets. Momentum profits stem from the winner shares in bull markets and from the loser stocks in bear markets. But, are momentum profits stronger following bull or bear markets? Recent studies have investigated the field without however reaching a consensus, since results from different data sets often conflict. Griffin et al. (2003) use data from international markets and report that momentum profits are stronger following bear markets and Rey and Schmid, (2003) using data from the Swiss Market, state that momentum profits are stronger in a sub-period where a bear market is present. However, Cooper et al. (2004) who employ US data find that momentum profits are stronger following bull markets. This study uses UK data and report that momentum profits are stronger following bear markets that perhaps shows a sign of mean reversion in the UK stock market.

This study undertakes an out-of-sample test of whether a strategy that combines long-term overreaction and momentum effects can generate significant abnormal profits. The overreaction anomaly utilises long-horizon returns and proposes a strategy that buys past losers and sells short prior winners. The momentum effect focuses on medium-horizon returns and suggests a strategy that buys prior winners and sells short past losers. The combination strategy buys past losers over the long-period and past winners over the medium-horizon. I report that the hybrid strategy provides significant abnormal profits at 1.29 per cent per month. This profitability is significantly larger than that gained by the counterpart reversal strategy, but only a little higher than that found by the momentum strategy. The hybrid strategy tends to outperform significantly both counterpart methods during strong bull markets.

This study reports that the continuation effect is associated with factors of which many have not been previously identified using any data set. This is important information for investors. Traders can achieve superior momentum returns following the conventional momentum strategy on shares with high volatility, on shares traded on an automated and auctions mechanisms and selecting to follow the momentum strategy in periods when the market return over the past six months was poor. This study also provides significant information for academics in the field. A significant portion of momentum profitability stems from the magnitude of volatility. When market is highly volatile, share prices tend to display wide out returns and therefore, high magnitude of momentum profitability is achieved. Nevertheless when investors invest in high volatility shares, they should be awarded with stronger returns for the risk they accept. This study contradicts the concept of Hong and Stein (1999) that the momentum effect arises from the gradual expansion of information among investors and contradicts the model of Daniel et al. (1998)

that the momentum effect stems from the investors' overconfidence that increases following the arrival of confirming news.

1.3 ORGANISATION OF THE STUDY

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Chapter 2

A BRIEF REVIEW OF THE EFFICIENT MARKET HYPOTHESIS DEBATE

2.1 INTRODUCTION

The aim of this chapter is to introduce the momentum effect within the context of the Efficient Market Hypothesis (EMH). The intention is to focus on information required to understand the subsequent empirical chapters and not to present a thorough literature review on the whole field[1]. This chapter approaches the question of whether investors can systematically achieve higher risk-adjusted returns than the market by following an investment strategy. This chapter concludes that the debate on the validity of stock market efficiency is far from over. We are a long way from suggesting an investment strategy that can provide certain abnormal profits in the future. The publication of successful investment strategies, which use past data inhibits those strategies from generating profitability in the future. If investors employ these strategies, they may cause the weakening of their capability to provide profitability.

This chapter is structured as follows: section 2.2 outlines the concept of market efficiency, section 2.3 reviews empirical findings on this topic, section 2.4 surveys results in support of the EMH, and the last section summarises the chapter.

[1] Fama (1970, 1991), Malkiel (2003) and Beechey et al. (2000) provide successful review papers on stock market efficiency.

2.2 THE CONCEPT OF THE EFFICIENT MARKET HYPOTHESIS

The theory of market efficiency constitutes one of the most interesting fields in finance. There are alternative definitions of an efficient market. The most dogmatic version of the EMH states that security prices fully reflect all available information. This version of the hypothesis suggests that a large number of rational investors exist in the market, and assumes that traders do not face any information and transaction costs. Owing to these strong assumptions, this version of the EMH is 'surely false' (Fama, 1991, pp. 1575).

Apart from the extreme definition of market efficiency, there is the less stringent version, which maintains that market efficiency holds where investors cannot follow trading rules that display systematic profits above the transaction cost and the risk premium (Jensen, 1978). Even if there were investment strategies that could achieve abnormal profitability, other investors would exploit any inefficiency rapidly and their arbitrage transactions would re-establish efficiency quickly.

Fama (1970) classifies the EMH into three forms according to the adjustment of share prices to different information. In the *weak form*, share prices reflect all the information in historical prices. Future equity prices cannot be predicted from past prices and hence, technical analysis cannot offer excess profitability. In the *semi-strong form*, security prices reflect not only information contained in historical prices but also all publicly available information. This form of efficiency implies that traders cannot achieve abnormal returns when they analyse information that is announced publicly, such as firms' earnings and dividend changes. Fundamental analysis cannot provide abnormal performance because prices adjust rapidly to newly published information and investors cannot exploit the inefficiency. In the *strong form*, prices reflect all information including private information. Even investors with inside information cannot benefit from their privileged news to earn abnormal returns.

In a more recent paper, Fama (1991) divides market efficiency into three slightly different concepts. The empirical findings that have been published in the post-1970 period allow re-definition of the previous classification. The *return predictability* group replaces the weak form. The new category is more generally applicable than the weak form as it additionally includes other forecasting variable findings. Beyond the use of past returns to predict future returns, it includes the capability of other factors, such as the market capitalisation of shares and the P/E ratio, to predict future returns. The *event studies* group replaces the semi-strong form and the *private information* category replaces the strong form. The difference between the old and the new group is the change of titles rather than the coverage of tests. Fama (1991) employed the new terminology because it was more descriptive.

2.3 EMPIRICAL FINDINGS

In this section, some of the most significant results opposed to the market efficiency in the post-1970 period are presented.

2.3.1 Winner-Loser Effect

The winner-loser hypothesis is perhaps one of the most significant recent stock market anomalies. Numerous studies have attempted to explain the effect, but academics cannot reach a consensus about what generates it. The winner-loser effect concerns three anomalies over different time horizons.

With the *momentum anomaly* (Jegadeesh and Titman, 1993), shares that achieve the best (lowest) performance over the previous three to twelve months continue to display higher (lower) than average returns over the subsequent three to twelve months. In an attempt to explain the continuation hypothesis, Moskowitz and Grinblatt (1999) argue that an industry factor can explain the abnormal returns. When they subtract an industry return from the corresponding stock return, the momentum strategy cannot demonstrate significant profitability. Chordia and Shivakumar (2001) report that the business cycles of an economy influence the continuation payoffs, the difference between the momentum profitability in expansionary and recessionary periods being 1.25 per cent per month. Lee and Swaminathan (2000) suggest that portfolios formed on the basis of different amounts of trading volume display different momentum profits. A high minus low trading volume portfolio achieves profitability of 0.91 per cent per month.

With the *long-term overreaction hypothesis* (DeBondt and Thaler, 1985), shares that perform well (badly) over the past three to five years tend to perform poorly (well) over the following three to five years. The past losers outperform the prior winners by approximately 25 to 32 per cent over a subsequent three to five years respectively. Zarowin (1990) associates the profitability of this anomaly with firm size. When past winners and losers are matched by size, the reversal of long-term profitability disappears.

With the *short-term overreaction effect* (e.g., Jegadeesh, 1990), securities that realise the best (worst) returns over the past one week to one month tend to obtain disappointing (high) returns over the subsequent one week to one month. A strategy that buys past losers and sells short prior winners provides returns of around 1.99 per cent per month. Kaul and Nimalendran (1990) associate the short-run overreaction anomaly with microstructure biases. They collect bid-to-bid data and demonstrate that a continuation in prices, rather than a reversal effect, is observed. Other researchers link short-term predictability with trading volume (e.g., Hameed and Ting, 2000) and show that there is a positive relationship between trading volume and short-term overreaction profitability.

2.3.2 Size Effect

The size effect states that small capitalisation shares achieve higher returns than large capitalisation securities. Banz (1981) examines the New York Stock Exchange (NYSE) over the 1931-1975 period, and demonstrates that the fifty smallest companies outperformed the fifty largest stocks by an average of 1 per cent per month. Reinganum (1981, 1982) reports differences in the risk-adjusted return of small and large firms to be as high as 30 per cent per year.

The profitability related to this size anomaly is also strong using non-US data. Small companies tend to generate significantly higher performances than large firms on the Belgium market (Hawanini et al., 1989), on the Japanese market (Hawanini, 1991), on the Mexico stock market (Herrera and Lockwood, 1994) and on the Korean equity market (Cheung et al., 1994). Both Banz (1985), examining data from 1955 to 1983, and Dimson and Marsh (1984), analysing returns from 1977 to 1983, find that small size stocks outperform their large size counterparts even using UK data. Banz finds that the compound annual return on the smallest portfolio exceeded that of the largest by 27 per cent while Dimson and Marsh report that that percentage is about 23 per cent.

Profits due to the size anomaly tend to vary across the different months of the year. Keim (1983) and Roll (1983) report that around half of the excess profitability of small capitalisation stocks is exhibited in the first five trading days of January. Reinganum (1982) concurs with this finding, and shows that small firms outperform their large capitalisation counterparts by 3 per cent on the first trading day of January.

However, not all research supports the existence of the size effect. Dimson et al. (2001), employing UK data, argue that the size effect does not apply when recent data are analysed. They show that small shares display higher returns than their large equity counterpart between 1955 and 1988. However, over the 1989-2000 period, large companies outperformed small shares by 4.3 per cent per annum.

2.3.3 January Effect

The January anomaly relates to the fact that shares demonstrate a significantly higher performance during the month of January. Rozeff and Kinney (1976) study NYSE shares over the 1904-1974 period and report that average stock returns for the month of January are 3.48 per cent, but only 0.42 per cent for the other months of the year.

Academics have attempted to explain the effect without reaching a consensus on what induces the January anomaly. One of the best-known explanations of the January effect is that of Keim and Roll (1982), who rationalise the January effect by invoking the tax-loss-selling hypothesis. Before the start of the new tax year, investors sell securities that have declined in value over the previous year. This happens as traders attempt to minimise their tax liability. At the beginning of the new tax year, investors re-balance their portfolios. They buy shares and thus, generate the January effect.

The tax-loss-selling hypothesis has itself attracted criticism because the January effect persists in countries where the start of the tax year is in months other than

January. For example, Australia operates a July/June tax year and, therefore, to be consistent with the tax-loss-selling hypothesis, shares should generate higher performances during the month of July. However, Brown et al. (1983) use Australian data to argue that shares still demonstrate high returns during January and not during July.

Another explanation for the January seasonality, the gamesmanship hypothesis, is based on the trading behaviour of institutional investors (e.g., Haugen and Lakonishok, 1988; Lakonishok et al., 1991). Large traders are net buyers of risky shares at the beginning of the year. In January, institutional investors are much less concerned about including well-known securities in their portfolios and they do not attempt to outperform benchmarks. Throughout the year, portfolios are rebalanced. Professional traders sell less well-known and poorly performing shares from their portfolios and buy recognised stocks with satisfactory recent performance.

Although most academics in the field have attempted to explain the effect, a number of findings demonstrate that the January effect does not remain robust using recent data. Mehdian and Perry (2002), investigating the January anomaly in US data, find that in the 1964-1987 period, the January effect is strong economically and statistically, but over the 1988-1998 period, the January anomaly does not provide statistically significant excess returns. Draper and Paudyal (1997) use UK data and find that after adjusting for transaction costs such as commission and bid-ask spread, the excess profits generated by the January effect disappear.

2.3.4 Weekend Effect

Within seasonal anomalies, different days of the week seem to generate asymmetric performance. French (1980) reports that security performances tend to be negative on Mondays and positive during other days of the week. Board and Sutcliffe (1988), using the FTSE All-Share Index over the 1962-1986 period, demonstrate that the weekend anomaly persists in the UK stock market. They show that an investor who sells short one million pounds' worth of shares on a Friday and buys back the equities on a Monday, would have achieved an average profit of three thousand pounds. However, Steeley (2001), using the FTSE100 index over the 1991-1998 period, argues that the weekend effect does not exist in recent data.

Rogalski (1984) attempts to link the weekend, the size and the January effects and concludes that all three anomalies are mutually associated. Constructing ten portfolios based on the size of companies, Rogalski reports that the Monday effect is present only in the smallest capitalisation portfolio. In addition, he found that during January the weekend effect is not valid, since in that particular month, average Monday returns are positive.

2.3.5 Value Effect

The value anomaly demonstrates that investors can achieve abnormal profitability by analysing the fundamental value of firms. Low P/E shares appear to outperform high P/E firms. Basu (1977), using US data, documents that low P/E stocks outperformed high P/E stocks by more than 7 per cent per year over the 1957-1971 period. Levis (1989) reports that the P/E effect is also present in the UK market employing data from April 1961 to March 1985. The average premium is 0.58 per cent per month. Strong and Xu (1997) show that the existence of the P/E effect on the LSE is confirmed using recent data.

In addition, high book-to-market companies seem to generate higher returns than low book-to-market equities. Chan et al. (1991) and Fama and French (1992) find that higher book-to-market ratios are associated with higher returns. Capaul et al. (1993) report that shares with high book-to-market generate monthly excess returns than shares with low book-to-market by 0.53 per cent using French stocks, 0.13 per cent employing data from Germany, 0.50 per cent using data from Japan and 0.23 per cent employing UK data.

2.3.6 Technical Analysis

Technical rules are based on chart analysis and on the belief that price patterns in the past will be repeated in the future. Technical analysts use a vast range of trading rules. One of the simplest technical rules is based on moving averages, where a trader gets buy and sell signals depending upon short and long moving average values. A buy signal exists when the short-term moving average rises above the long-term moving average and a sell signal arises when the short-term moving average falls below the long-term moving average. Another popular rule is the filter strategy, where an investor gets a buy (sell) signal, when the share price rises (falls) by more than a given percentage from its previous low (high) point.

Even though technical trading rules have been popular among mainly small investors, empirical findings have caused controversy regarding their predictive power. Results have varied when different data sets have been employed and alternative technical trading rules have been investigated. Brock et al. (1992) is perhaps the most important study that supports technical analysis. Using the Dow Jones index from 1897 to 1986, they find that applying simple trading rules such as moving average rules can achieve significant returns. However, Dawson and Steeley (2003), employing UK data, argue that technical analysis cannot generate significant profitability.

2.3.7 Value Line Ranking

The Value Line Investment Survey publishes a weekly ranking of shares from one to five according to their expected performance in the subsequent six to twelve months. Group 1 has the best return prospects and group 5 the worst. Black (1973) reports that the first ranking group achieves an excess return over that offered by the market of 10 per cent per year, while the fifth category demonstrates losses of 10 per cent per annum. Further studies (e.g., Copeland and Mayers, 1982; Stickel, 1985), which use different data sets, document that this anomaly is capable of achieving significant abnormal performance.

2.3.8 Weather Effect

The weather effect states that weather conditions influence stock market returns. Sunshine causes investors to be in a good mood and to be optimistic, while bad weather conditions cause traders to be pessimistic. Saunders (1993) reports that the NYSE index tends to display negative returns in cloudy weather conditions. Hirshleifer and Shumway (2001), employing data for 26 international markets, demonstrate that in most of the countries, sunshine is associated with positive share returns, but snow and rain do not influence traders' investment decisions.

2.3.9 Behavioural Finance

Besides the criticism of stock market anomalies, the efficient market hypothesis has faced attack from the field of behavioural finance[2]. Supporters of behavioural finance attempt a reconciliation of market efficiency and human behaviour. The EMH is based on the hypothesis that investors are rational. Behavioural finance argues against this assumption, and states that investors are human beings who make systematic mistakes when they invest in shares.

Many examples have demonstrated that investors do not behave rationally. For example, the majority (approximately 90 percent) of investors in the US, Japan and the UK do not utilise international diversification to diversify away fully the risk of their portfolios, but they tend to invest primarily in their domestic markets (French and Poterba, 1991). Traders tend to hold shares from companies that are in close geographical locations (Grinblatt and Keloharju, 2001). Investors, especially men rather than women, tend to trade shares very frequently, generating low performances (Barber and Odean, 2000). Investors are sometimes too optimistic, while at other times are too pessimistic (Lee et al., 1991).

Behavioural finance examines these irrationalities and their relevance to how share prices behave.

[2] Barberis and Thaler (2002) and Daniel et al. (2002) comprehensively review the subject.

2.4 CRITICISM TO ANOMALIES

The previous section demonstrated that there exist investment strategies that can achieve excess returns. Nevertheless, the foregoing analysis of stock market anomalies highlighted only one side of the coin, since challenges to the EMH have themselves been subject to challenge.

Researchers employ historical data when they undertake their studies. That there were anomalies in the past does not imply that they will necessarily remain in the future. As reported above, Dimson et al. (2001) and Steeley (2001) find that the size and the weekend effects respectively do not exist when recent data are used. When a strategy can achieve abnormal profits, numerous investors follow it, and gradually its ability to generate profitability disappears. Let's assume that traders attempt to exploit the January effect. They expect that shares will achieve higher returns in January rather than in the rest of the year, and, therefore, they would take their position in the market in December. The result would be the disappearance of the January effect, and the appearance of the December anomaly. In addition, academic analysis usually does not include costs such as transaction and information costs that traders face when they invest in shares. The inclusion of these costs can convert a profitable investment strategy into an unattractive trading rule.

Another significant criticism of stock market anomalies is that the profitability of anomalies appears fragile (Fama, 1998). Profits reflect the use of different sub-periods and equity markets. Profitability varies when value-weighted portfolios and equal-weighted portfolios are constructed. The profits of alternative effects are correlated (e.g., in the weekend effect; see Rogalski, 1984). Some anomalies do not present either economically or statistically significant returns (e.g., in the January effect; see Mehdian and Perry, 2002). Overall, Fama reports that it is not difficult to find strategies that enjoy excess returns when a specific period in an equity market is used. However, this does not imply that the market is inefficient.

Another criticism of stock market anomalies is the joint-hypothesis problem (Fama, 1991). Researchers examine the profits of an investment strategy after controlling for risk. The most common measurements of risk are given by the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965; and Black, 1972) that controls for the market factor, and the three-factor model (Fama and French, 1993) that controls for the market factor as well as for the size and the book-to-market of shares. The joint-hypothesis problem states that these asset-pricing models are only models, and not the EMH. When academics find that a strategy demonstrates significant profits after controlling for risk, this result does not imply that the market is inefficient. Instead, it indicates that the models that interpret risk may be inadequate and may not capture the return-risk relationship appropriately.

Supporters of the EMH argue that stock market anomalies are reliable investing tools, if professional investors acknowledge them and use them to systematically outperform the market. However, empirical findings (e.g., Malkiel, 2003) reveal that apart from a few managers such as Peter Lynch, Warren Buffet and John Neff, professional investors cannot beat the market. During the 1990s, about three-quarters of institutional investors failed to achieve higher performances than the market. Institutional traders also appear not to be characterised by consistent performances. The twenty mutual funds that achieved the highest performances during the 1970s did not even manage to outperform the market in 1980s.

Some stock market anomalies may appear due to data-snooping (Lo and MacKinlay, 1990). The majority of academics employ the same databases. The most common are the Datastream for various international stock markets, the London Share Price Database (LSPD) for the London Stock Exchange, and the Center for Research in Security Prices (CRSP) for US equity markets. These databases' coverage of shares is less than complete especially in their early years. For example, Datastream's coverage on the LSE is poor in the 1960s and 1970s (Nagel, 2000), LSPD provides only some of the UK listed companies in the pre-1975 period and is characterised by the thin trading problem (non-trading) which is especially apparent in small capitalisation companies.

Another potential explanation for the appearance of stock market anomalies is data mining. Academics, with the assistance of modern technology, can easily and quickly examine the capability of alternative investment strategies to demonstrate abnormal performance. It is likely that a strategy will appear capable of generating significant returns when a specific sub-period and frequency of data are used. Academics tend to send for publication only the particular strategy that reports interesting findings.

2.5 CONCLUSION

The debate over the validity of the EMH has generated numerous significant findings (Table 2.1). The supporters of stock market anomalies and behavioural finance have provided strong evidence against the hypothesis. However, they have only shed light on one side of the coin. Criticism of stock market anomalies has been substantial.

It is hard to decide which side of the debate to support. On the one hand, it is certain that share prices are not always efficient according to fundamental values. The recent Internet bubble of the late 1990s is one example where equity prices deviated significantly from their values. On the other hand, it seems difficult to suggest a certain investment strategy that will reliably achieve abnormal returns in the future. Stock market anomalies show that with past data, there are alternative strategies that, on average, tend to generate returns in excess of the market. However, this does not imply that these strategies can provide significant performance in the future. Publication of these successful strategies causes the gradual weakening of their ability to generate profits.

Overall, the debate over consistency of the market efficiency indicates the requirement for further investigation in the field. This study will investigate in depth the momentum effect.

Table 2.1

Summary of Chapter

Against EMH	In Favour EMH
Winner-Loser Effect DeBondt and Thaler (1985), Jegadeesh and Titman (1993), Jegadeesh (1990)	**Academic Research versus Real Investing**
Size Effect Banz (1981), Reinganum (1981, 1982), Dimson et al. (2001)	**Fragile Stock Market Anomalies** Fama (1998)
January Effect Rozeff and Kinney (1976), Keim and Roll (1982), Medhian and Perry (2002)	**Joint-Hypothesis Problem** Fama (1991)
Weekend Effect French (1980), Board and Sutcliffe (1988), Steeley (2001).	**Performance of Professional Traders** Malkiel (2003)
Value Effect Basu (1977), Fama and French (1992)	**Data-Snooping** Lo and MacKinlay (1990)
Technical Analysis Brock et al. (1992), Dawson and Steeley (2003).	**Data Mining**
Value Line Ranking Black (1973)	
Weather Effect Saunders (1993), Hirshleifer and Shumway (2001)	
Behavioural Finance Barberis and Thaler (2002), Daniel et al. (2001)	

Chapter 3

A LITERATURE REVIEW OF THE WINNER-LOSER ANOMALY

3.1 INTRODUCTION

This chapter presents an in depth literature review of one specific investment strategy. Because of the close relationship between momentum and short- and long-term overreaction effects, the whole winner-loser anomaly will be considered. An understanding of the momentum hypothesis requires an understanding of the winner-loser anomaly. The conviction is that all three categories seem to reflect a similar phenomenon, since all three categories suggest that equity prices exhibit patterns over different time horizons.

This chapter provides an innovative review of the winner-loser effect. Jegadeesh and Titman (2001a) present a comprehensive survey of the momentum effect, and Forbes (1996) and Power and Lonie (1993) present extensive reviews for the short- and long-term overreaction hypotheses. This study presents an integrated study of all three, to highlight the significance of cross-references among the three effects.

This chapter is structured as follows: sections 3.2, 3.3 and 3.4 survey literature relating to the long-term overreaction, the short-term reversal and the momentum effects respectively; section 3.5 reviews studies that rationalise more than one part of the winner-loser effect; and section 3.6 concludes the chapter.

3.2 LONG-TERM OVERREACTION EFFECT

3.2.1 Evidence

Research into the performance of past winner and loser portfolios came to prominence with DeBondt's and Thaler's article in the Journal of Finance in 1985- which noted for the first time the overreaction hypothesis. DeBondt and Thaler rank securities based on their returns over three to five years and divide them into portfolios. The 35 shares with the best performance are designated as the winner portfolio (W), while the 35 stocks with the worst performance constitute the loser category (L). They calculate the cumulative abnormal return of both groups (CAR_W, CAR_L) in the subsequent three to five years. They average the CARs generated over the whole period in both categories ($ACAR_W, ACAR_L$) and calculate the difference between them ($ACAR_L - ACAR_W$).

They conclude that, on average, shares with the worst (best) prior performances demonstrate positive (negative) returns over the subsequent three to five years (hence, $ACAR_L - ACAR_W > 0$). The past 35 losers outperformed the past 35 winners by approximately 25 and 32 per cent over the following three and five years respectively. DeBondt and Thaler report that the profitability of this reversal strategy mainly stems from the loser rather than the winner portfolio. In the case of three-year periods, past loser shares gain 20 per cent more than the market, while their winner counterparts display losses that are 5 per cent lower than the market[1].

[1] Dissanaike (1996) argues that the asymmetric reversal characteristic between winner and loser shares stems from the inappropriate measurement of returns. The test period return by itself is not a satisfactory measure of the strength of price reversal. Instead, the whole price movement from the

Using UK data, Power et al. (1991) and Campbell and Limmack (1997) concur with DeBondt and Thaler who employed US returns. Both UK studies identify that contrarian strategies can generate significant abnormal profitability. Power et al. use a list of the top 200 UK companies according to 'Management Today', to define winners and losers. The top 30 shares in the list, with the best performance, constitute the winner portfolio, while the bottom 30 equities, with the worst returns, comprise the loser group. Campbell and Limmack, using data from the London Business School Risk Measurement Service, investigate the long-run overreaction profitability in a much larger number of winner and loser shares; over 4,000 equities were analysed.

Extending the investigation beyond share returns, reversal profits appear strong using international stock index returns. Countries that demonstrate the best (lowest) performance over the previous three to five years become the loser (winner) countries over the subsequent three to five years. This finding persists for 16 national markets (Richards, 1997) and using 38 international countries and 16 developed markets (Bhojraj and Swaminathan, 2001).

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rank to the test period should be examined. Using UK data, Dissanaike documents that the loser and the winner portfolio experience approximately the same magnitude of abnormal profitability.

3.2.2 Alternative Explanations

Because of the magnitude of abnormal profitability found by DeBondt and Thaler, and since they presented a challenge to the weak form of the EMH, academics have attempted to explain the long-term overreaction results. They have sought possible reasons for the apparent predictability in share returns without being able to reach a consensus on what induces the anomaly.

One of the best known studies that questions overreaction is Zarowin (1990). Zarowin links the abnormal profitability of long-term overreaction to the well-known size effect. When he matches winners with losers of the same size, the profits from long-term reversals disappear, except during the month of January. In addition, Zarowin finds that when losers have lower capitalisation than their winner counterparts, there is evidence of overreaction. Nonetheless, when losers are larger than winners, no evidence of overreaction is present in the return data.

However, Zarowin's results do not hold when different data and different methodologies are used. Using UK data, Dissanaike (1997) documents that long-term overreaction profits persist for the FT500 Index that only utilises high capitalisation shares. Extending the investigation, Dissanaike (2002) analyses whether the long-term overreaction profits from a FT500 sample were due to the size effect. A portfolio of small capitalisation shares is compared with their large capitalisation counterparts, to determine whether any significant abnormal profits are caused by the size difference. Dissanaike discovers that although shares with small size generate higher contrarian profits than their large size counterparts, the long-term reversal effect displays higher profitability in all the individual test periods. Dissanaike concludes that there is a link between the size effect and the long-term overreaction hypothesis, but that the size anomaly alone is not able to explain all the abnormal returns earned by the overreaction strategy.

There is also some disagreement on whether risk can explain the long-term reversal effect. Fama and French (1996) find that the three-factor model (Fama and French, 1993) can explain the long-term reversal profitability.

The three-factor model is

$$R_{p,t} - R_{f,t} = a_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + e_{p,t} \qquad (3.1)$$

where $R_{p,t} - R_{f,t}$ is the excess return of a portfolio p, $R_{m,t} - R_{f,t}$ is the excess return on a market portfolio, SMB_t (Small Minus Big) shows the portfolio that buys the three small size portfolios and sells short the three big size portfolios. HML_t (High Minus Low) shows the portfolio that buys the three high book-to-market portfolios and sells short the three low book-to-market portfolios.

Fama and French examine the sensitivity of the slopes in the model and report that losers realise higher returns than their winners counterparts because losers are small capitalisation shares, while winners are securities in larger firms. The intercept of the model is almost zero; after employing for the three-factor model, the overreaction payoffs disappear.

Chan (1988) and Ball and Kothari (1989) define risk as the beta from applying the Capital Asset Pricing Model (see Sharpe, 1964; Lintner, 1965; and Black, 1972; $R_{p,t} - R_{f,t} = a_p + \beta_p(R_{m,t} - R_{f,t}) + e_{i,t}$). They demonstrate that the long-term overreaction effect can be explained by time-varying risk. Although the beta of losers is lower than the beta of winners in the rank period, by the end of the test period the beta of losers is higher than that of winners. Chan finds that the beta of losers increased by 0.21, while the beta of winners decreased by 0.22 over the test period. After controlling for changes in risk, only insignificant contrarian profits remain. For example, Ball and Kothari demonstrate that raw reversal profits are approximately 12-14 per cent per year, but after controlling for risk, contrarian profitability is less than 2 per cent per year. This suggests that reversal gains disappear after controlling for risk changes.

However, Dissanaike (1997), using UK data, uses a similar methodology to that employed by Chan and Ball and Kothari, and argues that risk explanations cannot explain the long-term overreaction evidence. For example, Dissanaike finds that the beta of winners is higher than the beta of losers in the test period. After controlling for risk according to the CAPM, the strategy of buying past losers and selling short previous winners earns significant profits of 0.74 per cent per month.

A further attack on the long-term overreaction effect argues that the anomaly arises from the inappropriate calculation of abnormal returns. Conrad and Kaul (1993) use the buy-and-hold approach where single-period returns are compounded, rather than using the typical cumulative abnormal return method, to examine the performance of the strategy. Abnormal profitability is measured as:

$$HRP(k) = (1+ER_1)(1+ER_2)...(1+ER_K)-1 \tag{3.2}$$

where HRP is the holding return period, k shows the number of months over the test period and ER_t shows the excess return of the portfolio in each test period.

Excluding January, the former approach yields long-term abnormal returns of -1.7 per cent over a three-year period. Stated differently, using an alternative methodology to calculate abnormal profits, the reversal strategy generates losses rather than gains.

Nonetheless, Conrad's and Kaul's critique has itself been subject to challenge. A large number of studies that have followed the buy-and-hold methodology have shown that the long-term profits from share price reversals remain economically and statistically significant (e.g., Dissanaike, 1997).

In short, since DeBondt and Thaler (1985) documented their long-term overreaction results, studies have attempted to explain the anomaly. However, none of the alternative explanations appear able to subsume the effect. Neither size, risk nor methodological criticisms seem able to fully rationalise the anomaly. Further investigation is needed, to explain the long-term overreaction hypothesis.

3.3 SHORT-TERM OVERREACTION EFFECT

3.3.1 Evidence

A few years after DeBondt and Thaler's article was published in 1985, academics analysed patterns in returns over shorter time periods. Howe (1986) uses a similar methodology to DeBondt and Thaler, and reports that shares realised a large positive or negative performance in the past week experienced a reversal performance in the subsequent weeks. Dyl and Maxfield (1987) demonstrate that the three securities that achieve the highest (lowest) one-day performance generate 1.8 (3.6) per cent lower (higher) return than the market index in the subsequent 10 trading days. Lehmann (1990) finds that by ranking securities based on their previous week's performance, past winner and loser portfolios display a reversal pattern the following week. Prior winners (losers) generate losses (gains) of between –0.35 to –0.55 (from 0.86 to 1.24) per cent in the subsequent week. In addition, Jegadeesh (1990) investigates patterns in monthly prices and reports that with a one-month lag, the risk-adjusted return of the arbitrage portfolio is 1.99 per cent.

Recent studies that use international data arrive at similar results to the pioneer studies. Bowman and Iverson (1998) and Antoniou et al. (2005) demonstrate evidence of short-run price reversal in share returns in the New Zealand and Athens Stock Exchanges respectively.

3.3.2 Alternative Explanations

As in the case of the long-term overreaction effect, academics have attempted to rationalise these short-term contrarian profits without being able to reach a consensus.

Some studies associate the short-run overreaction hypothesis with microstructure biases. Kaul and Nimalendran (1990) report that short-term overreaction profitability stems from the large bid-ask spreads of Nasdaq securities. They collect bid-to-bid data and document that in this new sample, a momentum rather than a reversal effect is observed. Moskowitz and Grinblatt (1999) arrive at a similar conclusion. They find that results based on industry strategies reveal the same positive and negative persistence in share returns consistent with Jegadeesh and Titman (1993) and DeBondt and Thaler (1985) respectively. Nonetheless, the industry strategy does not generate the short-term reversal found by Jegadeesh (1990), but the continuation effect. They argue that their industry-based analysis causes microstructure effects to disappear.

However, the critique of the above studies does not appear to be robust. A large number of investigations have shown that short-term reversal profitability remains economically and statistically significant after controlling for market frictions. Using UK data, Antoniou et al. (2002) demonstrate that results remain similar whether they use bid-to-bid or conventional data. In addition, they control for infrequent trading by removing shares that have not traded for four consecutive weeks, and document that in this new sample similar results are found to those reported in the full sample.

Other academics link short-term predictability to security trading volume (e.g., Hameed and Ting, 2000). These studies show that contrarian profits are positively related to stock trading volume. The high trading volume sub-sample generates significantly larger contrarian profits than the low trading volume portfolio. Although these studies suggest that trading volume can assist in explaining the magnitude of the profits earned by the short-run overreaction effect, volume does not account for all of the abnormal returns achieved. Low trading volume firms continue to generate positive contrarian profitability.

In short, after Howe (1986), Dyl and Maxfield (1987), Lehmann (1990) and Jegadeesh (1990) documented evidence of short-term overreaction in share returns, studies focused on explaining the anomaly. Nevertheless, neither microstructure effects nor trading volume appear able to explain the short-term overreaction profitability. Further analysis is required into the rationale behind the short-term reversal effect.

3.4 MOMENTUM EFFECT

3.4.1 Evidence

In order to address the issues raised in long- and short-term overreaction effects, Jegadeesh and Titman (1993) undertook a pioneering study, which discovered the momentum effect. The key difference is that they examined the pattern in portfolios of between three and twelve months.

Jegadeesh and Titman rank securities based on their performance in the previous three, six, nine and twelve months. Corresponding to each rank, they construct ten equal-weighted portfolios and calculate the performance of these decile portfolios in the subsequent three, six, nine and twelve test months. They compute momentum profitability by subtracting from the performance of the winner category, the return of the loser portfolio. They also repeat the above procedure by skipping a week between the rank and test period, to avoid market friction problems that have been documented in the short-term overreaction anomaly (e.g., Jegadeesh, 1990).

In contrast to the short- and long-term overreaction effects, Jegadeesh and Titman find evidence of a continuation pattern in security returns. The prior winner (loser) portfolio over the past three to twelve months remains a winner (loser) portfolio over the following three to twelve months. Almost all the alternative strategies generate significant momentum profitability. The most profitable strategy is the twelve months rank with a three month holding period, where the winner shares outperformed their loser counterparts by 1.49 per cent per month[2].

Jegadeesh's and Titman's findings appear robust when international data are used. Momentum profits are strong in 12 developed European markets (Rouwenhorst, 1998), in 29 out of 37 international markets (Griffin et al., 2003), in 17 out of 20 emerging stock exchanges (Rouwenhorst, 1999), in most of the countries of the G-7: USA, UK, France, Germany, Italy, Canada and Japan (Bacmann et al., 2001) and in Asian markets with the exception of Japan and Korea (Chui et al., 2000). Consistent with Griffin et al. (2003), the average monthly momentum profits are 1.63, 0.78, 0.32, 0.77 and 0.49 per cent in Africa, America (excluding the US market), Asia, Europe and the whole world respectively. With UK data, there is a disagreement on whether momentum abnormal profits are achievable. Liu et al. (1999) show that continuation profitability is strong over the 1977-1998 period. However, Hon and Tonks (2003) use some of the UK companies listed on the LSE, and argue that momentum strategies are not profitable before 1976.

Momentum strategies also appear to work in practical settings, since professional traders appear to employ momentum strategies for selecting stocks. Burch and Swaminathan (2001) investigate institutional investors' holding of stocks based on past share returns. They find that professional traders tend to increase their holdings for previous winner shares and slightly decrease their holdings for prior loser stocks.

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[2] Rey and Schmid (2003), using the Swiss market, report that considering only the best (worst) past return stock to indicate the winner (loser) 'portfolio', there is a significant increase of the magnitude of momentum profitability up to 4 per cent per month.

Grinblatt et al. (1995) examine 274 mutual funds and report that 77 per cent of the managers use the momentum investment tool. Brozynski et al. (2003), using primary survey data, state that the momentum strategy is a very widely used investing tool among fund managers in Germany. Riley (1999) reports that the winner fund manager in Standard and Poor's Micropal award in 1999 stated that he frequently followed continuation investment strategies.

Carhart (1997) investigates the persistence of equity mutual fund managers. Fund managers that achieved the highest (lowest) past performances over the previous year continue to perform well (disappointingly) over the following year. The best decile mutual funds outperform the counterpart worst decile mutual funds by 8 per cent per year. A four-factor model that considers the three factors from the three-factor model (Fama and French, 1993) and the momentum factor ($R_{p,t} - R_{f,t} = a_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + mWML_t + e_{p,t}$) can explain nearly half of the abnormal profits between the funds with the best and worst performances. The best (worst) decile mutual funds are strongly positive (negative) associated with the momentum factor, which shows that the performance of fund managers is strongly associated whether they follow the momentum strategy.

Extending the investigation beyond share returns, the momentum effect tends to persist even using industry and international stock index returns. Countries and industries that demonstrate the best (lowest) performance over the previous three to twelve months remain good (poor) countries and industries over the subsequent three to twelve months. Moskowitz and Grinblatt (1999) report that industry returns exhibit a degree of continuation, and Chan et al. (2000), employing 23 international markets, and Bhojraj and Swaminathan (2001), using 38 international countries and 16 developed countries, find that the international stock index returns demonstrate momentum.

3.4.2 Alternative Explanations

Because of the robustness of Jegadeesh's and Titman's finding, academics have attempted to explain the anomaly. Similar to the long- and short-term overreaction effects, they have followed various interesting ideas and methodologies without reaching a consensus. Unlike in the long- and short-term reversal studies, academics have identified different potential factors and employed alternative methodologies to study the momentum effect.

A number of studies attempt to rationalise the abnormal profits earned by momentum strategies in terms of risk. On the one hand, Ang et al. (2001) link the higher return of winners to the higher downside risk that they display. Winners demonstrate higher performance than their loser counterparts because they are characterised by higher correlation with the market index in a declining market. However, Fama and French (1996), using US data, and Liu et al. (1999), using UK data, find that the three-factor model (Fama and French, 1993) cannot explain momentum profitability. The monthly risk-adjusted abnormal returns of the winner portfolio remain significantly higher than those of its loser counterpart.

There is also a debate about the significance of the industry factor in explaining the momentum effect. Moskowitz and Grinblatt (1999) argue that an industry factor can explain the momentum hypothesis. They create industry portfolios and sort them on their past six-month returns. Firms in the three industries with the highest performance are bought, while the three industries with the lowest returns are sold short. The performances of these six industries are tracked over the subsequent six months. Momentum profits are then computed by calculating the performance of the winner industries minus the return of the loser industries. By following the industry momentum strategy, investors are able to generate returns of 0.43 per cent per month (t-statistic=4.24). Furthermore, by subtracting an industry return from the corresponding share return, the individual momentum strategy can generate only economically insignificant profits of 0.13 per cent per month.

However Moskowitz's and Grinblatt's results are not replicated when using different data-sets. Chordia and Shivakumar (2002) exclude Nasdaq stocks from Moskowitz's and Grinblatt's sample, and examine an alternative breakdown for defining winners and losers. They argue that in these circumstances, the individual momentum strategy experiences significant positive profits. Nijman et al. (2002) report that industries have only a relatively weak role in explaining the profitability of momentum strategies in European stock markets. Industry-based strategies can explain only 30 per cent of momentum profitability compared with 60 per cent achieved for individual shares.

Findings conflict even over the significance of business cycles for continuation payoffs. On the one hand, Chordia and Shivakumar (2002), using information from the National Bureau of Economic Research (NBER) to define the position of the business cycle, document that the magnitude of momentum profits is influenced by the stage of the business cycle of an economy. The difference between momentum profitability in expansionary and recessionary periods is economically and statistically significant, at 1.25 per cent per month. On the other hand, Griffin et al. (2003) demonstrate that the number of stock markets experiencing positive persistence during periods of recession (negative GDP growth) is the same (17 out of 22) as those showing positive persistence during periods of positive GDP growth.

Another possible explanation of the anomaly suggests that different momentum profits are generated in different trading volume sub-samples. Lee and Swaminathan (2000) sort shares into portfolios based on past returns and trading volume, and show that securities with high trading volumes display greater momentum profitability than their low trading volume counterparts. In the representative momentum strategy, where a six month rank period and a six month test period are analysed, a high minus low trading volume portfolio creates an abnormal profit of 0.91 per cent per month.

Although this study highlights the significance of trading volume in explaining some of the magnitude of momentum profitability, trading volume cannot subsume the momentum effect. Shares with low trading volume still experience positive profits due to the momentum strategy. Further, Drew et al. (2004), using Australian data from 1988 to 2002, report contradictory findings concerning the rank and test periods selected. Even though their findings concur with the results of Lee and Swaminathan when a rank (test) period of three (six) months is used, they conflict when rank and test periods are twelve months; firms with high (low) past trading volume generate 0.29 (1.1) per cent per month momentum profitability.

Studies have calculated the momentum profitability that is generated following bull and bear markets. Cooper et al. (2002), employing US data from between 1929 and 1995, report that momentum profits are stronger following bull markets; momentum profits that follow positive market returns are 0.93 per cent per month and continuation payoffs that follow negative market returns are –0.37 per cent per month.

However, Rey and Schmid (2003) argue that the opposite finding emerges. Using data from the Swiss Market, Rey and Schmid state that momentum profits are stronger in a sub-period where a bear market is present. The results of Griffin et al. (2003) concur with this finding and report that the monthly momentum profitability following bear (bull) markets is 1.53 (1.27) per cent in Africa, 0.77 (0.73) per cent in America, 0.55 (-0.10) per cent in Asia, 0.68 (0.76) per cent in Europe and 1.04 (0.31) per cent in US.

Findings from different studies are contradictory when academics investigate the influence of size on the magnitude of momentum profitability. Hou et al. (2003), using UK data, construct portfolios sorting first by past performance and then, by market capitalisation: they divide each past return portfolio (e.g., winners) into ten portfolios based on size. They find that momentum profits peak on the second and the seventh portfolios. This finding contradicts Hong et al. (2000), who use US data, and Doukas and McKnight (2003), who employ European data, since they report that beyond the first few small capitalisation portfolios, there is a continuous decline of momentum profits as the investor moves to portfolios of shares with higher market values.

Behavioural models have also been developed to rationalise the momentum hypothesis. Grinblatt and Han (2001) present a model that suggests that the disposition of investors to sell winners too quickly and to hold on to losers too long can explain the observed pattern in share returns. Loser share prices do not fall far enough, and need time to adjust to their fundamental values, while winner share prices do not rise enough and require some time to regain their equilibrium levels based on company fundamentals. Therefore, there is a positive spread between prices and their fundamental values for winners and a negative spread for losers. The momentum effect is generated by this convergence in which winners should have higher returns than losers.

George and Hwang (2004) also develop a behavioural model to explain their empirical findings. They introduce a new momentum strategy called the '52-week high strategy'. Buying (sell short) stocks that are near (far from) their 52-week high, investors can generate approximately double the profitability of the conventional momentum strategy (Jegadeesh and Titman, 1993) and the industry momentum strategy applied by Moskowitz and Grinblatt (1999). They explain this finding as follows: investors expect that shares that are close to the 52-week high will exhibit bearish conditions in the future, even though public information can promise further increases in share prices. The information finally prevails, generating a delayed increase in stock prices.

In short, although most findings highlight the robustness of the momentum effect when academics use different data, explanation of the rationale behind the effect appears to be the most intriguing issue in the literature. The alternative explanations of the effect are not unanimously supported by different data sets and methodologies. Neither risk, an industry factor, the business cycle, trading volume, bull and bear markets nor behavioural finance appear able to subsume the momentum effect. Further examination is required of the rationale behind the momentum hypothesis.

3.5 RECONCILIATION OF LONG-TERM REVERSAL EFFECT, SHORT-RUN OVERREACTION HYPOTHESIS AND MOMENTUM EFFECT

The previous three sections reported that all three anomalies produce similar effects over different time horizons. A large number of studies have attempted to rationalise the results, but academics are far from reaching a consensus regarding the various explanations that have been advanced. In order to reveal the significance of cross-references among the three effects, the following section reviews studies that rationalise more than one part of the winner-loser anomaly. Overall, the research reviewed draws on the behavioural finance literature and reports more convincing results.

In an attempt to explain the whole winner-loser effect rather than focussing only on part of the literature, Fama (1998) considers the underreaction and overreaction anomalies as a whole, rather than individually. Since academics report underreaction results (such as the momentum effect) as often as overreaction findings (such as the short- and long-term overreaction anomalies), Fama argues that, on average, these results are nothing more than deviations from the average market efficiency.

Recently, behavioural models have also been developed to account for the momentum and the long-term overreaction effects, but not for the short-term reversal hypothesis. Barberis et al. (1998) highlight the significance of investor sentiment to explain the winner-loser anomaly. They consider the trading patterns of investors within different uncertainty level. According to the model, the earnings of companies follow the random walk, however investors believe that earnings are either mean-reverting or trending based on their expectations. Evidence in the field of psychology shows that when people observe a variable trend, then because of the 'conservatism bias' (Edwards, 1968) they believe that the trend will reverse. Therefore, when investors observe a variable trend among positive and negative past earning results of a company, investors believe that such a trend will reverse itself. Due to their expectations, they underreact to new information, and the momentum effect is generated. Similarly, findings in the field of psychology shows that when people observe a clear trend, then because of the 'representativeness heuristic bias' (Tversky and Kahneman, 1974) they believe that in the future the trend will continue. Therefore, when there exists a series of positive or negative earnings results, investors expect that future signals will follow the same trend. Due to this outlook, they overreact to present information, and the long-run overreaction effect is created.

Daniel et al. (1998) develop another behavioural model to reconcile the momentum and the long-term overreaction effects. They employ different concepts from psychology than Barberis et al (1998). According to the overconfidence bias, investors overestimate the reliability of their private information, while they neglect the public information. Consistent to attribution theory (Bem, 1965), investors observe the outcomes of their actions and they update their confidence for their ability to pick winner share. If public information confirms investors' private information, the continuing overreaction of informed investors generates the momentum effect. Notice that this explanation of the momentum effect is contradicted with the literature, since it states that the momentum effect stems from a continuous overreaction rather than the usual concept of underreaction. If however the public signal contradicts the information that informed investors have, traders' confidence tends to fall because of the attribution bias and prices gradually revert to fundamentals. Therefore, the long-term overreaction effect appears.

In addition, Kim (2002) explains the momentum effect based on Andressen and Kraus (1988)'s finding that when prices display a significant trend over a period, objects tend to follow the trend. Stated differently, investors tend to buy a stock when its prices rise and to sell a share when its prices fall. The stronger the prices movement is, the stronger the tendency of investors to follow the trend. Where investors' decisions are based on this finding, continuation in the pattern of prices is displayed. In the long-term, the trend gradually declines because of the exit from the market of former momentum traders, and share prices revert to fundamental generating the long-term overreaction effect.

Focusing on agents rather than on cognitive biases, Hong and Stein (1999) and Du (2002) present two alternative behavioural models in order to explain both the momentum and the long-term overreaction effects. The behavioural model of Hong and Stein (1999) bases on two rational agents; newswatchers and momentum traders. Newswatchers observe some private information, but fail to be aware of the information that other investors have. Therefore, when private information of investors become public, prices adjust to new information and the momentum effect appears. Stated differently, the continuation hypothesis stems from the gradual expansion of information among investors. 'Momentum traders' are investors that follow the trend. Initially momentum investors implement simple strategies and achieve profits, eliminating quickly any underreaction. However, momentum investors eventually drive security prices to levels that are higher than their fundamental values and therefore, a subsequent reversal in share prices is generated. Within that price pattern, early momentum investors gain profits and late momentum traders generate loses.

Du (2002) suggests that there exist investors with confidence and non-confidence. Investors with a great deal of confidence buy and sell equities rapidly in order to adapt to new information, but traders with low confidence hesitate before making a decision. Because of the underreaction of low confident investors, an underreaction to information is evident and the momentum effect appears. On receipt of positive news, most investors buy shares immediately. A rapid increase in price encourages investors with lower confidence to consider adapting their position and the entry of more and more of them leads prices to rise above their fundamental values. Subsequently, prices revert to equilibrium once investors recognise the wrong valuation.

Since the publication of these theoretical models, academics have researched whether these models are supported by empirical data. Overall, the existing limited evidence seems to confirm the behavioural models. Bloomfield and Hales (2001) support the model of Barberis et al. (1998). In a psychological experiment, they demonstrate that 38 MBA-students underreact in circumstances where there are many reversals, but overreact to situations with repeated continuations.

Daniel and Titman (1999) examine whether the Daniel et al. (1998) model is supported when empirical data are in use. According to the model, the momentum effect stems from the overconfident investors and therefore, the momentum effect is likely to be stronger in shares that are difficult for valuation. They define this characteristic according to the book-to-market ratio of companies. Valuation of companies with low book-to-market ratios is more uncertain, since the valuation procedure bases on expected news and growth options, than the counterpart companies with high book-to-market values. Daniel and Titman (1999) support the Daniel et al. (1998) model because they report that momentum profits are stronger for securities that need subjective valuation. Shares with low book-to-market ratios experience higher continuation profitability than securities with high book-to-market values.

Hong et al. (2000), using US data, and Doukas and McKnight (2003), using information from 13 European countries, investigate whether the model of Hong and Stein (1999) holds using empirical data. They associate the speed of information that flows among investors with the size and the analyst coverage of companies. Information spreads slower among investors within companies with small capitalisation and with low analyst coverage rather than the counterpart companies with large capitalisation and with high analyst coverage. They support the theoretical findings of Hong and Stein behavioural model, since they report that continuation profits are higher for small than for large capitalisation shares, and for securities with low, rather than high, analyst coverage.

Chui et al. (2003) compare two of the behavioural models in respect of their ability to rationalise the momentum effect. Their analysis is based on the momentum profitability demonstrated in the real estate investment trusts (REITs) industry over different time periods. After 1990, shares in this industry have been much more difficult to value and they were characterised by more comprehensive analyst coverage. Therefore, according to Daniel et al. (1998), momentum profits should be stronger in the post-1990 period because the valuation was less certain. However, consistent with Hong and Stein (1999), continuation profitability should be higher in the pre-1990 period, because the spread of information was slower. Chui et al. support the Daniel et al. behavioural model because momentum profits in REITs are significantly greater after 1990.

In short, some studies have been able to account for more than one part of the winner-loser effect. This type of investigation is relatively recent, and is concentrated in the behavioural finance literature. The existing empirical findings, although limited, appear to support the theoretical predictions. Nevertheless, further cross-reference among the three anomalies needs to be carried out, even beyond the behavioural finance field. Almost none of the explanations rationalise all three parts of the winner-loser anomaly.

3.6 CONCLUSION

This chapter presented the literature review of the winner-loser effect. The conviction is that a close relationship exists among momentum and short- and long-term overreaction effects. All three are similar effects, but they operate over different time horizons. Therefore, the whole winner-loser anomaly was surveyed, rather than focussing on part of the literature only. Although most findings highlighted the robustness of the winner-loser effect demonstrated using different data sets, the rationale behind the effect appears to be the most intriguing issue in the literature. The alternative explanations of the effect were not unanimously supported by different data sets and methodologies; this indicates the need for further investigation into what generates the anomaly. This study examines in depth the momentum effect and aims to investigate factors that influence the momentum profitability that have not previously been identified (Tables 3.1, 3.2).

Table 3.1
Alternative Explanations of the Winner-Loser Anomaly

Long-Term Overreaction Hypothesis	Short-Term Overreaction Anomaly	Momentum Effect
Five Behavioural Models Barberis et al. (1998), Daniel et al. (1998), Hong and Stein (1999), Kim (2002) and Du (2002)	**Market Frictions** Kaul and Nimalendran (1990) and Moscowitz and Grinblatt (1999)	**Seven Behavioural Models** Barberis et al. (1998), Daniel et al. (1998), Hong and Stein (1999), Grinblatt and Han (2001), Kim (2002), Du (2002) and George and Hwang (2004)
Chance Result Fama (1998)	**Trading Volume** Hameed and Ting (2000)	**Chance Result** Fama (1998)
Risk (CAPM) Chan (1988) and Ball and Kothari (1989)		**Risk (Downside Risk)** Ang et al. (2001)
Risk (Three-Factor Model) Fama and French (1996)		**Business Cycle** Chordia and Shivakumar (2001)
False Methodology Conrad and Kaul (1993)		**Industry Factor** Moscowitz and Grinblatt (1999)
Size Effect Zarowin (1990)		**Trading Volume** Lee and Swaminathan (2000), Drew et al. (2004) and Glaser and Weber (2001)
		Size Effect Hou et al. (2003), Hong et al. (2000) and Doukas and McKnight (2003)
		Bull and Bear Markets Cooper et al. (2002), Rey and Schmid (2003) and Griffin et al. (2003)

Table 3.2

Studies Investigate the Momentum Effect Using UK Data

	Liu et al. (1999)	**Hon and Tonks (2003)**	**Hou et al. (2003)**	**Present thesis (2004)**
Data	Weekly share returns from Datastream	Monthly share returns from LSPD	I/B/E/S, Datastream	Monthly share returns from LSPD
Period	January 1977-December 1996	January 1955-December 1996	January 1988-December 2000	January 1975-October 2001
Definition of winners and losers	10 portfolios (10%)	10 portfolios (10%)	3 portfolios (30%-40%-30%)	5 portfolios (20%) used also 10 and 3 portfolios
Momentum strategies	Alternative momentum strategies from 3 to 12 rank and hold periods	Alternative momentum strategies from 3 to 24 rank and hold periods	The representative momentum strategy (the rank and hold periods are 6 months)	The representative momentum strategy (the rank and hold periods are 6 months)
Investigation	Controlling for beta and the three factor model Momentum profits in alternative sub-sample portfolios (size, book-to-market and cash earnings to price)	Adjusting for beta and size Momentum profits are not strong from 1955 to 1976	Controlling for size, book-to-market and analyst coverage.	Momentum profits in alternative stock market structures Adjusting for volatility Controlling for bull and bear markets

Chapter 4

DATA AND METHODOLOGY

4.1 DATA SELECTION

This study utilises three different samples (Table 4.1). In the full sample, monthly share returns of over 6,000 shares are collected from the London Share Price Database (LSPD) from January 1975 to October 2001. In the accounting sub-sample, accounting information on annual market value, book-to-market and trading volume of over 2,000 companies is collected from Datastream for an identical period. In the SETS sample, approximately 150 shares are selected that have been traded in the auction Stock Exchange Electronic Trading System (SETS) after October 1997.

Table 4.2 presents descriptive return statistics for the three samples. The average monthly return is 1.21 per cent for the full sample, 0.93 per cent for the accounting sub-sample and 0.35 per cent for the SETS sample. The SETS sample generates lower returns, since it is influenced by the bear market that occurred after the summer of 2000. Full sample, accounting and SETS sub-samples have a similar standard deviation. The skewness coefficients in all samples are negative showing skewness to the left. The kurtosis coefficients are significantly larger than 3 indicating that return distributions are leptokurtic and hence, data are peaked relative to the normal distribution. These results concur with other studies (e.g., Harris and Kucukozmen, 2001; Gettinby et al., 2004), which show that returns are not normally distributed. This study employs parametric as well as non-parametric tests to control for non-normality.

Table 4.1

Selection of Data

	Period	Sample	Characteristics
Full Sample	January 1975-October 2001	Over 6,000 shares	Monthly share returns from LSPD
Accounting Sub-Sample	January 1975-October 2001	Over 2,000 shares	Monthly share returns from LSPD Annual accounting information from Datastream: • Market value (datatype; MV) • Book-to-market (datatype; MTBV-reversed) • Relative trading volume (No of shares traded; VO/No of outstanding shares; NOSH)
SETS sample	October 1997-October 2001	Approximately 150 shares	Monthly share returns from LSPD Annual market value data (datatype;MV) from Datastream.

Table 4.2

Descriptive Statistics

	Full sample	Accounting Sub-sample	SETS sample
Mean	1.21%	0.93%	0.35%
Standard deviation	0.129	0.127	0.128
Skewness	-0.62	-0.22	-0.69
Kurtosis	18.40	17.09	9.38

4.1.1 Full Sample

This sample covers the period from January 1975 to October 2001. Before 1975, LSPD covers only part of the securities that were quoted on the UK stock market; only a random sample of 33 per cent of the full sample is displayed. After 1975, LSPD offers full coverage of all UK companies quoted on the LSE. The full sample covers all UK listed companies in the Master Index File. Over 6,000 listed and de-listed shares (companies that no longer exist) are examined[1]. The number of firms analysed in any given year ranges from 1,489 to 2,444 (Figure 4.1) where the number of companies examined tends to slightly decrease throughout the period. This happens because the number of listed shares on the LSE tends to decline.

In LSPD, monthly share returns are calculated as:

$$R_{i,t} = \ln\frac{(p_{i,t} + d_{i,t})}{p_{i,t-1}} \tag{4.1}$$

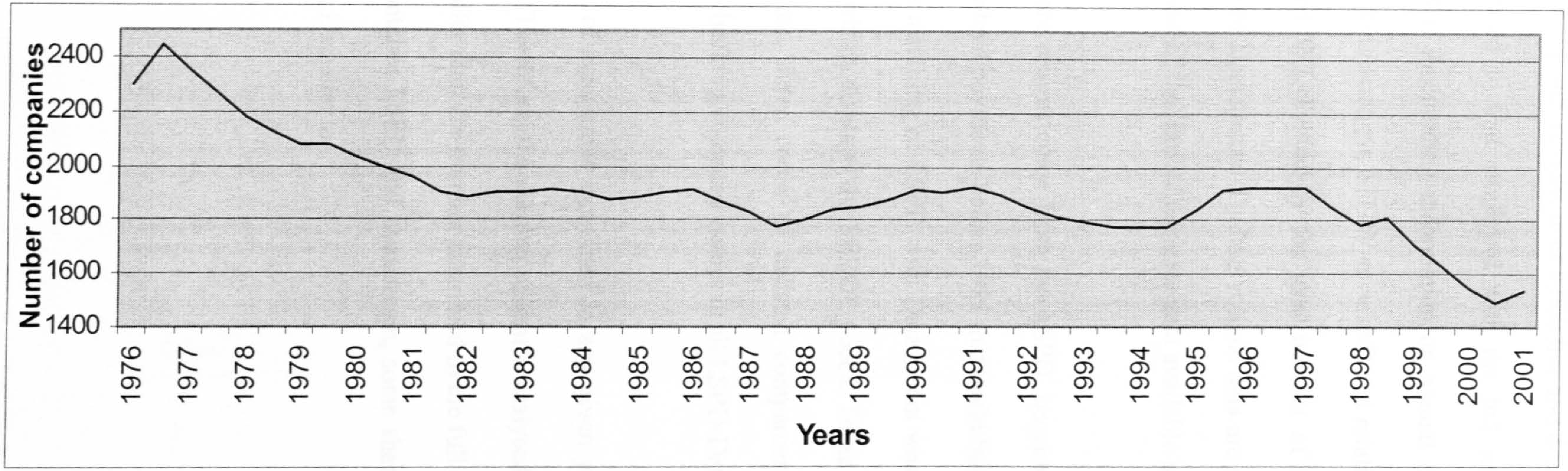
[1] The inclusion of dead companies ensures that the sample is free of survivorship bias. The sample contains companies that have entered or exited during the sample period.

where $R_{i,t}$ is the return of share i in time t, $p_{i,t}$ is the last recorded price for security i in month t, $p_{i,t-1}$ is the last recorded price in the previous month and $d_{i,t}$ represents the dividends that have been paid between t-1 and t.

Notice that LSPD share returns demonstrate a large non-trading indicator. There exist shares not traded over the last day of the month. Therefore, monthly returns reflect transactions that may occur days before the end of the month. Clare et al. (2002) use LSPD monthly returns and find that the non-trading indicator is more intense in the period from 1975 and 1981 and when small capitalisation companies are employed. The problem of non-trading can influence the autocorrelation of portfolio returns. Prices of non-frequent shares display a lag until the new information is impounded in them, but prices of frequently traded shares reflect quickly the new information. When both frequent and non-frequent shares form a portfolio, then frequent shares reflect information of time *t* and non-frequent shares reflect information of time *t-1*, generating an autocorrelation in portfolio returns. This study follows alternative tests to ensure that momentum profits do not stem from non-trading; I calculate the magnitude of continuation profits only in large capitalisation shares that do not exhibit the thin trading problem and I consider the momentum profitability generated for each test period separately to ensure that profits do not arise only during 1975-1981.

Figure 4.1

Number Of Companies Using the Full Sample



4.1.2 Accounting Sub-Sample

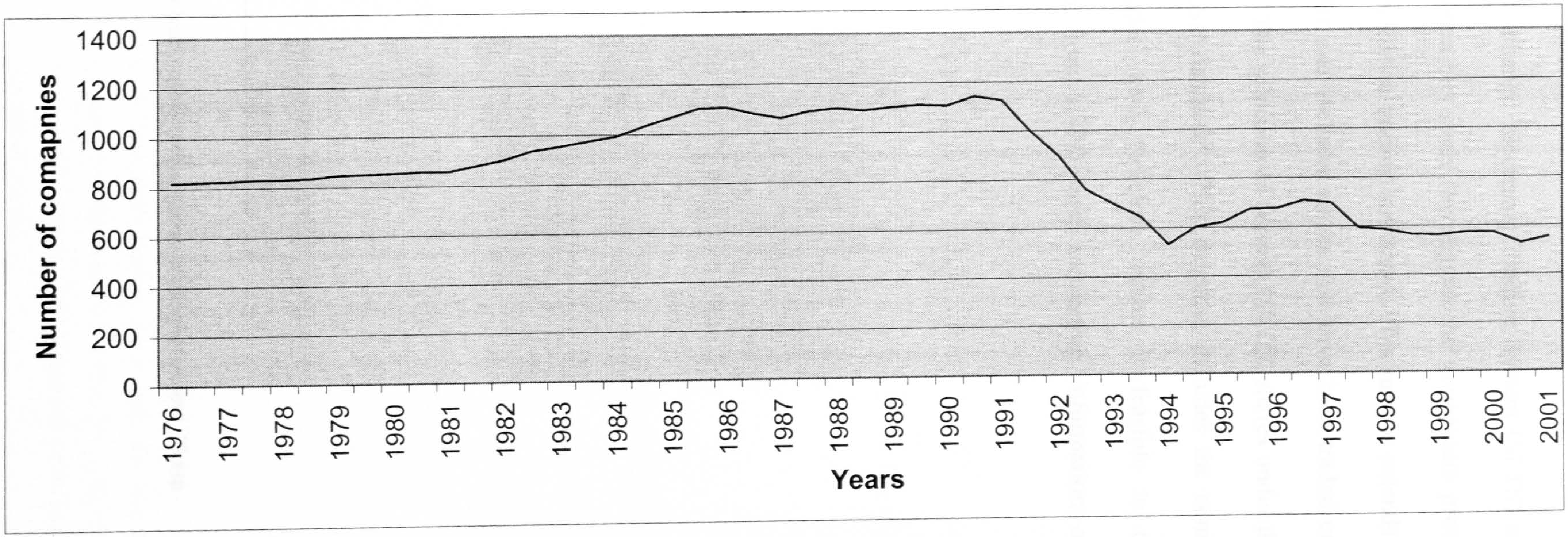
In the accounting sub-sample, over 2,000 live and dead stocks are collected using an identical period to that employed with the full sample; from January 1975 to October 2001. Accounting information on annual market value (datatype; MV), book-to-market (datatype; MTBV-reversed) and relative trading volume (number of shares traded VO divided by the total number of shares outstanding NOSH) is collected from Datastream. Trading volume data are selected only in the post-1991 period because of the limited turnover data available before 1991.

Monthly share returns come from the LSPD, because Datastream does not record detailed dividend payments before 1988 that could have been used to calculate share returns. The matching of LSPD with Datastream was achieved through the Master Index File, which displays the SEDOL codes. These SEDOL codes were in a few cases mistaken, since codes of delisted companies were re-used. I solved this problem by checking company names in all LSPD-Datastream matches.

The number of companies examined in any given year varies from 442 to 1,143 (Figure 4.2). Therefore, the number of shares analysed in the accounting sub-sample is much smaller than the number examined in the full sample. This happens because when one matches LSPD and Datastream, some shares recorded on the LSPD are not found on Datastream.

Figure 4.2

Number of Companies Using the Accounting Sub-Sample



4.1.3 SETS Sample

The Stock Exchange Electronic Trading System (SETS) sample is used only in chapter 6, when this study investigates the momentum profits generated in shares traded in alternative trading structures. This sample extends from October 1997 to October 2001 and includes stocks that have been traded under the auction SETS mechanism. The selection of around 150 UK shares under the SETS system comes from the LSE database[2]. This database includes the company names and their SEDOL codes, and, therefore, makes it feasible to obtain monthly return information from LSPD, and accounting information on market value from Datastream.

[2] http://www.londonstockexchange.com/trading/sets/about_15.asp

4.2 CALCULATION OF MOMENTUM PROFITABILITY

For the calculation of momentum profits only the representative momentum strategy is examined (6x6), where a six month ranking period with a six month test period are analysed (Figure 4.3). The majority of papers (e.g., Liu et al., 1999) follow this momentum strategy to investigate factors that influence momentum profitability. This study follows the same representative strategy in order for our findings to be comparable with the results of other research papers. Besides both Liu et al. (1999) and Hon and Tonks (2003) use UK data and report that the momentum effect tends to persist using various rank and test periods. This study does not consider essential to undertake the same test using a similar data set.

The first rank period is from January to June 1975. The performance of each share is calculated as:

$$RPR_i = \sum_{t=-7}^{-1} R_{i,t} \tag{4.2}$$

where RPR_i is the rank period return of security i and $R_{i,t}$ is the return of security i in month t over the past six months; from –7 month to –1 month. Based on their $RPR_i s$, all companies are ranked in ascending order. Shares are divided into five portfolios, each group comprising 20 per cent of the full sample. The first category (L) consists of shares with the lowest returns, while the fifth portfolio (W) includes securities with the best performance[3].

[3] Later, in chapter 6, this study defines shares with the best (winners) and worst (losers) performances using alternative definitions. Using three portfolios, past winners (W) and losers (L) each comprise 30 per cent of the sample. Constructing ten portfolios, winners and losers include the top and bottom 10 per cent of shares.

Consistent with Jegadeesh (1990), I intend to avoid the market friction problems that have been documented in the short-term overreaction effect. Transactions occur either in bid or ask prices and hence, share prices recorded include a measurement error equal to the bid-ask spread. When security returns are calculated in nearby periods, returns display a correlation because of the bid-ask problem (Roll, 1984). To eliminate the bid-ask influence, I skip one month (July 1975) and calculate the performances of portfolios over the following 6-month test period (August 1975 to January 1976). The performance of each portfolio is calculated as:

$$R_p = \sum_{t=0}^{6} \left(\sum_{i}^{N} \frac{R_{i,t}}{N} \right) \tag{4.3}$$

where R_p is the return of portfolio p, N is the number of stocks in each portfolio and $R_{i,t}$ is the return of security i in month t over the 'future' six months; from 'now' to six months later.

This procedure is repeated for each non-overlapping 6-month period. Subsequent rank periods are Jul 1975-Dec 1975...July 2000-Dec 2000. Their matching test periods are Feb 1976-July 1976...Feb 2001-July 2001. The abnormal profitability is indicated by the subtraction of the average R_W (AR_W) from the average R_L (AR_L)[4]. When

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[4] Portfolio test statistics are calculated as: $\frac{AR_P}{\sqrt{\sigma_P^2 / N_P}}$, where AR_P is the mean monthly return on portfolio p, $\sigma_P{}^2$ is the variance of portfolio p and N_p is the number of observations in portfolio p.

$$AR_W - AR_L > 0 \text{ [5]} \tag{4.4}$$

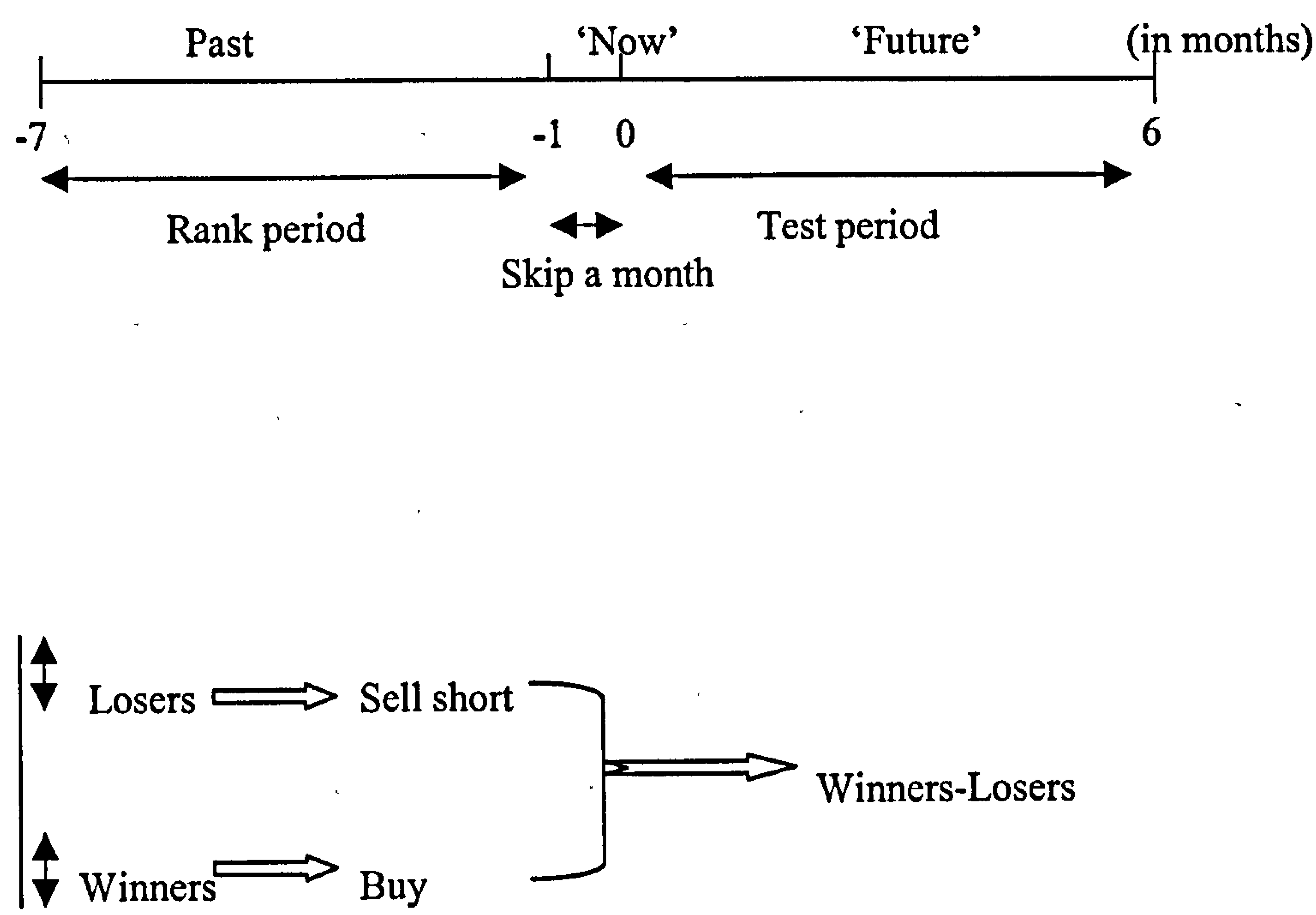
the momentum effect appears. When the result of the subtraction is negative, the reverse pattern emerges which implies that the overreaction hypothesis is supported. When the result is equal to zero, the market efficiency is efficient.

Notice that transaction costs that investors face in stock markets are ignored. As in the majority of studies in the field (e.g., Liu et al., 1999; Hon and Tonks, 2003), it is assumed that continuation profits are high enough to cover transaction costs. A cost of the magnitude of around 2 per cent cannot outweigh the momentum profitability, considering that momentum strategies are not transaction-intensive, and so the trading frequency is limited.

[5] The winner-loser portfolio test statistic is calculated as: $\dfrac{AR_W - AR_L}{\sqrt{\dfrac{\sigma_W^2}{N_W} + \dfrac{\sigma_L^2}{N_L}}}$, where AR_W is the mean monthly return on the winner portfolio, AR_L is the mean monthly return on the loser portfolio, σ_W^2 is the variance of the winner portfolio, σ_L^2 is the variance of the loser portfolio, N_W is the number of observations in the winner portfolio and N_L is the number of observations in the loser portfolio.

Figure 4.3

Calculation of Momentum Profits



Chapter 5

MOMENTUM PROFITS ON THE LONDON STOCK EXCHANGE

5.1 INTRODUCTION

This chapter discusses the initial empirical findings of this thesis regarding the profitability of the momentum strategy when analysed for the London Stock Exchange. Other studies (e.g., Liu et al., 1999) that employed UK and international data found that momentum profits tend to persist. This chapter investigates whether evidence of momentum profitability is present using a larger and more comprehensive sample of firms.

This chapter is organised as follows: the next section reports the empirical findings; and the final section discusses the foregoing analysis.

5.2 EMPIRICAL FINDINGS

5.2.1 Momentum Profitability employing the Full Sample

This section provides the initial empirical evidence, outlining the momentum profits generated using the full sample. Table 5.1 shows that the raw monthly portfolio returns are 0.05 per cent in the loser portfolio, 0.85 per cent in the second group, 1.05 per cent in the third group, 1.23 per cent in the fourth portfolio and 1.31 per cent in the winner portfolio[1]. Therefore, past winners outperform past losers on the following test period by 1.26 (W-L=1.31-0.05) per cent per month with a t-statistic equal to 2.26 (p-value<0.05). Winners outperformed losers in around 85 per cent of the test periods. These results indicate that momentum profits are economically and statistically significant on the LSE using my sample of firms. These results concur with the findings of other studies that use UK (e.g., Liu et al., 1999) and international evidence (e.g., Rouwenhorst, 1998).

The monthly portfolio returns further show that the anomaly is not restricted to the extreme winner and loser portfolios. Returns on the intermediate portfolios also reflect their prior ranking. Portfolios that achieved high (low) past performances tended to generate high (low) returns in the following period. This finding has been often unnoticed in the literature.

Table 5.1 further shows that momentum profits remain economically significant in three equal sub-periods, but that profits vary across the different sub-periods. Monthly continuation profitability is on average 0.75 per cent from 1975-1983, 1.71

[1] Numbers considered on the document are underlined on the corresponding Tables.

per cent from 1984-1992 and 1.33 per cent from 1993 to 2001. Momentum profits are driven by the winner portfolio between 1975-1983 and by the loser portfolio between 1984-1992 and 1993-2001. The profits for each test period may be further analysed. Figure 5.1 shows the portfolio performances and Figure 5.2 shows the momentum profits achieved from 1975 to 2001. This study reports that momentum profitability is significantly higher over the 1990-1993 sub-period. The finding that momentum profits are not persistent during different time periods for the LSE concurs with the results of Hon and Tonks (2003), who demonstrate that momentum strategies are not profitable in the sub-period from 1955 to 1976. However they are different from the findings of Liu et al. (1999), who suggest approximately the same momentum profitability between 1977-1987 and 1988-1998.

Using market-adjusted monthly portfolio performances, the magnitude of momentum profits is, as expected, exactly the same (1.26 per cent per month). The monthly market-adjusted portfolio returns are -1.29 per cent for losers, -0.48 per cent for the second group, -0.28 per cent for the third portfolio, -0.10 per cent for the fourth portfolio and -0.02 per cent for winners. The negative portfolio returns come from the choice of the value-weighted FTSE All Share index to proxy for the market. This finding is crucial considering the limitation of short selling in some countries. A strategy that buys the winner portfolio does not provide larger profits than the market index.

I also investigate whether there is a statistical difference in all five portfolio returns simultaneously. I found that portfolio returns are economically different among the five portfolios and now I examine whether they are also statistically different. I employ the one-way analysis of Variance (ANOVA) that shows the variation among the sample means in comparison with the variation within the samples. Using the portfolio returns, the F statistic is 2.047 with a p-value at 0.088, which shows that portfolio returns are not statistically different at 5% level. In other words, although winners outperform significantly losers, all five portfolios do not generate statistical significant different returns.

Appendix 5.1 investigates whether the selection of parametric statistics are appropriate and examines the statistical significance of the W-L returns when non-parametric statistics are employed.

Table 5.1

Momentum Profits using the Full Sample

	Raw Returns				Market-adjusted returns
	Full Period	**1975-1983**	**1984-1992**	**1993-2001**	**Full Period**
L	0.05%	1.38%	-0.78%	-0.46%	-1.29%
	0.11	3.26	-0.85	-0.68	-4.61
2	0.85%	1.73%	0.28%	0.54%	-0.48%
	2.54	4.22	0.36	1.17	-2.52
3	1.05%	1.87%	0.66%	0.63%	-0.28%
	3.38	4.60	0.91	1.50	-1.75
4	1.23%	2.01%	0.94%	0.74%	-0.10%
	3.97	5.14	1.28	1.82	-0.64
W	1.31%	2.13%	0.93%	0.87%	-0.02%
	3.51	5.25	1.04	1.57	-0.11
W-L	**1.26%**	0.75%	1.71%	1.33%	**1.26%**
	2.26	1.27	1.33	1.53	**3.54**

This table shows the momentum profits generated using the full sample. Shares are ranked based on their previous 6-month returns and five equal-weighted portfolios are formed. The performance of these quintile portfolios is calculated in the subsequent 6 months, after skipping a month between rank and test period. The momentum profitability (W-L) results from the subtraction of the performance of the past winner (W) from that of the prior loser (L) portfolio.

Two-tailed tests are used throughout the thesis.

Figure 5.1

Portfolio Performances

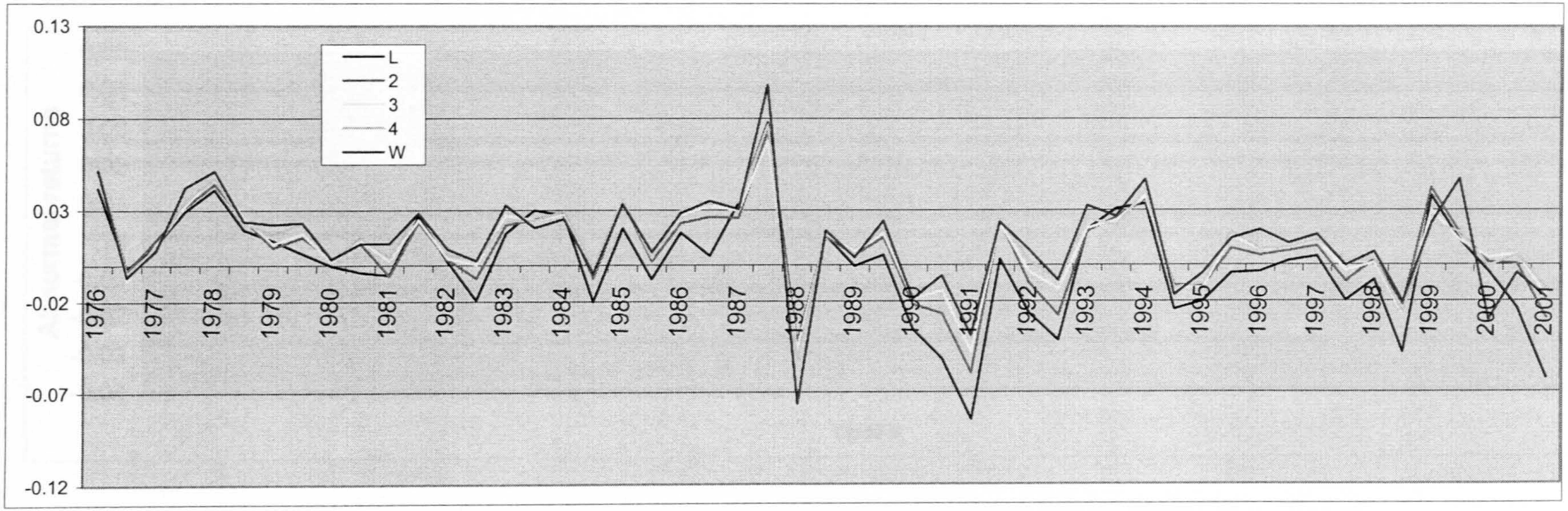
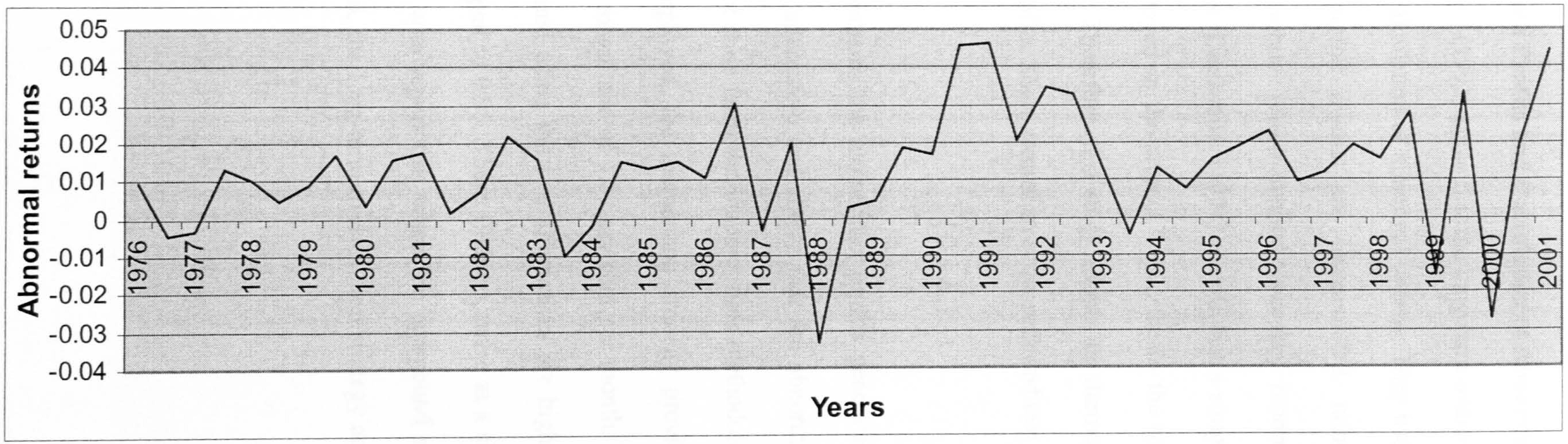


Figure 5.2

Momentum Profits (W-L) using the Full Sample



5.2.2 Momentum Profits and Calculation of Abnormal Returns

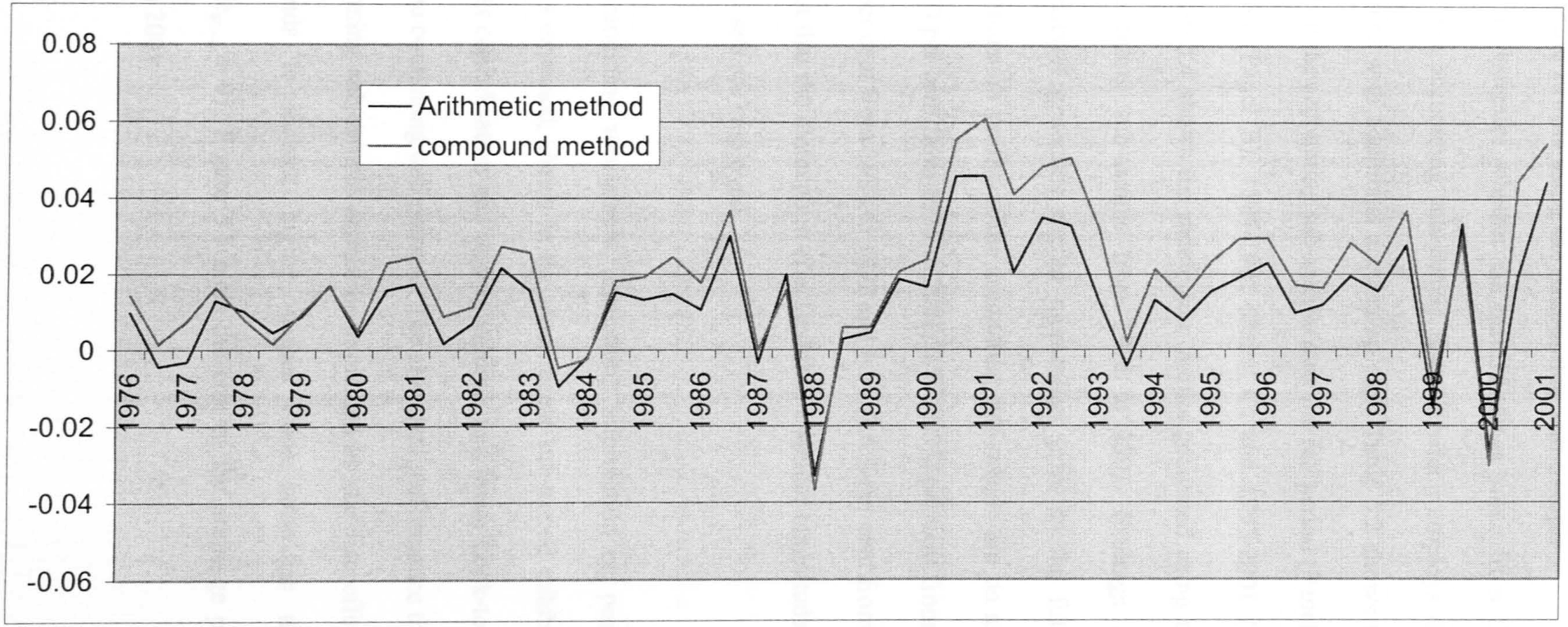
Conrad and Kaul (1993) argue that the long-term overreaction effect arises from the inappropriate calculation of abnormal returns. They use the buy-and-hold approach where single-period returns are compounded, rather than using the typical cumulative abnormal return method, and they report that the strategy provides negative profits. Dissanaike (1994) reports that a simple arithmetic method, which has been employed in the present thesis, biases the measurement of rank and test period returns. Therefore, this study adopts an alternative method to calculate the momentum profits. Share returns over the rank and test periods are measured as:

$$\prod_{t=1}^{T}(1+R_{it})-1 \tag{5.1}$$

Figure 5.3 compares the momentum profits generated by the arithmetic and the compounding alternative and shows that the abnormal profits of the momentum strategy do not arise from the inappropriate methodology. When the compounding method is employed, the momentum strategy provides even stronger abnormal profits at the magnitude of 1.89 per cent per month. Interestingly, the momentum profits generated using the two alternatives are highly correlated with a Pearson correlation equal to 0.95. These findings arrive at a similar conclusion with Power et al. (2001) who report that when the compound method to measure abnormal returns is used, the long-term overreaction strategy achieves even more impressive profits.

Figure 5.3

Momentum Profits using Alternative Calculation of Abnormal Returns



5.2.3 Momentum Profits using the Accounting Sub-Sample

This section investigates whether the main findings come from the full sample persist when the accounting sub-sample is used; which employs data for around 2000 companies with additional accounting data. Table 5.2 shows the momentum gains earned on the accounting sub-sample over the full period (Panel A) and during the 1975-1983 (Panel B), 1984-1992 (Panel C) and 1993-2001 (Panel D) sub-periods. Figure 5.4 shows the momentum profits generated using the full sample and the accounting sub-sample from 1975 to 2001. Findings show that the accounting dataset generates similar momentum gains to the full sample. The monthly continuation profits in the accounting sub-sample are on average 1.36 (t-statistic=3.88) per cent from 1975 to 2001, 0.77 (1.53) per cent from 1975 to 1983, 1.70 (2.52) per cent from 1984 to 1992 and 1.59 (2.67) per cent from 1993 to 2001. These suggest that the momentum effect exhibits a similar magnitude of gains when different data sets are employed.

Using the accounting sub-sample, accounting information on portfolios can be presented. As expected, shares in the most recent sub-period exhibit significantly higher market capitalisation and trading volume, and lower book-to-market values because of the continuing bull markets. The abnormal performance that is in present in the accounting sub-sample cannot be explained by the size effect. The winner portfolio tends to include higher market value securities than the loser portfolio ($Size_{W-L} > 0$). Figure 5.5 plots the size of the arbitrage portfolio (W-L) from 1975 to 2001.

In addition, following the methodology of Zarowin (1990), this study analyses separately the periods when losers are smaller than, and larger than winners. Zarowin investigates the magnitude of long-term overreaction profits using this approach and finds that when losers have lower capitalisation than their winner counterparts, there is evidence of overreaction and when losers are larger than winners, no evidence of overreaction is present in the return data. Searching for the momentum profits, I report that when winners are larger than losers, winners outperform losers by 1.55 per cent per month. When winners demonstrate a lower market value than their loser counterparts, winners outperform losers by lower gains at the magnitude of 0.92 per cent per month. These results indicate that following the methodology of Zarowin (1990), the size effect cannot explain the momentum profits, since momentum gains are stronger when winners are larger than losers.

Figure 5.7, which plots the trading volume of the arbitrage portfolio from 1991 to 2001, and Table 5.2 demonstrate that winners tend to be associated with higher trading volume than losers $(TradingVolume_{W-L} > 0)$. Table 5.2 and Figure 5.6 show that a monotonic trend is demonstrated in the book-to-market, where there is a fall when we move from losers to winners. This finding is consistent with Liu et al. (1999) and indicates that winners tend to be glamour stocks (e.g., dot companies), while losers seem to be value equities.

Table 5.2

Momentum Profits Employing the Accounting Sub-Sample

	Returns	t-statistics	Size (£ millions)	B/M	Trading Volume (No of shares traded/No of outstanding shares)
Panel A: Full Period					
L	0.00%	-0.01	232.40	1.86	0.62
2	0.72%	3.59	495.27	1.35	0.64
3	0.97%	5.46	619.12	1.21	0.64
4	1.07%	5.86	702.82	1.16	0.69
W	1.35%	6.41	501.36	0.98	0.87
W-L	**1.36%**	**3.88**	**268.96**	**-0.87**	**0.25**
Panel B: 1975-1983					
L	2.02%	5.13	34.77	3.24	N/A
2	2.27%	7.46	59.50	2.26	N/A
3	2.40%	7.80	62.22	2.03	N/A
4	2.53%	8.39	72.14	1.95	N/A
W	2.79%	8.83	60.07	1.48	N/A
W-L	**0.77%**	**1.53**	**25.30**	**-1.76**	N/A
Panel C: 1984-1992					
L	-0.52%	-1.01	100.28	1.27	0.44
2	0.44%	1.21	308.25	1.02	0.53
3	0.99%	3.16	402.45	1.01	0.55
4	1.14%	3.22	345.74	0.98	0.57
W	1.18%	2.70	281.60	0.99	0.69
W-L	**1.70%**	**2.52**	**171.32**	**-0.37**	**0.25**
Panel D: 1993-2001					
L	-0.78%	-1.62	543.84	1.11	0.66
2	0.14%	0.37	1143.69	0.73	0.66
3	0.26%	0.85	1385.41	0.65	0.66
4	0.27%	0.94	1635.71	0.57	0.73
W	0.80%	2.32	1125.70	0.51	0.91
W-L	**1.59%**	**2.67**	**616.02**	**-0.52**	**0.25**

This table demonstrates the momentum profits generated using the accounting sub-sample.

Figure 5.4

Momentum Profits using the Full sample and the Accounting Sub-Sample

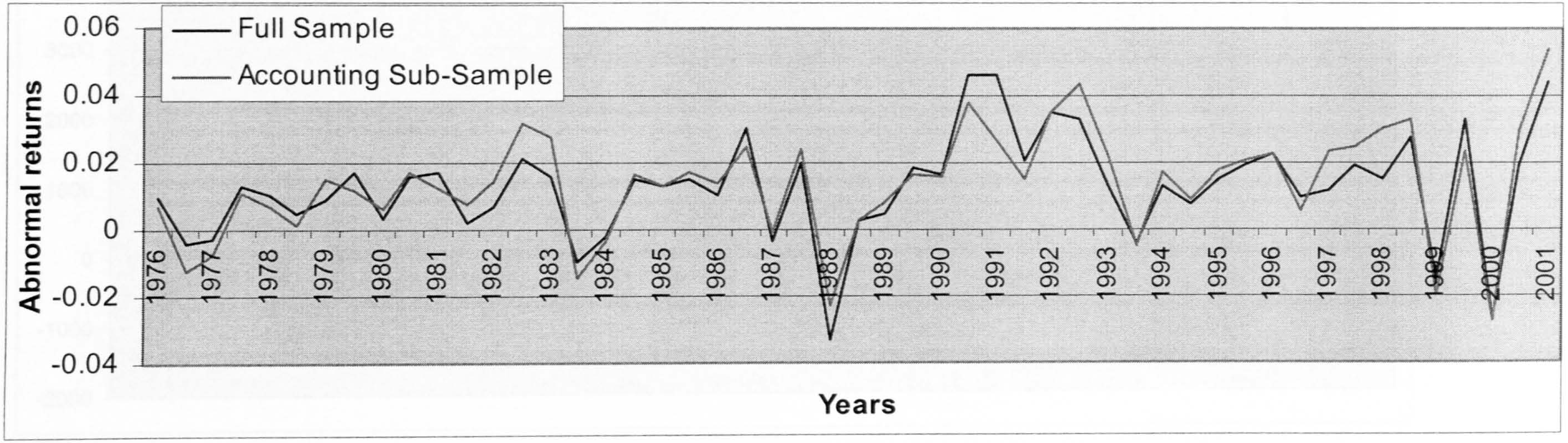


Figure 5.5

Size of the Arbitrage portfolio

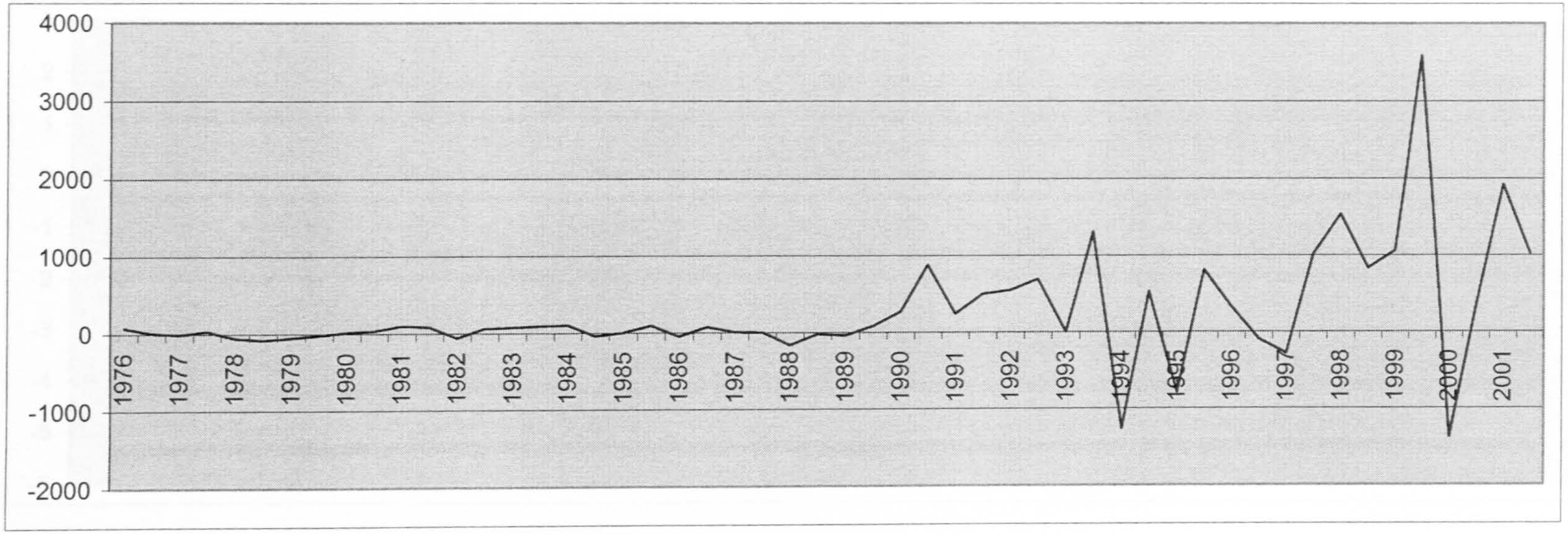


Figure 5.6

Book-to-Market of the Arbitrage Portfolio

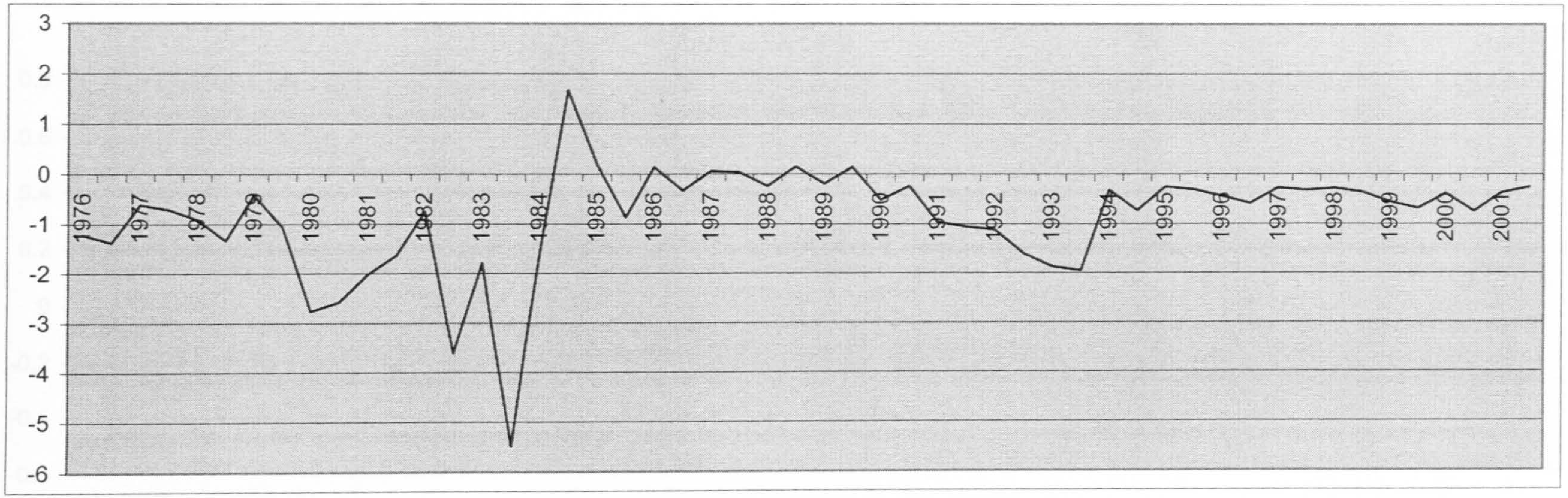
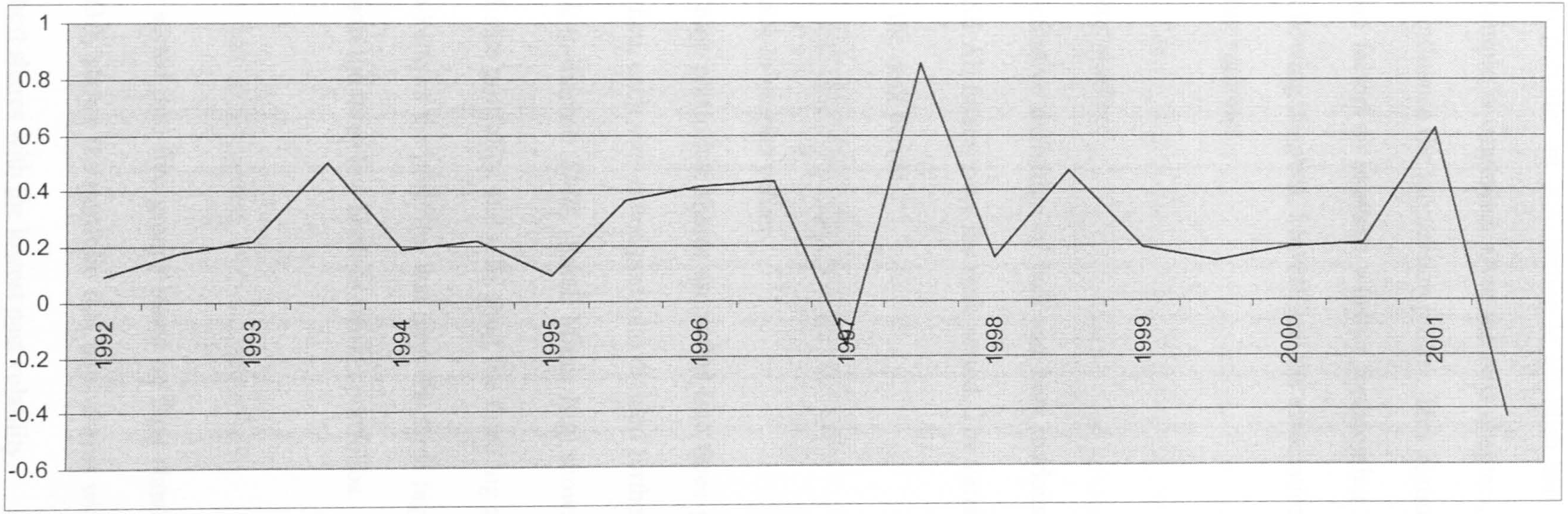


Figure 5.7

Trading Volume of the Arbitrage Portfolio



5.2.4 A Correlation Matrix for forthcoming Explanation Variables

This chapter provides an introduction to establish that momentum profits do exist when my sample is employed. Over the next chapters, I will investigate different factors that influence the momentum profits. This section examines the correlations among those factors to examine whether forthcoming results are may associated. Over the following chapters, I investigate the association of momentum profits with the following variables:

Bull and bear markets

The representative definition of bull and bear markets is when I use the market return (FTSE All Share) over the rank period. The variable $R_{m,-6}$ shows the market return over the rank period.

Size and book-to-market values

I generate nine portfolios; shares are sorted into three groups based on the market value and then, each size-sorted portfolio divided further into three portfolios based on the book-to-market. SMB_t (Small Minus Big) shows the portfolio that buys the three small size portfolios and sells short the three big size portfolios. HML_t (High Minus Low) shows the portfolio that buys the three high book-to-market portfolios and sells short the three low book-to-market portfolios.

Volatility

Shares are sorted into five groups based on their standard deviation over the rank period. *vHML* shows the portfolio that buys shares with the highest past volatility and sells short shares with the lowest past volatility.

Trading volume

Shares are sorted into three groups based on their trading volume over the one year before the test period. *tHML* shows the portfolio that buys shares with the highest past trading volume and sells short shares with the lowest past trading volume.

Table 5.3 shows the Pearson and Spearman rank correlations to examine the association among the variables. Pearson correlations assume that variables are normally distributed and Spearman rank correlations are the equivalent non-parametric test. Correlations among variables are very low and none is statistical significant. The strongest correlation is equal to -0.32 with a statistical insignificant p-value equal to 0.17. These findings show that the variables are not significantly associated and therefore, the findings among the different chapters are not associated either.

Table 5.3

Correlations

Spearman Rank Correlations

	$R_{m,-6}$	SMB_t	HML_t	$vHML_t$	$tHML_t$
$R_{m,-6}$		-0.03	0.04	0.15	0.03
(p-value)		(0.85)	(0.79)	(0.30)	(0.90)
SMB_t	0.12		0.15	-0.12	0.10
(p-value)	(0.17)		(0.30)	(0.93)	(0.66)
HML_t	0.01	0.14		-0.01	-0.09
(p-value)	(0.96)	(0.32)		0.50	(0.69)
$vHML_t$	0.16	0.00	-0.12		-0.32
(p-value)	(0.28)	(0.99)	(0.40)		(0.17)
$tHML_t$	0.01	0.17	-0.04	-0.14	
(p-value)	(0.79)	(0.48)	(0.87)	(0.57)	

Pearson Correlations

$R_{m,-6}$ shows the market return over the rank period. SMB_t shows the portfolio that buys the three small size portfolios and sells short the three big size portfolios. HML_t shows the portfolio that buys the three high book-to-market portfolios and sells short the three low book-to-market portfolios. $vHML$ shows the portfolio that buys shares with the highest rank period volatility and sells short shares with the lowest rank period volatility. $tHML$ shows the portfolio that buys shares with the highest one year before the test period trading volume and sells short shares with the lowest one year before the test period trading volume.

5.3 CONCLUSION

This chapter examined the momentum profits demonstrated using my sample of firms. The momentum profitability found is comparable with that other studies reported (e.g., Liu et al., 1999). This study documented that the anomaly is not restricted to the extreme winner and loser portfolios. Returns on the intermediate portfolios also reflect their prior ranking. The magnitude of the continuation payoffs further varies with the sub-period concerned. Momentum profitability is considerably higher between 1990 and 1993. Using market-adjusted monthly portfolio performances, this study reported that portfolio returns are negative, when the value-weighted FTSE All Share proxies the market. This finding is significant considering the limitation of short selling in some countries. A strategy that buys the winner portfolio does not provide larger profits than the market index.

I adopted the compound method of calculation of momentum returns. Conrad and Kaul (1993) argue that the long-term overreaction effect arises from the inappropriate calculation of abnormal returns and Dissanaike (1994) reports that a simple arithmetic method biases the measurement of rank and test period returns. I compared the momentum profits generated by the arithmetic and compounding alternatives and showed that the abnormal profits of the momentum strategy do not arise from the inappropriate methodology. When the compounding method is employed, the momentum strategy provides even stronger abnormal profits.

I further employed the accounting sub-sample that contains over 2000 shares with additional accounting data to undertake a robustness test. I found that momentum profits are identical when full sample and accounting sub-sample are employed.

This result indicates that the momentum effect demonstrates similar magnitude gains using different data sets. The abnormal performance that is evident in the accounting sub-sample cannot be explained by the size effect. The winner portfolio tends to include higher market value securities than the loser portfolio $(Size_{W-L} > 0)$ and momentum profits are larger in magnitude in periods when winners include larger size shares than losers. Further analysis showed that winners tend to display higher trading volume than losers $(TradingVolume_{W-L} > 0)$. A monotonic trend is demonstrated in the book-to-market, where there is a fall when we move from losers to winners. This finding is consistent with Liu et al. (1999) and indicates that winners tend to be glamour stocks, while losers seem to be value equities.

Appendix 5.1

Searching for Normality

I employed conventional t-statistics to investigate the statistical significance of momentum profits. However, this assumes that the distribution of momentum gains is normal (bell-shaped); t-statistics may generate biased results when employed in a non-normal distribution. This appendix aims to investigate whether the selection of t-statistics rather than non-parametric tests was proper by examining the normality of momentum profits. In other words, I study the following hypothesis:

Ho: momentum profits fit the normal distribution

H1: momentum profits do not fit the normal distribution.

I construct the histogram of data to judge normality. Figure 5.8 plots the frequencies and shows that momentum profits look approximately normal. A better graphical technique for assessing normality is based on a probability plot, which compares the actual variable points against the values expected from the normal distribution. If the sample of momentum profits follows the normal distribution, points will be concentrated around a straight line. Figure 5.9 shows that points do almost follow the straight line and indicate that momentum profits have a distribution close enough to normal to allow the use of t-statistics.

I further undertake statistical tests to examine the normality of abnormal profits. Using only an individual statistical test, you can have a false conclusion, since statistical tests can show significance when it does not exist (Type I error) or show that there exists no significance when it does exist (Type II error). Hence, I employ various goodness-of-fit tests for robustness.

Table 5.4 shows the descriptive statistics for momentum profits. The median is slightly larger than the average and removing the top and bottom 5 per cent of observations the new mean is 1.30 per cent per month that is almost similar with that generated by the full sample. These suggest that momentum gains are not driven by outliers. The minimum momentum return recorded is –3.29 per cent per month and the maximum continuation yield witnessed is 4.60 per cent per month. The skewness coefficient is slightly negative (-0.36) showing skewness to the left. The kurtosis coefficient is lower than 3 (1.29) indicating that returns distribution is platykurtic and hence, data are flat relative to the Gaussian distribution. However, since $\frac{skewness}{StdError} = \frac{-0.355}{0.333} = -1.06$ and $\frac{Kurtosis}{StdError} = \frac{1.291}{0.67} = 1.93$, both results are between –2 and +2. Thus, the distribution of momentum profits is normally distributed with 5% statistical significance. This suggests that based on kurtosis and skewness, a parametric test can be undertaken.

Another statistical test employed to investigate the normality is that by Jarque-Bera (1987) that is based on skewness and kurtosis of the sample. Until now I investigated whether momentum profits are normal considering the skewness and the kurtosis separately and found that the null hypothesis cannot be rejected. Now I investigate whether this finding persists when I control for these factors simultaneously. The Jarque-Bera test is calculated as:

$$JB = n[\frac{S^2}{6} + \frac{(K-3)^2}{24}] \tag{5.2}$$

where JB is the Jarque-Bera statistic, n shows the number of observations, S shows the skewness and K represents the kurtosis. High p-values (at least over 0.05) demonstrate that I cannot reject the null hypothesis that momentum profits fit the normal distribution. Jarque-Bera statistic takes the value of 7.42 with a p-value equal to 0.024. Therefore, employing the Jarque-Bera statistic, I can reject the normality assumption at 5% significance.

I further examine the Kolmogorov-Smirnov test, which generates the cumulative distribution of momentum profits and compares it with the expected cumulative normal distribution. The statistic D shows the maximum vertical deviation between the two distributions. Using our data, the Kolmogorov-Smirnov statistic D takes the value of 0.113 with a significant high p-value of 0.101. This suggests that using the Kolmogorov-Smirnov test, I cannot reject the null hypothesis for normality of momentum profits.

In addition, I examine the Shapiro-Wilk test (1965) that is usually employed for small sample sizes until 50. Having 51 observations, the Shapiro-Wilk test appears appropriate for my sample. The statistic W shows the evidence of normality where small values present non-normality. Using our data, the Shapiro-Wilk test W takes the value of 0.959 with a high p-value of 0.075. This indicates that using the Shapiro-Wilk test, I cannot reject the hypothesis that momentum profits are normally distributed.

Overall, the distribution of momentum profits tends to be normal. The histogram of momentum profits, the normal probability plot and most of normality tests show that the normal assumption cannot be rejected. These suggest that the selection of t-statistics to determine the statistical significance of abnormal returns is appropriate.

Non-Parametric Tests

Although momentum profits tend to follow the Gaussian distribution in most tests (beyond the Jarque-Bera statistic), as a robustness test, I also use non-parametric tests being aware that non-parametric tests are less powerful tools and the rejection rate is very low. I show the non-parametric tests only in key tables and I focus on them only when they indicate an opposite result to the parametric test findings.

The parametric test used is the t-test for two independent samples and the equivalent non-parametric test is the Mann-Whitney U test. The Mann-Whitney U test converts the scores on the continuous variable to ranks and then, finds the average rank in each group and evaluates whether the ranks for two groups differ significantly. For a statistically significant difference between the two samples to exist, the probability value p should be less than 0.05. Similar to the parametric t-test, I found that the Mann-Whitney U test shows that there exists a statistically significant difference between the winner and loser portfolio returns with a p-value equal to 0.027.

	Median	Parametric p-value	Non-parametric p-value
W-L	1.32%	0.026	0.027

I further used the parametric one-way analysis of variance (ANOVA) and the equivalent non-parametric test (Kruskal-Wallis test). The idea of the Kruskal-Wallis test is similar to Mann-Whitney U test where scores converted to ranks and the mean rank for each group is compared. The difference is that Mann-Whitney U test constructed to compare two groups and Kruskal-Wallis test constructed to compare more than two groups. Using the non-parametric Kruskal-Wallis test, the result concurs with that produced by the one-way analysis of variance (ANOVA). I document that Kruskal-Wallis test generates $p=0.159$ ($p>0.05$) and therefore, it does not exist statistically significant difference among the means of five portfolios.

Figure 5.8

Histogram of Momentum Profits

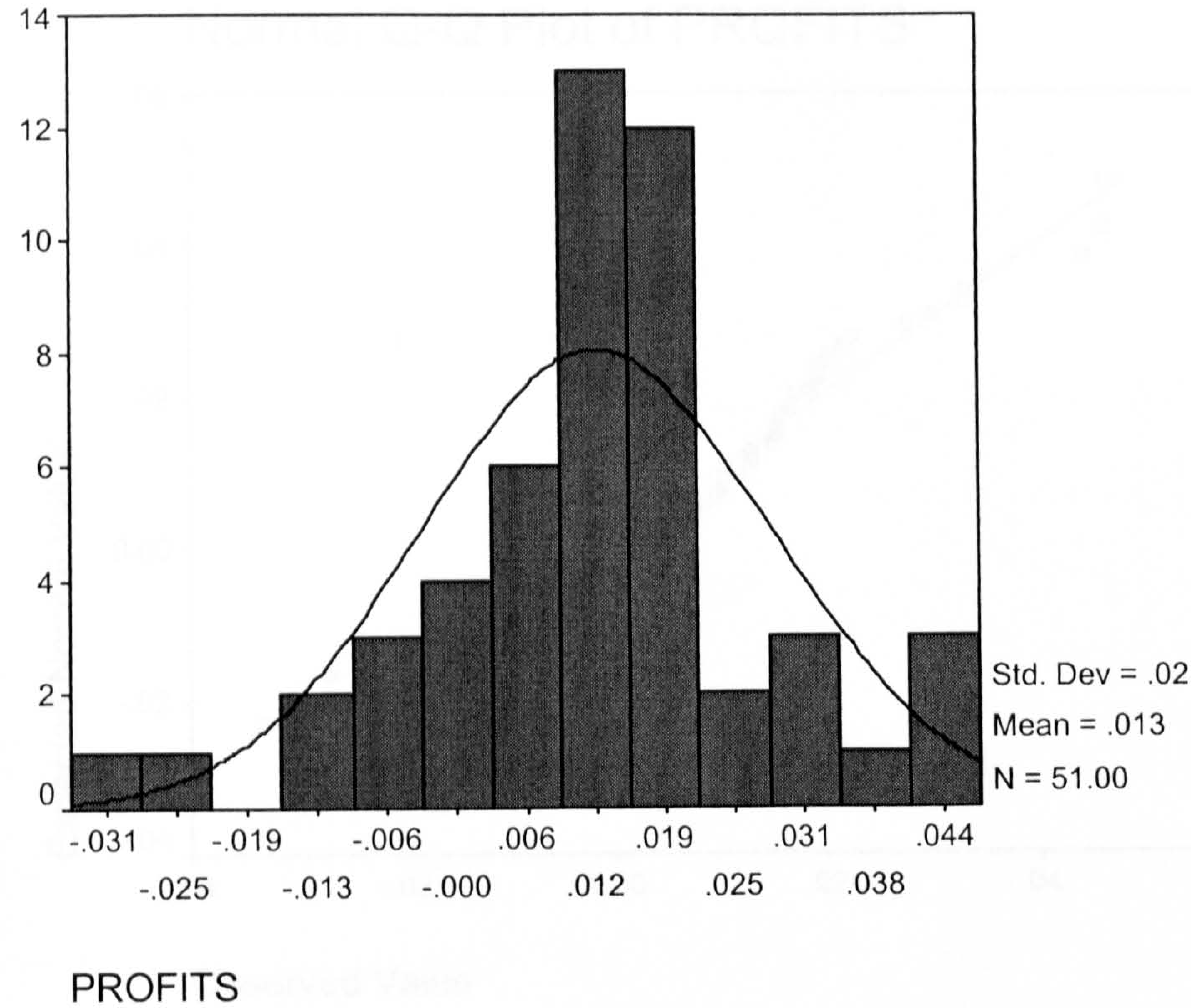


Figure 5.9

Normal Probability Plot

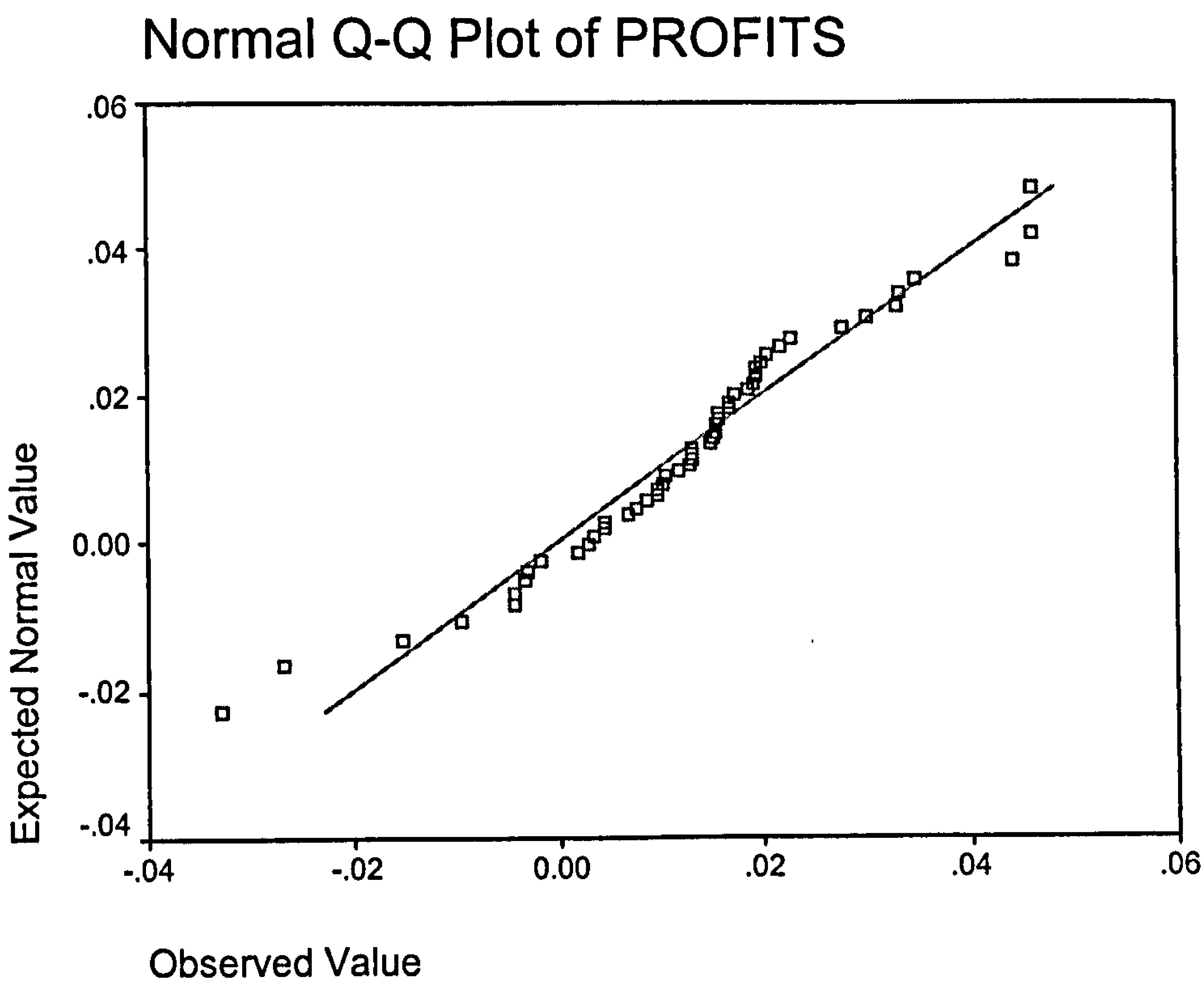


Table 5.4

Descriptive Statistics

Average	1.26%
Median	1.32%
Standard Deviation	0.016
Minimum	-3.29%
Maximum	4.60%
Skewness	-0.36
Kurtosis	1.29
Jarque-Bera	7.42 (p-value=0.024)
Kolmogorov-Smirnov	0.113 (p-value=0.101)
Shapiro-Wilk	0.959 (p-value=0.075)

Chapter 6

MOMENTUM PROFITS IN ALTERNATIVE STOCK MARKET STRUCTURES

6.1 INTRODUCTION

This chapter examines whether momentum profitability and different stock market trading systems (dealer, auction, floor and automated markets) are associated. To examine whether an association exists between stock market organisation and continuation profits, I examine the most significant changes have occurred to the structure of the London Stock Exchange in the past thirty years.

On 27th October 1986, an important change in the London Stock Exchange's history occurred that was nicknamed the Big Bang[1]. In a single day, the LSE experienced substantial alterations to the structure of the market as well as to the nature and number of participants. A major change that coincided with deregulation was the introduction of an electronic screen-based trading system called Stock Exchange Automated Quotation System (SEAQ)[2]. The new SEAQ mechanism was an electronic system capable of handling between eight and nine transactions per

[1] Tonks and Webb (1991) and Thomas (1986, 1989) present a comprehensive review of the deregulation process.

[2] The Big Bang was marked by additional significant changes. In the post-deregulation period, fixed commissions were eliminated and negotiated rates became available. Foreign firms allowed to become market makers, as well as member firms, had permission to act in a dual capacity whereby they were able not only to quote prices of securities (as jobbers) but also to act as agents (as brokers).

second as well as disseminating information widely and rapidly throughout the investor community with the Teletext Output Price Information Computer (TOPIC) network. All participants in the market could be informed through the TOPIC screens of securities information such as competing quotes, trading volumes, previous day's closing prices, and time of last trades. Hence, the adoption of recent technological advances in computing and telecommunications allowed face-to-face trading on the floor of the exchange to be replaced by telephone and electronic trading on the screen system. This study investigates the momentum profits generated before and after Big Bang. Chapter 5 reported that momentum profits vary accross different periods and therefore, I would expect continuation gains to be different before and after Big Bang.

A decade after the shift from the floor-based trading system to an electronic trading system, the UK stock market moved away from being a pure dealership market where market makers are the counter party in all transactions by quoting the bid (buy) and ask (sell) prices at which they will transact in securities. With the introduction of the Stock Exchange Electronic Trading System (SETS) on 20th October 1997, all FTSE100 stocks, and later since March 1998 some additional companies from the FTSE250 index, have been traded in an auction system where investors trade directly with each other without a market maker's intervention placing orders on a limit order book. Initially, only around 30 per cent of orders went through the SETS in relation to the dealership system. The LSE made some improvements to the new system to boost the percentage of transactions that used the auction system. For example, it abolished the minimum £4,000 order to boost the trading volume of small investors' transactions. Gradually, more and more transactions have been executed under the auction rather than the dealer mechanism. The average orders executed through the limit order book were 45.6 per cent in 1998, 49.9 per cent in 1999, 52.0 per cent in 2000 and 58.7 per cent in 2001 (Stock Exchange, 2002). This study examines the momentum gains demonstrated on shares traded on the SETS auction mechanism and on shares operated with the SEAQ dealer system.

The motivation to examine whether there exists a relationship between momentum profits and stock market structures is based on the fact that trading mechanisms influence market characteristics to which the momentum effect is linked. First, both momentum profits and market organisation appear to be associated with trading volume. Lee and Swaminathan (2000) show that securities with high trading volumes display greater momentum profitability than their low trading volume counterparts. In addition, Naidu and Rozeff (1994) and the Stock Exchange find that the Singapore Stock Exchange and the LSE respectively experienced rapid increases in trading volume in the post-automation period. Therefore, one would expect that automated markets, since they experience high trading volume, exhibit larger degree of momentum gains than floor markets.

Second, both momentum payoffs and market mechanisms tend to be associated with informational efficiency. Hong and Stein (1999) suggest that continuation gains come from the gradual expansion of information among investors while Chelley-Steeley (2003) demonstrates that the same shares adjust to their fundamental news more quickly when they trade on the Paris Bourse auction market than when they trade on the SEAQ International dealer system. Thus, according to Hong and Stein's

(1999) behavioural model, one would expect that auction markets, in which share prices adjust more quickly to news, would generate lower continuation profits than dealer markets.

Beyond the fact that trading mechanisms influence market characteristics to which the momentum effect is associated, alternative trading structures have been found to exert an important influence over the behaviour of equity returns. For example, trading systems influence the execution costs for investors. Auction mechanisms tend to generate lower execution costs for investors than dealer systems. Barclay et al. (1999), employing Nasdaq data, and Naik and Yadav (1999), studying LSE information, find that when both stock markets adopted auction market procedures in the post-1997 period, execution costs were reduced. In addition, automated systems involve higher transaction costs for investors than floor structures. Venkatamaran (2001) documents that shares from the Paris Bourse automated market are associated with higher execution costs than comparable shares on the NYSE floor system.

Different trading systems influence share return volatility. Auction mechanisms appear to generate higher return volatility than dealer trading systems. Chelley-Steeley (2002) shows that both the opening and closing returns of FTSE100 shares experienced a significant increase in volatility since the introduction of the SETS mechanism. Chelley-Steeley (2003) reports that cross-listed stocks display higher volatility when they trade on the Paris Bourse auction market rather than when they trade on the SEAQ International dealer market. Automated markets further tend to generate larger volatility than their counterparts that use floor systems. Naidu and

Rozeff (1994), studying the Singapore Stock Exchange, and Tonks and Webb (1991), studying the LSE, document a substantial increase of volatility in the post-automation period.

Trading systems have also an impact on institutional/small investors' preferences. Auction mechanisms favour retail investors, while dealer systems seem to attract institutional traders. De Jong et al. (1995) compare French shares listed both on the Paris Bourse and the SEAQ International. They find that the Paris Bourse auction market provides lower execution costs for small investors, but the SEAQ International dealer market offers better liquidity for large traders because market makers have to deal with large orders. Institutions seem also to prefer floor to automated systems. Large investors can better identify the traders who have inside information and thus, on the floor of a stock market, they can observe their investment strategies.

Auction mechanisms are also more transparent than dealer structures. Order-driven systems provide greater *pre-trade transparency*. In auction mechanisms, investors can get information from the limit order book on the particular price an order could execute. However, in dealer structures, only limited information is available. Apart from better transparency before a trade occurs, order-driven systems offer greater *post-trade transparency*. In auction systems, the real-time publication of trades is enforced, whereas in dealer structures, delays in publication may occur for large trades. This happens because market makers need time to unwind large transactions (Gemmill, 1996; and Board and Sutcliffe, 2000).

To sum up, given the influence that stock market structures can have over share returns, this study investigates whether alternative market structures can influence momentum profitability. I investigate momentum profits generated before and after Big Bang (floor vs automated mechanisms) and on shares traded on the SETS auction system and on the SEAQ dealer mechanism. The next section documents the empirical findings, and the final section presents conclusions.

6.2 EMPIRICAL FINDINGS

The empirical results in this chapter are divided into two main sections. First, I find that momentum profits are larger after Big Bang. I examine whether this finding persists when I use the accounting sub-sample and when I control for risk, size, and book-to-market. Second, I document that momentum gains are larger for shares traded on the SETS auction market.

6.2.1 Momentum Profits in Floor and Automated Systems

6.2.1.1 Initial Findings

On 27th October 1986 an electronic screen-based trading system called SEAQ was introduced. With the adoption of technological advances, a shift from the floor-based trading system to an electronic trading system occurred. This section investigates whether momentum profits are economically different before and after Big Bang. This chapter generates winner and loser portfolios choosing a different span of months in comparison with Chapter 4 because of the month that the Big Bang occurred.

Pre-Big Bang		Post-Big Bang	
Rank periods	Test periods	Rank periods	Test periods
Oct 1975-Mar 1976	May 1976-Oct 1976	Oct 1986-Mar 1987	May 1987-Oct 87
....	....	....	....
Oct 1985-Mar 1986	May 1986-Oct 1986	Oct 2000-Mar 2001	May 2001-Oct 01

The analysis of the automated system commences in October 1986, rather than November 1986, to keep the form of ranking and test periods in both structures. This is important since Grinblatt and Moskowitz (2000) report that momentum profits demonstrate seasonality.

This chapter defines shares with the best (winners) and worst (losers) performances using alternative definitions. Using three portfolios, past winners (W) and losers (L) each comprise 30 per cent of the sample. Constructing ten portfolios, winners and losers include the top and bottom 10 per cent of shares and generating five portfolios, winners and losers include the top and bottom 20 per cent of the sample. The present study controls for potential different momentum profitability generated before and after Big Bang because of the definition of the winner and loser portfolios.

Initially, Table 6.1 shows that momentum profits are economically and statistically significant on the LSE using three alternative percentages to define the winner and loser shares and using a different span of months in comparison with the previous Chapter. Past winners (W) outperform prior losers (L) over the test period by 0.96 per cent using three portfolios (Panel A), 1.18 per cent employing five portfolios (Panel B) and 1.53 per cent per month using ten portfolios (Panel C). As expected, more extreme winners and losers generate higher continuation profits. Interestingly, returns on the intermediate portfolios also reflect their prior ranking using all alternative definitions of winners and losers. Portfolios that achieved high (low) past performances tended to generate high (low) returns in the following period. This shows that the momentum effect is not only restricted to the extreme winners and losers.

Table 6.1 shows portfolio returns before and after Big Bang. Pre-Big Bang, monthly momentum profits are 0.41 per cent using three portfolios, 0.50 per cent employing five portfolios and 0.73 per cent using ten portfolios. These returns stem from the winner portfolio. Post-Big Bang, monthly continuation payoffs are 1.38 per cent when three portfolios are used, 1.69 per cent when five portfolios are employed and 2.14 per cent when ten portfolios are examined. These profits are mainly driven by the loser portfolio.

Therefore, shares traded during the automated sub-period generate significantly larger momentum returns than shares operated on the floor sub-period. Past winners outperform prior losers in 75 per cent and 92 per cent of test periods before and after Big Bang respectively. The difference in monthly momentum profits between shares traded in the automated period and their counterpart shares traded during the floor period is 0.97 (t-stat=2.42) per cent using three portfolios, 1.19 (t-stat=2.50) per cent using five portfolios and 1.41 (t-stat=2.38) per cent using ten portfolios. Figure 6.1 plots the continuation gains generated on the LSE and shows that most of the superior momentum profits during the automated sub-period arise during the years 1990-1993. The interruption of the lines in 1987 happens because we miss one test period at the time of the Big Bang

I also employ a non-parametric test to investigate the statistical significance of returns. Using the Mann-Whitney U test to compare the means of the W, L portfolios for the 10 portfolios, I find that the p-value is 0.003 ($p<0.05$)

using the entire period, 0.346 ($p>0.05$) using the floor period and 0.004 ($p<0.05$) for the automated period. Then, I find that the p-value is 0.036 when I compare floor and automated momentum returns. These suggest, as expected, that when using a non-parametric test the findings concur with those generated using a parametric test. Momentum profits are more pronounced in the automated period and the difference in momentum profits before and after Big Bang is statistically significant.

	Median		Parametric p-value		Non-parametric p-value	
	Floor	Automated	Floor	Automated	Floor	Automated
W-L (3 portfolios)	0.46%	1.13%	0.36	0.014	0.52	0.015
W-L (5 portfolios)	0.51%	1.34%	0.29	0.008	0.47	0.006
W-L (10 portfolios)	0.65%	1.74%	0.17	0.004	0.35	0.004

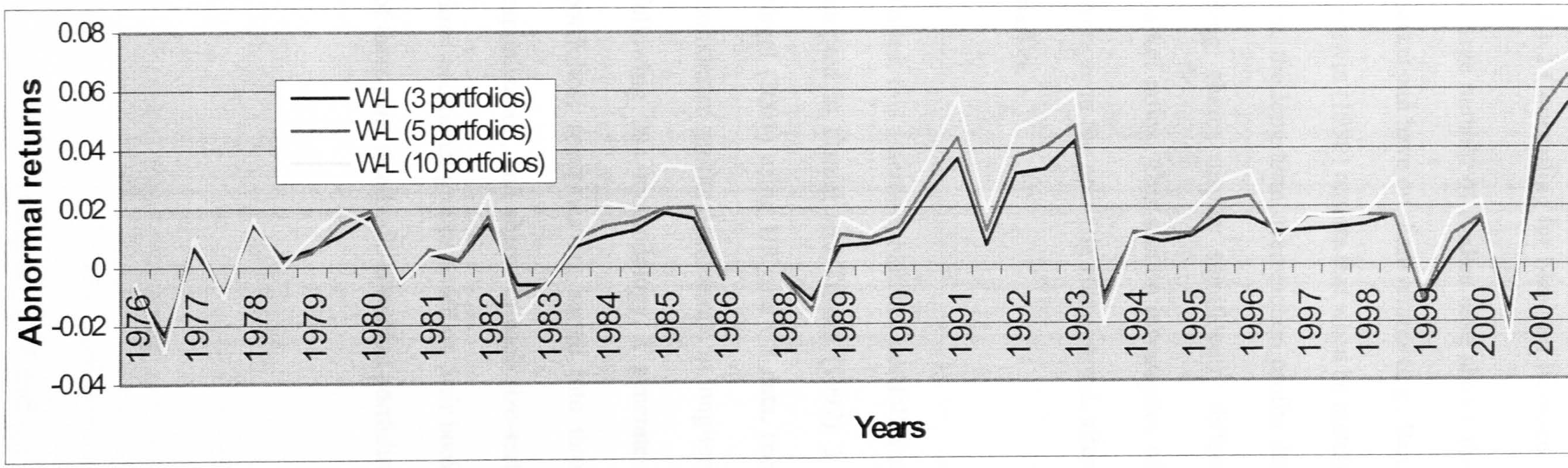
The finding that momentum profits are not persistent during different time periods on the LSE concurs with the results of Hon and Tonks (2003). They document that momentum strategies were profitable between 1955 and 1996, but that they did not offer profits between 1955 and 1976. However, Liu et al. (1999) report that momentum profitability remained approximately at the same level between 1977-1987 and 1988-1998. Continuation profits were 15.1 per cent per year from 1977 to 1987 and slightly higher 17.4 per cent per year from 1988 to 1998. Notice that Liu et al. and this study investigate similar sub-periods, without generating identical results. This divergence could be explained because Liu et al. examine share returns from Datastream, but this study investigates share returns from LSPD. Datastream returns are calculated using mid share prices, while LSPD returns are computed employing last traded share prices.

Table 6.1
Momentum Profits in Floor and Automated Systems

	Entire Period (1975-2001)	Floor Period (1975-1986)	Automated Period (1987-2001)
Panel A: 3 Portfolios			
L	0.17%	1.40%	-0.74%
	0.54	3.96	-1.63
2	0.99%	1.79%	0.41%
	5.57	7.52	1.66
W	1.13%	1.80%	0.64%
	5.51	6.73	2.16
W-L	0.96%	0.41%	1.38%
	2.58	0.92	2.55
Panel B: 5 Portfolios			
L	-0.01%	1.32%	-1.00%
	-0.04	3.46	-1.96
2	0.70%	1.62%	0.03%
	3.21	5.81	0.09
3	1.01%	1.84%	0.41%
	5.54	7.95	1.56
4	1.07%	1.78%	0.56%
	6.13	6.97	2.36
W	1.17%	1.82%	0.69%
	5.27	6.77	2.08
W-L	1.18%	0.50%	1.69%
	2.86	1.07	2.78
Panel C: 10 Portfolios			
L	-0.34%	1.15%	-1.44%
	-0.82	2.63	-2.39
2	0.31%	1.49%	-0.55%
	1.05	4.28	-1.30
3	0.54%	1.56%	-0.21%
	2.15	5.00	-0.60
4	0.86%	1.68%	0.26%
	4.47	6.57	0.97
5	1.01%	1.88%	0.37%
	5.53	8.23	1.44
6	1.00%	1.79%	0.43%
	5.34	7.44	1.58
7	1.08%	1.78%	0.57%
	6.42	7.14	2.53
8	1.07%	1.77%	0.56%
	5.76	6.54	2.21
9	1.14%	1.76%	0.69%
	5.42	6.53	2.22
W	1.19%	1.87%	0.70%
	4.94	6.74	1.89
W-L	1.53%	0.73%	2.14%
	3.23	1.40	3.02

This table shows the momentum profits using the full period and the automated and floor sub-periods. In the breakdown of *three portfolios*, we define 30 per cent of the full sample as the loser (L), 30 per cent as the winner (W) and 40 per cent as the intermediate portfolio. In the divisions of *five* and *ten* portfolios, each portfolio is classified with 20 and 10 per cent of the full sample respectively.

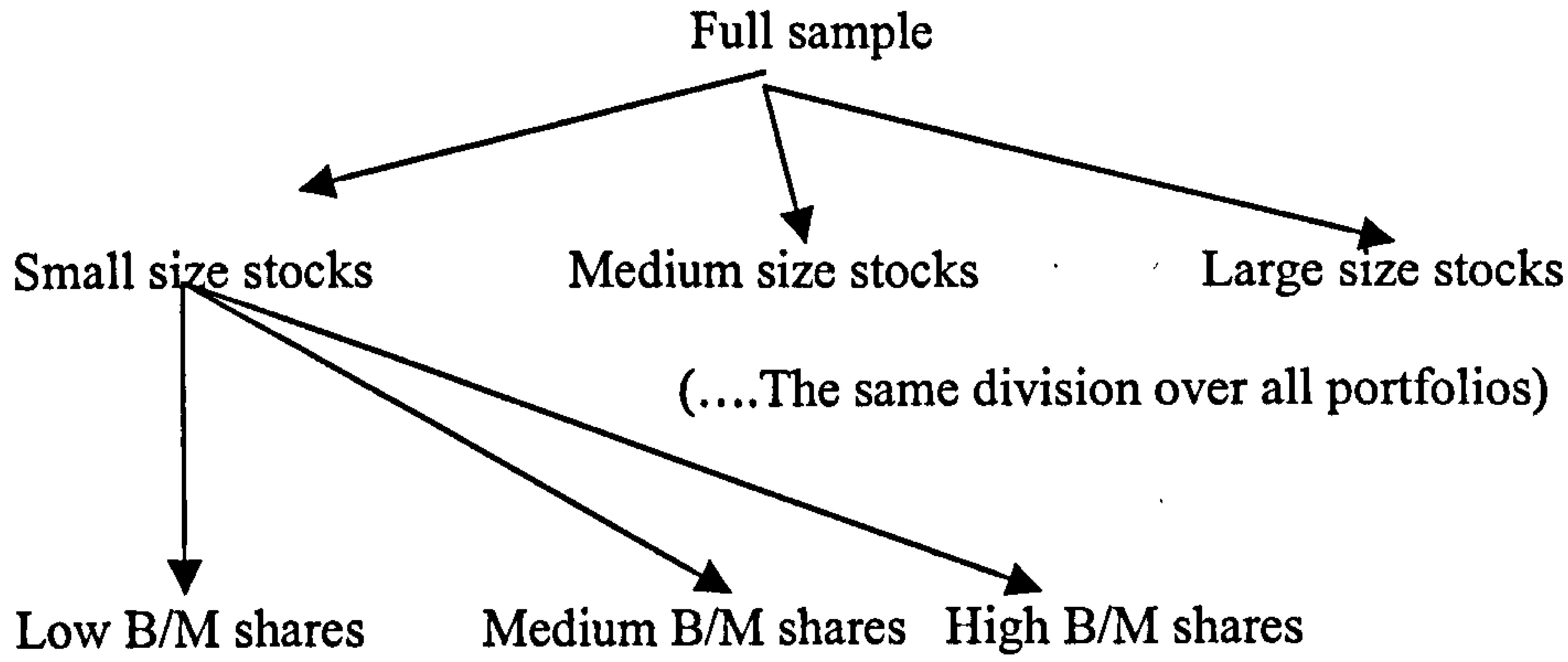
Figure 6.1
Momentum Profits in Floor and Automated Sub-Periods



6.2.1.2 Controlling for Size and Book-to-Market

A large number of studies have shown the influence that size and book-to-market can have on share returns (e.g., Banz, 1981; Fama and French, 1992). Zarowin (1990) reports that when he matches winners and losers of the same size, the long-term overreaction profits disappear. Before and after the Big Bang, shares display significantly different market values and book-to-market ratios. This section investigates whether momentum profits remain stronger in the post-Big Bang period, after controlling for size and book-to-market.

To test this assertion, matched portfolios are created similar to the approach adopted in Daniel and Titman (1997). I select this methodology because Nagel (2001) using UK and US data, reports that the reversal pattern that momentum profits demonstrate in long-term periods largely disappears after following this methodology. I generate nine size-book-to-market sorted portfolios; securities are sorted into three groups based on their market capitalisation, and shares in each size-sorted group are further divided into three additional groups based on their book-to-market. I calculate the returns of these nine size-book-to-market portfolios over the test period.



The performance of each security in the test period is calculated as:

$$R_{it}^{CH} = R_{it} - R_{t}^{CH} \tag{6.1}$$

where R_{it}^{CH} is the characteristic-adjusted return on security i in month t, R_{it} is the return on security i in month t, and R_{t}^{CH} is the return on a size-book-to-market matched portfolio in month t.

Panel A of Table 6.2 shows the unadjusted returns using the accounting sub-sample, which examines over 2000 shares with additional accounting data. I report that the accounting sub-sample demonstrates identical results to the full sample. This suggests that the finding that momentum profits are strong using UK data driven by the post-1987 period holds using a different data set.

Using the accounting sub-sample, accounting information for each portfolio can be observed. As expected, shares in the automated structure exhibit significantly higher market capitalisation and lower book-to-market ratios because of the continuing bull markets. Overall, size and book-to-market cannot explain the momentum profits on the LSE and the different momentum profits generated post- and pre- Big Bang. The winner portfolio includes higher market value shares than the loser portfolio when the entire period and both sub-periods are studied. The arbitrage portfolio in the post-Big Bang period even includes larger capitalisation companies than its counterpart arbitrage portfolio in the pre-Big Bang period. Hence, when size differences are considered, momentum profits in the post-Big Bang period should have been even greater.

Panel B of Table 6.2 shows the size and book-to-market adjusted portfolio returns. I find that after controlling for size and book-to-market ratios, momentum profits decrease significantly, especially when the automated system was in operation. Nevertheless, continuation profits are economically significant using the entire period and abnormal returns are still much higher in the post-Big Bang period. Stated differently, the difference in momentum profits between the floor and automated periods cannot be attributed to the characteristics of firms. The difference in momentum profitability between the two sub-periods remains significant, although smaller than that obtained from unadjusted returns. This finding suggests that size and book-to-market cannot explain the difference in momentum gains generated before and after Big Bang.

Table 6.2
Size and Book-to-Market Adjustment

		Entire Period	Floor Period	Automated Period
Panel A: Unadjusted Returns				
L		0.08%	1.40%	-0.87%
		0.24	3.29	-1.93
W		1.27%	2.06%	0.71%
		6.14	7.32	2.44
W-L		**1.19%**	**0.66%**	**1.58%**
		3.05	**1.29**	**2.94**
L	size	232.40	55.76	395.96
	B/M	1.86	2.58	1.18
W	size	501.36	70.87	870.36
	B/M	0.98	1.45	0.59
W-L	**size**	**268.96**	**14.45**	**504.62**
	B/M	**-0.87**	**-1.17**	**-0.60**
Panel B: Size and Book-to-Market Adjusted Returns				
L		-0.40%	-0.20%	-0.54%
		-1.35	-0.33	-2.21
W		0.39%	0.24%	0.49%
		1.20	0.42	1.43
W-L		**0.79%**	**0.45%**	**1.03%**
		1.80	**0.53**	**2.45**

This table demonstrates the momentum profitability generated in the full period, the automated and the floor sub-periods using the accounting sub-sample (Panel A) as well as the momentum profits that remain after adjusting for size and book-to-market (Panel B). We generate nine size-book-to-market sorted portfolios; securities are sorted into three groups based on their market capitalisation, and shares in each size-sorted group are further divided into three additional groups based on their book-to-market. I calculate the returns of these nine size-book-to-market portfolios over the test period. The performance of each security in the test period is calculated as: $R_{it}^{CH} = R_{it} - R_t^{CH}$, where R_{it}^{CH} is the characteristic-adjusted return on security i in month t, R_{it} is the return on security i in month t, and R_t^{CH} is the return on a size-book-to-market matched portfolio in month t.

6.2.1.3 Risk adjustments

Academics tend to investigate whether an investment strategy provides abnormal profits after controlling for risk, since profits on occasion disappear considering the risk. For example, Fama and French (1996) find that risk changes can explain the long-term reversal profitability. This section examines the momentum profits achieved in both floor and automated structures after controlling for risk.

Initially, this study controls for risk using the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965; and Black, 1972). I calculate the aggregate coefficient betas (e.g., Dimson, 1979) to overtake the problem of infrequent trading that conventional betas demonstrate (e.g., Scholes and Williams, 1977). Using portfolio returns over the rank period, I estimate the multiple regression of portfolio returns against lagging, matching and leading market returns. I select the number of leads and lags that are statistically significant.

$$R_{p,t} - R_{f,t} = a_p + \sum_{k=-n}^{n} \beta_p (R_{m,k,t} - R_{f,k,t}) + e_{i,t} \qquad (6.2)$$

where $R_{p,t}$ is the return of portfolio p in month t, $R_{f,t}$ is the one-month Treasury Bill rate in month t, and $R_{m,t}$ is the return of the proxy market (FTSE All-Share) in month t. The aggregate coefficient beta is the sum of betas with different leads and lags.

Table 6.3 shows the portfolios' aggregate betas. Results show that momentum profits cannot be explained by risk using the entire period. The winner portfolio demonstrates lower aggregate beta than its counterpart loser portfolio. Further, the difference in momentum profitability between the two structures cannot be attributed to systematic risk. Portfolios in the automated period tend to display higher betas, but the beta of the arbitrage portfolio (β_{W-L}) is –0.22 for the automated period and 0.31 for the floor period. Stated differently, the arbitrage portfolio generates higher performance and experiences lower risk using the automated period. After considering for risk differences, momentum profits in the post-Big Bang period should have been even larger than the data reveal.

I extend the investigation and calculate the aggregate betas of the arbitrage portfolio examining alternative lags and leads. Table 6.4 shows that when applying until three lags and three leads, the beta of the arbitrage portfolio is always positive during the floor sub-period and negative during the automated sub-period. For example, employing two lags and two leads, the beta of the arbitrage portfolio is –0.19 for the automated sub-period, but 0.40 for the floor sub-period. These results indicate that the CAPM cannot explain the difference in momentum gains demonstrated before and after Big Bang.

I undertake further investigation and define risk using an alternative model. In the literature, there has been a debate over the misspecification of risk. The CAPM has been subject severe criticism when recent data has been used (e.g., Strong and Xu, 1997), so other models have been developed to determine the risk-return relationship. Perhaps one of the most recent and well recognised models is the three-factor model by Fama and French (1993) that defines the risk as a function of beta, size and book-to-market. Liu et al. (1999) use UK data and report that after controlling for the three-factor model, momentum profits are lower than when the CAPM is applied. This suggests that the three-factor model captures the momentum gains better than the CAPM. Until now I have controlled for beta, size and book-to-market separately and find that they cannot capture the difference in momentum profits in alternative structures. Now I investigate whether this finding persists when I control for these factors simultaneously.

To control for the three-factor model, I estimate the following regression:

$$R_{p,t} - R_{f,t} = a_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + e_{p,t} \tag{6.3}$$

where $R_{p,t}$ is the return of portfolio p in month t, $R_{f,t}$ is the one-month Treasury Bill rate in month t, and $R_{m,t}$ is the return of the proxy market (FTSE All-Share) in month t. I generate nine portfolios; shares are sorted into three groups based on the market value and then, each size-sorted portfolio divided further into three portfolios based on the book-to-market. SMB_t (Small Minus Big) shows the portfolio that buys the three small size portfolios and sells short the three big size portfolios. HML_t (High Minus Low) shows the portfolio that buys the three high book-to-market portfolios and sells short the three low book-to-market portfolios.

Full sample

Small size stocks (A) Medium size stocks (B) Large size stocks (C)

(....The same division over all portfolios)

Low B/M shares (a) Medium B/M shares (b) High B/M shares (c)

SMB_t + Aa, Ab, Ac

- Ca, Cb, Cc

HML_t + Ac, Bc, Cc

- Aa, Ba, Ca

Table 6.5 shows the sensitivities and the constant of the model for the loser portfolio (Panel A), the winner portfolio (Panel B) and the arbitrage portfolio (Panel C). The alpha of the model demonstrates the abnormal profits that remained after considering for the three factors. Where market efficiency holds, alpha should be equal to zero. Findings show that the three-factor model cannot explain either the momentum profits generated on the LSE, or the stronger momentum profitability displayed in the automated sub-period. Continuation payoffs remain at 1.64 (t-statistic=4.45) per cent per month during the period of automation, but lower at 0.80 (2.49) per cent per month during the floor period. Interestingly, consistent with Liu et al. (1999) using UK data and Fama and French (1996) using US data, this study finds that the three-factor model cannot explain the momentum effect. The arbitrage portfolios display negative sensitivities in all three Fama and French factors[3].

Overall, after examining the risk-adjusted momentum profitability before and after Big Bang, continuation profits still tend to remain stronger on the automated sub-period. Using the CAPM to define risk, I found that the arbitrage portfolio on the post-Big Bang period generates higher abnormal returns experiencing lower risk. Employing the three-factor model, I reported that this alternative definition cannot capture the momentum profits on the LSE and momentum profits remain stronger on the automated period.

[3] I investigated whether the assumptions of multiple regression are fulfilled. However for space reasons, I do not present the results either in this chapter or in the following chapters. For example, I examined whether there exists a multicollinearity problem where independent variables are strongly associated. Therefore, after considering that there exists some association between independent variables with the dependent variable, I observed the tolerance magnitude where high tolerance implies no violation of the multicollinearity assumption. Further, I examined whether residuals are normally distributed by generating the normal probability plot (when residuals are normal, points lie in a reasonably straight line) and calculating other goodness-of-fit tests (e.g., Kolmogorov-Smirnov). I further examined the scatter plot of residuals to identify potential outliers, to observe whether points are reasonably distributed above and below the line and to examine whether residuals have approximately constant variance.

Table 6.3

Portfolio Aggregate Betas

	Entire period	Floor Period	Automated Period
L	1.51	0.91	1.81
2	1.17	0.85	1.37
3	1.14	0.92	1.29
4	1.10	0.93	1.22
5	1.08	0.91	1.19
6	1.08	0.98	1.14
7	1.12	1.04	1.17
8	1.09	0.93	1.21
9	1.18	1.03	1.29
W	1.42	1.22	1.59
W-L	**-0.09**	**0.31**	**-0.22**

This table shows the aggregate betas of the ten past return portfolios. We calculate the portfolio aggregate coefficient betas (e.g., Dimson, 1979), by running the multiple regression of portfolio returns against lagging, matching and leading market returns:

$$R_{p,t} - R_{f,t} = a_p + \sum_{k=-n}^{n} \beta_p (R_{m,k,t} - R_{f,k,t}) + e_{i,t}$$

where $R_{p,t}$ is the return of portfolio p in month t, $R_{f,t}$ is the one-month Treasury Bill rate in month t, and $R_{m,t}$ is the return of the proxy market (FTSE All-Share) in month t. We choose the number of leads and lags, for each of the ten past return portfolios, that are statistically significant. The aggregate coefficient beta is the sum of betas with different leads and lags.

Table 6.4

Aggregate Betas of the Arbitrage Portfolio

		-1		-2		-3
+1	F	0.26	F	0.44	F	0.51
	A	-0.34	A	-0.24	A	-0.21
+2	F	0.22	F	0.40	F	0.47
	A	-0.29	A	-0.19	A	-0.15
+3	F	0.22	F	0.40	F	0.48
	A	-0.32	A	-0.21	A	-0.17

This table demonstrates the aggregate betas that the arbitrage portfolio (W-L) displays into alternative leads and lags. F and A represent the floor and automated sub-periods respectively.

Table 6.5

Controlling for Risk with the Three-Factor Model

	Entire period	**Floor period**	**Automated period**
Panel A: Losers			
a_p	-1.26%	1.51%	-1.08%
	(-4.50)	(1.78)	(-2.63)
β_p	1.28	1.20	1.37
	(17.92)	(15.21)	(12.68)
s_p	0.87	1.07	0.69
	(9.01)	(8.98)	(5.25)
h_p	-0.18	0.09	-0.23
	(-1.97)	(0.82)	(-1.91)
$adj-R^2$	0.52	0.70	0.48
Panel B: Winners			
a_p	0.00%	2.30%	0.56%
	(0.00)	(2.77)	(1.04)
β_p	0.98	1.04	0.91
	(17.09)	(16.92)	(10.31)
s_p	0.59	0.69	0.52
	(7.63)	(7.52)	(4.76)
h_p	-0.35	-0.06	-0.45
	(-4.90)	(-0.64)	(-4.57)
$adj-R^2$	0.51	0.76	0.41
Panel C: Winners-Losers			
a_p	**1.26%**	**0.80%**	**1.64%**
	(4.99)	**(2.49)**	**(4.45)**
β_p	**-0.30**	**-0.16**	**-0.46**
	(-4.71)	**(-1.77)**	**(-4.96)**
s_p	**-0.28**	**-0.37**	**-0.18**
	(-3.23)	**(-2.67)**	**(-1.58)**
h_p	**-0.17**	**-0.15**	**-0.22**
	(-2.15)	**(-1.12)**	**(-2.16)**
$adj-R^2$	**0.09**	**0.06**	**0.14**

This table shows the robustness of Table 5.1 after adjusting for the three-factor model that controls for beta, size and book-to-market. We run the following regression:

$$R_{p,t} - R_{f,t} = a_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + e_{p,t}$$

where $R_{p,t}$ is the return of portfolio p in month t, $R_{f,t}$ is the one-month Treasury Bill rate in month t, and $R_{m,t}$ is the return of the proxy market (FTSE All-Share) in month t. SMB (Small minus Big) and HML (High minus Low) are the Fama and French small firm and book-to-market factors respectively, and to generate them, nine portfolios are formed by sorting first by size: low-, medium- and large-size portfolios and then by book-to-market: low-, medium- and high-book-to-market portfolios.

6.2.1.4 Employing a Different Dataset

During the periods when floor and automated systems operated, shares with different characteristics have been traded. Until now I have controlled for size, book-to-market and beta. This section undertakes another robustness test and investigates the momentum profitability that the same shares generate in both structures. Stated differently, I select stocks with return information for the duration of the whole sample period. I find that only 266 shares fulfil that condition. Then, I compare the momentum profitability achieved by these stocks in the automated and floor sub-periods.

Table 6.6 and Figure 6.2 demonstrate that the automated sub-period provides higher monthly momentum profits than the floor sub-period. This indicates that the superior momentum gains in the post-Big Bang period hold when a different data set is employed. Interestingly, beyond the full sample of over 6000 stocks and the accounting sub-sample of over 2000 companies, momentum profits remain economically significant even using this sub-sample of only 266 companies. Nevertheless, momentum profits are significantly lower than in the case of the full sample and the accounting sub-sample. This may be explained by the fact that shares that have return information for the whole 1975-2001 period, are high capitalisation equities. Consistent with Hong et al. (2000), there exists a negative relationship between size and momentum profitability, and therefore, this sample that includes high capitalisation shares would expect to generate relatively low momentum profits.

Using this small number of shares, I further examine whether momentum profits are stronger in the post-Big Bang period after considering bull and bear markets and once the three-factor model controls for risk. Overall, I find that the same results; momentum gains are most pronounced in the post-1987 period. Due to space considerations, I do not present the equivalent tables.

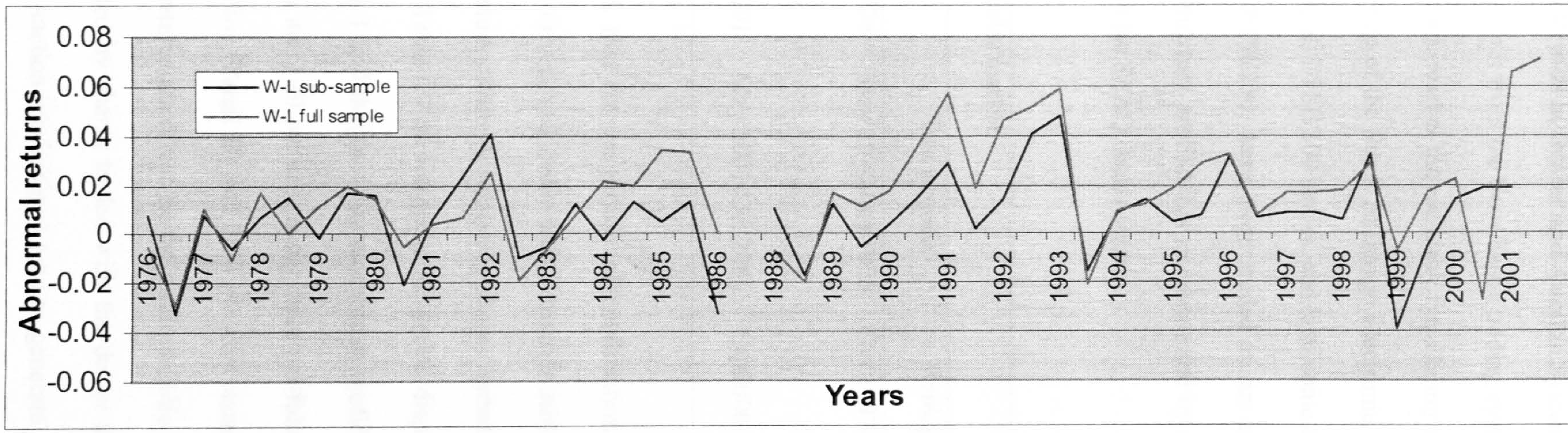
Table 6.6

Using a Different Data Set

	Entire Period	Floor Period	Automated Period
Panel A: 3 Portfolios			
L	0.88%	1.81%	0.21%
	4.24	7.04	0.70
W	1.34%	1.95%	0.89%
	9.40	11.23	4.23
W-L	**0.46%**	**0.14%**	**0.69%**
	1.81	**0.44**	**1.90**
Panel B: 5 Portfolios			
L	0.83%	1.87%	0.07%
	3.35	6.10	0.21
W	1.39%	2.04%	0.92%
	9.18	11.50	4.05
W-L	**0.56%**	**0.17%**	**0.85%**
	1.94	**0.48**	**2.04**
Panel C: 10 Portfolios			
L	0.58%	1.81%	-0.30%
	1.81	4.43	-0.67
W	1.47%	2.16%	0.97%
	7.67	9.40	3.40
W-L	**0.89%**	**0.35%**	**1.28%**
	2.36	**0.74**	**2.39**

This table investigates whether our previous results persist using a different data set. Using only 266 shares, with return information for the whole duration of our sample (1975-2001), I compare the momentum profitability that is demonstrated for the same stocks in the entire period and in the automated and floor sub-periods.

Figure 6.2
Momentum Profits employing Different Data Sets



6.2.2 Momentum Profits in Dealer and Auction Systems

A decade after the shift from the floor-based trading system to an electronic trading system, the UK stock market moved away from being a purely dealership market. With the introduction of the Stock Exchange Electronic Trading System (SETS) on 20th October 1997, all FTSE 100 stocks, and later some additional large companies' shares from the FTSE250, have been traded in an auction system. This study compares the momentum profitability demonstrated by stocks traded on the SETS mechanism and on the SEAQ dealer system.

Dealer market		Auction market	
Rank periods	Test periods	Rank periods	Test periods
Oct 1975-Mar 1976	May 1976-Oct 1976	Oct 1997-Mar 1998	May 1998-Oct 98
....	....	...	...
Oct 2000-Mar-2001	May 2001-Oct 2001	Oct2000-Mar 2001	May 2001-Oct 01

Table 6.7 reports that the magnitude of continuation profits is different when comparing quote-driven and order-driven mechanisms. Column 1 of Table 6.7 shows the momentum profits generated by shares traded with the SETS mechanism and Column 2 of Table 6.7 demonstrates the profits displayed by shares traded with the dealer system. I find that monthly momentum profits for shares traded with the SETS mechanism are 1.20 per cent using three portfolios (Panel A), 2.01 per cent using five portfolios (Panel B) and 2.94 per cent using ten portfolios (Panel C). These abnormal returns are driven by the loser portfolio and are significantly higher than those reported by shares traded with the dealer system from 1975 to 2001. Considering that auction mechanisms tend to generate lower execution costs than

dealer systems (e.g., Huang and Stoll, 1996), the difference in the profitability of momentum profits generated by the two mechanisms is even greater than the current data show.

One could argue that I compare the momentum profits that two mechanisms enjoy over different periods. Hence, I extend the investigation and examine the momentum profits gained by companies traded with the SETS auction system and the SEAQ dealer mechanism for the same period: from October 1997 to October 2001. Column 3 of Table 6.7 shows the returns achieved by companies traded with the SEAQ dealer system from October 1997 to October 2001. When I compare the magnitude of momentum profits that columns 1 and 3 display, I find that stocks operated with the SETS system generate almost identical momentum profits to shares traded on the SEAQ.

Nevertheless, until now I have not considered the large size of the companies traded with the SETS mechanism. Consistent with Hong et al. (2000), there exists a negative relationship between size and momentum profitability and therefore, shares operated on the SETS, which are the largest capitalisation shares on the LSE, would expect to generate low momentum profits. Given the influence that market value can have over momentum returns, I investigate the momentum profits achieved by companies traded on the SETS and SEAQ after taking account of size differences. To adjust for size, I calculate the momentum profitability of the 150 largest capitalisation shares that have been traded on the SEAQ dealer system. Column 4 of Table 6.7 reports the returns of these 150 shares. When I compare the findings of Columns 1, 3 and 4, I find that the largest 150 shares operated on the SEAQ mechanism generate significantly lower continuation profits than their counterpart companies traded on the SETS and the full sample of shares operated on SEAQ. This suggests that after allowing for size differences between the SETS and SEAQ samples, shares operated on the SETS system demonstrate significantly larger momentum returns than their counterpart companies traded on SEAQ.

I extend the investigation and undertake another robustness test. I calculate the continuation profits generated by the stocks on the SETS in the previous four years (1994-1997) when they were traded on the SEAQ system (Column 5 of Table 6.7). Column 6 of Table 6.7 shows the continuation profits demonstrated using the full sample from 1994 to 1997. Columns 1, 5 and 6 show that the SETS stocks generate significantly lower returns when they were traded on the dealer system between 1994 and 1997, while the full sample demonstrates strong profits.

Table 6.7
Momentum Profits in Dealer and Auction Systems

	(1) SETS Auction System (1997-2001)	(2) Dealer System (1975-2001)	(3) SEAQ Dealer System (1997-2001)	(4) 150 Largest SEAQ Shares (1997-2001)	(5) SETS Stocks (1994-1997)	(6) Full Sample (1994-1997)
Panel A: 3 Portfolios						
L	-0.79%	0.17%	-1.66%	-1.37%	1.42%	-0.29%
	-0.77	0.53	-1.64	-0.97	0.76	-0.56
W	0.41%	1.13%	-0.22%	-0.11%	1.85%	1.02%
	0.70	5.42	-0.28	-0.21	0.82	4.05
W-L	1.20%	**0.96%**	**1.45%**	**1.25%**	**0.43%**	**1.31%**
	1.08	**2.55**	**1.13**	**0.83**	**0.73**	**3.35**
Panel B: 5 Portfolios						
L	-1.14%	-0.04%	-2.17%	-1.99%	1.52%	-0.53%
	-0.85	-0.10	-1.90	-1.28	0.92	-1.15
W	0.88%	1.15%	-0.33%	-0.70%	2.06%	1.12%
	1.23	5.11	-0.35	-0.96	1.06	4.43
W-L	2.01%	**1.19%**	**1.85%**	**1.29%**	**0.54%**	**1.65%**
	1.33	**2.85**	**1.26**	**0.75**	**0.77**	**3.33**
Panel C: 10 Portfolios						
L	-2.07%	-0.35%	-2.79%	-2.38%	1.90%	-0.86%
	-1.09	-0.85	-2.13	-1.18	1.56	-1.65
W	0.86%	1.18%	-0.34%	-1.30%	3.01%	1.12%
	1.07	4.79	-0.32	-1.24	2.10	3.12
W-L	2.94%	**1.53%**	**2.45%**	**1.08%**	1.10	**1.98%**
	1.42	**3.21**	**1.46**	**0.48**	0.94	**3.09**

This table compares the momentum profitability demonstrated by stocks that have been traded using the SETS mechanism and that of other shares that have been traded under the SEAQ dealer system (Columns 1, 2 and 3). To adjust for size, we calculate the momentum profitability of the 150 largest capitalisation shares for each year that have been traded on the SEAQ dealer system (Column 4). Column 5 provides the continuation profits that are generated by the SETS stocks in the previous four years (1994-1997), when they were traded under the SEAQ dealer system.

6.3 CONCLUSION

This study introduced a factor that influences the momentum profits and has not been previously identified. I investigated whether the market organisation (e.g., automated, floor, dealer and auction systems) has an impact on the magnitude of continuation returns. The motivation for examining such an association was based on the influence that stock market structures can have over share returns. I used UK data and studied some of the most significant changes that occurred to the structure of the London Stock Exchange.

First, I considered the Big Bang, which occurred on 27th October 1986 and resulted in the introduction of the automated SEAQ system and the shift of the LSE from a floor-based market to an automated market. I calculated the momentum profits generated before and after Big Bang. Findings indicated that shares traded in an automated structure generate much higher continuation profits than equities transacted on a floor-based system. These results persisted after controlling for size, book-to-market, risk and market conditions. Findings confirm the results of Hon and Tonks (2003) who demonstrate that momentum strategies can not earn profits in a sub-period from 1955 to 1976, but they contradict the findings of Liu et al. (1999) who suggest approximately the same momentum profitability between 1977-1987 and 1988-1998. There is a difference between Liu et al. and this investigation, since they examine stock returns from Datastream and this study investigates share returns from the LSPD.

Second, I considered the introduction of the SETS auction mechanism, which occurred on 20th October 1997 and had as a result the shift of the LSE from the pure dealership market. All FTSE 100 stocks, and later some additional large companies from the FTSE250, have now traded on the SETS auction system. Results showed that shares traded on the SETS order-driven system tended to demonstrate larger continuation profits than shares traded on the SEAQ quote-driven system. The difference in momentum profits between the two structures increased significantly after considering size differences. Companies traded on SETS are the largest capitalisation shares and consistent with Hong et al. (2000), they would be expected to earn lower rather than higher momentum returns.

Beyond the finding that momentum profits vary under alternative market structures, other interesting results are reported. I found that momentum profits are significant when I use all listed companies on the LSE (over 6000 shares), a sub-sample of 2000 shares with additional accounting information and a small number of 266 stocks with complete return information from 1975 to 2001. I further documented that momentum profits persist after controlling for size, book-to-market and risk as defined by the CAPM and the three-factor model. These findings suggested that the momentum effect persists on the LSE using various data sets and after controlling for various factors that influence share returns.

Chapter 7

VOLATILITY AND MOMENTUM PROFITABILITY

7.1 INTRODUCTION

This chapter investigates the role of volatility in influencing momentum profits. Shares with high volatility display wide spread out returns and therefore, potential higher magnitude momentum profitability. Chapter 6 indicated that shares traded on the post-Big Bang automated system generated larger continuation payoffs than shares which transacted on the pre-Big Bang floor mechanism as well as equities traded on the SETS auction system demonstrate stronger momentum gains that companies traded on the SEAQ dealer system. Given that shares displayed higher volatility traded on the post-Big Bang period (Tonks and Webb, 1991) and on the SETS system (Chelley-Steeley, 2003), this chapter examines whether the different levels of momentum profitability achieved in alternative stock market structures arises from volatility.

This chapter also examines whether there exists an association between volatility, trading volume and the magnitude of continuation profits. Lee and Swaminathan (2000) show that securities with high trading volumes display greater momentum profitability than their low trading volume counterparts. Karpoff (1987), surveying the volatility-trading volume relationship, shows that the positive interrelationship between the two issues remains persistent in studies employing different periods, data-sets and time intervals (hourly, daily or weekly). As more new information flows to a market, more transactions occur and volatility becomes higher. In recent studies (e.g., Gallant et al., 1992; Lee and Rui, 2002), the positive relationship between volatility and trading volume appears robust across various financial markets such as equity, currency and futures. This chapter examines whether the positive association between trading volume (volatility) and momentum profits persists after controlling for volatility (trading volume).

This chapter is structured as follows: the next section presents the empirical findings; and section 7.3 summarises the chapter.

7.2 EMPIRICAL FINDINGS

7.2.1 Volatility and Momentum Profitability

This section examines the influence that volatility can have in determining momentum profits. Portfolios are formed by a two-way sort between the rank period share standard deviations (low-, 2-, 3-, 4-, and high-standard deviation) and rank period share returns (losers, 2, 3, 4 and winners). Stated another way, first, I generate five portfolios based on rank standard deviation and then, I calculate the momentum profitability that these portfolios achieve.

Panel A of Table 7.1 shows that moving to shares with higher rank period standard deviation, losers (winners) achieve returns of 0.72 (1.42), 0.63 (1.54), 0.50 (1.70), 0.08 (1.50) and -0.53 (0.94) per cent per month. Therefore, monthly continuation profits (W-L) are 0.70 per cent for the lowest volatility shares, 0.91 per cent for the second-lowest volatility companies, 1.20 per cent for the third-lowest volatility shares, 1.42 per cent for the fourth portfolio and 1.47 per cent for shares with the highest rank period volatility. Therefore, moving into shares with higher rank period volatility, there is a monotonic increase of continuation profitability driven by the loser portfolio. High volatility shares enjoy 0.77 (t-statistic=2.11) per cent higher monthly continuation profits than their counterpart low volatility companies. Notice that a strategy that buys winners with low rank period volatility and sells short losers with high rank period volatility generates monthly momentum profits of 1.95 per cent.

I also employ a non-parametric test to investigate the statistical significance of returns. Using the Mann-Whitney U test to compare the means of the W, L portfolios, I find that the p-value is 0.008 ($p<0.05$) using the low volatility shares, 0.001 using the second lowest volatility shares, 0.000 using the third lowest volatility companies, 0.000 employing the second highest volatility shares and 0.009 employing the highest volatility firms. Then, I find that the p-value is 0.020 ($p<0.05$) when I compare the momentum returns generated in the highest and lowest volatility shares. These suggest that when using a non-parametric test the findings concur with those generated using a parametric test. Momentum profits are more pronounced in high rank period volatility shares and the difference in momentum returns between high and low volatility shares is statistically significant.

	Volatility				
	Low	2	3	4	High
Median of W-L	0.65%	0.92%	1.13%	1.57%	1.60%
Parametric p-value of W-L	0.007	0.001	0.000	0.000	0.009
Non-parametric p-value of W-L	0.008	0.001	0.000	0.000	0.009

Findings may vary using different sub-periods and therefore, I examine whether the finding that momentum profits are most pronounced in high volatility shares persists in different sub-periods. Panel B and Panel C of Table 7.1 divide the full period into two sub-periods of similar duration; 1975-1987 and 1988-2001. The finding that there exists a positive relationship between volatility and momentum profitability tends to persist in both sub-periods. Figure 7.1 shows the momentum profits generated employing the full sample and using shares with the lowest- and the highest- rank period volatility. I find that shares with high rank period volatility enjoy larger momentum profits than stocks with low rank period volatility (and the full sample) in 71 (and 62) per cent of the test periods. These findings indicate that the link between shares with high volatility and high momentum profits persists in the majority of the test periods and is not driven by few extreme results.

Table 7.1

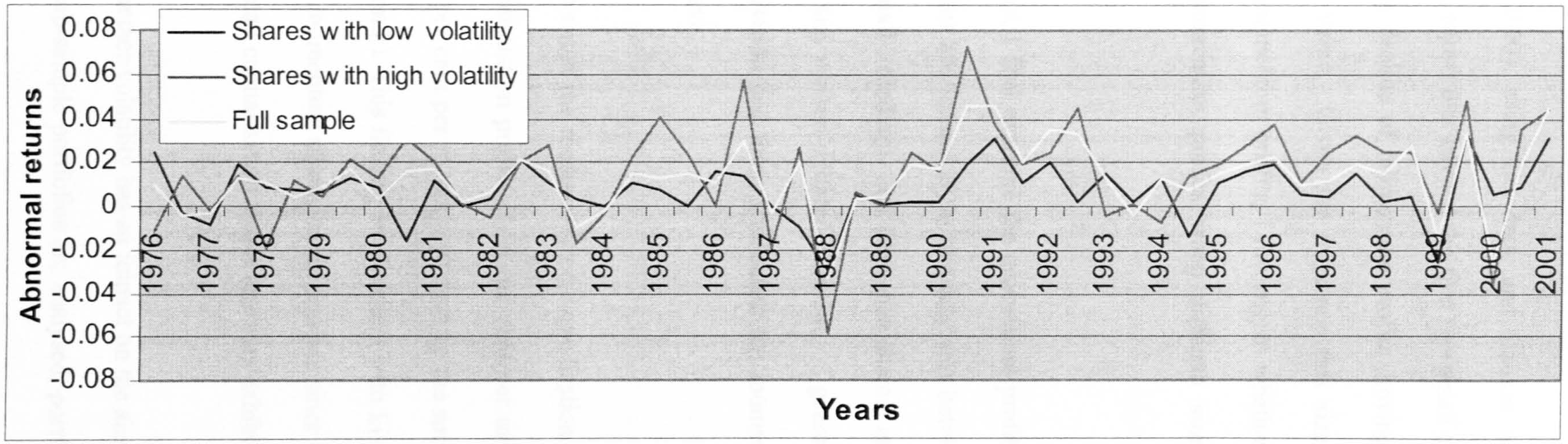
Volatility and Momentum Profits

		Volatility				
	Full Sample	**Low**	**2**	**3**	**4**	**High**
Panel A: Entire Period (1975-2001)						
L	0.05%	0.72%	0.63%	0.50%	0.08%	-0.53%
	0.11	3.56	3.06	2.11	0.25	-1.28
2	0.85%	1.29%	1.01%	0.93%	0.77%	0.30%
	2.54	8.17	6.44	5.11	3.54	0.83
3	1.05%	1.19%	1.26%	1.24%	0.96%	0.53%
	3.38	8.19	8.92	6.96	4.83	1.56
4	1.23%	1.24%	1.39%	1.33%	1.35%	0.85%
	3.97	8.66	8.98	8.91	7.47	2.60
W	1.31%	1.42%	1.54%	1.70%	1.50%	0.94%
	3.51	9.49	9.42	8.79	6.93	2.65
W-L	**1.26%**	**0.70%**	**0.91%**	**1.20%**	**1.42%**	**1.47%**
	2.26	**2.76**	**3.48**	**3.90**	**3.75**	**2.70**
Panel B: 1975-1987						
L	1.46%	1.58%	1.54%	1.69%	1.43%	1.18%
	5.17	5.91	6.40	5.98	4.49	2.60
2	1.88%	2.17%	1.81%	1.96%	1.79%	1.78%
	9.30	10.52	9.54	10.70	7.27	4.95
3	2.02%	1.87%	2.03%	2.09%	1.97%	2.13%
	10.52	9.54	10.30	10.76	8.62	6.35
4	2.18%	2.00%	2.21%	2.19%	2.21%	2.04%
	10.17	9.57	10.47	10.29	9.23	5.31
W	2.22%	2.04%	2.22%	2.50%	2.39%	2.03%
	7.18	10.39	9.44	9.42	8.43	4.44
W-L	**0.76%**	**0.47%**	**0.68%**	**0.81%**	**0.96%**	**0.85%**
	1.81	**1.40**	**2.02**	**2.08**	**2.26**	**1.32**
Panel C: 1988-2001						
L	-1.17%	-0.05%	-0.20%	-0.62%	-1.21%	-2.19%
	-2.74	-0.17	-0.64	-1.83	-2.47	-3.57
2	0.03%	0.50%	0.29%	-0.02%	-0.19%	-1.11%
	0.10	2.24	1.20	-0.07	-0.57	-1.90
3	0.29%	0.60%	0.57%	0.46%	0.03%	-1.01%
	1.22	2.80	2.96	1.61	0.11	-1.93
4	0.50%	0.55%	0.65%	0.55%	0.57%	-0.29%
	2.41	3.01	3.05	2.92	2.22	-0.58
W	0.61%	0.89%	0.95%	0.98%	0.69%	-0.07%
	1.98	3.88	4.19	3.57	2.18	-0.13
W-L	**1.79%**	**0.94%**	**1.16%**	**1.60%**	**1.90%**	**2.12%**
	3.38	**2.50**	**2.95**	**3.66**	**3.26**	**2.61**

This table examines the influence that volatility has in determining momentum profits. Portfolios are formed by a two-way sort between the rank period share standard deviation and rank period share returns. In other words, first, I generate five portfolios based on rank period standard deviation and then, I calculate the momentum profitability that these portfolios achieve.

Figure 7.1

Momentum Profitability in Shares with Different Past Volatility



7.2.2 Volatility, Size and Momentum Profits

Hong et al. (2000), using US data, and Doukas and McKnight (2003), using European data, report that beyond the first few small capitalisation portfolios, there is a continuous decline of momentum profits moving to portfolio of shares with higher market value. Given the influence that size of shares can have in the magnitude of momentum profits, I investigate whether volatility has an impact on the size of momentum profits when different size sub-sample portfolios are analysed.

To set the stage, I first examine the momentum profits generated in different size shares. Portfolios are formed by a two-way sort between one year before the test period size (small-, medium- and large-size shares) and rank period share returns (losers, 2, 3, 4 and winners). Stated differently, I generate three portfolios based on market capitalisation and then, I calculate the momentum profitability that these portfolios achieve.

Table 7.2 shows that the medium sized capitalisation portfolio (Panel B) displays the highest continuation profits (1.56 per cent per month), followed by the large (Panel C, 1.39 per cent per month) and then by the small size group (Panel A, 0.74 per cent per month). This finding is consistent with Liu et al. (1999) using UK data and shows that momentum strategies are feasible since they do generate profitability in other than small capitalisation shares that may exhibit liquidity problems.

To examine whether volatility has an impact on the size of momentum profits when different size sub-sample portfolios are analysed, portfolios are formed by a three-way sort among one year before the test period size (three portfolios), rank period standard deviation (five portfolios) and rank period share returns (five portfolios). Stated differently, I undertake the same methodology used over Table 7.1 for different size shares.

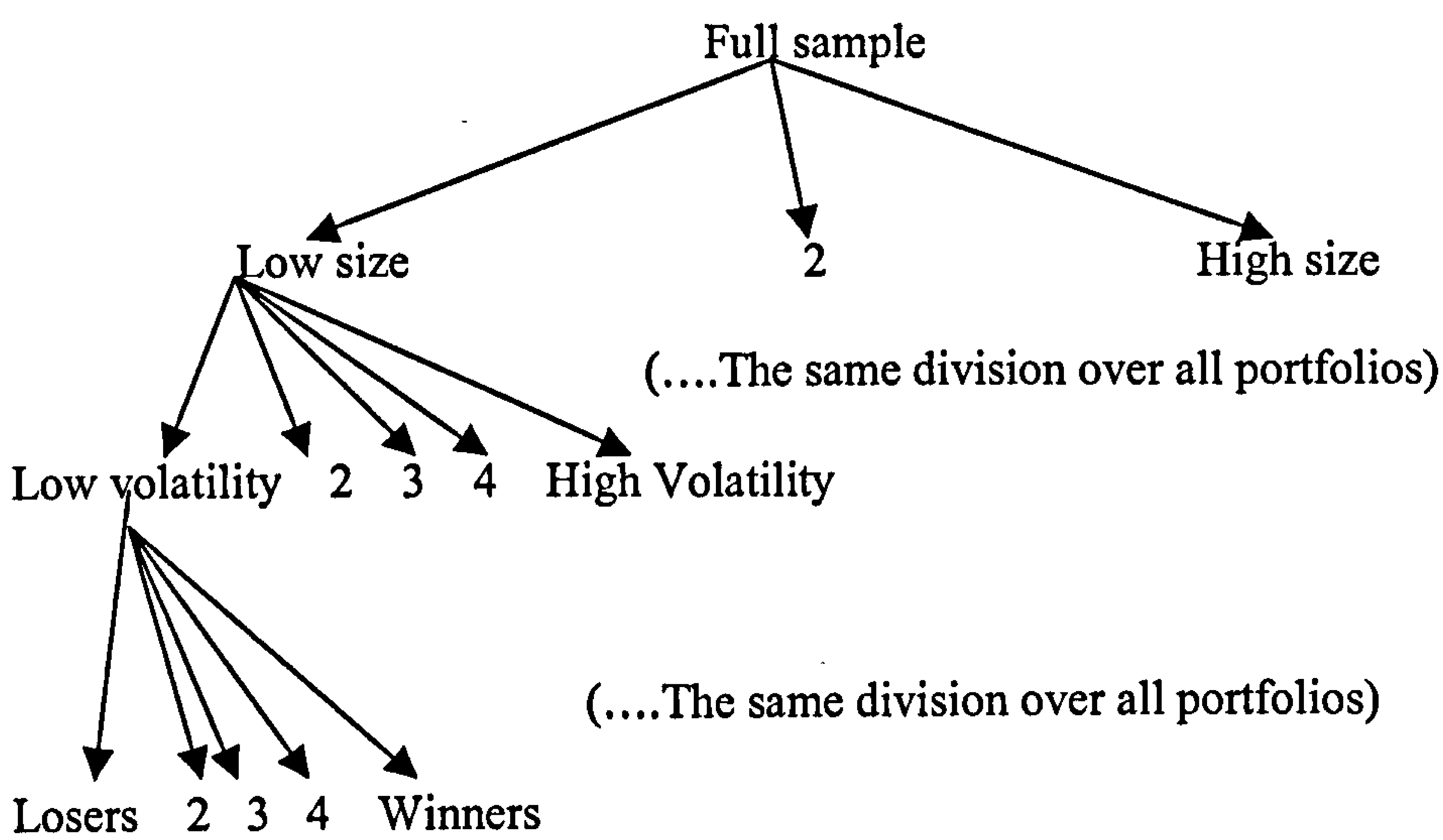


Table 7.2 reports that a monotonic increase in momentum profitability arises as the investors move into higher volatility shares for medium- (Panel B) and large-capitalisation companies (Panel C), but not for small-capitalisation companies (Panel A). For example, in the large capitalisation portfolio, shares with the highest rank period volatility generate 2.35 per cent per month momentum profits. This finding shows that the positive association between momentum profits and volatility holds when different size shares are associated, beyond small size shares.

Table 7.2

Size Sub-Samples

		Volatility				
	Corresponding-size portfolio	**Low**	**2**	**3**	**4**	**High**
Panel A: Small Capitalisation Portfolio						
L	0.58%	0.90%	0.93%	0.51%	0.84%	0.41%
	1.60	2.91	2.65	1.28	2.30	0.79
2	1.10%	1.33%	1.29%	1.05%	0.63%	0.73%
	3.88	5.47	4.58	3.11	1.83	1.54
3	1.29%	1.36%	1.39%	1.32%	1.08%	1.00%
	5.47	5.95	6.08	5.19	3.52	2.14
4	1.40%	1.43%	1.41%	1.70%	1.29%	0.46%
	5.34	7.18	5.57	6.12	4.03	1.22
W	1.32%	1.69%	1.71%	1.50%	1.70%	0.55%
	4.67	7.09	6.75	5.76	4.95	1.33
W-L	0.74%	**0.79%**	**0.78%**	**0.99%**	**0.85%**	**0.14%**
	1.62	**2.03**	**1.80**	**2.07**	**1.70**	**0.22**
Panel B: Medium Capitalisation Portfolio						
L	-0.18%	0.76%	0.46%	0.14%	-0.01%	-1.18%
	-0.50	3.32	1.90	0.54	-0.03	-2.52
2	0.68%	1.17%	0.91%	0.69%	0.50%	-0.45%
	3.03	6.92	4.55	2.85	1.73	-1.29
3	1.04%	1.18%	1.17%	1.32%	0.91%	-0.12%
	5.22	6.62	5.42	5.41	3.68	-0.35
4	1.25%	1.13%	1.35%	1.32%	1.18%	0.87%
	6.75	6.34	5.84	6.04	4.74	2.56
W	1.38%	1.54%	1.40%	1.68%	1.68%	0.73%
	6.37	8.78	6.76	6.59	7.77	2.18
W-L	1.56%	**0.79%**	**0.94%**	**1.53%**	**1.69%**	**1.91%**
	3.70	**2.74**	**2.92**	**4.19**	**4.23**	**3.32**
Panel C: Large Capitalisation Portfolio						
L	0.01%	0.63%	0.48%	0.49%	0.47%	-1.10%
	0.04	3.79	2.87	2.82	2.06	-2.88
2	1.05%	1.18%	1.10%	1.12%	0.90%	0.19%
	7.92	8.77	8.97	7.89	5.40	0.59
3	1.09%	1.23%	1.37%	1.15%	0.94%	0.68%
	10.80	10.61	11.49	8.65	6.01	3.16
4	1.23%	1.22%	1.30%	1.39%	1.13%	1.02%
	11.14	9.83	12.10	11.30	10.53	4.71
W	1.40%	1.28%	1.47%	1.55%	1.50%	1.25%
	10.48	8.34	11.35	12.24	9.37	4.64
W-L	1.39%	**0.65%**	**0.99%**	**1.07%**	**1.03%**	2.35%
	4.22	**2.85**	**4.71**	**4.99**	**3.71**	5.03

This table investigates whether volatility has an impact on the size of momentum profits when different size sub-sample portfolios are analysed. Portfolios are formed by a three-way sort among one year before the test period size (three portfolios), rank period standard deviation (five portfolios) and rank period share returns (five portfolios).

7.2.3 Alternative Stock Market Structures

Chapter 6 documented that alternative trading mechanisms, due to their different institutional features, generate different continuation profits; shares in the automated trading sub-period demonstrate higher momentum profitability than shares in the floor trading sub-period. Since the post-automated period on the LSE has been characterised by higher volatility (Tonks and Webb, 1991), and this chapter has shown that volatility is associated strongly with momentum profits, the current section studies whether the stronger momentum profitability in the automated trading sub-period can be attributed to volatility.

To test this assertion, I employ the concept of Sharpe ratio, which is widely used to examine the profitability of fund managers. The Sharpe ratio simply examines the return of a portfolio per unit of risk. Higher Sharpe ratio values imply stronger portfolio returns per unit of risk. I divide the portfolio returns achieved before and after the Big Bang with the standard deviation the portfolios displayed over the equivalent test periods.

Table 7.3 shows that the risk-adjusted W-L portfolios in both before and after Big Bang have a positive sign, which indicates that the adjusted for standard deviation winner portfolio achieves stronger return than the adjusted for standard deviation loser portfolio. This happens because winners achieve stronger returns and display lower standard deviation than counterpart losers. Then, I compare the adjusted for risk momentum returns generated before and after the deregulation. Table indicates that the stronger momentum returns generated in shares in the automated period cannot be captured by differences in volatility. The Sharpe ratio for the W-L portfolio is still stronger during the post-Big Bang period. This finding suggests that the organisation of a stock market influences the momentum profits even after considering differences in volatility.

Table 7.3

Standardised Returns

	Floor Sub-Period (1975-1986)	Automated Sub-Period (1987-2001)
L	0.11	-0.07
2	0.18	0.01
3	0.22	0.04
4	0.23	0.06
W	0.18	0.06
W-L	0.08	0.13

This table studies whether the higher momentum profitability in the automated than the floor sub-period (Chapter 6) can be attributed to volatility. I divide the portfolio returns achieved before and after the Big Bang with the standard deviation the portfolio displayed over the equivalent test periods. Higher values imply stronger portfolio returns per unit risk.

7.2.4 Volatility, Trading Volume and Momentum Profitability

One of the most significant studies in the field of momentum effect is that by Lee and Swaminathan (2000). They sort independently shares into portfolios based on past returns and trading volume, and show that securities with high trading volumes display greater momentum profitability than their low trading volume counterparts. However a positive association between volatility and trading volume exists (Karpoff, 1987), the more new information that flows to a market, the more transactions occur and the higher the volatility becomes. Since I reported the role of volatility in influencing momentum profits and Lee and Swaminathan reported the role of trading volume in influencing continuation profits, I investigate the intersections of various trading and volatility portfolios.

This study first undertakes an out-of-sample test to examine whether Lee and Swaminathan's result persists using UK data. I replicate Lee and Swaminathan (2000), by forming portfolios after a two-way independent sort between past stock returns and trading volume, to examine the significance of trading volume in momentum profits. I assign stocks to 5 portfolios based on returns over the rank period and one of three portfolios based on the trading volume 1 year before the test period. The intersections resulting from the two independent rankings give rise to 15 portfolios. I calculate the return of those portfolios over the subsequent test period.

Table 7.4 shows that results tend to be consistent with Lee and Swaminathan (2000) who employ US data. High trading volume shares generate larger momentum profits than the counterpart low trading volume shares. Momentum profits increase monotonically moving from shares with low trading volume to shares with high trading volume. Interestingly, only high trading volume shares generate statistical significant momentum profits. These findings suggest that the Lee and Swaminathan's finding persists when UK data are employed.

Since I reported that there exists a positive relationship between trading volume and continuation gains, then I investigate various intersections among trading volume and volatility portfolios. Portfolios are formed using a three-way independent sort between rank period stock returns, rank period standard deviation (low-, medium- and high-standard deviation) and one year before the test period trading volume (low-, medium- and high-volume). This methodology allows generating a more equal standard deviation (trading volume) match across different trading volume (standard deviation) portfolios. Stated differently, this test investigates the momentum profits generated in different volatility (trading volume) portfolios after matching for trading volume (volatility).

Table 7.5 shows the returns of the loser portfolio (Panel A), the winner portfolio (Panel B) and the arbitrage portfolio (Panel C). Results demonstrate that after controlling for volatility (trading volume), trading volume (volatility) tends to keep its ability to influence the momentum profitability. Only among medium volatility portfolios, trading volume cannot influence the magnitude of momentum profits. These findings suggest that the findings of Lee and Swaminathan and of this study tend to hold when the intersections between both findings are investigated.

Table 7.4

Momentum Profitability and Trading Volume

	Trading Volume		
	Low	2	High
L	-1.09%	-1.04%	-0.50%
	-1.78	-1.63	-0.86
2	-0.30%	0.07%	0.51%
	-0.44	0.17	1.06
3	-0.22%	0.73%	0.63%
	-0.45	1.97	1.68
4	-0.08%	0.28%	0.76%
	-0.14	0.71	2.03
W	0.37%	0.58%	1.37%
	0.79	1.06	3.37
W-L	1.46%	1.62%	1.87%
	1.90	1.93	2.63

This table replicates Lee and Swaminathan (2000), by forming portfolios after an *independent* two-way sort between past stock returns and trading volume, to examine the significance of trading volume in momentum profits. I assign stocks to 5 portfolios based on returns over the rank period and one of three portfolios based on the trading volume during 1 year before the test period. The intersections resulting from the two independent rankings give rise to 15 portfolios. I calculate the return of those portfolios over the subsequent test period.

Table 7.5

Volatility, Trading Volume and Momentum Profits

	Low Volume	Medium Volume	High Volume
Panel A: Losers			
Std L	1.00%	0.00%	-0.48%
	1.30	0.00	-0.93
Std M	-1.07%	-1.41%	0.60%
	-1.44	-2.01	0.88
Std H	-1.31%	-1.08%	-0.83%
	-1.80	-1.50	-1.15
Panel B: Winners			
Std L	1.50%	0.97%	1.76%
	2.67	2.15	2.93
Std M	0.66%	1.16%	0.91%
	1.28	1.74	1.62
Std H	-0.20%	0.09%	1.62%
	-0.30	0.12	2.83
Panel C: Arbitrage portfolio (W-L)			
Std L	**0.49%**	**0.96%**	**2.12%**
	0.85	**1.51**	**2.81**
Std M	**1.73%**	**2.58%**	**0.31%**
	1.91	**2.65**	**0.35**
Std H	**1.11%**	**1.18%**	**2.44%**
	1.11	**1.13**	**2.67**

This table examines whether trading volume affects momentum profitability after adjusting for volatility. Portfolios are formed using a three-way independent sort between rank period stock returns, rank period standard deviation (low-, medium- and high-standard deviation) and one year before the test period trading volume (low-, medium- and high-volume). This methodology allows generating a more equal standard deviation (trading volume) match across different trading volume (volatility) portfolios. *Std* denotes standard deviation.

7.3 CONCLUSION

This chapter examined whether momentum profitability is associated with firms' past volatility. I report that volatility has a significant impact on the size of momentum profits. Shares with high (low) rank period volatility tend to generate high (low) momentum profitability. For higher volatility equities, monthly continuation profits (W-L) are 0.70, 0.91, 1.20, 1.42 and 1.47 per cent, where the full sample displays momentum payoffs at 1.26 per cent per month. High volatility shares enjoy 0.77 (t-statistic=2.11) per cent higher monthly continuation profits than their counterpart low volatility companies. Volatility further has a positive impact on the size of momentum profits when medium- and large- capitalisation shares are employed. This is not true when small- size stocks are considered. It is further investigated the association between volatility, trading volume and the magnitude of continuation profits. After controlling for trading volume (volatility), volatility (trading volume) tends to keep influencing the magnitude of momentum profits.

Beyond the finding that momentum profits vary in portfolios formed on the basis of historical standard deviations, this study states further significant findings. Consistent with Liu et al. (1999) using UK data, it found that momentum strategies are feasible since they do provide profitability in other than only small capitalisation shares that exhibit liquidity problems. Constructing three size-portfolios, this study reports that the medium sized capitalisation portfolio displays the highest continuation profits (1.56 per cent per month), followed by the large (1.39 per cent per month) and then, by the small size group (0.74 per cent per month). Consistent further with Lee and Swaminathan (2000) who employ US data, this study shows that there exists a positive association between trading volume and momentum gains.

Chapter 8

MOMENTUM PROFITS FOLLOWING BULL AND BEAR MARKETS

8.1 INTRODUCTION

The aim of this chapter is to investigate the magnitude of momentum profitability in bull and bear markets. Momentum profits stem from the winner shares in bull markets and from the loser stocks in bear markets. But, are momentum profits stronger following bull or bear markets?

Recent studies have investigated the field without however reaching a consensus, since results from different data sets often conflict. Griffin et al. (2003) report that momentum profits are stronger following bear markets. The momentum profitability following bear markets is 1.53, 0.77, 0.55, 0.68 and 1.04 per cent per month in Africa, America, Asia, Europe and the US market respectively, while the continuation profits that follow bull markets tend to be lower, at 1.27, 0.73, -0.10, 0.76 and 0.31 respectively, in the same international markets. Rey and Schmid, (2003) using data from the Swiss Market, also state that momentum profits are stronger in a sub-period where a bear market is present.

However, Cooper et al. (2004) who employ US data alone from between 1929 and 1995 arrive at the opposite finding. Momentum profits that follow positive market returns are 0.93 per cent per month and continuation gains that follow negative market returns are –0.37 per cent per month. The paradox is that Griffin et al. (2003), among international markets, also include the US market from 1926 to 2000 and reach the opposite conclusion. Both studies employ monthly share returns for all NYSE and AMEX shares from CRSP and define bull and bear markets based on market performance. The different results that emerge when different data sets are examined pose an interesting query that requires further examination.

In addition, the impact of bull and bear markets in various finance fields shows that contradictory findings emerge when the full, the bull or the bear market periods are investigated. The beta-return relationship has been one of the most intriguing issues in modern finance[1]. Earlier studies (e.g., Black et al., 1972; Fama and MacBeth, 1973) reported that beta has only limited power to explain share returns. Results did not show a perfect relationship with the theoretical CAPM, but plot points were placed around the market line. Recent studies (e.g., Black, 1993; Fama and French, 1992) offer more criticism. Some researchers concluded that beta is dead and is not able to explain asset returns (e.g, Strong and Xu, 1997). However, Pettengill et al. (1995) examine beta in up and down markets. Using US data from 1936 to 1990, they find that in bull markets (when the market provides higher performance than the risk-free rate interest), there is a significant positive relation between beta and share returns, while in bear markets, there is an important negative association. Pettengill et al. (1995) conclude that beta is far from dead.

Value Line Ranking is a stock market anomaly that ranks shares from one to five according to their expected performances in the subsequent six to twelve months. Group 1 has the best return prospects, while group 5 the worst. Black (1973) reports that the top ranked group generates an excess return from the market of 10 per cent

[1] Fama and French (2003) extensively review the Capital Asset Pricing Model (CAPM).

per year, while the fifth category provides losses of 10 per cent per year. However, Moy et al. (1995) examine the profitability that Value Line Ranking provides in bull and bear markets. They find that this anomaly offers asymmetric profits; exceptionally high profits during bull markets (when market achieves positive return or higher performance than the risk-free rate interest), but a very poor performance during bear conditions. Thus, findings are contradictory depending upon whether the profitability of Value Line Ranking is analysed in the full period or in bull and bear markets separately.

In addition, the theory underpinning international diversification states that investors can maintain returns while reducing risk by holding shares from international exchanges (e.g., Solnik, 1974). This benefit stems from the negative correlation coefficients that may exist between returns in international stock markets. Butler and Joaquin (2002) examine the correlation in returns from countries in bear, normal and bull market periods. They find that when domestic returns move downwards, the equity prices in different international countries also decline. However, when domestic returns are normal or move upward, the same trend is not apparent in international data. In other words, the correlation among returns from different countries is significantly higher in down, rather than in calm and up, markets. Butler and Joaquin conclude that the benefits of diversification are weaker in bear market conditions.

Since studies using different data do not arrive at consensus for the association between momentum profits and bull and bear markets as well as since findings in various finance fields are not persistent when one investigates the full period or the bull and bear markets separately, this thesis intends to examine the magnitude of momentum profits following bull and bear markets using UK data. This chapter is organised as follows: section 8.2 reports the empirical findings, and section 8.3 concludes the chapter.

8.2 EMPIRICAL FINDINGS

8.2.1 Momentum Profits Following Bull and Bear Markets

I define bull and bear markets using two states; the state where average market returns (FTSE-All Share) prior to the test period are positive (bull condition) and negative (bear state). I examine various horizons to define the past market returns; using the performance of the market index over the past 1 month (Panel A of Table 8.1), 3 months (Panel B), 6 months (Panel C) and 12 months before the test period (Panel D)[2]. When longer periods to define the state of the market are employed, the number of periods in which the market index was negative is significantly lower due to the strong bull market on the LSE between 1975 and 2001. The market experienced negative performances in 20 (out of 51) periods when the 1 month definition is used, in 15 periods when the 3 months definition is employed, in 9 periods when the 6 months definition is used and in 7 periods when the 12 months definition is employed.

Table 8.1 shows that the momentum profits for all alternative definitions of bull and bear markets are stronger following bear conditions. For example, when the market performance over the previous six months is employed, monthly momentum profits are 1.86 per cent following bear markets and 1.13 per cent following bull markets. Therefore, investors can achieve superior momentum returns following the momentum strategy when the market returns over the past were poor. Momentum

[2] There are no negative average market returns when I consider the market performance in equal or longer than two-year periods. This happens because of the strong bull market on the UK market over the sample period.

profits are 1.26 per cent per month using the full periods, but investors can achieve monthly momentum profits of 1.55, 1.72, 1.86 and 2.15 undertaking the momentum strategy after the bear state. The longer the period to define the bear market, the smaller the number of periods in which the market index was negative and the stronger the momentum profits that achieved. Besides, investors that undertake the momentum strategy following the bear state are subject to limited buying and selling-short signals and thus, transaction costs can cover only a small part of the documented abnormal profitability.

Figures 8.1 to 8.4 show the momentum profits that generated following bull and bear markets for the alternative definitions of the states. An investor that adopts the momentum strategy after a bear state can hardly ever face losses throughout the sample period. The number of periods that a trader would achieve negative momentum returns is at maximum once.

Until now I investigated whether momentum profits vary following bull and bear markets. It is interesting to examine whether there exists a general association between momentum returns and past market returns. I separate seven states; 0-2 indicates the two periods when the market returns were at maximum, 0-5 shows the five periods when the market returns were the best and in a similar way I take also into account the periods; 0-10, 0-20, 0-30, 0-40 and 0-50. I employ this methodology for all four alternative definitions of the bull and bear states. Table 8.2 shows that including periods that past market returns were less significant, momentum profits tend to rise. For example, when the 6 months past market returns definition is employed, the monthly momentum profits are –1.16, -0.05, 0.17, 0.71, 1.00, 1.14 and 1.28 per cent moving to periods that include smaller magnitude of market profits. These findings indicate that a general negative association between W-L returns and past market performance exists.

In addition, a regression analysis is adopted to examine the relationship between momentum and market returns. Until now I investigated only the association between past market returns and continuation profits. It is interesting also to examine whether there is any association between the market returns over the test period and the momentum profits. I run the following regression:

$$W - L = a + b\_Past\_Market\_\mathrm{Re}turns + c\_Test\_Period\_Market\_returns + \varepsilon$$

Table 8.3 shows that the Pearson correlations between the dependent and both independent variables are negative. The stronger negative correlation is between momentum profits and lagged market returns, which is equal to -0.31 ($p<0.05$). Test period market returns and momentum profits are only slightly negative associated equal to –0.03. When the regression analysis is employed, the sensitivity on the lagged market factor is –0.31, which indicates a negative association between W-L and prior market returns and the coefficient is statistical significant at the 5% level. The sensitivity on the test period market factor shows that momentum profits are only slightly negative associated. These findings support that a general negative relationship between momentum profits and lagged market returns is documented when a new methodology is employed.

Table 8.1

Momentum Profitability Following Bull and Bear Markets

	$R_m \geq 0$	$R_m < 0$		$R_m \geq 0$	$R_m < 0$
	Panel A: 1 month			Panel B: 3 months	
L	-0.03%	0.17%	L	0.43%	-0.87%
	-0.05	0.37		0.84	-1.26
2	0.72%	1.06%	2	1.05%	0.38%
	1.42	2.89		2.44	0.74
3	0.92%	1.25%	3	1.22%	0.64%
	2.02	3.25		3.06	1.36
4	1.08%	1.47%	4	1.40%	0.84%
	2.37	3.83		3.46	1.87
W	1.04%	1.72%	W	1.50%	0.85%
	1.82	4.75		2.99	1.92
W-L	1.08%	1.55%	W-L	1.07%	1.72%
	1.26	2.67		1.50	2.09
	Panel C: 6 months			Panel D: 12 months	
L	0.18%	-1.02%	L	0.17%	-1.30%
	0.66	-1.14		0.62	-1.45
2	0.83%	0.55%	2	0.85%	0.29%
	4.27	0.86		4.42	0.45
3	1.02%	0.76%	3	1.01%	0.74%
	5.96	1.60		5.92	1.55
4	1.20%	0.96%	4	1.18%	1.01%
	6.80	2.63		6.70	2.77
W	1.32%	0.84%	W	1.30%	0.85%
	5.08	2.34		4.99	2.36
W-L	1.13%	1.86%	W-L	1.12%	2.15%
	2.98	1.92		3.04	1.82

$R_m \geq 0$ and $R_m < 0$ represent periods when the market index (FTSE-All share) generates positive and negative past performances respectively. Panels A, B, C and D use respectively 1, 3, 6 and 12 months market performance prior to the test period to define the bull and bear states.

Table 8.2. Momentum Profits and Past Market Returns

	0-2	0-5	0-10	0-20	0-30	0-40	0-50
Panel A: 1 month							
L	1.20%	0.15%	-0.65%	1.00%	-0.04%	-0.05%	-0.04%
	0.69	0.16	-0.75	1.45	-0.07	-0.11	-0.09
2	1.29%	0.64%	-0.02%	1.38%	0.67%	0.75%	0.76%
	0.69	0.82	-0.03	2.33	1.27	1.89	2.29
3	1.73%	0.90%	0.23%	1.51%	0.88%	0.96%	0.97%
	1.15	1.19	0.32	2.63	1.87	2.69	3.13
4	1.99%	0.98%	0.23%	1.61%	1.03%	1.12%	1.15%
	1.28	1.21	0.30	2.64	2.20	3.15	3.72
W	2.71%	1.27%	-0.20%	1.50%	1.00%	1.13%	1.23%
	1.78	1.33	-0.19	1.89	1.69	2.52	3.27
W-L	1.52%	1.12%	0.45%	0.50%	1.04%	1.18%	1.27%
	0.66	0.83	0.33	0.47	1.18	1.46	2.25
Panel B: 3 months							
L	-0.70%	1.02%	0.21%	0.97%	0.21%	0.06%	0.02%
	-0.19	0.67	0.24	1.49	0.35	0.11	0.04
2	-0.54%	1.18%	0.65%	1.55%	0.90%	0.83%	0.84%
	-0.15	0.78	0.80	2.59	1.77	2.02	2.43
3	-0.71%	0.88%	0.67%	1.59%	1.06%	1.02%	1.04%
	-0.18	0.59	0.88	2.75	2.23	2.68	3.25
4	-0.85%	0.53%	0.54%	1.62%	1.22%	1.21%	1.22%
	-0.19	0.34	0.68	2.63	2.56	3.17	3.82
W	-1.70%	-0.31%	0.14%	1.53%	1.24%	1.34%	1.30%
	-0.29	-0.14	0.13	1.94	2.12	2.86	3.38
W-L	-1.00%	-1.33%	-0.07%	0.56%	1.03%	1.28%	1.28%
	-0.14	-0.50	-0.05	0.55	1.23	1.85	2.23
Panel C: 6 months							
L	-0.07%	0.59%	0.80%	0.19%	0.16%	0.41%	0.02%
	-0.02	0.37	0.81	0.31	0.34	0.94	0.04
2	0.52%	1.07%	1.05%	0.79%	0.82%	1.05%	0.84%
	0.11	0.62	1.11	1.49	2.06	2.87	2.43
3	0.30%	1.05%	1.18%	0.89%	0.98%	1.24%	1.04%
	0.06	0.57	1.21	1.59	2.43	3.52	3.25
4	0.08%	0.96%	1.24%	0.94%	1.09%	1.43%	1.22%
	0.02	0.49	1.21	1.65	2.68	3.92	3.82
W	-1.23%	0.55%	0.97%	0.90%	1.16%	1.56%	1.30%
	-0.19	0.23	0.81	1.41	2.34	3.48	3.38
W-L	-1.16%	-0.05%	0.17%	0.71%	1.00%	1.14%	1.28%
	-0.54	-0.06	0.11	0.37	1.45	1.83	2.31
Panel D: 12 months							
L	1.98%	0.85%	0.62%	0.13%	0.11%	0.42%	0.10%
	0.89	0.57	0.63	0.20	0.19	0.96	0.23
2	2.50%	1.12%	1.18%	0.79%	0.76%	1.05%	0.87%
	0.89	0.69	1.35	1.43	1.68	2.80	2.52
3	2.22%	0.97%	1.14%	0.98%	0.96%	1.20%	1.06%
	0.73	0.57	1.17	1.72	2.18	3.35	3.32
4	2.46%	0.97%	1.24%	1.11%	1.14%	1.34%	1.25%
	0.84	0.54	1.22	1.91	2.48	3.67	3.90
W	2.26%	0.42%	1.00%	1.06%	1.12%	1.40%	1.35%
	0.77	0.19	0.86	1.64	2.02	3.19	3.51
W-L	0.27%	-0.42%	0.38%	0.93%	1.01%	0.98%	1.25%
	0.07	-0.16	0.25	1.01	1.31	1.57	2.18

This table shows the momentum profits generated in alternative past market returns. For example, 0-2 indicates the two periods when the market returns were at maximum, 0-5 shows the five periods when the market returns were the best and in a similar approach I take also into account the periods; 0-10, 0-20, 0-30, 0-40 and 0-50. Panels A, B, C and D use respectively 1, 3, 6 and 12 months market performance prior to the test period to define the bull and bear states.

Table 8.3

Momentum Profits, Past and Present Market Returns

$$W-L = a + b\_Past\_Market\_\text{Re}turns + c\_Test\_Period\_Market\_returns + \varepsilon$$

a	b	c	R^2
1.63%	-0.311	-0.008	0.06
(5.36)	(-2.26)	(-0.06)	

Pearson Correlation			
	W-L	Past Market Returns	Test Period Market Returns
W-L	1		
Past Market Returns	-0.31*	1	
Test Period Market Returns	-0.03	0.08	1

* $p < 0.05$

Figure 8.1

Momentum Profits following Bull and Bear States: 1 Month

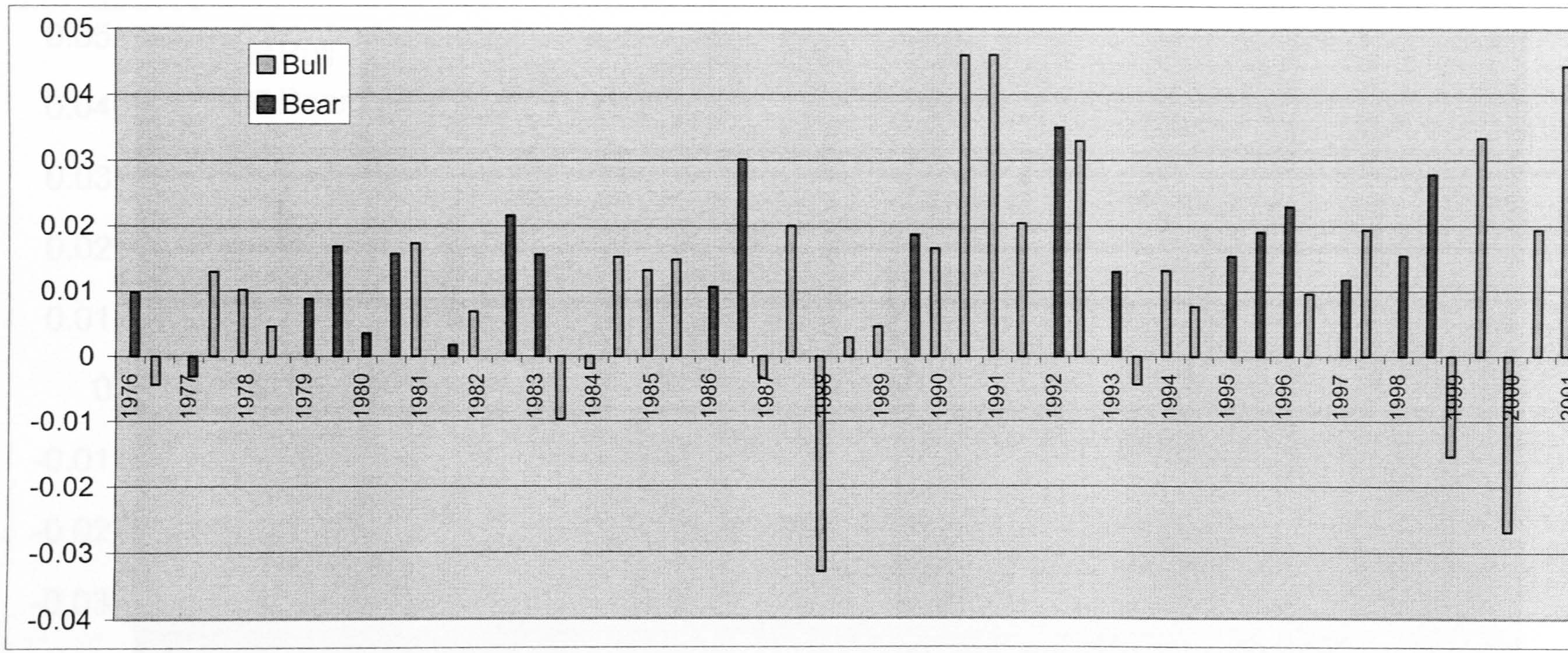


Figure 8.2

Momentum Profits following Bull and Bear States: 3 Months

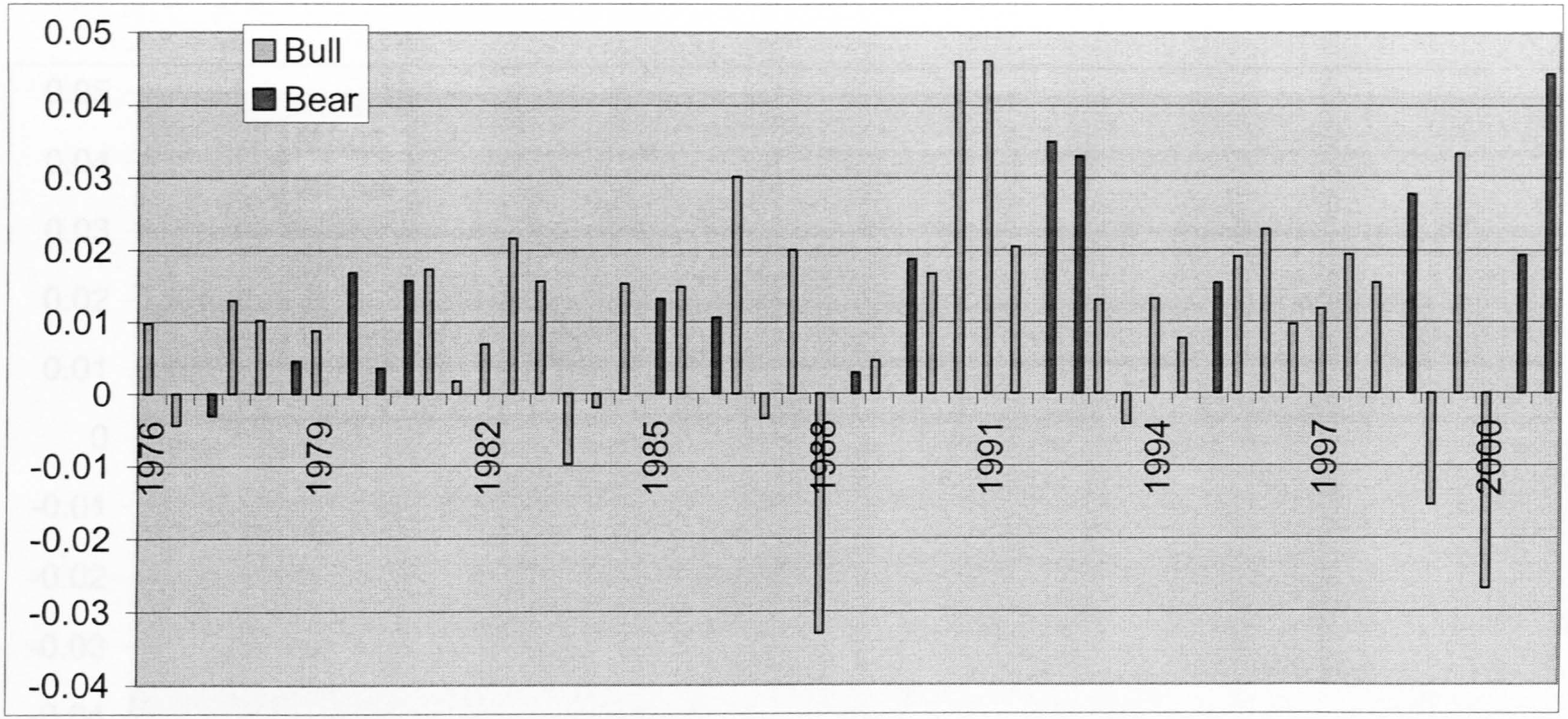


Figure 8.3

Momentum Profits following Bull and Bear States: 6 Months

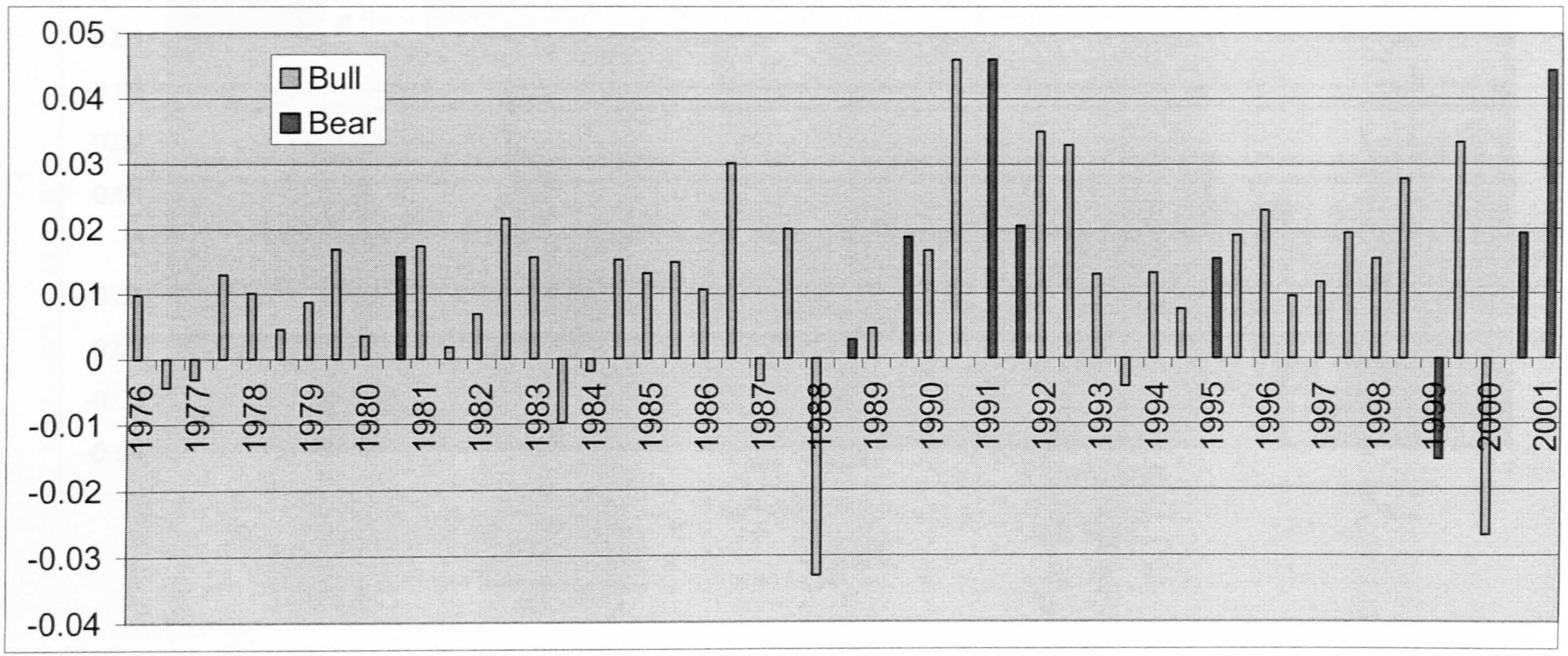
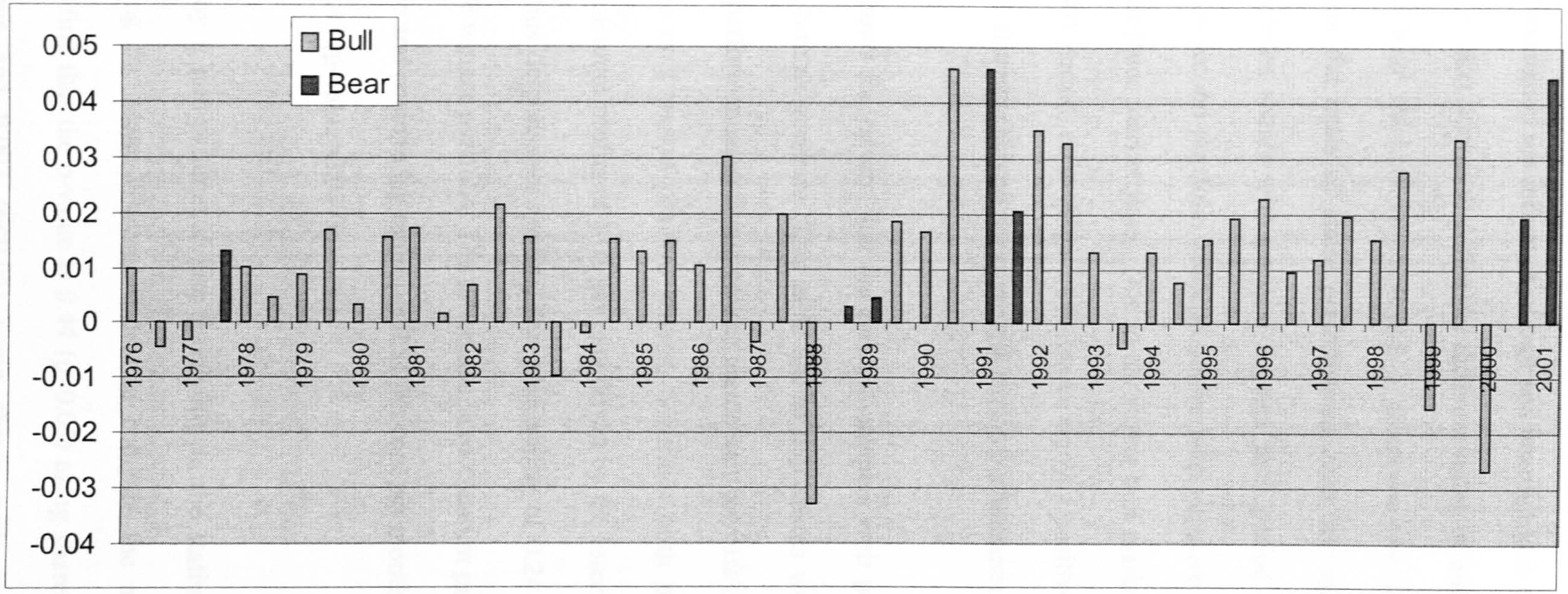


Figure 8.4

Momentum Profits following Bull and Bear States: 12 months



8.2.2 A More Extreme Definition of Bull and Bear Markets

Until now I examined the influence of bull and bear markets on momentum profits focusing on market returns to define the different states. A more extreme definition of bull and bear markets is employed. I construct two portfolios by sorting companies on the basis of share performances over the rank period. The first portfolio includes shares with positive average rank period returns (bull market state) and the second portfolio contains shares with negative average rank period performances (bear market state). Due to the strong bull market on the LSE during the 1975-2001 period, on average 1,184 stocks enjoyed positive rank period returns and only 701 shares achieved negative rank period performances.

Table 8.4 shows the returns that the two sub-samples with positive and negative rank period returns generate. This table shows that shares with negative average rank period performances generate greater momentum payoffs than their counterpart with average rank period positive returns. Securities with prior losses generate monthly momentum profits of 1.05 per cent driven by the loser portfolio and shares with past gains demonstrate continuation profitability of 0.24 per cent per month driven by the winner portfolio. The difference in momentum profits between shares with negative and positive lag returns is 0.81 per cent per month with a significant t-statistic of 2.43 (p-value=0.017).

I also employ a non-parametric test to investigate the statistical significance of returns. Using the Mann-Whitney U test to compare the means of the W, L portfolios, I find that the p-value is 0.44 ($p>0.05$) using shares with positive rank period returns and 0.003 ($p<0.05$) using shares with negative rank period performances. Then, I find that the p-value is 0.012 (p<0.05) when I compare the momentum returns generated in shares with positive and negative past returns. These suggest that using a non-parametric test findings concur with those generated using a parametric test. Momentum profits are more pronounced in shares with negative lag returns and the difference in momentum returns between shares with positive and negative returns is statistically significant.

	Median	Parametric p-value	Non-parametric p-value
W-L following bull markets	0.25%	0.41	0.44
W-L following bear markets	1.10%	0.011	0.003

This study further defines bull market for shares that provide positive returns for each month of the rank period. There are on average only 126 shares that meet that condition. Similar to the other definition of bull market, shares with positive returns in each of the rank period generate economically insignificant momentum profits of 0.31 (t-statistic=0.55) per cent per month.

To explain the large magnitude of momentum profits in shares with poor lagged returns, I consider the disposition effect that states that investors tend to sell winners and hold on to losers. Therefore, past loser shares appear to keep the momentum in returns, while prior winner shares tend not to display significant continuation in prices. The finding that momentum profits are stronger following bear markets is also consistent with Chapter 7 where I reported that there exists a strong positive association between momentum profits and volatility. Koutmos (1999) finds that volatility is significantly higher in bear markets. Considering the result of Chapter 7 with Koutmos's finding, we would expect that bear markets display high volatility and demonstrate high momentum profits.

I also address the issue in general and analyses whether the profitability of momentum strategies is related to past share returns. To test this assertion, five approximately equal number of stock portfolios are constructed based on monthly share returns in the rank period: shares with prior losses over –2 per cent, between -2 and 0 per cent, from 0 to 2 per cent, from 2 to 5 per cent and over 5 per cent and I calculate the continuation profits that the above five portfolios demonstrate.

Table 8.5 shows that when we move from securities with high prior losses to shares with large rank period gains, momentum profitability tends to fall. Monthly momentum profits are 0.89 per cent for shares with prior losses over –2 per cent, 0.18 per cent for shares with prior losses between -2 and 0 per cent, 0.04 per cent for companies with slight gains from 0 to 2 per cent, 0.22 per cent for shares with significant gains from 2 to 5 per cent and –0.42 per cent for firms with extreme past gains over 5 per cent. In other words, shares that demonstrated over 5 per cent past gains generate monthly continuation profits of –0.42 per cent. This suggests that there exists a negative association between share returns and momentum profits, which is driven by the loser portfolio.

Table 8.4

Momentum Profitability in Shares with Negative and Positive Past Returns

	$R_i \geq 0$	$R_i < 0$
L	0.97%	-0.31%
	6.16	-0.83
2	1.09%	0.22%
	7.35	0.85
3	1.12%	0.26%
	7.12	1.13
4	1.25%	0.59%
	7.00	3.05
W	1.21%	0.75%
	5.08	4.67
W-L	**0.24%**	**1.05%**
	0.84	**2.62**

This table indicates bull and bear markets applying to security returns. Two portfolios are formed by sorting by share performance over the rank period: shares with either positive or negative average rank returns, and I examine the continuation that these two portfolios demonstrate. $R_i \geq 0$ and $R_i < 0$ represent shares with positive and negative past performances respectively.

Table 8.5

Momentum Profitability and Past Share Returns

	$R_i < -2\%$	$-2\% \le R_i < 0\%$	$0\% \le R_i < 2\%$	$2\% \le R_i < 5\%$	$5\% \le R_i$
L	-0.54%	0.51%	1.03%	1.06%	1.33%
	-1.25	2.20	4.56	6.57	6.45
2	0.00%	0.70%	0.87%	1.01%	1.30%
	-0.01	3.56	5.53	5.32	5.90
3	0.19%	0.68%	1.03%	1.21%	1.35%
	0.66	3.51	6.86	7.59	5.76
4	-0.01%	0.74%	0.95%	1.33%	1.39%
	-0.06	4.14	5.61	7.14	5.82
W	0.35%	0.69%	1.07%	1.28%	0.91%
	1.72	4.24	7.20	6.88	2.62
W-L	**0.89%**	**0.18%**	**0.04%**	**0.22%**	**-0.42%**
	1.86	**0.63**	**0.14**	**0.88**	**-1.03**

This table addresses the issue in general and analyses whether the profitability of momentum strategies is related to past share returns. Five portfolios are constructed based on share returns in the rank period: shares with prior losses over -2, between -2 and 0, from 0 to 2, from 2 to 5 and over 5 per cent per month and I calculate the continuation that the above five portfolios demonstrate.

8.3 CONCLUSION

This chapter investigated whether different market states influence the magnitude of momentum profitability. The motivation to investigate that association is that opposite findings are emerged in various finance fields when the full, the bull or the bear market periods are investigated separately (e.g., Pettengill et al., 1995). Besides, Griffin et al. (2003) who employed international data, and Cooper et al. (2004) who used US data alone, found opposite findings according to which state generates stronger momentum profits. Griffin et al. document that continuation gains are stronger following bear markets and Cooper et al. report that momentum profits are larger following bull markets. This study investigated the momentum profits generated following bull and bear markets using UK data.

This study classified bull and bear markets based on two definitions: individual share returns and market index performances. Findings shown that continuation profits are stronger following negative share and market returns, which might be a reflection of mean reversion in the market. Shares with prior losses (gains) generate on average 1.05 (0.24) per cent monthly momentum profitability and when the lagged 6-month market returns are negative (positive), monthly momentum profits are 1.86 (1.13) per cent. These suggested that investors can achieve superior momentum returns following the momentum strategy when the market return over the rank period is negative.

One suggestion that may help explain the high momentum profits in shares with poor lagged returns would be to reconcile the findings of this chapter with the disposition effect that states that investors tend to sell winners and to hold on to losers. Therefore, past loser shares appear to keep the momentum in returns, while prior winner shares tend not to display significant continuation in prices.

Further analysis addressed the issue in general and analysed whether the profitability of momentum strategies is related to past market/share returns. I separated different states according to the past market and share performances and I run a regression to investigate whether the past market returns as an independent variable can influence significantly the momentum profits as a dependent variable. Overall, I found that tests supported the existence of a general negative association between momentum profits and market/share returns.

Chapter 9

REVERSAL, MOMENTUM AND HYBRID STRATEGIES

9.1 INTRODUCTION

Chapter 3 reviewed the winner-loser effect rather than the momentum effect only. The motivation was that momentum, short-, and long-term overreaction effects are similar anomalies using different time horizons. This section undertakes an out-of-sample test of whether a strategy that combines long-term overreaction and momentum effects can generate significant abnormal profits. The overreaction anomaly utilises long-horizon returns and proposes a strategy that buys past losers and sells short prior winners. The momentum effect focuses on medium-horizon returns and suggests a strategy that buys prior winners and sells short past losers. The combination strategy buys past losers over the long-period and past winners over the medium-horizon.

Balvers and Wu (2002) employ international market indexes and introduce a strategy that reconciles momentum and reversal effects. They bought country indexes with the best returns over the past medium-term horizon and with the worst returns over the prior long-term period. They report that the combination method generates significantly superior gains than the individual momentum and reversal strategies. This study examines whether Balvers and Wu's finding is limited to market index data only. I use share returns from the London Stock Exchange and employ only the representative momentum and overreaction strategies.

This chapter is organised as follows: section 9.2 reports the empirical findings and section 9.3 concludes the chapter.

9.2 EMPIRICAL FINDINGS

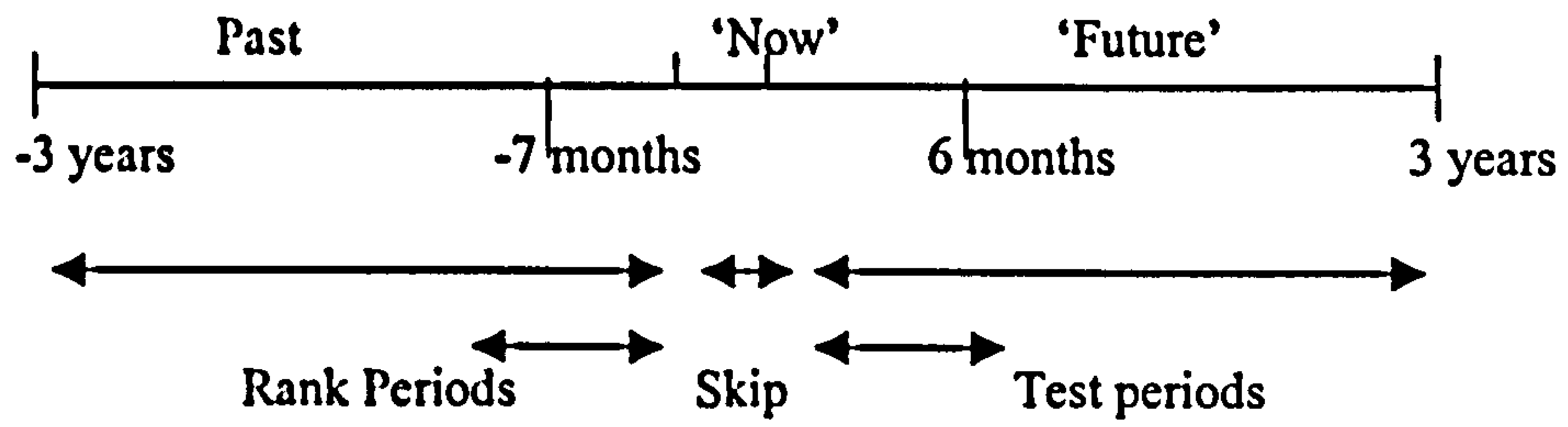
A similar methodology used for the momentum effect is applied to calculate the overreaction profits when different time horizons are analysed. To calculate the reversal profits, only the representative overreaction strategy is examined where three years rank and three years for the test period has being analysed. Five portfolios are generated by sorting shares on the basis of their previous three-year returns (rank period). W represents the portfolio with the best past performance and L indicates the portfolio with the worst prior return. I calculate the equal-weighted returns of the quintile portfolios over the following three years (test period). This procedure is repeated for each non-overlapping three-year period. The arbitrage portfolio L-W, which buys previous losers and sells short past winners, indicates the gains.

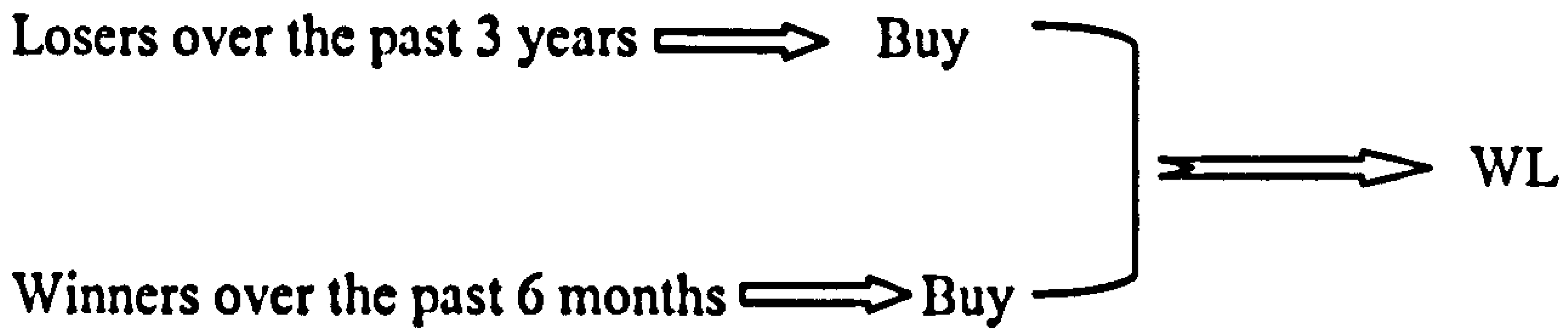
This study investigates whether the pure long-term reversal strategy generates economic profits using our sample of firms. Panel A of Table 9.1 shows that monthly portfolio returns are 0.83 per cent in the loser portfolio, 0.90 per cent in the second portfolio, 1.00 per cent in the third portfolio, 0.77 per cent in the fourth portfolio and 0.58 per cent in the winner portfolio. Therefore, past losers outperform prior winners over the test period by 0.25 (t-statistic=0.54) per cent per month. Although losers generate on average only slightly higher gains than their counterpart winners, losers outperformed winners in 75 per cent of the test periods.

Interestingly, the magnitude of profits is approximately five times lower using the reversal strategy than employing the counterpart momentum approach.

These results concur with the findings of Campbell and Limmack (1997) and Clare and Thomas (1995) who using UK data, report that contrarian payoffs are weaker than those documented by DeBondt and Thaler (1985) who employ US data. The basic difference between DeBondt and Thaler and this study is the definition of winners and losers. They only employ the top and bottom 35 stocks to form portfolios, when the selection of extreme winners and losers produces high reversal gains.

We now examine the profitability that a hybrid strategy can offer. This study investigates whether a strategy that buys prior winners over the previous six months and prior losers over the past three years can enjoy superior gains. Based on reversal and momentum portfolios, a hybrid strategy is followed. A portfolio is formed that buys past winners over the previous six months and past losers over the past three years. The performance of this portfolio is calculated over the subsequent test period. This strategy is defined as WL where W shows the portfolio bought in medium-horizon and L demonstrates the portfolio bought in long-horizon.





Consistent with Balvers and Wu (2002), Panel A of Table 9.1 shows that the combination portfolio achieves large profits at 1.29 (t-statistic=3.54) per cent per month driven by the winner portfolio. This suggests that this method enjoys significantly higher yield than the counterpart reversal strategy. However, in contrast to Balvers and Wu, the combination strategy demonstrates only a little higher return than the momentum method on its own. This suggests that Balvers and Wu's findings hold partially when we employ UK share returns.

This study further examines whether the profitability of the hybrid strategy varies during different sub-periods. Panel B of Table 9.1 studies the 1975-1987 period, when the returns across all quintile portfolios are strong, and shows that the WL strategy enjoys much higher payoffs than both reversal and momentum strategies. The magnitude of the hybrid profits extends to 2.01 (t-statistic=3.63) per cent per month. However, Panel C shows that from 1988 to 2001, when the performances across all quintile portfolios are low, the WL approach achieves gains of only 0.55 (t-statistic=1.31) per cent. Therefore, the out performance of the combination strategy is most pronounced in the first sub-period when all quintiles enjoy significant returns.

Table 9.1

Overreaction, momentum and hybrid strategies

	Reversal strategy	t-statistics	Momentum strategy	t-statistics	Hybrid strategy	t-statistics
Panel A: Entire period (1975-2001)						
L	0.83%	2.33	0.05%	0.11		
2	0.90%	2.75	0.85%	2.54		
3	1.00%	3.94	1.05%	3.38		
4	0.77%	2.67	1.23%	3.97		
W	0.58%	2.00	1.31%	3.51		
Arbitrage portfolios	0.25%	0.54	1.26%	2.26	1.29%	3.54
Panel B: 1975-1987						
L	1.59%	6.32	1.27%	2.65		
2	1.54%	5.02	1.72%	3.82		
3	1.48%	4.59	1.85%	4.14		
4	1.35%	4.31	2.01%	4.24		
W	1.17%	4.00	2.05%	3.52		
Arbitrage portfolios	0.42%	1.09	0.78%	1.03	2.01%	3.63
Panel C: 1988-2001						
L	0.07%	0.19	-1.13%	-1.90		
2	0.26%	0.71	0.02%	0.05		
3	0.52%	2.50	0.28%	0.73		
4	0.19%	0.74	0.49%	1.38		
W	0.00%	0.00	0.60%	1.37		
Arbitrage portfolios	0.07%	0.15	1.73%	2.34	0.55%	1.31

This table shows the momentum, reversal and combination profits generated. Following the reversal strategy, W and L portfolios are constructed based on share returns over the past three years and following the momentum method, they are constructed based on stock performances over the past six months. Arbitrage portfolios are: L-W in the reversal strategy, W-L in the momentum approach and WL (buy past winners over the previous six months and buy prior losers over the past three years) in the hybrid method.

9.3 CONCLUSION

This chapter briefly investigated whether investors can enjoy superior performances by combining the momentum and reversal effects. A combination portfolio was formed that buys past winners over the previous six months and past losers over the past three years. Overall, results concur partially with Balvers and Wu (2002). The hybrid strategy provides significant abnormal profits at 1.29 per cent per month. This profitability is significantly larger than that gained by the counterpart reversal strategy, but only a little higher than that found by the momentum strategy. The hybrid strategy tends to outperform significantly both counterpart methods during strong bull markets.

Chapter 10

CONCLUSIONS

10.1 SUMMARY

This study investigated a field concerned with stock market anomalies, by analysing the momentum effect that states that shares achieving the highest (lowest) performance over the previous three to twelve months continue to perform well (disappointingly) over the subsequent three to twelve months. The thesis was separated into eight main chapters.

Chapters 2 and 3 presented the review of the relevant literatures. Chapter 2 looked at the main topic of market efficiency and highlighted that the debate about the efficient market hypothesis is far from over. There are various investment strategies that promise risk-adjusted returns in excess of the market performance. For instance, small capitalisation shares achieve higher returns than their large capitalisation counterparts (Banz, 1981); shares demonstrate significantly higher performances during the month of January (Rozeff and Kiney, 1976); low P/E equities appear to outperform shares in high P/E firms (Basu, 1977). However, these stock market anomalies have themselves been the subject of severe criticism. Investigation has limitations in comparison to investing in stock markets, since academics use past data and do not include transaction and information costs; the profitability of stock market anomalies is sensitive to the market and the period analysed (Fama, 1998); professional traders cannot usually outperform the market on a consistent basis (Malkiel, 2003).

Chapter 3 provided a detailed survey of one specific investment strategy. Because of the close relationship between momentum, and short- and long-term overreaction effects, the whole winner-loser anomaly was surveyed. This study reviewed investigations that have rationalised the winner-loser effect by examining factors such as risk, size, trading volume, microstructure effects, industry, business cycle and behavioural finance. For example, Moskowitz and Grinblatt (1999) report that an industry factor can explain the momentum profits, Lee and Swaminathan (2000) document that different trading volume portfolios generate different momentum payoffs, Chordia and Shivakumar (2002) demonstrate that the business cycles of an economy influence the magnitude of continuation payoffs. Nevertheless, the rationale behind the effect appeared to be the most intriguing issue in the literature, since its alternative explanations were not supported by different data sets and methodologies. For instance, Chordia and Shivakumar (2002), excluding Nasdaq stocks from Moskowitz's and Grinblatt's sample and examining an alternative breakdown for defining winners and losers, argue that in these circumstances, the industry factor cannot explain the continuation profitability. The opposite findings emerge using different data sets indicating a need for further empirical investigation into the rationale behind this anomaly.

Since chapter 4 explained the selection of data and the methodology of calculating momentum profitability, Chapter 5 reported the continuation profits that are generated from my data. This study has found approximately the same magnitude of momentum profitability as other investigations that have employed UK (e.g., Liu et al., 1999) and international data (e.g., Rouwenhorst, 1998). Using two different samples, the full and the accounting sub-sample, it was demonstrated that the momentum profitability is slightly higher than 1 per cent per month, but that the magnitude varied according to the sub-period is analysed. Momentum profitability was considerably higher between 1989 and 1993. In addition, this thesis reported that the anomaly is not restricted to the extreme winner and loser portfolios, but occurs in all portfolios. The raw monthly portfolio returns are 0.05, 0.85, 1.05, 1.23 and 1.31 per cent when we move from the past losers to winners. Momentum profits became even stronger when I employed compounding portfolio returns, rather than simple arithmetic. This finding indicates that the momentum profits cannot be explained by different methods of calculating abnormal returns. Further analysis demonstrated that the size effect, trading volume and book-to-market ratios cannot subsume the profitability of the momentum effect. The winner portfolio tends to include shares with a higher market value and trading volume and lower book-to-market than the loser portfolio.

The subsequent chapters attempted to discover some factors that influence the momentum profitability and have not been previously tested. From the sixth to the eight chapter, three factors that influence the magnitude of continuation profitability were investigated. Chapter 6 reported that momentum profits are influenced by the particular trading mechanism under which shares are bought and sold. First, I considered the Big Bang, which occurred on 27th October 1986 and had as a result the introduction of the automated SEAQ system and the shift of the LSE from floor-based market to an automated market. I calculated the momentum profits generated before and after the Big Bang. Findings indicated that shares traded in an automated structure generate much higher continuation profits than equities operated on a floor-based system. These results persisted after controlling for size, book-to-market and risk. Findings confirm the results of Hon and Tonks (2003) who demonstrate that momentum strategies could not provide profitability in a sub-period from 1955 to 1976. But the results contradict the findings of Liu et al. (1999) who suggest approximately the same momentum profitability between 1977-1987 and 1988-1998. There is a difference between Liu et al. and this investigation, since they examine weekly stock returns from Datastream and this study investigates monthly share returns from the LSPD.

Second, I considered the introduction of the SETS auction mechanism, which occurred on 20th October 1997 and had as a result the shift of the LSE from the pure dealership market to the SETS system. All FTSE 100 stocks, and later some additional large companies from the FTSE250, have been traded on the SETS auction system. Results showed that shares traded on the SETS order-driven system tend to demonstrate larger continuation profits than shares traded on the SEAQ quote-driven system. The difference in momentum profits between the two structures increases significantly after considering size differences. Companies traded on SETS are the largest capitalisation shares and consistent with Hong et al. (2000), they would expect to demonstrate low rather than large momentum returns.

Beyond the finding that momentum profits vary under alternative market structures, Chapter 6 reported other interesting results. I found that momentum profits are significant when we use all listed companies on the LSE (over 6000 shares), a sub-sample of 2000 shares with additional accounting information and a small number of 266 stocks with complete return information from 1975 to 2001. It further documented that momentum profits persist after controlling for size, book-to-market and risk as defined by either the CAPM or the three-factor model. These findings suggest that the momentum effect persists on the LSE using various data sets and after controlling for various factors that influence share returns.

Chapter 7 examined whether momentum profitability is associated with firms' rank period volatility. I reported that volatility has a significant impact on the size of momentum profits. Shares with high (low) rank period volatility tend to generate high (low) momentum profitability. For higher volatility equities, monthly continuation profits (W-L) are 0.70, 0.91, 1.20, 1.42 and 1.47 per cent, where the full sample displays momentum payoffs at 1.26 per cent per month. High volatility shares enjoy 0.77 (t-statistic=2.11) per cent higher monthly continuation profits than their low volatility counterpart companies. Volatility further has a positive impact on the size of momentum profits when medium- and large- capitalisation shares are employed. This is not true when small- size stocks are considered. It is further investigated the association between volatility, trading volume and the magnitude of continuation profits. After controlling for trading volume (volatility), volatility (trading volume) tends to keep influencing the magnitude of momentum profits.

Beyond the finding that momentum profits vary in portfolios formed on the basis of historical standard deviations, this study states further significant findings. Consistent with Liu et al. (1999) using UK data, it found that momentum strategies are feasible since they do provide profitability in other than only small capitalisation shares that exhibit liquidity problems. Constructing three size-portfolios, this study reports that the medium sized capitalisation portfolio displays the highest continuation profits (1.56 per cent per month), followed by the large (1.39 per cent per month) and then, by the small size group (0.74 per cent per month). Consistent further with Lee and Swaminathan (2000) who employ US data, this study shows that there exists a positive association between trading volume and momentum gains.

Chapter 8 investigated whether different market states influence the magnitude of momentum profitability. The motivation to investigate such an association arises because contradictory findings emerge in various finance fields when the full, the bull or the bear market periods are investigated separately (e.g., Pettengill et al., 1995). This study classified bull and bear markets based on two definitions: individual share returns and market index performances. Findings show that continuation profits are stronger following bear markets. Shares with losses (gains) over the rank period generate on average 1.05 (0.24) per cent monthly momentum profitability; when the market returns are negative (positive) during the rank period, monthly momentum profits are 1.86 (1.13) per cent.

Further analysis addressed the issue in general and analysed whether the profitability of momentum strategies is related to past market/share returns. I separated different states according to the past market and share performances and I run a regression to investigate whether the rank period market returns as an independent variable can influence significantly the momentum profits as a dependent variable. Overall, I found that tests supported the existence of a general negative association between momentum profits and market/share returns.

Chapter 9 further investigated whether investors can enjoy superior performances by combining the momentum and reversal effects. A combination portfolio was formed that buys past winners over the previous six months and past losers over the past three years. Overall, results concur partially with Balvers and Wu (2002). The hybrid strategy provides significant abnormal profits at 1.29 per cent per month. This profitability is significantly larger than that gained by the counterpart reversal strategy, but only a little higher than that found by the momentum strategy. The hybrid strategy tends to outperform significantly both counterpart methods during strong bull markets.

10.2 IMPLICATIONS

This study reported important information for investors. Traders can generate superior momentum profits when they trade shares under automated than floor systems. Pre-Big Bang monthly momentum profits are 0.73 per cent under the floor system and 2.14 per cent under the automated system. Investors can achieve stronger momentum profits when they trade shares under an auction system, since monthly momentum profits for shares traded with the SETS mechanism are 2.94 per cent.

Investors can achieve superior momentum returns following the momentum strategy on shares with high volatility. When large capitalisation shares are employed, shares with the highest rank period volatility generate 2.35 per cent per month momentum profits. A combination strategy that buys winner shares with low rank period volatility and sells short loser shares with high rank period volatility generate momentum profits at the size of 1.95 per cent per month.

Traders can gain stronger size of abnormal returns selecting to follow the momentum strategy in periods when the market return over the past was poor. Investors can achieve monthly momentum profits of 1.55, 1.72, 1.86 and 2.15 undertaking the momentum strategy after the bear state. The longer the period to define the bear market, the smaller the number of periods in which the market index was negative and the stronger the momentum profits that achieved. Besides, investors that undertake the momentum strategy following the bear state are subject to limited buying and selling-short signals and thus, transaction costs can cover only a small part of the documented abnormal profitability. These findings are important for investors, since the momentum effect provides stronger returns in difficult-bear periods.

Investors can accomplish significant abnormal profits when they combine the momentum with the long-term overreaction effects. A strategy that buys the shares with the best returns over the previous 6 months and buys the shares with the worst returns over the past 3 years achieves large profits at 1.29 per cent per month. This profitability is only slightly higher than that achieved by the conventional momentum strategy. Nevertheless the advantage of the hybrid strategy is that proposes only to buy shares, while to follow the momentum strategy one has to sell-short shares, a strategy that is a subject of restrictions on the size, price and types of stocks.

This study further reported important information for academics. I documented strong findings against the weak form of stock market efficiency. When a simple strategy that bases on past share returns is employed, systematic profits are generated. The momentum strategy displays abnormal returns in around 85 per cent of the test periods. The momentum strategy is strong when different data are employed. I found that momentum profits are significant when I use all listed companies on the LSE (over 6000 shares), a sub-sample of 2000 shares with additional accounting information, the SETS sample of 150 shares and a small number of 266 stocks with complete return information from 1975 to 2001. Beyond economic significant profitability, the momentum effect also generates statistical significant abnormal returns. The W-L portfolio provides statistical significance at 5 percent when parametric and non-parametric methods were employed. The momentum profitability remains strong when different methods to calculate the abnormal profitability used. Both simple arithmetic average returns and compound returns report that the continuation strategy provides profitability. Momentum profits even remain when I control for other stock market anomalies such as the size and the book-to-market effects and when I control for risk defined by the CAPM and the three-factor model.

The evidence presented in this thesis helps further understanding of the pattern of share returns over medium-term horizons. A significant portion of momentum profitability stems from the magnitude of volatility. When market is highly volatile, share prices tend to display wide out returns and therefore, high magnitude of momentum profitability is achieved. Momentum profits tend to be significantly higher in recent periods, when the market has been characterised by high volatility. Nevertheless when investors invest in high volatility shares, they should be awarded with stronger returns for the risk they accept. Until now no other study shown the role of volatility in influencing momentum profits and I suggest that studies should incorporate volatility before undertaking a further investigation.

This study reported findings that contradict the concept of Hong and Stein (1999) that the momentum effect arises from the gradual expansion of information among investors. I reported that the SETS sample, in which share prices adjust more quickly to news, generate stronger continuation profits than the counterpart shares traded in the dealer structure. In addition, consistent to Hong and Stein model, when there exists a decreasing risk aversion, the result is a greater delayed overreaction and so, stronger momentum profits. Considering that the risk-aversion of investors decreases when their wealth increases (e.g., Campbell and Cochrane, 1999), the Hong and Stein model predicts that momentum profits are stronger following bull markets. This prediction contradicts the findings reported in this study, since momentum profits are significantly higher following bear markets. These findings show how fragile is the investigation of behavioural models when empirical data are used. Hong et al. (2000) and Doukas and McKnight (2003) associate the speed of information that flows among investors with the size and the analyst coverage of companies[1] and they support the theoretical findings of the model.

This study further documented results that contradict the model of Daniel et al. (1998) that the momentum effect stems from the investors' overconfidence that increases following the arrival of confirming news. Traders' overconfidence increase when the movement of the market is upward, since share prices tend to go higher and investors attribute the gains to their skills. Therefore, the model would predict that momentum profits are stronger following bull markets. This prediction contradicts the findings reported in this study, since momentum profits are significantly higher following bear markets. Again this finding shows how fragile is the investigation of behavioural models when empirical data are used. Daniel and Titman (1999) associate the overconfidence of investors with shares that are difficult for valuation (based on book-to-market values) and support the theoretical findings of the model.

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[1] Information spreads slower among investors within companies with small capitalisation and with low analyst coverage rather than the counterpart companies with large capitalisation and with high analyst coverage.

10.3 LIMITATIONS

This study is subject to limitations. Small investors would have difficulties to follow the momentum strategy. We defined winner and loser portfolios employing 30, 20 and 10 per cent of the sample. This implies that an investor should buy and sell-short some hundreds of stocks to employ the strategy. Small investors are not in the financial position to undertake those strategies. I propose that small traders can follow the strategy using limited number of winners and losers, expected high variability of their returns.

I assumed that investors can sell short shares without any limitation. There are restrictions on the size, price and types of stocks investors can sell short. For example, traders cannot sell penny stocks and cannot sell short in a declining market, there are even markets that short-selling is against the law, some investors consider short-selling an immoral trading method against the benefit of their country. The momentum strategy proposes to buy past winners to take advantage of bull markets and to sell short prior losers to protect your gains during bear markets. Since stock markets in the long-term tend to move upward, buying only the winner portfolio can generate significant profits in the long-term.

This study further used past data to investigate the profitability of the momentum strategy. A strategy that provides profits using past data does not imply that can offer abnormal profits in the future. For example, widely known stock market anomalies such as the size and weekend effects gradually tend to lose their ability to generate profitability (e.g., Dimson et al., 2001). I predict that one or two decades later, the momentum strategy will not be able to beat the market. Investors will attempt to employ the strategy and gradually its ability to generate profitability will disappear.

Finally, this study employed simple t-statistics and equivalent non-parametric tests (Mann-Whitney U and Kruskal-Wallis tests) to investigate the statistical significance of momentum returns. Nevertheless this study did not use a bootstrap analysis to examine the statistical significance. Liu et al. (1999) use bootstrapped t-statistics and find that p-values become significantly higher.

10.4 POTENTIAL FUTURE INVESTIGATION

This study poses interesting questions that require further examination. First, this thesis investigated some of original factors that influence the magnitude of momentum profitability: stock market structures, volatility and bull and bear markets. The query that emerges is whether these factors can still be shown to influence continuation profits when using different data sets. For instance, further analysis could investigate the momentum profitability generated when the same shares are traded on the LSE dealer market and the Paris Bourse auction market. In addition, potential work could examine whether shares with different past volatility demonstrate significantly different momentum payoffs using European, Asian and US data.

Potential future analysis could examine the significance of the factors that have been investigated in this study concerning the short- and long-term overreaction profitability. Chapter 3 documented that momentum, and short- and long-term overreaction effects are similar; like the two faces of the same coin. Further work could examine the magnitude of long- and short-term overreaction profitability in bull and bear markets, under alternative stock market structures, and in shares with different volatility.

Analysis could also examine additional factors that influence momentum profits, e.g., calculation of continuation profits using opening and closing prices. Since opening and closing prices demonstrate different volatility, they would be expected to generate different momentum profitability. In addition, transaction costs could be considered: this thesis assumes that momentum profits are high enough to cover any transaction costs, but further analysis could investigate whether transaction costs have been underestimated in the relevant UK literature. Finally, evidence for seasonality in momentum profits could be sought, since there has to date been no examination of continuation payoffs using UK data in different months of the year.

Future investigation thus could provide further evidence that will aid understanding of the return patterns over short-, medium- and long-term periods.

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