PRICE MOMENTUM IN THE UK STOCK MARKET

A thesis submitted to the University of Manchester for the Degree of Doctor of Philosophy in the Faculty of Economic and Social Studies

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CONTENTS

List of Tables

List of Figures

Abstract

This thesis, as the title suggests, is concerned with the examination and analysis of price momentum using UK data. The objective is to test the efficient market hypothesis (EMH).

Price momentum can be defined as the positive persistence in stock returns over intermediate time horizons. That is, at medium-term horizons ranging from three to twelve months, stock returns exhibit momentum—past winning stocks (good performers) continue to perform well and past losing stocks (poor performers) continue to perform poorly.

Price momentum can be tested by implementing momentum strategies of buying past winners (e.g., stocks in the top performance decile) and selling past losers (e.g., stocks in the bottom performance decile). If momentum profits obtained from implementing momentum strategies are statistically significant, and if the significant momentum profits cannot be subsumed by possible risk sources, we might conclude that the momentum effect exists and the market fails the basic test of weak-form efficiency since past prices predict future prices.

The analysis shows that significant momentum profits are present in the UK over the period 1977 to 1998. An analysis of sub-period results, seasonal effects, and the persistence of momentum profits confirms the robustness of the results. Controlling for factors known to be associated with differences in average returns, such as size,

stock price, book-to-market ratio, and cash earnings-to-price ratio, cannot explain momentum profits. I also confirm that serial correlation in common factors and delayed price reaction to common factor realisations cannot account for momentum profits. Further analysis shows that both a momentum effect and the phenomenon of post-earnings-announcement drift (PAD) are pronounced over the period 1992 to 1998. However, the significant PAD effect does not subsume the momentum effect. Rather, momentum seems to be stronger and longer-lived than PAD. Price momentum therefore remains a significant phenomenon, after controlling for PAD, in UK stock returns.

DECLARATION

No Portion of the work referred to this thesis has been submitted in support of an application for another degree of qualification of this or any other university or other institute of learning.

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Weimin Liu

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To Lijuan

CHAPTER 1

INTRODUCTION

The hypothesis of capital market efficiency has attracted a great deal of interest and critical comment since the 1960s. It says that the prices of securities instantaneously and fully reflect all available relevant information. This is a general definition, and a very strong hypothesis. Obviously, it would not be easy to empirically test such a hypothesis if we could not distinguish which set of information is relevant. Fama (1970) has identified three different types of information, and categorised three forms of market efficiency accordingly: weak form, semi-strong form, and strong form market efficiency. Each of the three forms deals with a different type of information. Specifically, weak form tests are tests of whether future returns are predictable from past returns. Semi-strong form tests concentrate on whether publicly available information is fully reflected in current prices. Strong form tests examine whether any investors have private information that is not fully reflected in market prices. In his review article of 1991, Fama (1991) changes the terminology of weak form tests to tests for return predictability, semi-strong form tests to event studies, and strong form tests to tests for private information. The efficient market hypothesis (EMH) relies on the ability of arbitrageurs to recognise that prices are out of line and to make a profit by driving them to an equilibrium value consistent with available information. Consequently, the EMH should be jointly tested with a model of asset pricing.

Empirical evidence for or against the EMH takes many forms. There are two inefficiencies in stock returns that have so far proved robust to alternative controls for risk, other documented anomalies, and microstructure effects. One exploits patterns in historical returns and so constitutes one of the most simple or naïve attempts to profit from stock mispricing. The other is based on the most prominent regular public announcement made by stock market companies. The former is medium-term price momentum, which goes against weak form efficiency; the latter is post-earning-announcement drift (PAD), which contradicts semi-strong form efficiency. This thesis focuses on the examination of the momentum effect in the UK stock market as well as the PAD phenomenon. However, the examination of PAD is not the preliminary interest of this thesis. Instead, it is stimulated by the striking momentum effect in UK returns. In other words, the motivation for examining PAD is to investigate the link between the two, especially to discover whether momentum can be partially or completely explained by PAD. In this thesis I choose different benchmarks for expected return in inferring the empirical results, such as market-adjusted, CAPM-adjusted, market-model-adjusted, and Fama-French-three-factor-model-adjusted performances.

It is natural to think of the well-known long-term contrarian effect (overreaction hypothesis) first examined by DeBondt and Thaler (1985) when we discuss momentum. Overreaction runs counter to momentum just because of the different time horizons to which they relate. Recent behavioural theories have developed to explore the relation between the two opposite effects. However, the long-term overreaction hypothesis has given rise to many controversies. Fama (1998) believes that long-term contrarian profits are chance results, and market efficiency should not be abandoned. By contrast, the medium-term momentum effect first tested by Jegadeesh and Titman (1993) does not seem to be controversial, though it is much less clear what might be driving it. For example, it cannot be subsumed by the Fama-French three-factor model. Carhart (1997) even augments the Fama-French three-factor model with a momentum factor when analysing the persistence of mutual fund performance in the US. Behavioural theories try to explain momentum based on investor irrationality.

The medium-term momentum effect is still a quite new phenomenon. Fama and French (1996) suggest that out-of-sample tests of momentum strategies on international data are desirable, to establish whether US evidence is the result of data snooping. Rouwenhorst (1998) examines an international momentum strategy using stocks from 12 European countries (including the UK) over the period 1980 to 1995. Rouwenhorst finds that price momentum is present in all countries as well as in an internationally diversified momentum portfolio. However, the UK sample examined in Rouwenhorst's study is restricted to 494 stocks, and apart from controlling for size there is no detailed analysis of the possible risks of UK momentum returns. There is no other published study of momentum strategies for the UK. This thesis attempts to fill this gap, by examining medium-term momentum strategies on a large sample of UK stocks over the period January 1977 to June 1998. In addition, an analysis of momentum strategies provides additional evidence on the informational efficiency of the UK stock market. In particular, it offers evidence on the ability of the UK stock market to impound information over the intermediate-time horizon. If momentum profits exist, the UK stock market fails the basic test of weak-form efficiency, since past returns predict future returns. A study of momentum strategies also aims to improve our understanding of how UK stock prices respond to particular types of information. If momentum profits exist and cannot be explained by market-wide information, then they imply stock prices that only gradually impound *firm-specific* information. This is indeed the case, and gives me the motivation for examining the PAD phenomenon in explaining the momentum effect as mentioned above.

This thesis provides a comprehensive test of the profitability of momentum strategies in the UK stock market. Roughly speaking, this study has three parts. Empirical tests aimed at establishing the presence of a price momentum effect in the UK are carried out in Part 1. Part 2 examines whether the momentum effect documented in Part 1 is attributable to systematic risk, other possible risk factors, or to established anomalies such as size, stock price, book-to-market ratio, and cash earnings-to-price ratio effects.[1] Part 3 examines whether the momentum effect is due to earnings news; this includes examining a PAD (post-earnings-announcement drift) trading strategy linked to standardised unexpected earnings, short-term price reaction around earnings announcements, analyst forecast errors, and revisions in analysts' earnings forecasts. In Part 3, I also examine the effect of number of analysts. Parts 1 and 2 concentrate on tests for return predictability, and Part 3 on event studies. The analysis is conducted based on three samples. One is a comprehensive sample of UK stocks (the *full sample* including 4,182 stocks). One is a restricted sample of stocks with suitable accounting data for book value and cash earnings-to-price ratio available (the *accounting sample* including 2,434 stocks). The third is another restricted sample that further requires

[1] In this thesis I do not definitively distinguish the two terms: risk factor and anomaly. In fact, there are no clear classifications on this in the current literature. Size and book-to-market can now generally be categorised as risk factors (e.g., they have been included in the Fama-French three-factor model) although both of them were once viewed as anomalies. Further, stock price and cash earnings-to-price ratio could also be proxies for risk or market microstructure effects, while phenomena like PAD etc. that contradict the EMH would be regarded as anomalies.

semi-annual earnings announcements, and I/B/E/S earnings forecasts data available (the *earnings sample* including 835 stocks). The sample period for the first two samples that are examined in Parts 1 and 2 is 1977 to 1998, and it is 1988 to 1998 for the earnings sample that is studied in Part 3.

The empirical evidence documented in Part 1 of this thesis shows that significant momentum profits are available in the UK over the period 1977 to 1998 on both the full and accounting samples. An analysis of sub-period results, seasonal effects, and the persistence of momentum profits confirms the robustness of the results. Bootstrap tests of significance suggest that the results are robust to any skewness bias or higher order moment non-normality in momentum returns. The empirical results of Parts 2 and 3 confirm the presence of size, stock price, book-to-market ratio, cash earnings-to-price ratio, number of analysts, and PAD effects in UK stock returns. However, crucially for the current study, neither systematic risk nor any of these other effects in isolation can explain momentum profits. Similar to the US evidence, momentum effects are not subsumed by the Fama-French three-factor model. Adjusting for the Fama-French three-factor model after controlling for cash earnings-to-price ratio or PAD leaves momentum profits intact. Furthermore, I also confirm that neither serial correlation in common factor realisations nor delayed stock price reaction to common factor realisations can explain momentum profits. These results show that the momentum effect is an important, independent phenomenon in UK stock returns.

This thesis constitutes the first in-depth study of momentum strategies in a stock market outside of the US and represents a strong out-of-sample test to explore whether US results are market specific or due to data snooping. The thorough and up-to-date examinations performed in this thesis not only add significantly to the understanding of the momentum effect, but this research also contributes significantly to issues of informational efficiency in the UK stock market. As predicted, the empirical results provide evidence on how the UK stock market impounds information in the intermediate-time horizon and improve our understanding of how UK stock prices respond to publicly available information on earnings announcements. In addition, I hope that the description and documentation of the data, research methodology, and analysis can serve as a reference for subsequent researchers in this and related areas of capital market research.

This thesis is organised as follows. Chapter 2 provides a literature review of the over- and under-reaction hypotheses. Chapter 3 describes the study sample, data, and research methodology used in this thesis to examine the momentum effect. In chapter 3 I also report results on the presence of momentum profits for both the full and accounting samples. This includes a set of sub-period results, an analysis of seasonality, and an examination of whether momentum profits persist outside twelve-month ranking and holding periods. Chapter 3 forms the first part (Part 1) of this thesis. Part 2 of this thesis is formed by Chapter 4, which investigates the possible sources of momentum profits, reporting the results of controlling for alternative sources of risk suggested by recent contributions to the literature. The final part of this thesis (Part 3) consists of Chapters 5 and 6. Chapter 5 describes the earnings sample, data and PAD trading strategies, and presents evidence of PAD related to different earnings surprise variables. A brief literature review of PAD is also provided in Chapter 5. In Chapter 6, I first re-examine the momentum effect based on the earnings sample, and find that significant momentum profits are still available. Whether the pronounced PAD documented in Chapter 5 can subsume momentum is also examined in Chapter 6. As a by-product, Chapter 6 also provides evidence on whether momentum can account for PAD. Chapter 7, the final chapter, summarises the results, offers conclusions, and suggests avenues for future research.

CHAPTER 2

LITERATURE REVIEW OF OVER- AND UNDER-REACTION HYPOTHESES

2.1 Introduction

The efficient market hypothesis (EMH) has been one of the dominant themes in the finance literature since the 1960s. A great amount of literature appears in this area. For instance, Cootner (1964) and Fama (1965) support the Random Walk Hypothesis (RWH) and confirm the unpredictability of stock price changes.

However, based on Fama's (1970) classification of weak form, semi-strong form and strong form market efficiency, numerous empirical tests have documented results that are contrary to the EMH. Among these, DeBondt and Thaler's (1985, 1987) articles are an important challenge to market rationality and as such have received a fair amount of attention. They put forward and provide supporting evidence for the well-known long-term overreaction hypothesis, that the contrarian strategy of buying past 3- to 5-year losers and selling past 3- to 5-year winners is profitable. Merton (1987) considers the work of DeBondt and Thaler to be particularly noteworthy because it represents a first attempt at a formal test of cognitive misperceptions theories as applied to the general stock market. However, the long-term overreaction hypothesis has given rise to much controversy. Based on empirical tests in the US or in world-wide markets such as UK, Japan, Spain and so on, other authors have either supported or refuted the long-term overreaction hypothesis. Although the long-term overreaction hypothesis has been questioned by many researchers, its existence is still an open issue. Lehmann (1990) and Jegadeesh (1990) also find evidence of short-term return reversals, and contrarian strategies that select stocks based on their returns in the previous week or month generate significant abnormal returns.

Interestingly, over the intermediate time horizon of three to twelve months, Jegadeesh and Titman (1993), and Chan, Jegadeesh and Lakonishok (1996) document a momentum effect—stocks with high returns over the past three to twelve months tend to have high returns over the following three to twelve months. As a result, momentum strategies (relative strength strategies) that buy past winners and sell past losers over the intermediate time horizon realise significant abnormal returns. The authors attribute the momentum effect to market under-reaction—the market responds only gradually to new information. Although the under-reaction hypothesis is exactly the opposite of the overreaction hypothesis, both hypotheses go against the efficient market hypothesis.

Recently, behavioural finance theories based on investors who are not fully rational have been developed to try to accommodate simultaneous over-reaction and under-reaction. There are three influential studies. One is Barberis, Shleifer and Vishny's (1998) model of the representative heuristic and conservatism. The second is Daniel, Hirshleifer and Subrahmanyam's (1998) model of informed and uninformed investors.

The final one is Hong and Stein's (1999) model of news watchers and momentum traders.

This chapter reviews the literature on both the overreaction and under-reaction hypotheses over the long, short, and intermediate time horizons. The short-term horizon can be referred to as time intervals of 4 weeks or less; time intervals of over two years can be categorised as a long-term horizon; and intervals that are somewhere between short- and long-term horizons are intermediate. In this thesis the intermediate horizon is particularly attributed to 3 to 12 months.

Section 2.2 reviews the literature on the long-term overreaction hypothesis. The literature review with respect to short-term return reversals is given in Section 2.3. In Section 2.4 I review the intermediate-term under-reaction hypothesis. Section 2.5 reviews behavioural finance theories that attempt to explain the simultaneous effects of under-reaction at medium-term horizons and overreaction at long-term horizons. A summary is given in Section 2.6.

2.2 Long-term Overreaction

A study in experimental psychology by Kahneman and Tversky (1982) finds that people tend to overreact to unexpected and dramatic events. Applying this viewpoint to the stock market, DeBondt and Thaler (1985, 1987) believe that investors tend to overreact to unusually good or bad recent share-price performance and disregard the long-term view. When the future turns out to be less extreme than that predicted, investors gradually recognise their mistake and, hence, correct it. This behaviour causes the well-known pattern of share price reversal. In other words, extreme movements in stock prices are followed by subsequent price movements in the opposite direction.

As mentioned above DeBondt and Thaler's long-term overreaction hypothesis has resulted in sharp debates. These debates generally fall into two categories trying to explain the long-term overreaction hypothesis.

(i) *How expected return and thus abnormal return is calculated.* Thus, some researchers focus on performance measure problems. Different methods of calculating expected return (or abnormal return) have been used to re-examine DeBondt and Thaler's (1985, 1987) findings such as adjusting for time-varying risk, using buy-and-hold abnormal return instead of DeBondt and Thaler's cumulative average residual return (CAR) and so forth.

(ii) *How much of the overreaction effect is really another effect?* Is the overreaction effect genuinely a predictable price correction or is it a manifestation of other effects such as the small-firm, low-price, and seasonal effects, etc.

This section gives a review of each area of controversy mentioned above in turn. Subsection 2.2.1 reviews DeBondt and Thaler's (1985, 1987) methodology and findings. In Subsection 2.2.2 the performance measure problems are reviewed. Subsection 2.2.3 describes the explanations of other effects for the overreaction hypothesis.

2.2.1 DeBondt and Thaler's (1985, 1987) Methodology and Findings

(i) Overreaction Hypothesis and Test Methodology

DeBondt and Thaler believe that investors' behaviour in securities markets violate Bayes' rule. This is characterised as overreaction. Namely, in forming expectations, investors give too much weight to the past performance of firms and too little to the fact that performance tends to mean-revert. In theory, overreaction should not exist in a rational world because of the process of arbitrage. The anomaly is addressed by Russell and Thaler (1985)—the existence of some rational agents is not sufficient to guarantee a rational expectations equilibrium in an economy with some of what they call quasi-rational agents. The overreaction hypothesis goes against weak form market efficiency, which can mathematically be described as:

$$E[\tilde{u}_{it} | I_{t-1}] = 0, \qquad (2.2.1)$$

where $\tilde{u}_{it}$ is the abnormal return of security (or portfolio) i at time t, and I_{t-1} is historical information available at t. Equation (2.2.1) indicates that in a weak form efficient market a non-zero abnormal return cannot be earned based on past information.

To test overreaction, DeBondt and Thaler establish two portfolios of winner and loser stocks based on the design of Beaver and Landsman (1981). Winning stocks and losing stocks are determined by their past 3- to 5-year performances. The long-term overreaction hypothesis predicts that winner (loser) portfolio will under-perform (over-perform) the market in the subsequent 3- to 5-years test periods. Algebraically, the overreaction hypothesis suggests that,

$$E[\tilde{u}_{Wt} | I_{t-1}] < 0, \text{ and } E[\tilde{u}_{Lt} | I_{t-1}] > 0,$$

where $\tilde{u}_{Wt}$ and $\tilde{u}_{Lt}$ are abnormal returns of winner portfolio and loser portfolio in the subsequent test periods.

In order to estimate the residual returns of $\tilde{u}_{Wt}$ and $\tilde{u}_{Lt}$, an equilibrium model must be specified. DeBondt and Thaler use three types of returns residuals: market-adjusted excess returns; market model residuals; and excess returns measured relative to the Sharpe-Lintner version of the Capital Asset Pricing Model (CAPM). DeBondt and Thaler (1985) report results based on market-adjusted excess returns. The specific procedure of their empirical tests is as follows.

First, using monthly returns of NYSE common stocks from 1926 to 1982, DeBondt and Thaler establish winner and loser portfolios by ranking stocks' prior (e.g., 3-year formation period) cumulative excess returns (CU). The N highest (lowest) CU stocks form winner (loser) portfolio ($N = 35, 50, 82$ are examined). The subsequent periods are called test periods. For the 3-year case (i.e., 3-year formation period and 3-year test period), the step is repeated 16 times on non-overlapping data over the sample period.

Second, DeBondt and Thaler calculate the winner and loser portfolios' cumulative average residual returns (CAR) and average CAR ($ACAR$) for each test period. The average residual return (AR) of portfolio P (winner portfolio or loser portfolio) in a particular month is calculated as,

$$AR_{P,n,t} = \frac{1}{N}\sum_{i=1}^{N}(R_{P,n,t,i} - R_{m,n,t}), \qquad (2.2.2)$$

where $n = n$th test period (for the 3-year case, $n = 1,2,..., 16$); N is the number of securities in portfolio P; $R_{P,n,t,i}$ is the ith stock return in portfolio P for month t (for the 3-year case, $t = 1,2,..., 36$) in the nth test period; $R_{m,n,t}$ is the corresponding equally-weighted market return.

A portfolio's (winner or loser) cumulative average residual return for a particular test period n, $CAR_{P,n,t}$, is computed as,

$$CAR_{P,n,t} = \sum_{\tau=1}^{t} AR_{P,n,\tau} . \qquad (2.2.3)$$

The corresponding $ACAR$ for portfolio P over the whole test period is given by,

$$ACAR_{P,t} = \frac{1}{K}\sum_{n=1}^{K} CAR_{P,n,t} , \qquad (2.2.4)$$

where K is the number of total test periods (for the 3-year case, $K = 16$).

The overreaction hypothesis predicts that for $t > 0$,

$$ACAR_{W,t} < 0, \qquad (2.2.5)$$

and

$$ACAR_{L,t} > 0, \qquad (2.2.6)$$

where W and L stand for winner portfolio and loser portfolio, respectively.

The inequalities of (2.2.5) and (2.2.6) imply that

$$DACAR_t = ACAR_{L,t} - ACAR_{W,t} > 0, \qquad (2.2.7)$$

where $DACAR_t$ is the profit earned by the contrarian portfolio (arbitrage portfolio) of buying past loser stocks and shorting past winner stocks. DeBondt and Thaler thus conduct the tests for the three inequalities of (2.2.5), (2.2.6) and (2.2.7).

(ii) Empirical Results

DeBondt and Thaler's (1985) empirical results confirm the inequalities of $ACAR_{W,t} < 0$ and $ACAR_{L,t} > 0$, and the 36-month contrarian profit, $DACAR_{36}$, is 24.6 per cent. Further investigation shows that the results are consistent with the turn-of-the-year effect and seasonality. Most of the excess returns are realised in January. However, DeBondt and Thaler believe that this is qualitatively different from the

January effect and, more generally, from seasonality in stock prices. Moreover, by comparing the extreme portfolios' CAPM-betas, which are estimated from formation periods, the loser portfolio not only outperforms the winner portfolio, they are also significantly less risky.

In their 1987 article, DeBondt and Thaler provide further evidence and conclude that abnormal returns for losers in the test period are negatively related to performance in the formation period. In addition, the earnings of winning and losing firms show a reversal pattern. These results coincide with the overreaction hypothesis. They also find that the significant profits of the contrarian strategy are not primarily a size effect. Finally, they argue that the contrarian profits cannot be attributed to changes in risk as measured by CAPM-betas.

Apparently, DeBondt and Thaler's empirical results are based on their methodology design. As mentioned previously, their findings are disputed by subsequent studies. The following subsection reviews the suggestions of calculating abnormal returns and the corresponding results.

2.2.2 Performance Measurement Problems

Subsequent studies have shown that the performance measures used in DeBondt and Thaler (1985) have potential biases in inferring their empirical results. Chan (1988), and Ball and Kothari (1989) consider that it is not comprehensive if ignoring the time-varying risk. Conrad and Kaul (1993), and Dissanaike (1994) point out that a buy-and-hold performance measure is less biased than the *CAR* method used by DeBondt and Thaler. (Subsequent studies also criticise the buy-and-hold method in measuring long-term stock performance. See discussion below and Fama (1998)).

(1) Buy-and-hold Measure

Conrad and Kaul (1993) concentrate on examining the bias of the CAR measure. They show that measurement error in observed prices due to bid-ask spreads and price discreteness, leads to substantial spurious returns to long-term zero-investment contrarian strategies because single-period returns are upwardly biased. The approximate bias in single-period returns is given by $s_i^2/4$, and the observed single-period return is given by,

$$E[R_{it}^0] \approx E[R_{it}] + \frac{s_i^2}{4}, \qquad (2.2.8)$$

where R_{it}^0 is the measured return; R_{it} is the true return; $s_i = \frac{P_A - P_B}{(P_A + P_B)/2}$, the proportional spread of security i; P_A is the ask price; P_B is the bid price; $(P_A + P_B)/2$ is the true price. Note that s_i is assumed to be time-invariant.

Based on equation (2.2.8) the observed $ACAR$ and $DACAR$ can be derived as

$$ACAR_P^0(k) \approx ACAR_P(k) + k(B_P - B_M), \qquad (2.2.9)$$

$$DACAR^0(k) \approx DACAR(k) + k(B_L - B_W), \qquad (2.2.10)$$

where $ACAR_p^0(k)$ and $DACAR^0(k)$ are the observed $ACAR$ and $DACAR$ that are calculated using equations (2.2.4) and (2.2.7) with $t = k$, respectively; $ACAR_p(k)$ and $DACAR(k)$ are true measures of $ACAR$ and $DACAR$, respectively; $B_p = \frac{1}{N}\sum_{i=1}^{N}\frac{s_i^2}{4}$, the upward bias due to the bid-ask spread in a single-period return of portfolio P (P = loser portfolio (L), or winner portfolio (W), or market index (M)); N is the number of securities in portfolio P.

Apparently, the estimates of $ACAR$ and $DACAR$ will be biased further along with the increase of k (for the 3-year case in DeBondt and Thaler (1985), k = 1,2,..., 36). In particular, the estimate of $DACAR$ will be upwardly biased if losing stocks are low-priced relative to winning stocks since s_i will be large when price, $(P_A + P_B)/2$, is low.

Therefore, Conrad and Kaul (1993) suggest a buy-and-hold performance evaluation measure. Using a buy-and-hold measure, security i's return over k holding periods, $HPR_i(k)$, is computed as,

$$HPR_i(k) = \prod_{\tau=1}^{k}(1 + R_\tau) - 1, \qquad (2.2.11)$$

where R_τ is the τ th single-period return of security i.

The average market-adjusted holding-period abnormal return of portfolio P over k holding periods, $AHPAR_p(k)$, is calculated as,

$$AHPAR_P(k) = \frac{1}{N}\sum_{i=1}^{N} HPR_i(k) - \frac{1}{I}\sum_{j=1}^{I} HPR_{mj}(k), \qquad (2.2.12)$$

where N is the number of securities in portfolio P; $HPR_i(k)$ is the buy-and-hold return of security i in portfolio P, over k holding periods; $HPR_{mj}(k)$ is the buy-and-hold return of security j in the market index, over k holding periods; and I is the total number of securities in the market index.

Because the bias of $s_i^2/4$ is invariant with respect to the length of the measurement interval, the observed $AHPAR_P(k)$ of portfolio P, $AHPAR_P^O(k)$, is given by

$$AHPAR_P^O(k) \approx AHPAR_P^T(k) + (B_P - B_M), \qquad (2.2.13)$$

where $AHPAR_P^T(k)$ is the true $AHPAR_P(k)$.

In addition, the observed buy-and-hold contrarian profit, $DAHPAR^O(k)$, is given by

$$DAHPAR^O(k) \approx DAHPAR^T(k) + (B_L - B_W), \qquad (2.2.14)$$

where $DAHPAR^T(k)$ is the true contrarian profit.

Comparing equations (2.2.13) and (2.2.14) with equations (2.2.9) and (2.2.10), it can be seen that the buy-and-hold method reduces the upward bias of the contrarian return.

Conrad and Kaul (1993) report empirical results confirming the bias hypothesis. For instance, for their sample the $DACAR(36) = 37.5\%$, while the $DAHPAR(36) = 27.1\%$. Moreover, Conrad and Kaul further analyse the source of the bias of CAR by regression analysis. They find that the bias in CARs is related to prices and not to size. Further, both $DACAR$ and $DAHPAR$ heavily concentrate on January. This is consistent with DeBondt and Thaler's (1985, 1987) findings. However, further investigation of price-based investment strategies indicates that the January effect is a low-price phenomenon rather than overreaction because the returns to the price-based portfolio are at least twice as large as those earned by the performance-based portfolio. The price effect will be discussed in the next subsection.

Dissanaike (1994) points out two problems of the CAR measure. First, the CAR-based performance bears little relation to returns that would actually accrue to an investor. Second, the CAR method biases the measurement of rank-period returns and, thus, affects the composition of the winner and loser portfolios.

Dissanaike (1994) compares three different methods of calculating market-adjusted k-month abnormal return: the CAR method, the buy-and-hold method (BH), and the re-balancing method (RB). The formulas that calculate a portfolio's market-adjusted k-month abnormal return using CAR and BH methods are given by equations

(2.2.3) and (2.2.12), respectively. A portfolio's (say portfolio P's) market-adjusted k-month abnormal return using the RB method is given by,

$$RBAR_P(k) = [\prod_{\tau=0}^{k}(1+R_{P\tau})-1]-[\prod_{\tau=0}^{k}(1+R_{m\tau})-1], \qquad (2.2.15)$$

where $R_{P\tau}$ is the equally-weighted return of portfolio P, and $R_{m\tau}$ is the market return. Note that for a one-security portfolio equation (2.2.12) is equivalent to equation (2.2.15), but this is not true for a portfolio in which two or more stocks are included.

Dissanaike (1994) uses all the constituent stocks of the FT500 index in his empirical test. As expected, different measures lead to different winning and losing stocks. The performances of the contrarian strategy implemented using CAR, BH, and RB methods are so different that they could produce different conclusions on the overreaction hypothesis.

The methods of calculating abnormal returns mentioned above are market-adjusted. Chan (1988), and Ball and Kothari (1989) argue that the winner–loser results of DeBondt and Thaler are due to a failure to use risk-adjusted returns.

(2) Time-varying Risk

Chan (1988) finds that the risks of winner and loser stocks are not constant over time. He suggests that the selections of losers and winners are associated with real economic situations such as recession and expansion. These are reflected in the correlation between risk (beta) and the market premium (i.e., $R_{mt} - R_{ft}$, where R_{mt} is the market return, and R_{ft} is the risk-free rate).

Chan (1988) examines size characteristics, and finds that both winner and loser portfolios experience large changes in market value during the rank period. The median loser stock is bigger than the median winner stock at the beginning of most rank periods, but smaller at the end of the rank periods. The average changes are –45% and 365% for loser and winner portfolios, respectively. Because size is a good proxy for risk, as argued in the size-effect literature (e.g., decreases in size may lead to increases in leverage), Chan (1988) considers that the estimated beta in the rank period will be a biased estimate of the beta for the test period. Specifically, the rank-period beta underestimates the test-period beta for the stocks in the loser portfolio because size decreases while risk increases in the rank period. For the winner portfolio the bias is in the opposite direction. DeBondt and Thaler (1985) dismiss these facts. Hence, Chan argues that the results obtained by DeBondt and Thaler may be incorrect, and suggests that the test-period beta should be used to make the risk adjustment.

In order to test the time-varying risk hypothesis, Chan (1988) estimates the following regression for each event period (from ranking period to testing period):

$$R_{Pt} - R_{ft} = \alpha_{1P}(1 - D_t) + \alpha_{2P} D_t + \beta_P (R_{mt} - R_{ft}) + \beta_{PD}(R_{mt} - R_{ft}) D_t + \varepsilon_{Pt}, \quad (2.2.16)$$

where R_{Pt} is the monthly return of portfolio P ($P = L, W, L-W$); $R_{mt} - R_{ft}$ is the market premium; $t = 1, 2, \ldots, 72$ for the 3-year ranking and 3-year testing periods; D_t is a dummy variable equal to zero in the ranking period (i.e., from $t = 1$ to $t = 36$) and to one in the testing period (i.e., from $t = 37$ to $t = 72$).

The regression equation of (2.2.16) indicates that α_{1P} and α_{2P} are abnormal returns (Jensen's performance index) in the ranking and testing periods, respectively; β_P and $\beta_P + \beta_{PD}$ are betas of portfolio P in the ranking and testing periods, respectively.

The regressing results show that the contrarian profit is relatively small, and it is, on average, insignificant (i.e., the null hypothesis of $\hat{\alpha}_{2,L-W} = 0$ cannot be rejected). In addition, portfolio risk changes from ranking to testing periods. This is indicated by β_{PD}, which is significantly different from zero for portfolio P. The change is remarkable as the estimated ranking-period beta is smaller for the loser portfolio and bigger for the winner portfolio, and the opposite results appear in the testing period. Therefore, DeBondt and Thaler's (1985) conclusion is questioned. Furthermore, Chan (1988) points out that estimation of abnormal return is sensitive to different empirical assumptions and methods through the comparison of different return adjustments such as market-adjusted, ranking-period-beta-adjusted and testing-period-beta-adjusted returns. Chan believes that the risk-adjustment procedure is successful in explaining most of the return difference between loser and winner portfolios because it is able to capture the correlation between the time-varying betas and the market-risk premium. The illustration is as follows.

Since,

$$R_{Pt} - R_{ft} = \alpha_{Pt} + \beta_{Pt}(R_{mt} - R_{ft}) + \varepsilon_{Pt}, \qquad (2.2.17)$$

then

$$E[R_{Pt} - R_{ft}] = \overline{\alpha}_P + \overline{\beta}_P E[(R_{mt} - R_{ft})] + Cov(\beta_{Pt}, R_{mt} - R_{ft}), \qquad (2.2.18)$$

where α_{Pt} and β_{Pt} are assumed to be constant within a test period, but they change in moving to a different test period; $\overline{\alpha}_P$ and $\overline{\beta}_P$ are averages of α_{Pt} and β_{Pt} over the whole test period.

Equation (2.2.18) implies that the mean risk-adjusted return, $E[R_{Pt} - R_{ft}] - \overline{\beta}_P E[(R_{mt} - R_{ft})]$, contains the true excess return $\overline{\alpha}_P$ and the covariance term, $Cov(\beta_{Pt}, R_{mt} - R_{ft})$. Thus, if the covariance term is positive, the intercept from equation (2.2.17) over all testing periods will be overestimated since the intercept will contain the covariance term. Chan (1988) provides an explanation for the positive correlation between the time-varying betas (β_{Pt}) and the market-risk premium ($R_{mt} - R_{ft}$). He considers that betas are correlated with real activity. Chan (1988) demonstrates that,

"... betas increase as the stock values fall. If the stocks that go into the loser portfolio suffer larger losses in recession than in economic expansion, the portfolio beta will be negatively related to the level of economic activity. Similar effects in the opposite direction may affect the winner portfolios. ... Because the expected market-risk premium is probably also negatively correlated with the level of the economic activity, it will be positively correlated with the loser portfolio's beta and negatively correlated with the winner portfolio's beta." (p.162).

Consequently, the difference between the betas of the loser and winner portfolios will be positively correlated with the market-risk premium.

Ball and Kothari (1989) also consider that the expected return (risk) will be time-varying. This may be caused by variation in expected returns on the market portfolio, in relative risks of firms' investments, and in leverage. As a result, controlling for time-varying expected returns is necessary when examining the overreaction hypothesis.

Ball and Kothari's (1989) methodology is slightly different from DeBondt and Thaler's (1985), and Chan's (1988). At the beginning of each calendar year they assign securities in equal numbers to 20 vitile portfolios based on ranked total returns over the past five years (ranking period). The post-ranking period is also 5 years. Although the CRSP monthly returns are used they use annual buy-and-hold returns in their study. The reason is that the dispersion in betas increases with the return measurement interval and the size effect is insignificant when annual-return betas are used (see Handa, Kothari and Wasley, 1989). Accordingly, using annual returns highlights the time-varying risks and avoids confounding with the size effect in estimated abnormal returns. Unlike in Chan (1988), where beta is assumed to be constant within particular ranking and testing periods but allowed to vary in different ranking periods and testing periods, Ball and Kothari (1989) allow beta to vary for each event-time year τ ($\tau = -4,-3,\dots,5$). Therefore, they perform the following regression:

$$R_{Pt}(\tau) - R_{ft}(\tau) = \alpha_P(\tau) + \beta_P(\tau)[R_{mt}(\tau) - R_{ft}(\tau)] + \varepsilon_{Pt}(\tau)\,, \qquad (2.2.19)$$

where $R_{Pt}(\tau)$ is the annual buy-and-hold return on portfolio P for calendar year t ($t = 1,2,\dots,52$) and event year τ ($\tau = -4,-3,\dots,5$); $R_{mt}(\tau)$ is the market return; and $R_{ft}(\tau)$ is the risk-free rate.

Because for each portfolio the 52 annual-return observations are constructed from strictly non-overlapping data, in spite of each portfolio being constructed from overlapping data, this provides a well-behaved time series from which CAPM parameters can be estimated. Thus, Ball and Kothari (1989) believe that this method is likely to detect the risk shifts.

The empirical results in Ball and Kothari (1989) show that the correlation of the average annual abnormal returns between ranking and post-ranking periods is significantly negative when risk is allowed to vary. This seems to be consistent with the overreaction effect. However, the test-period abnormal returns are distributed over a narrow range of 1.7% to –2.7% although the ranking-period abnormal returns are monotonically increasing (ranging from –24% for portfolio 1 (loser) to 32.1% for portfolio 20 (winner)) over the 20 portfolios. This indicates that relative stock performance in one period is of little assistance in predicting large or economically significant abnormal returns, which is qualitatively consistent with the market efficiency hypothesis.

However, Ball and Kothari (1989) notice that the apparently conflicting results mentioned above could be due to the CAPM being an imperfect model. For example, the results reveal that the high-beta portfolios generally earn small positive abnormal returns, whereas the low-beta portfolios earn small negative abnormal returns in the test period. This pattern can not be explained by the CAPM, but is consistent with a size effect. Hence, Ball and Kothari (1989) further examine the ability of the size effect to explain the overreaction hypothesis. This will be reviewed in the next subsection. In short, after controlling for risk, the magnitudes of the abnormal returns (both absolute and relative) suggest that the degree of the overreaction effect, if any, is small. Further, in examining DeBondt and Thaler's (1985, 1987) findings after controlling for risk, when they construct winner and loser portfolios in which each portfolio includes 50 securities, there are no significant abnormal returns found in the 5-year test period both in the winner portfolio and the loser portfolio.

DeBondt and Thaler (1987) disagree with Chan's (1988) explanation of the up- and down-market.[1] To test Chan's explanation, DeBondt and Thaler (1987) implement the following regression analysis for the contrarian portfolio over the test period:

$$R_{Pt} = \alpha_P + \beta_{Pu}(R_{mt} - R_{ft})D + \beta_{Pd}(R_{mt} - R_{ft})(1 - D) + \varepsilon_{Pt}\,, \qquad (2.2.20)$$

[1] Chan (1988) argues that the "portfolio selection procedure picks very risky losers when the expected market-risk premium is high and less risky losers when the expected market-risk premium is low, so that the difference in risk between losers and winners is positively correlated to the market-risk premium." (p. 162).

where D is a dummy variable that equals one if $R_{mt} > 0$ and zero otherwise; β_{Pu} is the up-market beta and β_{Pd} is the down-market beta.

DeBondt and Thaler's (1987) results of running equation (2.2.20) reveal that the intercept, α_P, is insignificant. However, they argue that the CAPM-beta adjustment is inappropriate as "it seems odd to say that a portfolio with a beta of 1.602 in up markets and 0.591 in down markets is riskier than one with up and down betas of 0.854 and 1.439" (p. 569). Yet, equation (2.2.20) does not reflect Chan's (1988) up and down markets effect since it is estimated only in the test period. Chan's (1988) explanation is that the portfolio selection procedure, which picks riskier losers when the expected market risk premium is high and less risky losers when the expected market risk premium is low, is in the ranking period rather than in the test period.

In contrast, Ball, Kothari and Shanken's (1995) regression is closely related to the ranking-period market risk premium. Their regression equation is

$$R_{Pt}(\tau) - R_{ft}(\tau) = \alpha_P(\tau) + \beta_P(\tau)(R_{mt} - R_{ft}) +$$
$$\delta_P(\tau)\{Avg[R_{mt}(-4,0) - R_{ft}(-4,0)] - Avg(R_{mt} - R_{ft})\} + \varepsilon_{Pt}(\tau), \qquad (2.2.21)$$

where $R_{Pt}(\tau)$ is the annual buy-and-hold return of portfolio P ($P = L, W$) in calendar year t and event-year τ; Avg stands for average; $\delta_P(\tau)$ measures the sensitivity of portfolio P's beta to the market return over the ranking period; $R_{mt}(-4,0)$ and $R_{ft}(-4,0)$ are market return and risk-free rate over the past 5-year ranking period, respectively.

Equation (2.2.21) implies that portfolio beta varies in calendar time, conditional on the realised market risk premium of $Avg[R_{mt}(-4,0) - R_{ft}(-4,0)]$ over the ranking period. In the light of Chan's (1988) interpretation, $\delta_P(\tau)$ of the contrarian portfolio will be negative, indicating that when the expected market-risk premium of $Avg(R_{mt} - R_{ft})$ is high, relative risk is high. In other words, the contrarian portfolio's beta is lower when the ranking period market return is high.

The empirical results in Ball, Kothari and Shanken (1995) show that the systematic risk estimates coincide with Chan (1988), Ball and Kothari (1989). The loser portfolio's beta exceeds the winner portfolio's beta. The estimate of $\delta_P(\tau)$ is generally consistent with the hypothesised result that the contrarian portfolio's $\delta_P(\tau)$ is negative. However, Ball, Kothari and Shanken (1995) find that the performances of a December-end ranking portfolio and a June-end ranking portfolio are different. For instance, the average annual contrarian profit is 4.6% for the December-end contrarian portfolio, whereas the June-end equivalent is –1.4%. This indicates that the contrarian strategy's estimated abnormal return is sensitive to the choice of ranking-period end. This sensitivity may be caused by other factors that affect the contrarian portfolio performance. In effect, a number of factors such as size, price, seasonality, etc. have been studied to account for the overreaction effect. The following subsection reviews whether the contrarian profits are due to investors' overreaction or other effects.

2.2.3 Overreaction or other Manifestations?

Several anomalies such as size, price, book-to-market, etc. have been documented in the finance literature. Naturally, subsequent researches have tried to explain the long-term overreaction hypothesis by taking into account these anomalies.

(1) The Size Effect

Banz (1981) documents the well-known size effect, which says that average returns on small stocks are too high given their beta estimates, and average returns on large firms are too low. Because stocks in the loser portfolio tend to be small, as observed, some researchers have studied whether the abnormal return of the contrarian investment strategy is due to the size effect.

Zarowin (1989) examines the size effect in his study of overreaction to corporate earnings information. In his study, stocks are ranked by an earnings performance measure:

$$PERF_{iT} = \frac{\Delta x_{iT}}{\sigma_{\Delta x_i}}, \qquad (2.2.22)$$

where Δx_{iT} is firm i's earnings change from last year to this year, and $\sigma_{\Delta x_i}$ is the standard deviation of firm i's earnings changes over the previous five years. The stocks are sorted into quintile portfolios based on this earnings performance measure: quintile 1 contains the poorest earners (loser portfolio), while quintile 5 consists of the highest earners (winner portfolio).

The *CAR* method shows that the loser portfolio outperforms the winner portfolio by 16.6 percent ($t = 2.9$) over the 36-month test period. After controlling for risk, the loser portfolio still outperforms the winner portfolio. However, Zarowin (1989) finds that the poorest earners are significantly smaller than the best earners. Zarowin (1989), thus, examines the size explanation for the empirical results by analysing size-matched and performance-matched portfolios. The tests show that the size-matched portfolios (i.e., the portfolio of the smallest loser minus the smallest winner, and the portfolio of the largest loser minus the largest winner) earn no significant. In contrast, the abnormal returns obtained from the performance-matched portfolios (i.e., the portfolio of the smallest loser minus the largest loser, and the portfolio of smallest winner minus the largest winner) are statistically significant. The results are consistent with the size effect, and the overreaction seems to be a manifestation of the size effect.

Zarowin (1990) re-examines the overreaction hypothesis following DeBondt and Thaler's (1985) procedure (i.e., ranking stocks using their prior returns). The results confirm DeBondt and Thaler's findings. The average 3-year contrarian profit is 17.4% ($t = 2.51$) in which 87 percent comes in Januarys. Zarowin (1990) finds that the loser portfolio is significantly riskier than the winner portfolio. However, after controlling for risk, the results show that the Jensen performance index is significantly different from zero for all months and for February–December, but it is insignificant for January. These results indicate that the loser portfolio outperforms the winner portfolio even after controlling for risk, and this is not due to the January performance. This contradicts Chan (1988). Zarowin (1990), then examines the role of size because he finds that in 13 of the 17 test periods the mean size of the loser portfolio is smaller the mean size of the winner portfolio, and loser stocks tend to be small firms. Similar to the method adopted in Zarowin (1989), Zarowin (1990) forms five size-matched portfolios. The Jensen performance tests for the five size-matched portfolios show that the loser portfolio outperforms the winner portfolio only in January. There is no differential performance between loser and winner portfolios outside of January. Regressing 36-month-test-period CAR on size and 36-month-ranking-period CAR confirms the findings that the size-controlled results are not consistent with the overreaction hypothesis, but are consistent with the size effect and the January seasonality.

Zarowin (1990) also finds from the results of size-matched portfolios that most of the CARs are realised in January, especially in the first January. Zarowin (1990) considers that if there is overreaction, it is most likely to occur in the first January under the assumption of a lack of January effect. To test this hypothesis, Zarowin repeats the original analysis by changing each ranking period ending at 30/6/YY, and each test period beginning at 1/7/YY, respectively. The results show that loser portfolios still significantly outperform winner portfolios in January, but there is no July (the first month of each test period) effect found. Therefore, Zarowin (1990) concludes that the January CARs are not due to overreaction but to a January effect.

Clare and Thomas (1995) examine the overreaction hypothesis using UK data. They adopt the CAR metric and Jensen's regression in their study. They find that the loser portfolio outperforms the winner portfolio over 2- and 3-year periods, but the magnitude of out-performance is small (1.68% per annum for the 2-year case). In addition, Clare and Thomas (1995) also examine the size effect using Zarowin's

(1989, 1990) techniques. They document that small firms outperform large firms. Moreover, they find that there is only weak evidence for seasonal differences in the performances of loser and winner portfolios. Clare and Thomas (1995), thus, conclude that the overreaction effect is probably due to the size effect.

It should be noted that both Zarowin (1989, 1990) and Clare and Thomas (1995) use the *CAR* method that has been questioned by researchers, as reviewed in the last subsection. Consequently, their results may not be repeated using the buy-and-hold method. In addition, Clare and Thomas' (1995) results obtained with and without adjusting for risk are quite different. For instance, for the 3-year case there is no overreaction found when without risk adjustment, but the Jensen regression gives completely the opposite conclusion. On the one hand, this may be due to the fact that computing abnormal return is sensitive to different empirical methods as pointed out by Chan (1988). On the other hand, Clare and Thomas (1995) do not take into account time-varying risk. Accordingly, their results are open to doubt.

(2) The Price Effect

Conrad and Kaul (1993) argue the size effect explanation of the overreaction hypothesis. Based on regression analyses, they find that there are no relations between size and holding-period abnormal return conditioning on price, while the relation between price and holding-period stock performance is significantly negative.

To further examine the price effect, Conrad and Kaul (1993) conduct an analysis of price-based investment strategies. Stocks in the sample are sorted in descending order at the beginning of each test period. The top and bottom 35 firms are assigned into high- and low-price portfolios based on each sorting, and their subsequent performances over one-, two-, and three-year periods are evaluated. The empirical results reveal that the arbitrage portfolio of low-price portfolio minus high-price portfolio realises substantially higher holding-period profit than the contrarian portfolio of loser portfolio minus winner portfolio does. Their results also show that the holding-period returns to both performance-based and price-based arbitrage portfolios heavily concentrate in January. Since the returns to the price-based portfolio are at least twice as large as those earned by the performance-based portfolio, the 'January effect' appears to be a low-price phenomenon.

Ball, Kothari and Shanken (1995) also document the low-price effect. They find that much of the reported profitability of contrarian strategies is driven by low-priced loser stocks. They show that the mean contrarian profit over the 5-year holding period is 91%, but a $\$\frac{1}{8}$th price increase can dramatically reduce this profit. In their sample, there are 2,700 polled loser stocks over the sample period. Among these are 359 stocks (accounting for 13.3%) that are priced at \$1 or less. Excluding stocks priced \$1 or less has a substantial reduction on the average return for the loser portfolio, which declines from 163% to 116%.

Note that these debates or explanations of the long-term overreaction hypothesis separately focus on one factor such as time-varying risk, size, and low price, etc. Recently, Fama and French (1996) show that long-term contrarian returns can be captured by their three-factor model. The three factors are market, size, and book-to-market ratio, and the detailed description on the three-factor model is given in Chapter

4 of this thesis. This is consistent with the previous explanation of time-varying risk and suggests that the CAPM suffers from the bad-model problem. As Fama (1998) illustrates, the bad-model problem is more serious when analysing long-term returns because bad-model errors in expected return grow faster with the return horizon than do errors in the volatility of returns. In fact, empirical studies have proved that the CAPM does not completely describe expected returns. In addition, Mitchell and Stafford (1997) point out that buy-and-hold abnormal returns are likely to grow with the return horizon even when there is no abnormal return after the first period. Fama (1998) thus suggests that formal inferences about long-term returns should adopt the CAR method rather than buy-and-hold abnormal returns.

2.3 Short-term Overreaction

Using US data Lehmann (1990) and Jegadeesh (1990) document a phenomenon of short-term return reversal. Lehmann (1990) designs a useful test to detect whether there is a measured arbitrage opportunity in the stock market. The basic idea is that if we can find such a measured arbitrage opportunity after controlling for certain effects such as bid-ask spreads, transaction costs and so on, the market is inefficient.

The methodology adopted by Lehmann (1990) is different from those commonly used in the research of long-term overreaction hypothesis. Lehmann (1990) uses all stocks listed on the New York and American Stock Exchanges. At the beginning of each week these stocks are divided into winners and losers, which winners and losers determined based on the previous full week's returns, the previous four-day returns, and on the returns two, three, four, thirteen, twenty-six, and fifty-two weeks ago. After each formation of winners and losers, the profits of the arbitrage portfolio of buying previous losers and selling previous winners are calculated for the following week as,

$$\pi_{t,k} = \sum_{i=1}^{N} w_{i,t-k}(R_{it} - \overline{R}_t), \qquad (2.3.1)$$

where N is the number of all stocks listed on the New York and American Stock Exchanges; R_{it} is security i's return in week t; $\overline{R}_t$ is the return of an equally-weighted portfolio of these N stocks in week t; $w_{i,t-k}$ is the weight invested in security i, which is determined by returns in the previous period, $t-k$ ($k=1$, first four days of previous week, 2, 3, 4, 13, 26, and 52 are examined) and is given by,

$$w_{i,t-k} = \frac{-(R_{i,t-k} - \overline{R}_{t-k})}{\sum_{R_{i,t-k} > \overline{R}_{t-k}} (R_{i,t-k} - \overline{R}_{t-k})}. \qquad (2.3.2)$$

Positive $w_{i,t-k}$ implies that security i is a past loser and will be bought in the contrarian portfolio. Negative $w_{i,t-k}$ implies that security i is a past winner and will be sold in the contrarian portfolio. Therefore, equation (2.3.1) describes the difference in returns between the loser and winner portfolios in week t based on the performances in the previous period, $t-k$. This method can be used to detect sources of market inefficiency that give rise to particular short-term arbitrage opportunities.

The empirical results in Lehmann (1990) show that the contrarian portfolio earns positive profits in roughly 90% of the weeks. If the strategy is viewed as having a half-year horizon, the profits are positive in each of the twenty-six-week periods covered by the data (i.e., $\sum_{\tau=t+1}^{t+26} \pi_{\tau,k} > 0$), and the mean profits on these strategies over the 26-week periods are more than three times their standard deviations. In addition, there is little persistence in the return reversal effects. On average, the profits of the contrarian portfolio are diminished over the next month. Obviously, it is difficult to account for these results within the efficient market framework. In effect, the results strongly suggest rejection of the market efficiency hypothesis because the results remain unchanged after correcting for the mismeasurement of security returns due to bid-ask spreads and for plausible levels of transactions costs. For example, the arbitrage portfolio based on the first four-day returns in the previous week, which can mitigate bid-ask spread bias as the market may accommodate the bid-ask bias in a day or two in a sufficiently liquid market, has an apparent pattern of price reversals. And the contrarian strategies still yield measured arbitrage profits after allowing for transactions costs of 0.20 percent. Further, it is difficult to interpret the arbitrage profits as reflecting time-varying risk since "it is certainly difficult to rationalise such a short-term relation" (p. 18).

In explaining the evidence of short-run return reversals Lehmann (1990) suggests that "the return reversals associated with winners and losers probably reflect imbalances in the market for short-run liquidity" (p. 26). This involves the behaviour of patient and impatient traders. The observed return reversals are suggestive of an inefficient market where stock prices overreact to information.

A few other explanations have been put forward to account for the short-term reversals in stock prices documented by Lehmann (1990) and Jegadeesh (1990). Kaul and Nimalendran (1990) and Jegadeesh and Titman (1995a) examine whether bid-ask spreads can explain the short-term price reversals. Jegadeesh and Titman's (1995a) empirical results show that most of the short-term return reversals can be explained by the way dealers set bid and ask prices, taking into account their inventory imbalances. They believe that the apparent contrarian trading profits are compensation for bearing inventory risk and cannot be realised by traders transacting at bid and ask prices. Consequently, Jegadeesh and Titman (1995a) conclude that the prior findings of short-term price reversals are not necessarily inconsistent with an efficient market. Lo and Mackinlay (1990) suggest that a large part of the short-term contrarian profits may be due to lead-lag effects between stocks. For example, they seem to be attributable to a delayed stock price reaction to common factors rather than to overreaction.

2.4 Intermediate-term Under-reaction

Jegadeesh and Titman (1993) document a phenomenon of under-reaction behaviour of investors over an intermediate horizon of three to twelve months. They find that stocks that generate higher than average returns in one period also generate higher than average returns in the period that follows, and vice versa. They show that if winners and losers are formed based on the past returns of 3–12 months and held for 3–12 months after portfolio formation, the relative strength strategy (or momentum strategy) of buying past winners and selling past losers is quite profitable. To find the sources of the momentum profits, Jegadeesh and Titman (1993) conduct a series of investigations mainly using the 6×6 strategy that is formed on 6-month lagged returns and held for 6 months.

First, the momentum strategy implies that,

$$\pi = E[(r_{it} - \bar{r}_t)(r_{i,t-1} - \bar{r}_{t-1})] > 0 , \qquad (2.4.1)$$

where r_{it} is the return on security i in period t and $\bar{r}_t$ is the cross-sectional average return in period t. For the 6×6 strategy the length of a period is six months.

Note that equation (2.4.1) is the same as equation (2.3.1) implemented in Lehmann (1990) except for the sign. Equation (2.4.1) thus expresses the momentum profit, which is called the weighted relative strength strategy (WRSS) in Jegadeesh and Titman (1993). Jegadeesh and Titman (1993) find that the returns of the WRSS are closely related to the returns of the decile momentum portfolio. The correlation between the two is 0.95. As a result, Jegadeesh and Titman (1993) use equation (2.4.1) to distinguish different sources of the momentum profits by introducing a model describing stock returns.

Jegadeesh and Titman (1993) adopt a one-factor model in their study, and suggest three potential sources of the momentum profit. The first is the cross-sectional dispersion in expected returns. The second is related to the serial covariance of factor portfolio returns. The last is the average serial covariance of the firm-specific components of returns. If the momentum profits are due to the last source, then the results suggest market inefficiency. Otherwise, they may be attributed to compensation for bearing systematic risk and need not be an indication of market inefficiency. In this thesis I also perform a similar decomposition of the momentum profits. For a detailed analysis see Appendix 4A in Chapter 4.

Using a market index as a proxy for the single-factor portfolio, Jegadeesh and Titman's (1993) empirical results indicate that the serial covariance of factor portfolio returns (the second potential source of the momentum profits) is unlikely to be the source of the momentum profits.

To find whether the momentum profits are attributable to cross-sectional dispersion in expected returns (the first potential source of momentum profits), Jegadeesh and Titman (1993) examine the profitability of the momentum strategy within size- and beta-based sub-samples. The idea is that cross-sectional dispersion in expected returns should be less within these sub-samples than in the full sample. As a result, when the momentum strategy is implemented on stocks within each sub-sample rather than on all the stocks in the full sample, the momentum profits will be less if they are related to differences in expected returns. However, the profits need not be reduced in these sub-samples if momentum profits are due to serial covariance in idiosyncratic returns (the third potential source of momentum profits as mentioned above). The results show that momentum profits are of approximately the same magnitude when the momentum strategy is implemented on the various sub-samples of stocks as when it is implemented on the entire sample. The momentum profits hence are less likely due to cross-sectional differences in the systematic risk of the stocks in the sample (the first potential source of the momentum profits).

After excluding the first two potential sources of momentum profits, Jegadeesh and Titman (1993) conclude that momentum profits are attributable to serial correlation in the firm-specific component of returns (the third potential source of momentum profits). In other words, momentum profits are related to market under-reaction to firm-specific information.

However, Jegadeesh and Titman's (1993) results are obtained under certain assumptions such as a one-factor model of the return generating process. If the assumptions are not true, their conclusions might be incorrect. Meanwhile, the results within size-based sub-samples show that momentum profits appear to be somewhat related to firm size. For example, the largest-size-based sub-sample generates lower momentum profits than other two size-based sub-samples. Jegadeesh and Titman (1993) do not examine the extent to which momentum profits are attributable to the size effect. Furthermore, the results within the size- and beta-based sub-samples also show that risk-adjusted abnormal returns are significantly positive for winners, while they are insignificant for losers. Therefore, the momentum profits are due to the buy side of the transaction rather than the sell side.[2] This seems to indicate that investors under-react to good news while they react to bad news impartially over the intermediate horizon. If this is the case, investors are really risk-averse and they are conservative in making investment decisions. Nevertheless, this general conclusion needs to be examined further.

[2] The risk-adjusted abnormal returns are obtained from the CAPM estimates based on the value-weighted market index.

Chan, Jegadeesh and Lakonishok (1996) further examine the profitability of the price momentum documented in Jegadeesh and Titman (1993) by taking into account the post-earnings-announcement drift (PAD).[3] Their one-way analysis reveals that both price momentum and PAD effects are striking over the intermediate horizon. However, the crucial point is that neither effect subsumes the other. This is shown by a two-way analysis, which indicates that prior returns as well as each of the earnings surprise variables[4] have marginal predictive power for the post-portfolio-formation drifts in returns. In addition, investigation of the sub-sample formed by large firms, which alleviates potential problems such as survivor bias, size, and low-price effects, gives similar results although the arbitrage profits are somewhat smaller than in the full sample. Finally, the Fama–French three-factor model shows that winner and momentum portfolios realise significantly positive abnormal returns and past losers still suffer from loss. In other words, the observed pattern in momentum profits does not alter after adjusting for size and book-to-market factors although the winner concentrates more heavily on glamour stocks, loading negatively on the book-to-market factor and the loser is oriented towards value stocks, loading positively on the book-to-market factor. In brief, the results in Chan, Jegadeesh and Lakonishok (1996) suggest that the stock market responds only gradually to new information. In this thesis, I also examine the PAD phenomenon and the relation between price momentum and PAD effect. A brief literature review of PAD is provided in Chapter 5.

[3] Chan, Jegadeesh and Lakonishok (1996) refer to PAD as earnings momentum.

[4] Chan, Jegadeesh and Lakonishok (1996) use three measures of earnings surprise. One is the standardised unexpected earnings (*SUE*); one is the short-term price reaction around the earnings

Subsequent empirical studies of momentum strategies have also tried to explain the sources of their apparent profits. Conrad and Kaul (1998) suggest that cross-sectional variation in mean returns can explain profits to momentum strategies on NYSE/AMEX stocks over the period 1948–1989. Grundy and Martin (1998) find that a momentum strategy applied to NYSE/AMEX stocks over the period 1966–1995 earns Fama-French three-factor risk-adjusted returns of more than 1.3 percent per month. Neither cross-sectional variability in expected returns nor industry risk can explain these profits. Moreover, a momentum strategy that ranks stocks on their stock-specific return component outperforms one that ranks on total return. Moskowitz and Grinblatt (1999) find that industry portfolios exhibit significant momentum and industry momentum strategies are more profitable than individual stock momentum strategies. They show that for the most part the momentum profits from individual stocks tend to be insignificant after controlling for industry momentum. However, Hong, Lim, and Stein (1999) document the results that the momentum profits are not driven by industry factors. As mentioned above, Grundy and Martin (1998) also show that momentum profits are not attributable to industry risk.

All of the studies on momentum strategies reviewed above are based on US data. Rouwenhorst (1998) examines an international momentum strategy using stocks from 12 European countries. The data covers the period 1980 to 1995. Using the methodology of Jegadeesh and Titman (1993), Rouwenhorst finds that return continuation is present in all countries, and an international diversified momentum strategy earns returns of around 1 percent per month.

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announcement; and the final one is the cumulative revision in analysts' earnings forecasts over the prior six months.

Based on the UK data, Macdonald and Power (1992, 1993) examine the persistence in stock returns. Their conclusion is that the UK stock market is efficient. However, in their studies, they mainly use the variance ratio test and the re-scaled range statistic, which are different from the US-based studies mentioned above. In addition, the samples used in their studies are too small (e.g., the sample size is 40 firms in their 1993 study and 100 firms in their 1992 study) to represent the stock market behaviour. In addition, the two statistics also have certain shortcomings. For instance, they cannot give quantitative results though they can be used for qualitative analyses. Rouwenhorst's (1998) study extends to the UK, but the UK sample is restricted to 494 stocks, and apart from controlling for size there is no detailed analysis of the possible risks of UK momentum returns. There is no other published study of momentum strategies for the UK.

2.5 Behavioural Finance Theories

The above reviews show that investors tend to overreact to new information over long- and short-term horizons, while they under-react over intermediate horizon. A natural question is why do investors behave differently over different time horizons? Behavioural theories based on investors who are not fully rational have been developed to answer this question. Specifically, these theories attempt to explain the simultaneous effects of under-reaction at medium-term horizons and overreaction at long-term horizons.

Barberis, Shleifer and Vishny (BSV 1998) develop a model motivated by the *representative heuristic*—whereby investors too readily label stocks based on recent data, ignoring the more complete statistical evidence on stock types—and *conservatism*—whereby investors are slow to update models in the face of new evidence. The former effect encourages overreaction, the latter under-reaction. In their specific model, company earnings follow a random walk, but investors believe earnings are either mean-reverting (regime 1) or trending (regime 2). There is a regime-switching probability between regimes 1 and 2, but investors assume regime 1 is more likely. Overreaction occurs after a string of either positive or negative earnings shocks, which cements belief regime 2. For instance, after a string of positive earnings shocks, although the next shock is equally likely to be positive or negative, there is less reaction to a positive shock, which is expected, than to a negative shock, which is not expected. The result is that the subsequent return, on average, is negative. Under-reaction occurs when belief regime 1 holds. Investors believe earnings shocks are more likely to be reversed, while in fact they are as likely to continue as to reverse. When a reversal occurs there is less price reaction than when a continuation occurs, and momentum is the outcome. The overall result is that momentum is the more likely outcome in the medium term, overreation the more likely outcome in the longer term.

The behavioural model of Daniel, Hirshleifer, and Subrahmanyam (DHS 1998) has two types of investors, informed and uninformed. The DHS model has different behavioural foundations than the BSV model. The uninformed investors are not subject to judgement biases. However, informed investors, who determine prices, are subject to two biases: they are overconfident and they attribute favourable outcomes to their own skill. Specifically, informed investors place greater confidence in private information and they tend to interpret public information that confirms their views as confirming their ability and public information that contradicts their views as noise. The interpretations for such behaviours in DHS is that overconfidence leads informed investors to exaggerate the precision of their private signals about a stock's value, whereas self-attribution causes them to underweight public signals about value. Thus, on average, news generates momentum in the medium-term because of overreaction to private information and under-reaction to public information, but the weight of public information eventually overwhelms the behavioural biases and produces long-term reversals.

Finally, Hong and Stein (HS 1999) develop a model with two types of agents: news watchers and momentum traders. News watchers form strategies based on private information—which diffuses slowly to other news watchers—and they ignore the information in current or past prices. Momentum traders do condition their trades on past prices, but their strategies are simple functions of past prices. 'Early' momentum traders themselves create momentum, encouraging 'late' momentum traders, eventually resulting in overreaction. In the interpretation of momentum, Hong and Stein (1999) emphasise heterogeneity across investors, who observe different pieces of private information at different points of time. They make two key assumptions: (1) firm-specific information diffuses gradually across the investing public; and (2) investors cannot perform the rational-expectations trick of extracting information from prices. Taken together, these two assumptions generate under-reaction and positive return autocorrelations.

As reviewed above, the three models are based on different behavioural promises. Nevertheless, the DHS predictions are close to those of BSV, and the DHS model shares the empirical successes and failures of the BSV and HS models. For instance, in the DHS model, the price response in the period of announcement of what DHS call selective event is incomplete because informed investors overweight their prior beliefs about the stock's value. The BSV model would produce a similar result due to the conservatism bias. While these three behavioural theories each explain the simultaneous existence of medium-term under-reaction and long-term overreaction, the phenomena they are designed to explain, Fama (1998) argues that they fail to explain the bigger picture. For example, the BSV model fails to explain the long-term post-event abnormal returns of the same sign as long-term pre-event returns associated with dividend omissions and initiations, stock splits, proxy contests, and spinoffs. The DHS model predicts that so-call selective events—those such as stock repurchases that are timed by management to take advantage of stock mispricing—are associated with price momentum. Fama points out that this prediction is inconsistent with evidence of post-announcement returns with the opposite sign to announcement returns associated with exchange listings, proxy fights, and IPOs (and with the zero followed by negative returns for acquiring firms in mergers).

2.6 Summary

Both the overreaction hypothesis and the under-reaction hypothesis directly challenge the efficient market hypothesis (EMH). The long-term overreaction hypothesis documented by DeBondt and Thaler (1985) has now been long debated. Empirical evidence shows that the choice of how log-run expected return (or abnormal return) is measured is important. There is significant controversy of whether the results of long-term reversals are real or the result of using the wrong model for measuring expected returns. For instance, Conrad and Kaul (1993) and Dissanaike (1994) show that DeBondt and Thaler's adoption of the *CAR* method produces a serious bias in measuring performance and suggest using a buy-and-hold measure. Chan (1988) and Ball and Kothari (1989) argue that DeBondt and Thaler's long-term contrarian profits are due to a failure to adjust for time-varying risk. Fama and French (1996) show that their three-factor model is able to account for the long-term contrarian profits. In addition, a number of researchers attribute 'overreaction' to other phenomena. Zarowin (1989, 1990), Clare and Thomas (1995) and others conclude that the size effect is responsible for the contrarian strategy returns. Conrad and Kaul (1993) and Ball, Kothari and Shanken (1995) document the price effect in explaining long-term contrarian profits. For the short-term returns reversals documented by Lehmann (1990) and Jegadeesh (1990) they can generally be explained by market micro-structure variables such as bid-ask spreads and so on. Because of the controversial evidence against the overreaction hypothesis, Fama (1998) believes that market efficiency should not be abandoned.

By contrast, the intermediate-term continuation of returns (momentum effect) documented by Jegadeesh and Titman (1993) is less contested. As the momentum effect has established itself as a robust phenomenon, at least in the US, Carhart (1997) even augments the Fama-French three-factor model with a momentum factor when analysing the mutual fund performance in the US. This is also the reason why the fashionable behavioural theories based on market irrationality rather than informational inefficiency have been developed to attempt to explain the medium-term under-reaction hypothesis and the relation between it and the long-term overreaction hypothesis. However, Fama (1998) argues that the intermediate-term momentum effect is still a quite new phenomenon, and suggests that further tests are in order. This is also one of the aims this thesis proposes to achieve.

CHAPTER 3

EMPIRICAL EVIDENCE OF A MOMENTUM EFFECT

3.1 Introduction

This chapter examines whether significant evidence of a momentum effect over the intermediate time horizon of three to twelve months can be found in the UK stock market. The following section describes the sample and data collected. Trading strategies that are used to test for a momentum effect are described in Section 3.3. Section 3.4 reports the results obtained from the sample containing 4182 LSPD companies. The empirical results obtained based on a restricted sample called accounting sample are documented in Section 3.5. The conclusions from these two samples are the same. The momentum effect is quite pronounced in both samples. Further studies in this thesis will focus on the accounting sample. Section 3.6 analyses different sub-periods to see whether the momentum effect documented in Section 3.4 and Section 3.5 is due to any particular period. In Section 3.7 I examine whether the momentum effect is attributable to seasonality. Section 3.8 examines the persistence of the momentum effect over longer periods of two to three years. Section 3.9 summarises this chapter.

3.2 Sample and Data Collected

For any research into market efficiency based on empirical evidence, an appropriate set of securities is a key factor. In my study, the sample is chosen from the London Share Price Database (LSPD), which contains the complete history for all UK companies quoted since 1975. Specifically, the sample is the same as the LSPD from January 1977 to December 1996 except for the restriction requiring that the stocks can be found on Datastream. This is because I will use weekly data in my study while LSPD only contains monthly data. Thus, the data such as adjusted price, unadjusted price (UP), market value (MV), cash flow to price ratio (C/P) and book value are collected from Datastream. However, the sample period is chosen from January 1977 to June 1998. See the description on this below.

There are 4871 stocks including all kinds of securities (e.g., USM, OTC, AIM stocks, etc.) on the LSPD between January 1977 and December 1996. Among them there are 689 stocks that are not found on Datastream. Therefore, the sample chosen includes 4182 stocks containing both dead stocks and currently existing stocks. Nevertheless, the sample is still a good representation of the UK stock market. This can be seen by examining the 689 stocks that are on the LSPD but not on Datastream. Firstly, compared to the complete sample size of 4871 stocks this is relatively small. Further examining the components of the 689 stocks I find that there are 308 stocks whose lives are shorter than 2 years.[1] This is due to the fact that when stocks become dead, the data is kept and is available on Datastream on a selective basis only. In addition to

[1] Because my sample period is January 1977 to June 1998, which will be explained soon, the short-life

the short-life stocks, there are 137 financial stocks (financials and investment trusts) that are in the 689 stocks. Table 3.2.1 shows the details of the components of the 689 stocks after considering the short-life and financial stocks.

Table 3.2.1 Components of the 689 stocks

Short-life stocks	Financials and Investment Trusts	USM stocks	Secondary shares of existing Co from Jan. 1978	Odd foreign mining & bank shares	Irish, Scottish and odd Co quoted in SEDOL from Jan. 1978	Hoare Govett small Co index	O.T.C. Companies	Others
308	137	18	14	4	37	7	2	162

However, it should be noted that the 4182 stocks are chosen depending only on the availability of price, *UP* and *MV* on Datastream rather than on C/P, book value data and so on. This sample of including 4182 stocks is denoted as *full sample* in this thesis. The availability of book value and C/P on Datastream introduces further restrictions on the sample size. These restrictions are introduced when constructing the *accounting sample*, which will be defined in Section 3.5. In addition, although the sample is chosen from January 1977 to December 1996, the weekly data is collected from 29/12/1976 to 24/6/1998. This can give the first week return in 1977, and ensures that stocks issued in December 1996 have certain amount of data available. The details of the data collected over this period of more than 20 years are as follows.

(1) Weekly Adjusted Share Price Data between 29/12/76 and 24/6/98

The weekly stock prices consist of Wednesday prices. This is different from studies of long-term overreaction where monthly data is commonly used. The reasons are that, on the one hand, the observations would be insufficient if monthly data were used for studying momentum strategies over the relatively short intermediate horizon of 3

stocks also include those that are delisted before 1/1/79, and those that are listed after 31/5/1996.

months to one year. On the other hand, the possible Monday effect, holiday effect and end-of-month effect can be minimised through the use of weekly Wednesday data.[2] In addition, the use of weekly data is also different from the studies of Jegadeesh and Titman (1993), and Chan, Jegadeesh and Lakonishok (1996) where daily data is used. These differences will give us another insight to see the reaction of the stock market over the intermediate time horizon. Further, the prices collected are adjusted for subsequent capital changes such as stock splits and rights issues. Finally, the adjusted prices as well as the unadjusted ones, which will be described below, are mid-point prices. Thus, the bid–ask bounce effect will not be an issue for this study as the use of mid-point prices.

(2) Dividend Data

This collection is due to the fact that the adjusted prices mentioned at (1) are not adjusted for dividend payments. In this thesis returns are adjusted for dividend payments, and are calculated as

$$r_{\tau_w} = \frac{P_{\tau_w} + d_{\tau_w} - P_{\tau_w - 1}}{P_{\tau_w - 1}}, \qquad (3.2.1)$$

where r_{τ_w} is return for period τ_w, P_{τ_w} is ex-dividend price at τ_w and d_{τ_w} is dividend payment associated with ex-dividend date τ_w. Note that gross dividends are used and the calculation ignores tax and re-investment charges.

[2] Cross (1973), French (1980), Gibbons and Hess (1981) find that Monday returns are on average lower than returns on other days. Ariel (1987, 1990) documents the holiday effect and the end-of-month effect that returns are on average higher the day before a holiday and the last day of the month. In the UK, the bank holidays (except for Christmas and New Year) are usually on Monday and Friday, while Wednesday is neither the day before Monday or before Friday. Meanwhile, the last two days of some months are not Wednesday. For example, the last Wednesday in January 1977 is 26/1/77.

However, detailed dividend payment data are only available on Datastream from 1988 onwards. Therefore, the dividend data for January 1977 to December 1987 are collected from LSPD. Adjusting Datastream prices for dividends is still not straightforward, as both LSPD and Datastream make their own capitalisation adjustments to share prices, and their definitions of dividends and capital changes are slightly different. For example, some capital distributions are referred to as dividends on LSPD, but are treated as capitalisations on Datastream. In addition, comparing the types of dividends defined on LSPD and Datastream, there are some unclear cases where Datastream and LSPD differ in their treatment of dividends. Liquidation distributions and capital repayments are treated by LSPD as dividends, but there are no clear specifications on Datastream. To ascertain the unclear cases, I have examined the dividends recorded on LSPD from January 1977 to December 1987. I find that there are 75 dividends that may be referred to as unclear cases.[3] Table 3.2.2 summarises the 75 LSPD dividends.

Table 3.2.2 The 75 LSPD Dividends

Liquidation Distribution	Final and Bonus	Bonus	Capital Distribution	Final and special distribution	Capital repayment	First interim and capital distribution	Final and capital distribution
33	17	9	7	5	2	1	1

By examining Datastream's adjusted and unadjusted prices and adjustment factors around the ex-dates of the 75 LSPD dividends, I find that out of these 75 LSPD dividends there are only 7 cases (for 6 stocks) in which they are treated as capitalisations by Datastream. Hence, the differences are corrected and appropriate

[3] To be careful, the 75 cases include those dividends with LSPD dividend types being Bonus (5), Capital distribution (7), Liquidation distribution (10), Capital repayment (11), Final and Bonus (95), Final and Capital distribution (97), First interim and Capital distribution (17), Final and Special distribution (96). Numbers in brackets are LSPD markers that indicate the types of dividends. (see

adjustments are made to LSPD dividends in calculating pre-1988 returns. For the post-87 period, adjusted gross dividends come from Datastream.

To reduce survival bias, the returns are assigned to be –1 at the delisting week for those whose types of deaths defined on LSPD are 7, 14, 16, 20 and 21;[4] and to be 0 for others such as acquisition, takeover, merger, etc.. Note that the setting of delisting return of –1 could bias the results in favour of finding momentum for loser stocks since the true return may not be -100% in all cases (shareholders sometimes get something back, eventually, even when a company liquidates).[5] On the other hand, the setting of delisting return of 0 for takeover and merger and so on may still be probably biased against finding return continuation. This is because the delisting return may not be 0 for acquired companies if the ranking period includes the bid date. These companies usually experience high returns immediately after the takeover bid and could well be winners.[6]

(3) Market Value (MV) Data

A firm's MV is its stock price multiplied by the number of ordinary stocks in issue. It is a useful measure of the relative size of companies, and will be used to examine the well-known size effect, and to describe firms' characteristics.

LSPD Reference Manual, Version 10.0).

[4] The types of deaths of 7, 14, 16, 20 and 21 are liquidation, quotation cancelled for reason unknown (no dealings to be continued), receiver appointed/liquidation, in administration/administrative receivership, and cancelled assumed valueless, respectively. (see LSPD Reference Manual Version 10.0).

[5] I check the sensitivity of the empirical results to assigning delisting returns of 0 to all dead stocks. Although momentum profits are slightly reduced as expected, the overall results of this study, in particular the significance of momentum profits, are confirmed.

[6] For instance, event studies show that mergers and tender offers are on average wealth-enhancing for the stockholders of the target firms (Mandelker, 1974, Dodd and Ruback , 1977, Bradley, 1980, Dodd, 1980, Asquith, 1983).

(4) Unadjusted Price (UP) Data

UP is used to examine the low-price effect documented by Conrad and Kaul (1993). This is different from the adjusted price used to calculate security return. In this study, the Datastream unadjusted price is adopted when doing any ranking based on price.

(5) Cash Earnings to Price Ratio (C/P) and Book Value Data[7]

Because investors are concerned with the firm's capabilities of paying dividends, they lay stress on the cash flow (cash earnings) of the firm's operations, proxied as net retention (earned for ordinary minus ordinary dividends) plus depreciation plus deferred tax. The C/P ratio is of prime interest to investors, and, at any given date, it is the cash earnings per share for the appropriate financial year divided by price. It reflects the market's view of the company's growth potential and the business risks involved. A useful rule of thumb is to regard the C/P ratio as the number of year's cash earnings per share represented by the share price. An alternative to the C/P ratio is the ratio of earnings to price (E/P). However, accounting earnings may be a misleading and biased estimate of the economic earnings with which shareholders are concerned. Cash flow per share is less manipulable and, therefore, possibly a less biased estimate of economically important flows accruing to the firm's shareholders. Accordingly, I will examine the C/P ratio, and not examine the E/P ratio in this thesis.

Book value is equal to equity capital and reserves (accounting item 305) minus total intangibles (accounting item 344), and it is used to compute book-to-market ratio

[7] Datastream provides the price to cash earnings ratio (P/C) on a daily basis. In this thesis the C/P ratio is examined.

(B/M). B/M is another useful ratio to measure a company's performance. When a company's C/P and B/M go very high, the company may well be a value stock (distressed stock), while low C/P and low B/M suggest a glamour stock (strong stock, growth stock). Researchers such as Fama and French (1992, 1993, 1996), and Lakonishok, Shleifer, and Vishny (1994) have found that average returns on common stocks are related to C/P and B/M. High C/P and B/M stocks have higher average returns than low C/P and B/M stocks. Lakonishok, Shleifer and Vishny (1994) and Fama and French (1995) also show that high C/P and B/M firms tend to have persistently low earnings; low C/P and B/M firms tend to have persistently high earnings. Lakonishok, Shleifer and Vishny (1994) and Haugen (1995) believe that the market undervalues value stocks and overvalues glamour stocks. These will be examined to see whether the momentum profits, if any, are due to the C/P and B/M effects.

Note that cash flow and book value are lagged but price and MV are contemporaneous when computing C/P and B/M ratios, respectively. This is because a company's fiscal year end is different from the date when the company actually reports to the marketplace. In the UK the period between fiscal year end and reporting date can be as long as 6 months. Therefore, cash flow and book value used to compute C/P and B/M ratios are lagged at least 6 months.[8] Because the fiscal

[8] The C/P ratio provided by Datastream does not adjust for the time lag. However, because we can obtain the daily Datastream C/P ratio, the 6-month-lagged cash flow can be derived from the Datastream C/P ratio. Suppose that Company A's 6-month-lagged Datastream cash flow (C_{-6}) to price (P_{-6}) ratio is x_{-6}, i.e., $\frac{C_{-6}}{P_{-6}} = x_{-6}$. Since the price data have been collected, the 6-month-

year ends differ across companies, for some companies the lagged period may approach more than one year. For example, assuming the current date is 1/4/1997 and company A's fiscal year end is on 31st December each year, the cash flow and book value used in the current C/P and B/M ratios are those reported for 31/12/1995, while price and MV are for 1/4/1997.

3.3 Methodology and Trading Strategies

There are two approaches commonly adopted to test return profitability in the literature. One focuses on time series analysis. For instance, Fama (1965) finds that the first-order autocorrelations of daily individual returns are positive. Fisher (1966) reports positive autocorrelations of monthly returns on diversified portfolios that are larger than those for individual stocks. Lo and Mackinlay (1988), and Conrad and Kaul (1988) document positive autocorrelation of weekly returns on size-grouped portfolios, and more so for portfolios of small stocks. The second approach is based on trading strategies. Following DeBondt and Thaler's (1985, 1987) studies, who use the winner-loser method originally proposed by Beaver and Landsman (1983), quintile- and decile-portfolio analyses are commonly adopted. These analyses focus on the time-aggregated momentum (or contrarian) portfolio profits, which reflect the payoff to an intertemporally well-diversified strategy. Based on the hypothesis tests and regression analyses for such portfolio profits, they are usually jointly tested with

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lagged cash flow, C_{-6}, is calculated by $x_{-6}P_{-6}$. Hence, the company's C/P used in this thesis is equilibrium models such as CAPM and the multifactor model. These methods are not only intuitive but they can also be directly applied by investors. This thesis mainly analyses 10 decile portfolios, and the *momentum portfolio* of decile winner minus decile loser (arbitrage portfolio). The basic research design used to form the trading strategies and test procedures is as follows.

The basic idea of the price momentum strategies is that if stock prices under-react to information, buying past performance winners and selling past performance losers will realise significant profits in the future. To test the underreaction hypothesis over the intermediate time horizon, Jegadeesh and Titman (1993) examine a number of trading strategies. For comparison similar trading strategies are constructed for this study. Specifically, the appropriate length of the portfolio formation periods (rank periods) and the holding periods (test periods) is chosen from 3 months to 12 months. Let RM stand for the number of months in the rank period ($RM = 3,6,9,12$), and TM for the number of months in the test period ($TM = 3,6,9,12$). Further, let us refer to a strategy that selects stocks on the basis of returns over the past RM months and holds them for TM months as $RM \times TM$ strategies. This gives a total of 16 $RM \times TM$ strategies. Likewise, to avoid some of the price pressure and lagged reaction effects, a second set of 16 $RM \times TM$ strategies that skip a week between the portfolio formation period and the test period are also examined.[9]

In this study, however, these strategies include portfolios with non-overlapping test periods. This is different from Jegadeesh and Titman's (1993) study, where the

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given by $\frac{x_{-6}P_{-6}}{P_0}$, where P_0 is current price.

[9] The price pressure and lagged reaction effects could distort the results when there is no delay between

portfolios are constructed with overlapping test periods. Therefore, for each $RM \times TM$ strategy, there are $(258 - RM)/TM$ non-overlapping test periods.[10] For instance, there are 85 non-overlapping test periods for the 3×3 strategy (i.e., $(258-3)/3$), and 20 non-overlapping test periods for the 12×12 strategy.

For each $RM \times TM$ strategy, each stock is required to have at least RM -month returns plus two more week's returns at the beginning of each test period. This ensures that each qualifying stock has at least one more week's return available in the test period when skipping a week after the portfolio formation. From Section 3.5 onwards, the extra two more week's returns are reduced to one more week's return because from that section onwards the case of skipping a week between rank and test periods will not be examined. This requirement of an extra one or two more week's returns seems to be reasonable. If a stock is delisted at the beginning of test period, investors will not choose it. In addition, investors may have delisting information in advance.

In order to select stocks to form different portfolios, at the end of each rank period $t-1$, the RM -month buy-and-hold return for each qualifying stock i over the rank period, $R_{i,t-1}$, is computed as,[11]

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rank and test periods. Skipping a week between rank and test periods should eliminate these effects.

[10] 258 is the number of months of the full sample period from January 1977 to June 1998, that is, 1121 weeks. Note that the number of non-overlapping test periods for the $RM \times TM$ strategy should precisely be denoted as $\text{int}[(258-RM)/TM]$. For example, for the 9×9 strategy, the number of non-overlapping test periods is $\text{int}[(258-9)/9] = \text{int}[27.67] = 27$.

[11] In this study t stands for the test period. Security i's return over the test period ($t-1$ to t) is, therefore, denoted $R_{i,t}$. This means that $R_{i,t-1}$ is security i's return over the previous test period, $t-2$ to $t-1$. However, if RM equals TM, which is mainly the case in this study, security i's return in $t-1$ over the rank period is the same as $R_{i,t-1}$. In this case, there is no confusion involved in denoting security i's rank-period return in $t-1$ as $R_{i,t-1}$. If, however, RM is not equal to TM, this notation is not appropriate. Since the case of RM being equal to TM is the main case studied here, I do not offer alternative notation for the ranking-period return.

$$R_{i,t-1} = \prod_{\tau_w=-RW}^{-1}(1+r_{i\tau_w})-1, \qquad (3.3.1)$$

where RW is the number of weeks in the rank period and $r_{i\tau_w}$ is the weekly return of security i in period τ_w.

At the end of each test period t, the TM-month buy-and-hold return for each qualifying stock i over the test period (perhaps less than TM months due to delisting), R_{it}, is calculated as,

$$R_{it} = \prod_{\tau_w=0}^{TW-1}(1+r_{i\tau_w})-1, \qquad (3.3.2)$$

where TW is the number of weeks in the test period.

In this study all compound returns over time are computed using the buy-and-hold method.

Although decile portfolios are mainly used to analyse the momentum effect, I first adopt Lehmann's (1990) weighting technique to find whether there is a measured arbitrage opportunity. Then I carry out the decile analyses if the measured arbitrage opportunity does exist. These analyses are discussed next.

Following Lehmann (1990), at the beginning of each test period the stocks in the sample are divided into a winner portfolio and a loser portfolio based on their past RM-month buy-and-hold returns. The winner (loser) portfolio includes those stocks whose past RM-month buy-and-hold returns are greater than (less than or equal to) the past RM-month return of a within-sample equally-weighted market index[12] at the end of each rank period $t-1$, $R_{m,t-1}$. The momentum portfolio is created by buying past winners and selling short past losers at the beginning of each test period, holding this position for TM months. With this strategy, the momentum portfolio weight ($w_{i,t-1}$) assigned to stock i at the beginning of each holding period $t-1$ is,

$$w_{i,t-1} = \frac{R_{i,t-1} - R_{m,t-1}}{\sum\limits_{R_{i,t-1}-R_{m,t-1}>0} (R_{i,t-1} - R_{m,t-1})}. \qquad (3.3.3)$$

This weight means that the number of pounds invested in each security is proportional to the rank period's return ($R_{i,t-1}$) less the rank-period return of the equally-weighted market index ($R_{m,t-1}$). The factor of proportionality is the inverse of the sum of the positive deviations of individual security returns over the rank period from this market return. Positive $w_{i,t-1}$ means that the stock is a winner and should be bought using $w_{i,t-1}$ pounds. Negative $w_{i,t-1}$ means that the stock is a loser and should be sold short by $|w_{i,t-1}|$ pounds. Because the money invested in the long and short sides of the

[12] At the end of each rank period $t-1$, the return of the within-sample equally-weighted market index over the past RM months, $R_{m,t-1}$, is

$$R_{m,t-1} = \frac{1}{N_{t-1}} \sum_{i=1}^{N_{t-1}} R_{i,t-1},$$

where N_{t-1} is the number of qualifying stocks in the sample at $t-1$ and $R_{i,t-1}$ is the RM-month buy-momentum portfolio varies over time depending on the return realisations over the rank period, this weighting method not only captures the effect underreaction implies, but it also re-normalises the momentum portfolio weights each test period by the random factor of proportionality, so that the investment at the beginning of each test period is always £1 long and short. Thus, the momentum portfolio is an arbitrage portfolio (zero-cost portfolio).[13] At the end of each test period both winners' and losers' TM -month returns over the TM -month test period are calculated.[14] The profit of this momentum strategy at the end of each test period t, denoted π_t, is

$$\pi_t = \sum_{i=1}^{N_{t-1}} w_{i,t-1} R_{it} , \qquad (3.3.4)$$

where N_{t-1} is the number of qualifying stocks in the sample at the beginning of test period $t-1$ and R_{it}, which is given by equation (3.3.2), is security i's buy-and-hold return over the TM -month test period. Equation (3.3.4) provides a good analytical method for examining the sources of the profitability of the momentum strategy. For detailed analyses see Appendix 4A in Chapter 4.

The decile analyses are carried out in a similar way. At the beginning of each test

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and-hold return for security i over the rank period, which is given by equation (3.3.1).

[13] Lo and Mackinlay (1990) and Jegadeesh and Titman (1995b) also use the weighting technique in their studies of overreaction, but in a slightly different way. In their studies, the factor of the proportionality is set to be the inverse of the number of stocks in the sample. Thus, their contrarian portfolio of long past losers and short past winners are arbitrage portfolios as well, but the investment in the long and short sides is not equal to one unit of money.

[14] At the end of each test period t, portfolio (winner or loser) returns over the TM -month test period, R_{Pt}, are computed by

$$R_{Pt} = \sum_{i=1}^{n_{P,t-1}} w_{i,t-1} R_{it} ,$$

where $n_{P,t-1}$ is the number of stocks the W (L) contains at the beginning of the test period.

period $t-1$ the securities are sorted in ascending order based on their returns in the past RM months. Based on each sorting, the qualifying stocks are allocated to ten equally-weighted decile portfolios. The top decile portfolio is the loser portfolio and the bottom decile is the winner portfolio. The momentum portfolio of buying past winners and selling past losers is still an arbitrage portfolio since the strategy also makes the momentum portfolio long and short one pound of winners and losers at the beginning of each test period. At the end of each test period, the ten equally-weighted decile portfolio returns and the momentum portfolio return over the TM -month test period are calculated. At the end of each test period t, any equally-weighted decile portfolio's return over the TM -month test period, $R_{DP,t}$, is given by

$$R_{DP,t} = \frac{1}{n_{DP,t-1}} \sum_{i=1}^{n_{DP,t-1}} R_{it} \, , \qquad (3.3.5)$$

where $n_{DP,t-1}$ is the number of stocks in the decile portfolio at the beginning of each test period $t-1$ and R_{it} is the buy-and-hold return over the test period of security i that is in the decile portfolio.

At the end of each test period t, the decile momentum portfolio's profit over the TM -month test period, $\pi_{DP,t}$, is computed as,

$$\pi_{DP,t} = R_{DW,t} - R_{DL,t} \, , \qquad (3.3.6)$$

where $R_{DW,t}$ is the decile winner portfolio's return over the TM -month test period and $R_{DL,t}$ is the decile loser portfolio's return over the test period. Both $R_{DW,t}$ and $R_{DL,t}$ are calculated using equation (3.3.5).

For each $RM \times TM$ strategy, these procedures result in $(258 - RM)/TM$ independent (non-overlapping) test-period returns for each portfolio over the full sample period. For instance, there are 42 independent semi-annual test-period returns for each portfolio from July 1977 to June 1998 for the 6×6 strategy. Consequently, the standard hypothesis tests such as t-test and F-test can be adopted directly to test the mean value of each portfolio over the sample period (i.e., the cross-sectional and time-series average).[15] That is, the t-statistic of the portfolio mean return over the sample period is calculated by

$$t = \frac{\overline{R}_P \sqrt{T}}{\sigma_{R_P}}, \qquad (3.3.7)$$

where T is the number of the test periods, $\overline{R}_P$ is the mean return of the portfolio concerned, and σ_{R_P} is the standard deviation of portfolio return over the T test periods.

The F-statistic is used to test whether the mean returns of portfolios we are interested in are equal. Assuming that there are K portfolios and portfolio i has n_i observations

[15] This non-overlapping strategy may have the issues raised in Conrad and Kaul (1998) of small sample estimation bias and reduced power from using non-overlapping observations. However, the issues seem not to be serious. In Chapter 6 I re-examine the momentum strategy by using overlapping observations, and similar results and magnitude of momentum profits are found.

($i = 1,2,...,K$), under the null hypothesis that the mean values of the K portfolios are equal,

$$\frac{\frac{1}{K-1}\left(\sum_{i=1}^{K} n_i \overline{R}_i^2 - n\overline{R}^2\right)}{\frac{1}{n-K}\left(\sum_{i=1}^{K}\sum_{j=1}^{n_i} R_{ij}^2 - \sum_{i=1}^{K} n_i \overline{R}_i^2\right)} \sim F(K-1, n-K), \qquad (3.3.8)$$

where R_{ij} is the j^{th} observation of portfolio i, and

$$n = \sum_{i=1}^{K} n_i, \qquad \overline{R}_i = \frac{1}{n_i}\sum_{j=1}^{n_i} R_{ij}, \qquad \overline{R} = \frac{1}{n}\sum_{i=1}^{K}\sum_{j=1}^{n_i} R_{ij}.$$

Further, for each portfolio of 3×3, 6×6, 9×9 and 12×12 strategies the monthly returns in each test period are also calculated.[16] For the 6×6 strategy this leads to 252 non-overlapping test-period monthly returns over the full sample period. I then estimate the systematic risks (βs) and Fama and French's (1993, 1996) three-factor model using the monthly returns on each decile portfolio and momentum portfolio, with the value-weighted portfolio of all stocks in the sample as the proxy for the market. The reason of the use of monthly returns is that monthly returns are commonly used in estimating βs and the three-factor model, so the estimates using monthly returns can be directly compared with previous studies. Meanwhile, using monthly returns may partially overcome the interval effect on estimated βs.[17] An

[16] The monthly portfolio returns are constructed as equally-weighted averages of the monthly security buy-and-hold returns. The test-period monthly buy-and-hold returns of securities are calculated in the same way that equation (3.3.2) is used to compute the test-period TM -month buy-and-hold returns of securities, except that TW should be the number of weeks in one month.

[17] Dimson (1979) finds for the UK that the estimated βs of infrequently traded shares rise as the

interval of one month seems to be a moderate choice although it may also reduce the effect from using weekly returns. Using a value-weighted rather than an equally-weighted market index is worthwhile because this gives additional weight to larger companies and less to smaller companies where standard methodologies (e.g., the Fama-French three factor model) may not work so well. Value weighting is also more consistent with the underlying economics (with how economic wealth is invested). Furthermore, it can reduce the bias in estimating betas caused by serial correlation in the market index because a value-weighted market index will show smaller serial correlation than an equally weighted market index as demonstrated in Cohen et al. (1986):

> ... "since an equally weighted index gives more weight to thinner issues, and since these issues display stronger serial cross-correlation among themselves (due to greater price-adjustment delays), an equally weighted index will exhibit greater positive serial correlation than a similarly constructed value-weighted market index." ... (p. 120).

3.4 Results Based on the Sample Including 4182 LSPD Stocks:

Preliminary Evidence on the Momentum Effect

This section evaluates the performance of the portfolio strategies described in the last section. These strategies are applied to virtually all securities recorded in the LSPD between January 1977 and December 1996 except those that are not available on Datastream.

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interval increases, while, to a lesser extent, the opposite holds for frequently traded shares.

Table 3.4.1 presents the average returns of winner and loser portfolios as well as the arbitrage (winner minus loser) portfolio, for the 32 strategies described in the last section. These results are obtained using Lehmann's (1990) weighting technique. Panel A reports the results of portfolios formed immediately after the lagged returns are measured for the purpose of portfolio formation. Panel B in Table 3.4.1 shows the results of portfolios formed one week after the lagged returns used for forming these portfolios are measured. The results are obviously not consistent with the efficient market hypothesis. All profits of the zero-cost portfolios are positive. All these results are statistically significant except for the 3×3 strategy implemented without skipping a week between rank and test periods. This means that past winners still outperform past losers over the intermediate time horizon. Specifically, the measured arbitrage opportunity is quite pronounced. For each $RM \times TM$ strategy the momentum profits are consistently positive over the $(258 - RM)/TM$ test periods covered by the data. For instance, there are 30 momentum returns that are positive over the 42 test periods for the 6×6 strategy. The most significant one is the 12×3 strategy, which selects stocks based on their returns over the previous 12 months and then holds the momentum portfolio for 3 months. This momentum strategy yields an average quarterly return of 4.554% (t-statistic is 5.86) when there is no time lag between the rank period and the test period, and it yields an average quarterly return of 4.963% (t-statistic is 7.06) when skipping a week between the rank period and the test period.[18]

[18] The quarterly return of 4.554% is equivalent to a monthly return of 1.4955%, a semi-annual return of

Table 3.4.1 Average Returns Obtained Using Lehmann's Weighting Technique

The winner portfolio (W), loser portfolio (L) and momentum portfolio ($W-L$) are constructed based on the past RM-month securities returns. This weighting strategy divides all stocks in the sample into two groups, winner and loser, depending on whether the past RM-month buy-and-hold returns of individual stocks are greater than the past RM-month return of the within-sample equally-weighted market index. The money (weight) invested in each stock is given by equation (3.3.3). For each $RM \times TM$ strategy portfolio's average TM-month test-period returns ($\mathrm{Re}\mathit{turn}$) over the sample period, t-statistics ($t-stat$), minimum (Min), maximum (Max) and the number of the observations (Obs) are reported in this table. Panel A shows the results of portfolios formed without skipping a week between rank period and test period. Panel B presents the corresponding results when skipping a week between rank period and test period. The sample period is January 1977 to June 1998.

9.3154%, a 9-month return of 14.2936% and an annual return of 19.4985%.

Strategy	Portfolio	Return	t-stat	Min	Max	Return	t-stat	Min	Max	Obs
		Panel A				Panel B				
3×3	W	0.06900	5.94	−0.378	0.336	0.06873	5.89	−0.363	0.405	85
	L	0.05068	3.86	−0.267	0.569	0.04099	3.34	−0.259	0.302	85
	W−L	0.01832	1.79	−0.693	0.119	0.02774	4.59	−0.213	0.113	85
3×6	W	0.12736	4.87	−0.303	0.524	0.12784	4.75	−0.312	0.473	42
	L	0.08713	2.92	−0.273	0.655	0.09033	2.84	−0.288	0.755	42
	W−L	0.04024	2.55	−0.390	0.204	0.03752	2.13	−0.469	0.202	42
3×9	W	0.22302	4.53	−0.270	1.113	0.22375	4.43	−0.279	1.144	28
	L	0.12608	2.65	−0.289	0.861	0.12692	2.67	−0.314	0.869	28
	W−L	0.09694	4.76	−0.133	0.282	0.09684	4.84	−0.133	0.275	28
3×12	W	0.27244	5.18	−0.176	0.711	0.27546	5.04	−0.167	0.696	21
	L	0.17665	3.49	−0.260	0.564	0.17975	3.47	−0.241	0.591	21
	W−L	0.09579	3.97	−0.137	0.335	0.09571	3.83	−0.161	0.367	21
6×3	W	0.06979	5.93	−0.415	0.345	0.06902	5.80	−0.402	0.405	84
	L	0.04269	3.40	−0.280	0.389	0.03546	2.81	−0.283	0.376	84
	W−L	0.02711	2.98	−0.433	0.144	0.03356	4.46	−0.183	0.148	84
6×6	W	0.14477	5.48	−0.290	0.754	0.14438	5.48	−0.255	0.775	42
	L	0.09155	3.42	−0.252	0.646	0.07814	2.83	−0.340	0.608	42
	W−L	0.05322	2.75	−0.352	0.230	0.06624	3.89	−0.324	0.222	42
6×9	W	0.21735	6.93	−0.131	0.553	0.21566	6.73	−0.135	0.554	28
	L	0.10291	2.98	−0.382	0.468	0.10565	2.97	−0.377	0.483	28
	W−L	0.11445	6.03	−0.097	0.255	0.11001	5.62	−0.109	0.247	28
6×12	W	0.32242	5.45	−0.153	0.892	0.32115	5.38	−0.147	0.869	21
	L	0.17697	3.68	−0.194	0.798	0.16183	2.98	−0.295	0.806	21
	W−L	0.14545	4.07	−0.157	0.562	0.15932	4.95	−0.148	0.517	21
9×3	W	0.07469	6.38	−0.421	0.331	0.07443	6.32	−0.400	0.387	83
	L	0.03811	3.16	−0.293	0.367	0.03268	2.65	−0.295	0.358	83
	W−L	0.03658	4.89	−0.295	0.168	0.04175	6.48	−0.176	0.158	83
9×6	W	0.14737	5.61	−0.364	0.567	0.14662	5.39	−0.367	0.511	41
	L	0.06585	2.34	−0.278	0.547	0.06855	2.31	−0.292	0.638	41
	W−L	0.08152	5.48	−0.194	0.217	0.07807	4.90	−0.197	0.222	41
9×9	W	0.21912	4.92	−0.217	0.754	0.21818	4.87	−0.209	0.772	27
	L	0.13704	2.78	−0.244	0.837	0.12686	2.37	−0.261	0.932	27
	W−L	0.08208	3.14	−0.287	0.303	0.09132	3.31	−0.353	0.307	27
9×12	W	0.30591	4.24	−0.337	1.095	0.30520	4.00	−0.346	1.193	20
	L	0.20049	2.45	−0.324	1.120	0.20766	2.42	−0.338	1.140	20
	W−L	0.10542	2.86	−0.257	0.354	0.09753	2.46	−0.345	0.357	20
12×3	W	0.08015	6.70	−0.429	0.331	0.07932	6.54	−0.408	0.379	82
	L	0.03461	2.91	−0.287	0.358	0.02969	2.41	−0.286	0.354	82
	W−L	0.04554	5.86	−0.253	0.186	0.04963	7.06	−0.178	0.188	82
12×6	W	0.15918	5.84	−0.284	0.713	0.15768	5.89	−0.249	0.716	41
	L	0.07624	2.86	−0.245	0.614	0.06812	2.48	−0.335	0.590	41
	W−L	0.08295	4.65	−0.230	0.305	0.08957	5.33	−0.218	0.288	41
12×9	W	0.22523	4.63	−0.325	1.028	0.22485	4.46	−0.336	1.081	27
	L	0.11278	2.33	−0.267	0.837	0.11434	2.40	−0.290	0.834	27
	W−L	0.11245	3.84	−0.269	0.431	0.11051	3.77	−0.279	0.425	27
12×12	W	0.27450	6.11	−0.168	0.620	0.27385	6.02	−0.177	0.597	20
	L	0.17253	3.19	−0.343	0.785	0.17274	3.24	−0.346	0.765	20
	W−L	0.10197	2.66	−0.277	0.463	0.10112	2.65	−0.293	0.484	20

Having found that the measured arbitrage opportunity does exist, the following analysis examines the performance of the decile portfolios. The results for the decile winner, decile loser and the decile winner minus loser are reported in Table 3.4.2 for each strategy. Again, Panel A and Panel B in Table 3.4.2 document the results obtained without and with skipping a week between portfolio formation period and holding period, respectively. Note that the number of the observations for each portfolio over the full sample period is not shown in Table 3.4.2, instead, the correlation coefficients between the momentum returns obtained from Lehmann's weighting strategy and decile strategy are reported in the last column in Table 3.4.2. For the number of the observations of each portfolio see Table 3.4.1.

Table 3.4.2 Average Returns of Decile Winner (W), Loser (L) and Momentum Portfolio ($W-L$)

At the beginning of each test period, qualifying stocks in the sample are sorted in ascending order based on their past RM -month buy-and-hold returns. An equally-weighted portfolio of stocks in the top decile comprises the loser portfolio (L) and will be sold short, while an equally-weighted portfolio of stocks in the bottom decile comprises the winner portfolio (W) and will be bought. For each $RM \times TM$ strategy, these portfolios' average TM -month returns ($\mathrm{Re}turn$), t-statistics ($t-stat$), minimum (Min), and maximum (Max) are summarised in this table. Panel A shows the results of portfolios formed without skipping a week between rank period and test period. Panel B are the corresponding results when skipping a week between rank period and test period. The last column in this table reports the correlation coefficients ($Corr$) between momentum returns of Lehmann's weighting strategy and decile momentum returns when not skipping a week between rank period and test period. The sample period is January 1977 to June 1998.

Strategy	Portfolio	Return	$t-stat$	Min	Max	Return	$t-stat$	Min	Max	$Corr$
			Panel A				**Panel B**			
3×3	W	0.06932	5.85	−0.373	0.371	0.06944	5.77	−0.357	0.443	
	L	0.04449	3.22	−0.323	0.398	0.03594	2.53	−0.305	0.374	
	$W-L$	0.02483	2.90	−0.403	0.128	0.03351	4.61	−0.284	0.135	0.900
3×6	W	0.13341	5.10	−0.299	0.527	0.13423	5.03	−0.301	0.532	
	L	0.07694	2.19	−0.317	0.797	0.07931	2.13	−0.333	0.932	
	$W-L$	0.05647	2.86	−0.551	0.230	0.05492	2.45	−0.667	0.228	0.923
3×9	W	0.23511	4.51	−0.270	1.265	0.23861	4.46	−0.275	1.289	
	L	0.11590	2.02	−0.333	1.028	0.11620	2.05	−0.354	1.035	
	$W-L$	0.11921	4.82	−0.206	0.344	0.12241	5.04	−0.202	0.326	0.813
3×12	W	0.27898	5.29	−0.165	0.745	0.28447	5.16	−0.161	0.730	
	L	0.16962	2.86	−0.320	0.651	0.17243	2.81	−0.296	0.648	
	$W-L$	0.10935	3.91	−0.202	0.258	0.11204	3.94	−0.216	0.275	0.893
6×3	W	0.07510	6.51	−0.400	0.324	0.07475	6.43	−0.387	0.383	
	L	0.03454	2.48	−0.344	0.418	0.02763	1.92	−0.340	0.406	
	$W-L$	0.04055	4.41	−0.348	0.179	0.04712	5.63	−0.198	0.172	0.917
6×6	W	0.15175	5.81	−0.282	0.706	0.15271	5.85	−0.249	0.735	
	L	0.07761	2.43	−0.314	0.754	0.06504	2.00	−0.378	0.708	
	$W-L$	0.07414	3.27	−0.455	0.329	0.08767	4.17	−0.417	0.306	0.914
6×9	W	0.23654	7.69	−0.114	0.534	0.23650	7.61	−0.115	0.533	
	L	0.07657	1.87	−0.475	0.557	0.07980	1.90	−0.466	0.580	
	$W-L$	0.15997	6.42	−0.091	0.360	0.15670	6.16	−0.129	0.351	0.867
6×12	W	0.32230	5.86	−0.137	0.778	0.32237	5.75	−0.134	0.789	
	L	0.15464	2.65	−0.288	0.921	0.14308	2.24	−0.361	0.924	
	$W-L$	0.16766	5.23	−0.143	0.475	0.17929	5.60	−0.135	0.462	0.804
9×3	W	0.08009	6.82	−0.399	0.341	0.08012	6.77	−0.378	0.380	
	L	0.03341	2.32	−0.352	0.439	0.02619	1.78	−0.352	0.434	
	$W-L$	0.04668	4.99	−0.351	0.213	0.05393	6.45	−0.167	0.205	0.937
9×6	W	0.16144	6.00	−0.332	0.604	0.16029	5.79	−0.336	0.546	
	L	0.05117	1.48	−0.358	0.675	0.05462	1.50	−0.365	0.791	
	$W-L$	0.11027	5.80	−0.256	0.350	0.10567	5.09	−0.338	0.371	0.919
9×9	W	0.23613	5.25	−0.180	0.871	0.23494	5.23	−0.175	0.875	
	L	0.12793	2.12	−0.317	1.060	0.11489	1.75	−0.342	1.17	
	$W-L$	0.10820	3.05	−0.500	0.388	0.12005	3.14	−0.580	0.419	0.926
9×12	W	0.32964	4.38	−0.298	1.241	0.32830	4.20	−0.312	1.274	
	L	0.20254	1.95	−0.379	1.451	0.21319	1.96	−0.390	1.471	
	$W-L$	0.12710	2.55	−0.429	0.481	0.11511	2.07	−0.555	0.482	0.922
12×3	W	0.08354	6.81	−0.410	0.358	0.08286	6.72	−0.391	0.413	
	L	0.02974	2.10	−0.345	0.450	0.02181	1.49	−0.352	0.442	
	$W-L$	0.05380	5.45	−0.339	0.219	0.06105	6.78	−0.170	0.201	0.919
12×6	W	0.16485	5.99	−0.277	0.760	0.16247	5.98	−0.241	0.765	
	L	0.06976	2.13	−0.318	0.776	0.05830	1.75	−0.398	0.746	
	$W-L$	0.09509	4.19	−0.360	0.326	0.10417	4.79	−0.347	0.311	0.940
12×9	W	0.23858	4.78	−0.302	1.127	0.23602	4.55	−0.311	1.175	
	L	0.08912	1.54	−0.324	0.969	0.09080	1.60	−0.344	0.963	
	$W-L$	0.14945	4.76	−0.251	0.418	0.14522	4.69	−0.246	0.399	0.915
12×12	W	0.27946	6.52	−0.178	0.671	0.27643	6.38	−0.185	0.659	
	L	0.16096	2.56	−0.408	0.869	0.16118	2.61	−0.410	0.833	
	$W-L$	0.11850	2.89	−0.318	0.390	0.11525	2.89	−0.327	0.397	0.880

It was expected that the mean returns of decile winner, loser and winner minus loser would be similar to the corresponding mean returns obtained using Lehmann's weighting strategy. In fact, their patterns are identical. The mean returns of all the momentum portfolios are positive, and they are statistically significant. Comparing the results, the most significant momentum strategy is still the 12×3 strategy, which yields 5.380% per quarter (t-statistic is 5.45) when there is no time lag between rank and test periods and 6.105% per quarter (t-statistic is 6.78) when skipping a week after portfolio formation. This is not surprising because both methods reflect the same idea. Lehmann's weighting strategy gives a big weight (positive or negative) to a stock experiencing extreme performance over the past rank period, while the decile momentum portfolio is directly formed by decile winners and decile losers. Their close relationship can also be seen from the correlation coefficients between their momentum returns, which are shown in the last column in Table 3.4.2.

From Panel A and Panel B in Table 3.4.1 and Table 3.4.2 we can see that for each strategy the results obtained without and with skipping a week between rank period and test period are almost identical. The possible price pressure and lagged reaction have virtually no effects on the results. This implies that such effects are not important. Accordingly, I will drop the 'skip a week' analysis hereafter.

One important issue ignored in obtaining the results reported in Table 3.4.1 and 3.4.2 is transaction costs. However, the strategies using non-overlapping test periods do not involve very frequent trading (i.e., the frequency of trading is TM months for the $RM \times TM$ strategy). In addition, for some stocks their holding positions (long or short) are not necessarily closed in the following test period(s) since they may still be winners or losers at the beginning of the following test period(s).[19] For example, with the 6×6 strategy Electrocomponents plc is a winner on 1/7/1977 and it is still a winner on 1/1/1978. Thus, the portfolio turnover will not be huge for the decile momentum strategies. Although it is not clear what transaction costs are relevant, a transaction cost of 0.5% per security per pound in each test period does not affect the profitability of these momentum portfolios. For instance, for the 6×6 strategy without skipping a week between rank period and test period the average semi-annual momentum return is 6.41% (t-statistics is 2.83) after adjusting for the 0.5% transaction cost. As a result, the transaction cost will be ignored in this study.

Table 3.4.3 provides a more detailed description of each decile portfolio and the decile momentum portfolio for 3×3, 6×6, 9×9 and 12×12 strategies when not skipping a week after portfolio formations. Other strategies and the case that skips a week between rank period and test period have very similar results, and they are not reported here. This table reports the portfolios' test-period β, MV and UP besides the mean return and its standard deviation (std) and t-statistic ($t-stat$). The test-period βs are the Scholes-Williams betas estimated from the test-period monthly returns with respect to the value-weighted monthly returns of securities in the sample.[20] The use of the Scholes-Williams beta estimates is due to price-adjustment delays and trading frictions that cause the observed returns on securities to depart from their true values.

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[19] In this case the weight will change, but the amount is very small since the change in the number of stocks in the sample is not big over the intermediate time horizon.

[20] The Scholes-Williams beta estimates are defined as

$$\beta = \sum_{k=-1}^{1} \frac{b_k}{1+2\rho},$$

where b_k are the slope coefficients from three separate OLS regressions,

$$r_{P\tau} = a_k + b_k r_{m,\tau+k} + e_{P\tau}, \qquad k = -1, 0, +1,$$

and where $r_{P\tau}$ is the return on portfolio P in month τ, $r_{m\tau}$ is the value-weighted return of securities

These delays may result from infrequent trading, so that reported returns reflect dated transactions and are therefore non-synchronous across securities, or from frictions in the trading process that cause adjustment lags in quotation prices. In turn, these price-adjustment delays not only result in serial correlation in observed security returns, but they also lead to auto-correlation in market index returns. As a result, the ordinary-least-squares-estimated beta is biased. This bias is corrected in the Scholes-Williams beta estimator by taking the serial correlation into account. Although a generalised Scholes-Williams beta estimator has been proposed by Cohen et al. (1986), the higher orders of autocorrelations required in the generalised estimator are, in general, not statistically significant. For example, the second order auto-correlation of the value-weighted within-sample market index is insignificant. Hence, in this study the Scholes-Williams beta estimates are used to account for the portfolios' systematic risks. The portfolios' MV and UP reported in Table 3.4.3 are cross-sectional and time-series averages. That is, at the beginning of each test period, equally-weighted MV and UP for each portfolio are computed, giving rise to $(258-RM)/TM$ market values and UPs for each portfolio over the full sample period. The average of the $(258-RM)/TM$ market values and UPs for each portfolio are reported in Table 3.4.3. The same procedure is used in this thesis for calculating a portfolio's average C/P ratio and B/M ratio.

Table 3.4.3 Decile Portfolios' Performance and Characteristics

This table summarises the ten decile portfolios' and decile momentum portfolios' average TM-month returns ($Return$) and their standard deviations (Std), t-statistics ($t-stat$), Scholes-Williams betas ($SW-\beta$), average market values (MV, in million of pounds) and average unadjusted prices (UP) for 3×3, 6×6, 9×9 and 12×12 strategies. Numbers in parentheses are t-statistics of $W-L$'s MV and UP, respectively. $D2$ stands for the second decile portfolio, $D3$ for the third decile portfolio and so on. The sample period is from January 1977 to June 1998.

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in the sample in month τ, ρ is the first-order auto-correlation of $r_{m\tau}$.

Strategy	Portfolio	$Return$	Std	$t-stat$	$SW-\beta$	MV	UP	Obs
	L	0.04449	0.128	3.22	1.1251	79.50	95.23	85
	$D2$	0.03889	0.099	3.63	1.0241	145.64	165.03	85
	$D3$	0.04714	0.088	4.96	0.8935	176.89	183.18	85
	$D4$	0.04710	0.088	4.94	0.9396	205.71	204.52	85
	$D5$	0.04917	0.087	5.21	0.9264	227.44	210.17	85
3×3	$D6$	0.05453	0.090	5.58	0.9659	249.31	211.31	85
	$D7$	0.05325	0.089	5.50	0.9301	260.32	222.23	85
	$D8$	0.05452	0.090	5.60	0.9554	273.24	219.89	85
	$D9$	0.06013	0.096	5.80	1.004	280.10	233.24	85
	W	0.06932	0.109	5.85	1.0414	162.02	224.98	85
	$W-L$	0.02483	0.079	2.90	−0.0837	82.52	129.75	85
						(2.97)	(6.37)	
	L	0.07761	0.207	2.43	1.0835	64.34	104.60	42
	$D2$	0.08760	0.166	3.41	0.9734	133.58	133.68	42
	$D3$	0.09459	0.155	3.95	0.9320	171.42	170.30	42
	$D4$	0.08950	0.135	4.29	0.8334	197.80	184.12	42
	$D5$	0.10036	0.137	4.77	0.9746	213.79	222.79	42
6×6	$D6$	0.10232	0.134	4.96	0.9498	263.29	201.30	42
	$D7$	0.10975	0.136	5.25	0.9582	252.49	244.32	42
	$D8$	0.11615	0.134	5.61	0.9525	289.76	241.04	42
	$D9$	0.13021	0.145	5.83	1.0201	279.16	221.17	42
	W	0.15175	0.169	5.81	1.0469	183.64	237.99	42
	$W-L$	0.07415	0.147	3.27	−0.0366	119.30	133.39	42
						(2.82)	(3.67)	
	L	0.12793	0.314	2.12	1.0593	46.30	81.71	27
	$D2$	0.11922	0.241	2.57	1.0738	116.86	130.37	27
	$D3$	0.13540	0.205	3.42	0.9475	180.36	195.11	27
	$D4$	0.14130	0.194	3.78	0.9330	212.86	190.67	27
	$D5$	0.15319	0.180	4.43	0.8763	210.31	194.40	27
9×9	$D6$	0.15116	0.183	4.30	0.9411	252.84	236.11	27
	$D7$	0.15159	0.190	4.14	0.9390	257.04	230.40	27
	$D8$	0.18045	0.189	4.96	0.9679	296.86	233.50	27
	$D9$	0.19245	0.207	4.82	0.9792	261.41	264.00	27
	W	0.23613	0.234	5.25	1.0835	156.58	236.06	27
	$W-L$	0.10820	0.185	3.05	0.0242	110.29	154.36	27
						(3.30)	(7.92)	
	L	0.16096	0.281	2.56	1.1324	56.06	69.29	20
	$D2$	0.17260	0.257	3.00	0.9857	100.92	114.43	20
	$D3$	0.18065	0.196	4.12	0.9513	172.29	157.93	20
	$D4$	0.19324	0.173	5.00	0.9566	206.91	173.64	20
	$D5$	0.19871	0.170	5.22	0.9461	227.85	191.68	20
12×12	$D6$	0.21650	0.168	5.77	0.8939	225.19	196.65	20
	$D7$	0.22288	0.151	6.61	0.9646	241.59	265.01	20
	$D8$	0.21964	0.152	6.47	0.9643	299.25	288.34	20
	$D9$	0.21787	0.137	7.13	0.9974	247.80	223.30	20
	W	0.27946	0.192	6.52	1.1063	165.52	235.45	20
	$W-L$	0.11850	0.184	2.89	−0.0261	109.45	166.16	20
						(2.41)	(8.28)	

From the results in Table 3.4.3, the average returns show a near monotonic increase from the loser decile to the winner decile. This pattern can be seen from Figure 3.4.1, which graphs the decile portfolio returns for the 4 strategies reported in Table 3.4.3.

Moreover, each loser portfolio has the highest standard deviation and highest systematic risk (Scholes-Williams beta) except for the 9×9 strategy where the winner's beta is higher than the loser's. This evidence suggests that systematic risk cannot explain the momentum profits. The decile portfolios' UP s show that the loser has the lowest average UP for each strategy, and the winners' UP s are significantly greater than the losers' UP s. Therefore, the momentum profits are not likely to be due to the effect of low-priced stocks documented by Conrad and Kaul (1993). Furthermore, for each strategy the average market values of the stocks (MV) in the different decile portfolios show that both past winner and loser portfolios consist of smaller than average stocks, with the stocks in the loser portfolio being on average smaller than the stocks in the winner portfolio. This evidence partially supports the size effect, if the size effect is positive in the UK, as winners tend to be small firms. Even so, the momentum profits cannot be attributed to the small-firm effect completely; losers are on average smaller than winners after all. Detailed analysis on how small firms would affect the results is conducted in the following chapters.

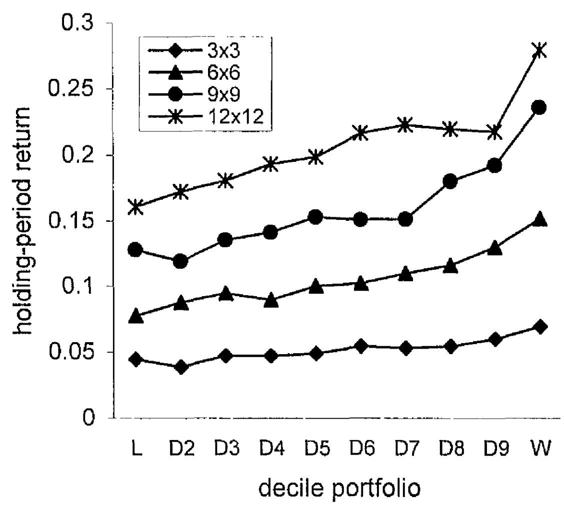

Figure 3.4.1 Holding-period Returns of Decile Portfolios

In this section, however, I will not further examine where the momentum profits come from based on the full sample containing the 4182 LSPD stocks. The reason is that the sample includes all kinds of UK stocks from January 1977 to December 1996 such as USM stocks, OTC stocks, etc. Such kinds of stocks may cause quotation problems and involve non-synchronous trading. Furthermore, financial firms normally have high leverage (gearing), but the high leverage probably does not have the same meaning as for non-financial firms. Including financial firms in the sample may bias the results because of the debt/equity effect documented by Bhandari (1988).[21] Some researchers such as Fama and French (1992) exclude from their analysis all financial firms. Barber and Lyon (1997) reveal that the empirical results are similar for financial and non-financial firms when analysing the relation between size, book-to-market, and security returns. To avoid the possible biases as well as to include more data in the sample such as C/P and B/M etc., further examinations will be carried out based on another sample (a sub-sample of the full sample), denoted the *accounting sample*, which will be defined in the next section. Analysing the accounting sample will also help to find whether there is a sample-specific problem.

3.5 Empirical Results Based on the Accounting Sample

For this section I restrict the analysis to an accounting sample which includes those firms with accounting data of C/P and B/M available. The accounting sample is

[21] Bhandari (1988) finds that expected common stock returns are positively related to the debt/equity ratio, controlling for beta and firm size. This study will not examine the leverage effect since the B/M, MV and Fama and French's three factor model seems to absorb the role of leverage.

taken out from the full sample including 4182 LSPD stocks analysed in the last section. In this accounting sample financial firms are excluded.[22] As mentioned in the last section, the LSPD includes all kinds of stocks. Thus, besides excluding financial firms in the accounting sample I also exclude those whose sample indicators in the LSPD Reference Manual (Version 10) are:

(1) Secondary shares of existing companies from January 1978;

(2) Irish, Scottish and odd companies quoted in SEDOL from January 1978;

(3) Odd foreign mining and banking shares;

(4) Unlisted securities market (USM);

(5) Third market companies;

(6) O.T.C. companies;

(7) Split trusts;

(8) Alternative investment market (AIM).

Obviously, the name "accounting sample" is not accurate. Nevertheless, it can be used to reflect the main contents of the sub-sample. Under these restrictions, there are 2434 stocks in the accounting sample from January 1977 to December 1996. Compared with the sample examined in the last section, the reduction is considerable (from 4182 stocks to 2434 stocks). Because this sample contains more information such as C/P and B/M data, further examinations will concentrate on the accounting sample.

First of all, based on the accounting sample I repeat the calculations conducted in the last section without skipping a week between rank period and test period. Table 3.5.1 reports the empirical results. Panel A shows each strategy's average TM-month returns for winner (W), loser (L) and winner minus loser ($W-L$) obtained using

[22] Financial firms are those firms with LSPD industrial classification codes ranging from 710 to 980,

Lehmann's weighting strategy, and Panel B shows the decile portfolios' (W, L, and $W-L$) results. Clearly both Panel A's and Panel B's results are quite similar because of the internal relations between Lehmann's weighting strategy and the decile analyses discussed in the last section. As a result, I will concentrate on the decile analyses in the rest of this thesis.

Table 3.5.1 Average Returns Based on the Accounting sample

This table reports the average TM-month test-period returns ($Return$) and t-statistics ($t-stat$) of the 16 strategies' winners (W), losers (L) and momentum ($W-L$) portfolios. Panel A summarises the results obtained using Lehmann's weighting strategy, and Panel B reports the corresponding results when using decile portfolios. In this table, $No+$ stands for the number of positive momentum returns over the sample period for each strategy, and Obs is the number of observations. The sample period is January 1977 to June 1998.

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including both Financials and Investment Trusts (see LSPD Reference Manual, 1997, Version 10.0).

Strategy	Portfolio	Return	$t-stat$	$No+$	Return	$t-stat$	$No+$	Obs
		Panel	A			Panel	B	
3×3	W	0.07050	6.06		0.07482	6.50		85
	L	0.04437	3.78		0.04144	3.05		85
	$W-L$	0.02613	4.43	61	0.03338	4.62	58	85
3×6	W	0.14060	5.17		0.14830	5.39		42
	L	0.09604	3.32		0.08407	2.58		42
	$W-L$	0.04456	3.74	30	0.06423	4.25	32	42
3×9	W	0.23034	4.82		0.24248	5.15		28
	L	0.14645	3.14		0.14183	2.50		28
	$W-L$	0.08389	4.10	23	0.10065	4.87	23	28
3×12	W	0.28057	5.40		0.30082	5.59		21
	L	0.19965	3.66		0.18936	2.99		21
	$W-L$	0.08093	2.76	16	0.11146	3.43	17	21
6×3	W	0.07520	6.54		0.07894	6.85		84
	L	0.03867	3.26		0.03432	2.56		84
	$W-L$	0.03653	5.83	65	0.04462	5.62	64	84
6×6	W	0.14877	5.92		0.15776	6.29		42
	L	0.08306	3.25		0.07969	2.63		42
	$W-L$	0.06572	4.60	31	0.07807	4.54	32	42
6×9	W	0.23061	7.10		0.24428	7.36		28
	L	0.12119	3.28		0.11303	2.59		28
	$W-L$	0.10942	5.45	22	0.13125	5.26	22	28
6×12	W	0.34581	5.56		0.34760	6.10		21
	L	0.17382	3.08		0.16660	2.54		21
	$W-L$	0.17199	4.64	18	0.18100	5.62	18	21
9×3	W	0.07687	6.55		0.08270	7.06		83
	L	0.03639	3.09		0.03289	2.38		83
	$W-L$	0.04048	6.67	65	0.04981	6.29	62	83
9×6	W	0.15694	5.74		0.17112	6.09		41
	L	0.07582	2.77		0.06587	1.98		41
	$W-L$	0.08111	5.65	34	0.10525	6.11	34	41
9×9	W	0.24180	5.43		0.25807	5.82		27
	L	0.12976	2.73		0.12124	2.13		27
	$W-L$	0.11204	4.39	23	0.13683	4.23	22	27
9×12	W	0.32409	4.31		0.33703	4.45		20
	L	0.20690	2.55		0.19988	2.20		20
	$W-L$	0.11719	3.62	17	0.13715	3.29	16	20
12×3	W	0.08454	7.07		0.08640	7.11		82
	L	0.03292	2.81		0.03120	2.26		82
	$W-L$	0.05162	7.53	64	0.05520	6.24	65	82
12×6	W	0.16638	6.35		0.16552	6.52		41
	L	0.07372	2.85		0.07493	2.41		41
	$W-L$	0.09266	5.55	34	0.09059	4.52	31	41
12×9	W	0.24363	4.87		0.23908	4.83		27
	L	0.12305	2.68		0.10577	2.02		27
	$W-L$	0.12058	3.80	23	0.13331	4.49	23	27
12×12	W	0.30618	6.59		0.28071	6.74		20
	L	0.18511	3.57		0.18304	3.16		20
	$W-L$	0.12107	2.92	15	0.09767	2.54	15	20

The results in Table 3.5.1 give the same conclusions as those found in the last section. All average momentum returns obtained from both methods are positive, and they are all statistically significant. More specifically, all momentum profits of the 16 strategies are consistently positive. This can be seen from the number of the positive momentum returns ($No+$) of each strategy over the full sample period reported in this table. For example, there are 32 positive momentum returns over the 42 test periods for the 6×6 decile strategy. Hence, it is not necessary to conduct further robustness tests on the momentum profits by using non-parametric tests such as the sign test, rank test and so on. However, recent studies (Barber and Lyon (1997), and Lyon, Barber and Tsai (1999)) have documented a positive skewness bias in long-horizon abnormal returns, resulting in standard parametric significance tests being mis-specified. Since the momentum analysis is based on intermediate horizons, the non-normality bias may not be a serious issue in this study. To further check whether the previous results are biased by non-normalities in returns I apply a bootstrap analysis to the momentum profits from the full and accounting samples for strategies $RM \times TM$ where $RM = TM$. The test procedure and the results are presented in Appendix 3A. The bootstrap test shows that the significance levels are reduced in every case in comparison with significance levels associated with the t-statistics reported previously. Yet, the crucial result for the present analysis is that momentum profits remain clearly significant, giving bootstrap p-values of less than 1% in most cases (see Table 3A.1 in Appendix 3A).

In addition, the empirical results in Table 3.5.1 also show that the most significant momentum portfolio still selects stocks based on their returns over the previous 12 months and then holds the position for 3 months. This strategy yields 5.162% per quarter (shown in Panel A) when using Lehmann's weighting method and it yields 5.520% per quarter (shown in Panel B) when the decile momentum portfolio is considered. This finding is the same as in the US market where the most successful momentum strategy is also the 12×3 strategy as reported in Jegadeesh and Titman (1993). All these results further confirm the momentum effect, and suggest that there is no sample-specific problem found.

From Table 3.5.1 we can see that for a given TM-month holding period the momentum profits are slightly different (generally increasing) as the rank period changes from 3 months to 12 months. However, the differences are statistically insignificant. All null hypotheses that for a given TM-month holding period the returns on each 4 decile portfolios (e.g., 4 loser portfolios) and on the 4 momentum portfolios are jointly equal for the 4 different rank periods of 3, 6, 9, and 12 months cannot be rejected. For example, the F-statistic computed under the hypothesis that the momentum returns of the 3×6, 6×6, 9×6 and 12×6 strategies (the given TM-month test period is 6 months) are jointly equal is 0.7832 with a p-value of 0.51. Therefore, I will generally report the results of 3×3, 6×6, 9×9 and 12×12 strategies in the following analyses. Further for more detailed analyses in the subsequent sections and chapters, I will only report the results of the 6×6 strategy as in Jegadeesh and Titman (1993), and Chan, Jegadeesh and Lakonishok (1996) although all other strategies are also examined. Comparing the results of the 16 strategies, the results for the 6×6 strategy are clearly representative of the results for the other strategies.

From this section and Section 3.4 we have seen that the momentum effect is remarkable over the full sample period of January 1977 to June 1998. However, these results may be due to a particular sub-period. This is examined in the following section.

3.6 Sub-period Analysis

This section examines the decile portfolios' and the decile momentum portfolio's performance in each of two 11-year sub-periods to see whether the momentum profits documented in previous sections are caused by a particular period. Table 3.6.1 summarises the 6×6 strategy's results for the two sub-periods of January 1977 to December 1987 and July 1987 to June 1998. Panel A and Panel B of Table 3.6.1 present the average portfolios' semi-annual test-period buy-and-hold returns (ret_6) for the two 11-year sub-periods, respectively. The t-statistics are shown in parentheses.

Table 3.6.1 Average Portfolios' Returns in the Two 11-year Sub-periods

The decile portfolios are formed based on 6-month past buy-and-hold returns and hold for 6 months. At the beginning of each test-period, the stocks are sorted in ascending order on the basis of 6-month past returns. The equally-weighted portfolio of stocks in the lowest past return decile is the loser portfolio (L), the equally-weighted portfolio of stocks in the next decile is denoted as portfolio $D2$, and so on. The equally-weighted portfolio of stocks in the highest past return decile is the winner portfolio (W). The momentum portfolio is the winner portfolio minus the loser portfolio ($W-L$). The average 6-month holding-period returns (ret_6) of the decile portfolios and the decile momentum portfolio in the two 11-year sub-periods are reported in this table. Panel A summarises the results of the sub-period of January 1977 to December 1987, and Panel B presents the results of the sub-period of July 1987 to June 1998. Numbers shown in parentheses are t-statistics.

	L	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	W	$W-L$
	Panel A: January 1977 to December 1987										
ret_6	0.1297 (3.09)	0.1352 (4.03)	0.1368 (4.47)	0.1217 (4.03)	0.1517 (4.66)	0.1524 (4.81)	0.1560 (4.49)	0.1586 (4.99)	0.1773 (4.41)	0.2025 (4.96)	0.0728 (3.01)
	Panel B: July 1987 to June 1998										
ret_6	0.0297 (0.71)	0.0303 (0.90)	0.0401 (1.48)	0.0437 (1.70)	0.0509 (2.09)	0.0625 (2.76)	0.0693 (3.04)	0.0790 (3.38)	0.0909 (3.90)	0.1130 (4.23)	0.0834 (3.33)

The results in Table 3.6.1 show that the momentum effect found in previous sections is not attributable to any particular period. Both momentum returns realised in the two 11-year sub-periods are statistically positive. The average 6-month return of the winner minus loser portfolio ($W - L$) is 7.28% with a t-statistic of 3.01 in the sub-period of January 1977 to December 1987, and it is equal to 8.34% with a t-statistic of 3.33 in the sub-period of July 1987 to June 1998. Comparing the decile portfolios' returns, it is clear that winner portfolios (W) are still winners and loser portfolios' performances are still poor during the test periods in each sub-period. This evidence is consistent with previous findings. However, the profitability is reduced in the most recent 11 years for the 10 decile portfolios and the reduction is considerable. On average, the loser portfolio through the fourth decile portfolio ($D4$) gives returns that are insignificantly different from zero during the 6-month test periods in the sub-period of July 1987 to June 1998. And yet the momentum effect is not reduced in this sub-period, rather it is slightly more pronounced than in the sub-period of January 1977 to December 1987. Further examinations of the performances in different sub-period are given in the next chapter.

3.7 Analysis of Seasonality

The well-known January phenomenon has been documented in many empirical studies in the US, UK and other countries. For instance, Rozeff and Kinney (1976) report that January returns are higher than in any other month in the US market. Gultekin and Gultekin (1983) examine the monthly stock returns from 17 countries and find that average January returns are significantly larger than returns in the other eleven months for 13 of the 17 countries analysed. Recently, Clare and Thomas (1992, 1995) report the existence of a January, March, and April effect in the UK stock market. There is no definite conclusion regarding seasonality although some researchers have suggested tax-loss selling as an explanation of the January seasonal in the US market. However, this explanation is of limited use in the UK since the tax year ends in April. While this is an interesting issue, I do not examine it here. Instead, I will concentrate on the examination to ascertain whether there are any seasonalities and whether the momentum profits can be explained by them.

Table 3.7.1 reports the average returns in each calendar month for each decile portfolio and the momentum portfolio, together with the all month case (All) and the non-January case ($NoJan$) (i.e., from February to December) for the 6×6 strategy.[23] $F-stat$ are F-statistics calculated under the null hypothesis that for a given portfolio the average returns in January (Jan) through December (Dec) are jointly equal, and their probabilities are given by $p-Value$. Numbers in parentheses are t-statistics. The strong seasonal patterns are eye-catching. Comparing the returns through the twelve calendar months decile portfolios generally realise the highest return in January with the loser portfolio exhibiting the largest January return of 7.11 percent with a t-statistic of 5.40. In addition, the February effect is also pronounced, and the second highest return of each decile portfolio is generally realised in this month. Moreover, the returns of the decile portfolios in March and April are also higher than the returns in May through December. All the F-statistics confirm the differences at a significance level of 5%. Thus, the hypothesis that for a given portfolio the average

[23] The analysis is based on weekly returns falling within calendar months.

returns in January through December are jointly equal is rejected. Because the loser portfolio has a higher average return in January than other decile portfolios, and the loser contains more small firms than others as documented in Section 3.4, these findings are the same as the US market. However, this cannot be attributed to tax-loss selling because the tax year ends in April in the UK. The tax-loss selling hypothesis, hence, is questionable.[24] This evidence is consistent with other researchers' arguments that debate the tax-loss-selling hypothesis. For instance, Constantinides' (1984) optimal tax trading rule does not predict the January seasonal by itself. Chan's (1986) empirical results are also inconsistent with a model that explains the January seasonal by optimal tax-loss selling.

Table 3.7.1 Analysis of Seasonality

The decile portfolios are formed based on 6-month past returns and held for 6 months. The equally-weighted portfolio of stocks in the lowest past return decile is the loser portfolio (L); the equally-weighted portfolio of stocks in the next decile is portfolio $D2$, and so on. The equally-weighted portfolio of stocks in the highest past return decile is the winner portfolio (W). This table presents the average returns in each calendar month of each decile portfolio and the momentum portfolio ($W-L$). Meanwhile, the average monthly returns on the portfolios for the all month case (All) and the non-January ($NoJan$) case are also described in this table. $F-stat$ are F-statistics computed under the null hypothesis that for a given portfolio the average returns in January (Jan) through December (Dec) are jointly equal. $p-Value$ are p-values of the F-statistics. Numbers shown in parentheses are t-statistics. The sample period is January 1977 to June 1998.

[24] Brown, Keim, Kleidon and Marsh (1983) demonstrate that tax laws influence investors' portfolio decisions by encouraging the sale of securities that have experienced recent price declines so that the (short term) capital loss can be offset against taxable income. Small firm stocks are likely candidates for tax-loss selling since these stocks typically have higher variances of price changes and, therefore, larger probabilities of larger price declines. Heavy selling pressure depresses the price of loser stocks. After the tax year-end, the price pressure disappears and prices rebound to equilibrium levels. Thus, loser stocks display large returns at the beginning of the new tax year.

Month	L	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	W	$W-L$
All	0.0125 (3.33)	0.0130 (4.02)	0.0140 (4.83)	0.0128 (4.70)	0.0155 (5.59)	0.0168 (5.97)	0.0175 (6.25)	0.0186 (6.55)	0.0205 (7.14)	0.0245 (7.49)	0.0120 (4.97)
NoJan	0.0071 (1.92)	0.0100 (3.01)	0.0119 (3.93)	0.0107 (3.74)	0.0134 (4.63)	0.0148 (5.00)	0.0160 (5.37)	0.0165 (5.51)	0.0187 (6.13)	0.0221 (6.36)	0.0149 (6.21)
Jan	0.0711 (5.40)	0.0458 (4.22)	0.0372 (4.09)	0.0363 (4.73)	0.0379 (4.81)	0.0392 (4.98)	0.0342 (5.04)	0.0411 (6.04)	0.0404 (6.13)	0.0511 (7.62)	−0.0200 (−2.06)
Feb	0.0367 (2.55)	0.0363 (3.28)	0.0267 (2.36)	0.0301 (3.33)	0.0346 (4.27)	0.0373 (4.53)	0.0308 (3.78)	0.0372 (4.84)	0.0409 (4.83)	0.0462 (5.71)	0.0095 (0.92)
Mar	0.0133 (0.93)	0.0255 (2.17)	0.0254 (2.49)	0.0256 (2.54)	0.0294 (3.06)	0.0306 (3.04)	0.0348 (3.46)	0.0345 (3.48)	0.0353 (3.45)	0.0315 (2.95)	0.0183 (1.83)
Apr	0.0254 (2.30)	0.0265 (2.70)	0.0262 (3.38)	0.0240 (3.21)	0.0270 (3.67)	0.0311 (4.04)	0.0274 (4.14)	0.0276 (4.27)	0.0274 (4.15)	0.0259 (3.57)	0.0005 (0.06)
May	0.0130 (1.21)	0.0191 (2.15)	0.0179 (2.02)	0.0155 (2.20)	0.0169 (2.30)	0.0173 (2.14)	0.0219 (2.82)	0.0178 (2.61)	0.0259 (3.67)	0.0356 (3.72)	0.0226 (2.91)
June	−0.0139 (−1.06)	−0.0080 (−0.78)	0.0008 (0.10)	0.0018 (0.23)	0.0016 (0.19)	0.0058 (0.69)	0.0050 (0.56)	0.0021 (0.26)	0.0075 (0.86)	0.0046 (0.51)	0.0185 (2.67)
July	−0.0091 (−0.69)	−0.0008 (−0.06)	0.0039 (0.36)	0.0046 (0.46)	0.0064 (0.66)	0.0052 (0.54)	0.0100 (1.06)	0.0125 (0.98)	0.0125 (1.16)	0.0198 (1.19)	0.0289 (2.81)
Aug	0.0163 (1.23)	0.0147 (1.32)	0.0161 (1.32)	0.0161 (1.46)	0.0160 (1.53)	0.0210 (2.10)	0.0214 (2.05)	0.0214 (1.90)	0.0248 (2.31)	0.0294 (2.46)	0.0131 (1.83)
Sep	−0.0042 (−0.37)	−0.0013 (−0.12)	0.0019 (0.21)	−0.0002 (−0.02)	0.0083 (0.89)	0.0056 (0.59)	0.0131 (1.19)	0.0151 (1.49)	0.0135 (1.20)	0.0193 (1.69)	0.0235 (4.05)
Oct	−0.0029 (−0.24)	−0.0088 (−0.67)	−0.0067 (−0.50)	−0.0073 (−0.56)	−0.0053 (−0.36)	−0.0048 (−0.34)	−0.0044 (−0.30)	−0.0005 (−0.04)	−0.0010 (−0.07)	0.0037 (0.22)	0.0065 (0.72)
Nov	−0.0069 (−0.61)	−0.0019 (−0.20)	0.0014 (0.18)	−0.0019 (−0.22)	−0.0022 (−0.26)	−0.0015 (−0.17)	−0.0016 (−0.17)	−0.0024 (−0.26)	−0.0010 (−0.10)	0.0077 (0.65)	0.0147 (2.80)
Dec	0.0109 (1.46)	0.0087 (1.28)	0.0171 (2.41)	0.0090 (1.28)	0.0147 (1.79)	0.0153 (1.72)	0.0180 (2.26)	0.0165 (2.17)	0.0198 (2.45)	0.0190 (2.43)	0.0081 (2.04)
$F-stat$	3.81	2.78	1.89	2.31	2.38	2.56	1.97	2.32	2.26	1.89	2.53
$p-Value$	0.0000	0.0021	0.0408	0.0103	0.0082	0.0044	0.0320	0.0101	0.0123	0.0409	0.0050

However, the interesting feature shown in Table 3.7.1 is that the strong seasonal patterns do not influence the profitability of the momentum portfolio. The all month case (All) shows that the average monthly return on the momentum portfolio ($W-L$) is 1.20 percent with a t-statistic of 4.97, while its average return is 1.49% per month with a t-statistic of 6.21 when the January return is not included. This says that the average monthly return realised in the non-January case is even larger than in the all month case because the average January return on the momentum portfolio is negative (−2.00% with a t-statistic of −2.06). All other calendar months' returns on the momentum portfolio are positive. Amongst them the momentum returns in May, June, July, September, November and December are statistically positive with the

July return of 2.89% (t-statistic is 2.81) being the highest one. The evidence shows that the momentum profits are not due to seasonality, rather, the strong January seasonal reduces the momentum profits, and the strong February and April seasonals contribute little to the momentum profits.

So far we have found that the momentum effect is quite pronounced in the UK market. However, is it limited within the intermediate horizon of 3 to 12 months, as documented in the US market? The following section examines the persistence of the momentum effect over the long-term horizon.

3.8 Persistence Analysis

In this section I examine the persistence of the momentum effect. The returns of the decile portfolios and the momentum portfolio are tracked over long-term horizons of 2- and 3-year periods following the portfolio formation date. In addition, portfolio returns over the past three-year period are also examined to see the persistence of the portfolio performance. This examination is prompted by the long-term overreaction hypothesis. If the positions of the decile portfolios formed on the basis of past RM-month returns of stocks do not change over the past 3-year period (i.e., if losers and winners are still losers and winners over the past 3 years, respectively), and if the long-term overreaction hypothesis is true, we expect the momentum returns to vanish or even be significantly negative over the long-term holding periods of 2 and 3 years.

To increase the power of the hypothesis tests, the 6×6 strategy will be examined in this section including portfolios with overlapping long-term holding periods (2 and 3 years) and the past 3-year period. Specifically, the overlapping long-term returns are calculated as follows: for the 6×6 strategy, the decile portfolios are formed semi-annually based on the past 6-month stock returns and held for 2 and 3 years. These decile portfolios' past 3-year returns are also computed. Table 3.8.1 reports the average returns of the long-term holding periods (2 and 3 years) and the past 3-year period for the 6×6 strategy's decile portfolios and the momentum portfolio. For comparison, the average 6-month test-period returns (ret_6) and the average 6-month rank-period returns (ret_{-6}) of the portfolios are also presented in this table. Moreover, the average 12-month returns, denoted as ret_{12}, following the portfolios' formation are reported in Table 3.8.1 (i.e., the 6×12 strategy's results) as well. In this table, ret_{-36}, ret_{24} and ret_{36} stand for the buy-and-hold average past-three-year return, average 2-year-test-period return and average 3-year-test-period return, respectively. The t-statistics are shown in parentheses. Because the long-term returns are overlapping, the t-statistics for ret_{-36}, ret_{24} and ret_{36} are computed using the autocorrelation-consistent Newey-West standard errors.[25]

[25] Following White's (1980) suggestion for heteroskedasticity, Newey and West (1987) devise an estimator of a heteroskedasticity and auto-correlation consistent covariance matrix. Here, for the particular case the Newey-West standard error of the long-term mean return is given by

$$\frac{1}{T}\sqrt{\sum_{t=1}^{T} e_t^2 + 2\sum_{j=1}^{l}\sum_{t=j+1}^{T}[(1-\frac{j}{l+1})e_t e_{t-j}]},$$

where e_t is the return deviation from its mean, T is the number of observations, and l is the number of lags. Note that I compute the standard error by choosing the lag number (l) of 5 first. Then I calculate it again by setting l to be 6. I find that the results are almost the same for 5 or 6 lags. Thus, the lag number of 6 is used when computing the Newey-West standard errors.

Table 3.8.1 Persistence Analysis

The decile portfolios are formed semi-annually based on past 6-month returns. The equally weighted portfolio of stocks in the lowest past return decile is the loser portfolio (L), the equally-weighted portfolio of stocks in the next decile is denoted as portfolio $D2$, and so on. The equally-weighted portfolio of stocks in the highest past return decile is the winner portfolio (W). $W-L$ is the momentum portfolio. This table summarises the average 6-month 1-, 2-, and 3-year returns (ret_6, ret_{12}, ret_{24} and ret_{36}) for the portfolios after portfolio formation. In addition, the average 6-month-rank-period returns (ret_{-6}) and the average past 3-year returns (ret_{-36}) of the portfolios are also presented in this table. Note that the average one-year returns (ret_{12}) following portfolio formation are the results of the 6×12 strategy, which are not overlapping. The 2- and 3-year holding-period returns and the past 3-year returns are overlapping. Numbers in parentheses are t-statistics. For the long-term overlapping returns, the t-statistics of the long-term return means are computed using the auto-correlation-consistent Newey-West standard errors. The sample period is January 1977 to June 1998.

	L	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	W	$W-L$
ret_{-6}	−0.3384	−0.1495	−0.0653	−0.0031	0.0539	0.1111	0.1718	0.2471	0.3612	0.7753	1.1137
	(−16.36)	(−7.87)	(−3.46)	(−0.16)	(2.71)	(5.27)	(7.55)	(9.81)	(12.3)	(14.9)	(28.2)
ret_{-36}	0.1035	0.4023	0.5847	0.6671	0.8001	0.8957	1.0377	1.1523	1.3553	2.3690	2.2655
	(0.57)	(2.38)	(3.40)	(4.22)	(4.56)	(4.40)	(5.38)	(5.96)	(5.63)	(4.03)	(4.96)
ret_6	0.0797	0.0827	0.0884	0.0827	0.1013	0.1074	0.1126	0.1188	0.1341	0.1578	0.0781
	(2.63)	(3.32)	(4.11)	(4.03)	(4.70)	(5.24)	(5.22)	(5.80)	(5.61)	(6.29)	(4.54)
ret_{12}	0.1666	0.1485	0.1534	0.1501	0.1594	0.1784	0.2141	0.2140	0.2555	0.3476	0.1810
	(2.54)	(2.67)	(3.14)	(3.22)	(3.33)	(4.39)	(4.06)	(4.70)	(5.59)	(6.10)	(5.62)
ret_{24}	0.4735	0.4901	0.4444	0.4244	0.4780	0.5159	0.5050	0.5123	0.5186	0.6045	0.1310
	(3.17)	(3.46)	(3.59)	(3.36)	(3.57)	(3.91)	(4.04)	(4.22)	(4.18)	(4.93)	(3.04)
ret_{36}	0.8777	0.8367	0.7702	0.7230	0.7982	0.8462	0.8242	0.8095	0.8252	0.9339	0.0562
	(3.54)	(3.67)	(3.73)	(3.59)	(3.53)	(3.80)	(4.05)	(3.95)	(3.87)	(4.31)	(0.63)

The results in Table 3.8.1 show that backward persistence is apparent. As in the semi-annual rank-period returns (ret_{-6}), the past 3-year returns (ret_{-36}) of the loser portfolio through the winner portfolio are monotonically increasing. The average past-3-year return of the momentum portfolio ($W-L$) is 226.55% (t-statistic is 4.96). In other words, the past 6-month loser and winner portfolios retain the same positions over the past 3 years. However, mean reversion is not so pronounced over the 2- and 3-year holding periods. Although mean reversion can be seen from the poor past performers of L, $D2$ and $D3$, the same evidence is not obvious for the good past performers. The momentum returns are still positive over the 2- and 3-year holding periods (the average 2-year momentum return is 13.10% with a t-statistic of 3.04, and the average 3-year momentum return is 5.62% with a t-statistic of 0.63).

However, the price momentum does not last beyond a one-year holding period. The average momentum return over the 3-year holding period is statistically insignificant, and the average 6-month momentum return of 7.81% is economically greater than the average 3-year momentum return of 5.62%. Because the average 1-year-test-period momentum return is 18.10% (t-statistic of 5.62), it is obvious that the average momentum returns realised in years 2 and 3 must be negative. From the preliminary evidence reported in Table 3.4.3 we have seen that loser portfolios have the lowest average MV and they are riskier than winner portfolios; the negative momentum returns in years 2 and 3 may be explained by systematic risk and the size effect. However, regardless of overreaction, systematic risk or the size effect, the evidence of initially positive average momentum returns and then negative beyond a one-year holding period indicates that the momentum portfolio does not tend to pick stocks that have high unconditional expected returns, and that the observed price changes in the first year after the portfolio formation may be temporary. In other words, the momentum effect does not persist beyond one year. These findings are similar to the US market where cumulative returns of the momentum portfolio from one month to thirty-six months appear to be an inverted U shape as documented in Jegadeesh and Titman (1993).

3.9 Summary

This Chapter examines price momentum in the UK stock market during the period of January 1977 to June 1998. The empirical results show that past winners continue to outperform past losers over the intermediate-term horizon of 3 to 12 months. A number of momentum trading strategies show significant momentum returns based on either samples of including 4182 LSPD stocks or non-financial stocks. For instance, the decile momentum portfolio of the 6×6 strategy that selects stocks based on their past 6-month returns and hold them for 6 months realises a semi-annual arbitrage return of 7.81% on average.

Further investigations show that the profitability of the momentum strategies is not confined to any particular sub-period. Momentum returns realised in the two 11-year sub-periods are statistically positive. In addition, seasonal patterns are pronounced in the UK stock market. And yet the strong January seasonality contributes negatively to the momentum profits, and the contributions of the February and April seasonalities to the momentum profits are insignificant. Hence, the significant momentum returns are not due to seasonalities. Moreover, the momentum effect does not persist beyond one year. The average momentum profits realised in years 2 and 3 after portfolio formations are negative. This evidence indicates that the momentum effect is indeed limited to within one year, and suggests that part of the momentum effect may be temporary. However, the long-term return reversal is not so pronounced: the average 2- and 3-year holding-period momentum returns are still positive although the latter is not significant.[26]

It is difficult to account for the empirical results within the efficient markets framework. The remarkable momentum profits remain unchanged even when the

[26] For some strategies (e.g., 9×9, 12×12, etc.) their average 3-year holding-period returns are negative, but they are never significant. Note that this evidence does not imply that the overreaction phenomenon does not exist because the ranking periods are restricted to the intermediate-term horizon which are not consistent with the long-term ranking periods used in the long-term overreaction studies.

sample has been considerably reduced from 4182 stocks to 2434 stocks. In addition, the strong price momentum effect persists after corrections for possible measurement errors in security returns due to price pressure and lagged price reaction. Further, adjusting for a transaction cost of 0.5% per security does not influence the profitability of the momentum strategy. The preliminary evidence found based on the 4182 LSPD stocks shows that the momentum profits may not be explained by systematic risk and low-price effect. Perhaps there is a relation between firm size and the momentum profits as both losers and winners tend to be small firms. Obviously, further examinations to explain the momentum effect are needed, and these are conducted in Chapter 4.

Finally, it should be noted that short selling is difficult in the UK. However, this restriction does not affect the results because loser portfolios, selling side, do not contribute to the momentum returns. This evidence can be seen in Chapter 4.

Appendix 3A

Robustness against Non-normalities

In this appendix I perform a robustness check by applying a non-parametric bootstrap test to examine whether the results documented in this chapter are biased by skewness in portfolio returns. The approach that I adopt is the bootstrap shift method (Noreen 1989). This non-parametric analysis is conducted to the momentum profits from the full and accounting samples for 3×3, 6×6, 9×9 and 12×12 strategies. The procedure for the bootstrap test is as follows.

For each winner (W), loser (L), and winner minus loser ($W-L$) portfolios I conduct a 50% re-sampling, with replacement, from the original samples of portfolio returns and calculate the mean return. This exercise is repeated 10,000 times. I then compute the overall mean return of these 10,000 re-samples and subtract this from each individual mean return. Finally, I rank the mean-shifted 10,000 mean returns. The bootstrapped p-values for the original W, L, and $W-L$ portfolio mean returns are given according to where these figures fall in the distribution of ranked mean-shifted mean returns. Table 3A.1 summarises the results of this analysis. Panel A of Table 3A.1 is for the full sample and the parametric p-values are calculated from the t-statistics presented in Table 3.4.2. Panel B of Table 3A.1 shows the results of accounting sample with the parametric p-values being computed from the t-statistics presented in Table 3.5.1.

Table 3A.1 Bootstrapped p-values for the Full and Accounting Samples

This table reports the average TM-month returns ($Return$) and bootstrapped p-values, for 4 $RM \times TM$ strategies where $RM = TM$, of winner (W), loser (L) and momentum ($W-L$) portfolios. Panel A summarises the results obtained for the full sample, and Panel B reports the corresponding results for the accounting sample. The $Return$ columns repeat figures in Tables 3.4.2 and 3.5.1. The parametric $p-value$ columns report p-values corresponding to the t-statistics in Tables 3.4.2 and 3.5.1. The sample period is January 1977 to June 1998.

Strategy	Portfolio	*Return*	Parametric $p-value$	Bootstrapped $p-value$	*Return*	Parametric $p-value$	Bootstrapped $p-value$
		Panel A: Full Sample			**Panel B:** Accounting Sample		
3×3	W	0.06932	0.0000	0.0000	0.07482	0.0000	0.0000
	L	0.04449	0.0009	0.0119	0.04144	0.0015	0.0162
	$W-L$	0.02483	0.0024	0.0107	0.03338	0.0000	0.0006
6×6	W	0.15175	0.0000	0.0002	0.15776	0.0000	0.0000
	L	0.07761	0.0097	0.0495	0.07969	0.0059	0.0344
	$W-L$	0.07414	0.0011	0.0042	0.07807	0.0000	0.0003
9×9	W	0.23613	0.0000	0.0002	0.25807	0.0000	0.0001
	L	0.12793	0.0215	0.0692	0.12124	0.0210	0.0672
	$W-L$	0.10820	0.0025	0.0067	0.13683	0.0001	0.0002
12×12	W	0.27946	0.0000	0.0000	0.28071	0.0000	0.0000
	L	0.16096	0.0091	0.0369	0.18304	0.0024	0.0153
	$W-L$	0.11850	0.0044	0.0105	0.09767	0.0095	0.0191

Apparently, significant levels are reduced in every case in comparison with significance levels associated with the parametric p-values. However, the results of the bootstrap test do not suggest rejecting the significant momentum profits. In fact, the momentum profits remain clearly significant since the highest bootstrapped p-value is 1.91% and in most cases the bootstrapped p-values are less than 1%. For the test procedure described above, the bootstrap test should be robust to any form of non-normality provided only that the bootstrapped sampling distribution fairly represents the shape of the sampling distribution under the null hypothesis. This robustness check provides further confidence on the presence of the momentum effect.

CHAPTER 4

SYSTEMATIC RISK, OTHER SYSTEMATIC EFFECTS, AND THE MOMENTUM PHENOMENON

4.1 Introduction

In Chapter 3 the empirical results show that the momentum effect is pronounced in the UK stock market. However, the results may be due to the lack of adjustment for systematic risk. If the winner portfolio tends to pick up riskier stocks than the loser portfolio, the momentum effect may be attributed to compensation for bearing systematic risk and need not be an indication of market inefficiency. On the other hand, the momentum returns documented in Chapter 3 may also be due to other manifestations such as small-size, low-price, high-B/M and high-C/P effects.[1] This chapter examines whether the momentum effect can be explained by systematic risk and other systematic effects; the analysis is based on the accounting sample.

The rest of this chapter is organised as follows. The next section describes each decile portfolio's and momentum portfolio's systematic risk and other characteristics such as

[1] As mentioned in Chapter 1, these effects can also be regarded as possible proxies for systematic risk. Although beta is the only source of systematic risk in the CAPM, other sources of risk may be systematic in other models. For convenience of description, in this study beta coefficient is referred to

MV, UP, C/P and B/M. Section 4.3 investigates the numbers of small firms, low-price firms, high-C/P firms and high-B/M firms each decile portfolio contains. Section 4.4 carries out a time-series regression to adjust for size and B/M factors using the Fama-French three-factor model. Section 4.5 reports the results after controlling for C/P. Section 4.6 documents the results obtained in various sub-samples stratified on the basis of MV, UP, B/M and C/P. Section 4.7 concludes this chapter.

4.2 Portfolio Abnormal Returns and Characteristics

To ascertain whether the momentum effect documented in Chapter 3 can be explained by systematic risk and other risk factors, this section investigates each portfolio's systematic risk and other characteristics such as MV, UP, C/P, and B/M.

Table 4.2.1 gives a description of each decile portfolio's average TM-month abnormal return and characteristics such as Scholes-Williams beta ($SW\text{-}\beta$), MV, UP, C/P and B/M for the 3×3, 6×6, 9×9 and 12×12 strategies.[2] Note that the Scholes-Williams betas are estimated from a portfolio's test-period monthly returns with respect to the value-weighted monthly market returns. The value-weighted

as systematic risk, and size, price, book-to-market ratio and cash earnings-to-price ratio are regarded as other systematic effects or other risk factors.

[2] As described in Chapter 3, portfolios' average MV, UP, C/P, and B/M are cross-sectional and time-series averages. Namely, for a given portfolio they are averaged across stocks within each test period and then averaged across test periods. Same procedure is used when calculating portfolio's average number of analysts in the following chapters.

monthly market returns are constructed from the accounting sample. In the subsequent studies, this value-weighted index will be used as a proxy for the market, unless otherwise stated. In addition, the average TM-month abnormal returns reported in Table 4.2.1 are market-adjusted with respect to a TM-month value-weighted index, R_{Mt}, which is also constructed using the accounting sample. The method for calculating the average abnormal returns of the decile portfolios over the sample period is as follows. The market-adjusted TM-month abnormal return of security i at the end of each test period t, AR_{it}, is computed first, and it is given by

$$AR_{it} = R_{it} - R_{Mt}, \qquad (4.2.1)$$

where R_{it} is the buy-and-hold return of security i over the TM-month test period and it is given by equation (3.3.2), and R_{Mt} is the value-weighted market return over the TM-month test period of $t-1$ to t, and it is constructed within the accounting sample. The TM-month market-adjusted abnormal return of the decile portfolio concerned at the end of each test period t, $AR_{DP,t}$, is

$$AR_{DP,t} = \frac{1}{n_{DP,t-1}} \sum_{i=1}^{n_{DP,t-1}} AR_{it} , \qquad (4.2.2)$$

where $n_{DP,t-1}$ is the number of stocks in the decile portfolio at the beginning of the test period $t-1$.

Each decile portfolio's market-adjusted average TM -month abnormal return over the sample period, $\overline{AR}_{DP}$, is given by

$$\overline{AR}_{DP} = \frac{1}{T}\sum_{t=1}^{T} AR_{DP,t}\ , \qquad (4.2.3)$$

where T is the number of test periods, equal to $\text{int}[(258 - RM)/TM]$ for the $RM \times TM$ strategy over the full sample period (258 months).

The decile momentum returns are not affected by the market-adjustment since the winner's abnormal return, AR_{Wt}, minus the loser's abnormal return, AR_{Lt}, is still equal to the winner's return, R_{Wt}, minus the loser's return, R_{Lt}. That is,

$$AR_{Wt} - AR_{Lt} = (R_{Wt} - R_{Mt}) - (R_{Lt} - R_{Mt}) = R_{Wt} - R_{Lt}\ .$$

However, choosing a benchmark to get decile portfolios' abnormal returns can help to see losers' and winners' contribution to the momentum profits. In other words, we can easily find where the momentum profits mainly come from by examining their abnormal returns. Choosing a correct benchmark to obtain the true abnormal returns is, however, an important issue. There are a number of choices commonly used in the literature, but the empirical results in this study are not sensitive to different benchmarks. The results of the empirical analyses are similar whichever of the market-adjusted abnormal returns, market-model-adjusted abnormal returns, CAPM-adjusted abnormal returns and multifactor-model-adjusted abnormal returns are used. These will be compared in the subsequent analyses.

Table 4.2.1 Portfolio Performance and Characteristics

The stocks in the accounting sample are sorted in ascending order at the beginning of each test period based on their past RM-month buy-and-hold returns. The first decile (top decile) is the loser (L), and the last (bottom) decile is the winner (W). This table summarises the average TM-month market-adjusted abnormal returns ($\overline{AR}_{DP}$) of each decile portfolio and decile momentum portfolio for the 3×3, 6×6, 9×9 and 12×12 strategies. The decile portfolios' average market value (MV, in million pounds), Scholes-Williams beta ($SW\text{–}\beta$), average UP, C/P, and B/M are also reported in this table. The numbers shown in the square brackets are t-statistics of momentum portfolios' MV, UP, C/P, and B/M, respectively. $F10s$ are F-statistics, which are computed under the null hypothesis that for each $RM\times TM$ strategy the average abnormal returns (or average MV, or UP, or C/P, or B/M) on loser (L) through winner (W) are jointly equal. $F8s$ are F-statistics computed under the null hypothesis that for each $RM\times TM$ strategy the average abnormal returns (or average MV, or UP, or C/P, or B/M) on $D2$ (the second decile portfolio) through $D9$ (the 9th decile portfolio) are jointly equal. The numbers given in parentheses following the F-statistics are p-values of the F-statistics. The sample period is January 1977 to June 1998.

Strategy	Portfolio	$\overline{AR}_{DP}$	$t-stat$	$SW\text{-}\beta$	MV	UP	C/P	B/M
	L	−0.00645	−0.64	1.1485	81.17	92.99	0.0203	1.7569
	$D2$	−0.00692	−0.95	1.0175	154.70	158.85	0.1334	1.4745
	$D3$	−0.00103	−0.16	0.9751	221.30	183.91	0.1303	1.3913
	$D4$	−0.00186	−0.31	0.9447	232.98	213.82	0.1344	1.2768
	$D5$	0.00089	0.16	0.9431	308.37	226.68	0.1491	1.2564
3×3	$D6$	0.00459	0.86	0.9534	317.14	240.00	0.1621	1.1977
	$D7$	0.00632	1.18	0.9470	320.43	218.10	0.1506	1.0352
	$D8$	0.00959	1.74	0.9873	304.61	237.89	0.1543	1.0317
	$D9$	0.01391	2.33	1.0491	272.39	238.71	0.1530	1.0421
	W	0.02694	3.81	1.0336	156.37	211.85	0.1282	1.0342
	$W-L$	0.03338	4.62	−0.1149	75.20	118.86	0.1080	−0.7227
					[2.53]	[5.55]	[6.55]	[−4.17]
	$F10$	2.43 (0.01)			9.15 (0.00)	6.72 (0.00)	14.05 (0.00)	4.92 (0.00)
	$F8$	1.27 (0.26)			4.17(0.00)	2.51 (0.01)	1.46 (0.18)	3.29 (0.002)
	L	−0.01369	−0.58	1.1159	74.14	84.05	−0.0090	1.7117
	$D2$	−0.01064	−0.52	0.9943	140.71	168.42	0.1361	1.6212
	$D3$	−0.00497	−0.31	0.9209	219.50	166.75	0.1388	1.5123
	$D4$	−0.01068	−0.77	0.9121	232.22	215.44	0.1386	1.2650
	$D5$	0.00787	0.56	0.9611	264.74	198.10	0.1563	1.2138
6×6	$D6$	0.01407	1.10	0.9601	309.89	218.86	0.1565	1.1757
	$D7$	0.01926	1.57	0.9706	325.88	216.83	0.1565	1.1647
	$D8$	0.02538	2.00	0.9593	348.84	281.10	0.1577	1.0144
	$D9$	0.04072	3.07	1.0647	291.99	218.31	0.1644	1.0127
	W	0.06438	4.34	1.0764	152.10	255.11	0.1308	0.8367
	$W-L$	0.07807	4.54	−0.0395	77.96	171.06	0.1398	−0.8750
					[2.13]	[4.05]	[5.75]	[−3.69]
	$F10$	2.60 (0.006)			5.28 (0.00)	4.19 (0.00)	11.54 (0.00)	3.29 (0.00)
	$F8$	1.58 (0.14)			2.59 (0.01)	1.97 (0.06)	0.70 (0.67)	2.44 (0.02)
	L	−0.01512	−0.34	1.0576	51.86	85.66	−0.0340	1.8915
	$D2$	−0.00002	−0.001	1.0386	124.05	123.92	0.1151	1.6752
	$D3$	−0.01428	−0.54	0.9668	203.45	210.94	0.1401	1.5387
	$D4$	−0.00120	−0.05	0.9412	251.36	184.42	0.1521	1.1944
	$D5$	0.00491	0.24	0.9608	286.05	197.07	0.1522	1.2390
9×9	$D6$	0.01290	0.62	0.9250	310.63	208.96	0.1535	1.0638
	$D7$	0.04095	1.67	1.0134	301.69	228.37	0.1556	1.1444
	$D8$	0.04679	2.37	0.9876	334.98	279.55	0.1608	1.1875
	$D9$	0.06639	2.96	0.9948	277.27	289.13	0.1521	0.9202
	W	0.12171	4.61	1.0961	141.45	235.58	0.1409	0.6760
	$W-L$	0.13683	4.23	0.0385	89.59	149.92	0.1749	−1.2155
					[2.79]	[7.13]	[4.95]	[−3.13]
	$F10$	2.53 (0.008)			4.07 (0.00)	3.25 (0.00)	10.55 (0.00)	3.05 (0.00)
	$F8$	1.38 (0.22)			1.78 (0.09)	1.92 (0.07)	1.03 (0.41)	2.18 (0.04)
	L	−0.00082	−0.02	1.1671	44.06	71.81	−0.0293	1.6698
	$D2$	0.00333	0.06	1.0181	124.10	118.06	0.1215	1.8473
	$D3$	0.00029	0.007	0.9699	198.45	153.96	0.1342	1.9492
	$D4$	−0.01153	−0.37	0.9203	278.76	169.21	0.1516	1.2933
	$D5$	0.01957	0.59	0.9756	295.61	190.87	0.1606	1.2833
12×12	$D6$	0.03777	1.07	0.9942	286.66	283.17	0.1692	1.0945
	$D7$	0.04456	1.53	0.9750	348.92	214.94	0.1684	1.0847
	$D8$	0.04090	1.64	0.9912	309.27	315.12	0.1612	1.0992
	$D9$	0.07821	2.84	0.9929	235.22	236.43	0.1643	1.0368
	W	0.09686	3.09	1.1113	167.99	237.40	0.1387	0.6563
	$W-L$	0.09767	2.54	−0.0558	123.93	165.59	0.1679	−1.0135
					[2.55]	[6.45]	[3.54]	[−2.61]
	$F10$	0.94 (0.49)			2.95 (0.00)	2.95 (0.00)	7.16 (0.00)	2.81 (0.004)
	$F8$	0.69 (0.68)			1.43 (0.20)	1.96 (0.06)	1.14 (0.34)	2.65 (0.01)

The results in Table 4.2.1 show that the patterns of each portfolio's performance, beta, MV, and UP are the same as those documented in Table 3.4.3, where the full sample of 4182 LSPD stocks is analysed. Comparing winner performances to other decile performances we can see that adjusting for the market still gives winners the highest statistically significant positive abnormal returns in the test periods. By contrast, the losers still show poor performance in the test periods, and they usually perform worse than the market although the differences tend to be insignificant. The evidence of significant winner performance and insignificant loser performance seems to indicate that the momentum returns are principally due to winner portfolios rather than loser portfolios.[3] The portfolios' (W, L, $W-L$) performances can be seen from Figure 4.2.1, which plots the abnormal returns over the 42 test periods for the 6×6 strategy. In addition, the F-statistics ($F8$) computed under the null hypothesis that for each $RM \times TM$ strategy the average abnormal returns on the second decile portfolio through the 9th decile portfolio are jointly equal are all statistically insignificant, but the F-statistics ($F10$) computed under the null that the average abnormal returns on loser through winner are jointly equal are all statistically significant except for the 12×12 strategy. These are consistent with the t-statistics. The insignificant $F10$ of the 12×12 strategy and its smaller returns of winner and momentum portfolios than the 9×9 strategy seem to indicate that the persistence of the momentum effect is reduced after a 9-month holding period. For detailed analyses on the persistence of the momentum effect see Chapter 3.

[3] The CAPM adjusted returns show a similar result. After adjusting for the Fama-French three-factor model the contribution of winner portfolio to the momentum profits are also relatively higher than loser's, but loser portfolio's contribution to the momentum profits is significant in this case. These can be found in Section 4.4 of this chapter.

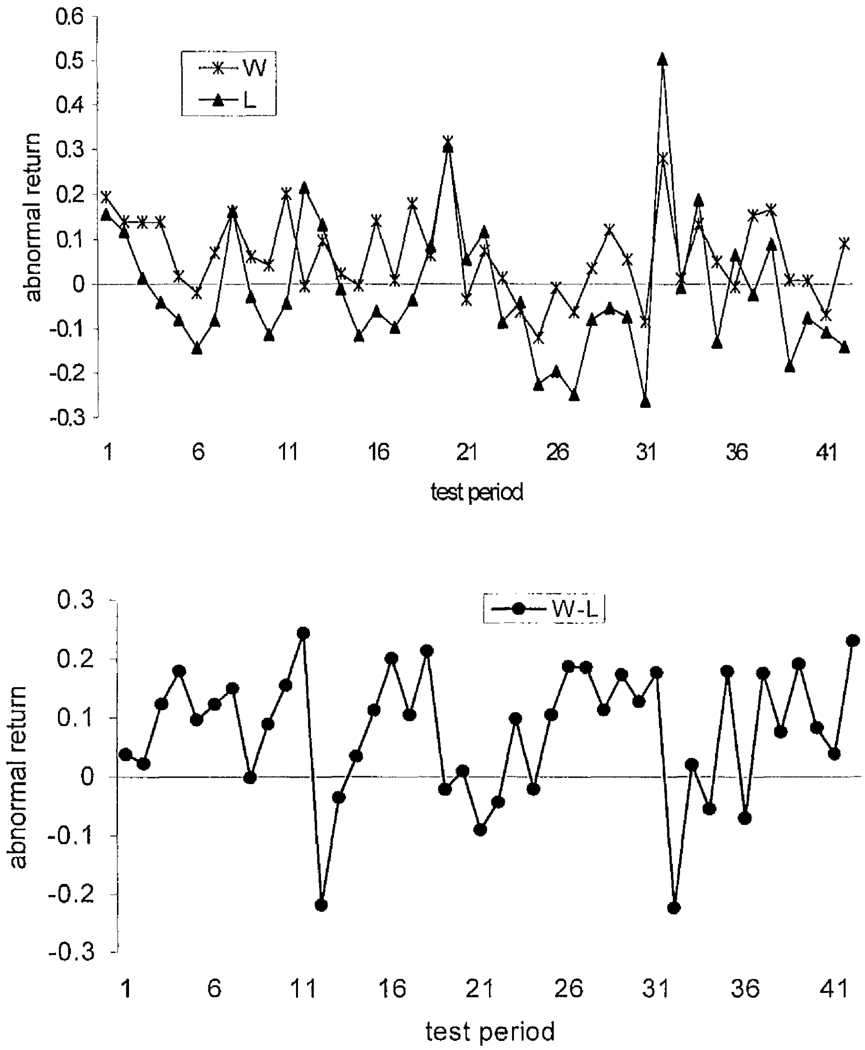

Figure 4.2.1 Market-adjusted abnormal returns for the 6×6 strategy

The Scholes-Williams betas in Table 4.2.1 show that the poor-performing losers have the highest systematic risk over the test periods, so that the Scholes-Williams betas of the momentum portfolios are negative except for the 9×9 strategy. Hence the adjusted market model cannot explain the momentum profits. The same conclusions are found by using the CAPM model and the Fama-French (1993) three-factor model whose estimates will be reported in subsequent sections.

Other characteristics of the decile portfolios such as MV, UP, C/P, and B/M show that both winner and loser portfolios still tend to select small firms with the loser's MV being on average smaller than the winner's. This evidence seems to reflect the size effect to some extent. The average UP is generally increasing from loser through winner with the loser's UP being lowest and the winner's UP being significantly greater than the loser's. This pattern suggests that momentum profits are unlikely to be related to the low-price effect. An interesting feature in Table 4.2.1 is that the patterns in average C/P and B/M are not consistent. Loser portfolios have the lowest average C/P ratios. The t-statistics shown in square brackets and the F-statistics show that for each strategy the winner's C/P is statistically greater than the loser's although the winner's C/P is slightly smaller than those of the fourth decile portfolio through the 9th decile portfolio. This evidence indicates that there may be some relation between the momentum profits and the C/P effect. However, for each strategy the lowest average C/P of the loser portfolio does not contribute to the momentum profits because the momentum profits are essentially due to the winner's performance rather than the loser's. Meanwhile, for each strategy the winner's average C/P is, in general, the second lowest. Thus we may expect that the relationship between the momentum profits and the C/P ratios is not strong. Further examinations are carried out in the subsequent sections. In contrast, the B/M ratios are monotonically decreasing from loser portfolio to winner portfolio. Each strategy shows that the loser portfolio has, in general, the highest B/M ratio, and the winner portfolio has the lowest B/M ratio with the loser's B/M ratio being significantly greater than the winner's. These results indicate that winner stocks tend to be glamour stocks and loser stocks tend to be value stocks. These findings are similar to the US market as documented in Chan, Jegadeesh and Lakonishok (1996), "The portfolio of past losers contains stocks with relatively depressed past earnings and cash flow, while the portfolio of past winners contains glamour stocks that have done well in the past". The evidence of glamour winner and value loser implies that the momentum profits are less likely to be due to the B/M effect.

4.3 Numbers of Small Firms, Low-price Firms, High-C/P Firms, and High-B/M Firms in Portfolios

As we saw in the last section, both winner and loser portfolios have smaller average MV, and winner portfolios have higher average C/P than loser portfolios. If momentum profits are related to the size effect, the number of small stocks in the winner portfolio should consistently be larger than the number of small stocks in the loser portfolio over the sample period. On the other hand, if the arbitrage returns are due to the C/P effect, the number of high-C/P stocks in the winner portfolio should consistently be greater than the number of high-C/P stocks in the loser portfolio over the sample period.[4] Table 4.3.1 reports each decile portfolio's average numbers of small stocks and high-C/P stocks over the 42 test periods for the 6×6 strategy. To further confirm if there is any relation between the momentum profits and low-price and high-B/M effects, I also examine the number of low-UP firms and high-B/M firms in each decile portfolio for the 6×6 strategy, and the results are also reported in

Table 4.3.1. In Table 4.3.1, numbers shown in parentheses are the proportions of average numbers of small stocks (*Small–MV*), low-*UP* stocks ($Low-UP$), high-C/P stocks ($High-C/P$), and high-B/M stocks ($High-B/M$) found in the total small stocks, total low-price stocks, total high-C/P stocks and total high-B/M stocks, respectively. The last column, denoted as *No+*, shows the numbers of test periods in which the number of small firms, low-*UP* firms, high-C/P firms and high-B/M firms are greater in the winner portfolio than in the loser portfolio. Panel A summarises the results based on the breakpoint of 1/3 stocks. In other words, at the beginning of each test period the 1/3 smallest and 1/3 lowest-*UP* stocks in the accounting sample are referred to as small stocks and low-price stocks, respectively. The 1/3 highest-C/P and 1/3 highest-B/M stocks are designated high-C/P and high-B/M stocks, respectively. Panel B reports the results when using the quintile (1/5) as a breakpoint.

Table 4.3.1 Numbers of Small Firms, Low-price Firms, High-C/P Firms, and High-B/M Firms in the Decile Portfolios

The decile portfolios of the 6×6 strategy are formed based on 6-month past returns and held for 6 months. The equally-weighted portfolio of stocks in the lowest past return decile is the loser portfolio (L); the equally-weighted portfolio of stocks in the next decile is portfolio $D2$; and so on. The equally- weighted portfolio of stocks in the highest past return decile is the winner portfolio (W). The average numbers of small firms ($Small-MV$), low-price firms ($Low-UP$), high-C/P firms (*High*-C/P) and high-B/M firms (*High–B/M*) in the decile portfolios over the 42 test periods are reported in this table. The last column, denoted as $No+$, shows the numbers of test periods in which the number of small stocks, low-price stocks, high-C/P stocks and high-B/M stocks in the winner portfolio are greater than in the loser portfolio. Panel A gives the results when referring to the 1/3 smallest stocks in the accounting sample as small stocks, 1/3 lowest-*UP* stocks as low-price stocks, 1/3 highest-C/P stocks as high-C/P stocks and 1/3 highest-B/M stocks as high-B/M stocks. Panel B shows the results when using the quintile breakpoint. Numbers given in parentheses are the proportions of average numbers of small stocks, low-*UP* stocks, high-C/P stocks, and high-B/M stocks found in the total small stocks, total low-*UP* stocks, total high-C/P stocks, and total high-B/M stocks, respectively. The sample period is January 1977 to June 1998.

[4] Theses can only be predicated on the grounds that these effects are positive. These effects are confirmed in the following sections and chapters.

	L	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	W	No +
					Panel A: (1/3 breakpoint)						
Small − MV	68.24 (0.164)	51.74 (0.124)	45.17 (0.108)	39.24 (0.094)	38.57 (0.093)	34.31 (0.082)	32.00 (0.077)	32.67 (0.078)	33.26 (0.080)	41.57 (0.100)	3
Low − UP	81.00 (0.196)	55.57 (0.134)	45.12 (0.109)	37.348 (0.091)	35.45 (0.086)	32.45 (0.078)	30.26 (0.073)	28.40 (0.069)	30.83 (0.074)	37.60 (0.091)	2
High − C/P	37.98 (0.093)	44.90 (0.110)	45.14 (0.111)	43.48 (0.107)	42.74 (0.105)	41.43 (0.102)	39.19 (0.096)	37.74 (0.093)	39.57 (0.097)	34.45 (0.085)	14
High − B/M	58.60 (0.149)	52.69 (0.134)	45.33 (0.116)	42.52 (0.108)	39.83 (0.102)	36.52 (0.093)	32.79 (0.084)	30.31 (0.077)	29.14 (0.074)	24.40 (0.062)	2
					Panel B: (1/5 breakpoint)						
Small − MV	45.95 (0.184)	31.83 (0.128)	28.60 (0.115)	23.55 (0.094)	21.88 (0.088)	20.29 (0.081)	18.26 (0.073)	18.10 (0.073)	17.83 (0.072)	23.12 (0.093)	4
Low − UP	58.24 (0.236)	34.00 (0.138)	27.00 (0.109)	21.86 (0.088)	19.67 (0.079)	17.29 (0.070)	15.86 (0.064)	15.90 (0.064)	16.57 (0.067)	20.93 (0.085)	1
High − C/P	26.90 (0.111)	28.90 (0.119)	26.55 (0.109)	26.19 (0.108)	24.83 (0.102)	23.24 (0.096)	22.38 (0.092)	20.95 (0.086)	23.10 (0.095)	20.36 (0.084)	11
High − B/M	41.57 (0.177)	33.67 (0.144)	27.38 (0.117)	24.74 (0.105)	23 (0.098)	21.02 (0.090)	17.74 (0.076)	17.14 (0.073)	15.33 (0.065)	13.10 (0.056)	2

It is clear that the momentum effect documented previously cannot be attributed to small size, low-price, and high-B/M effects from the facts reported in Table 4.3.1. When we designate the $1/3$ smallest stocks in the accounting sample as small stocks, the results in Panel A of Table 4.3.1 show that the average number of small firms over the 42 test periods is 68.24 in the loser portfolio, which accounts for 16.4% of the total small stocks, while it is 41.57 in the winner portfolio, which accounts for 10.0% of the total small stocks. The number of small stocks in the loser portfolio is noticeably greater than in the winner portfolio and other portfolios, and over the 42 test periods there are only 3 test periods in which the numbers of small stocks in the winner portfolio are greater than in the loser portfolio. When the $1/5$ smallest stocks in the sample are designated as small stocks at the beginning of each test period, the results shown in Panel B of Table 4.3.1 are more unfavourable to the size effect. The loser portfolio contains 18.4% small firms on average, while only 9.3% small firms are included in the winner portfolio. Meanwhile, there are only 4 test periods in which the numbers of small stocks in the winner portfolio exceed the numbers of small firms the loser portfolio contains. Similar results can be found for the low-UP and high-

B/M cases by analysing the numbers of the low-price firms and high-B/M firms in each decile portfolio. Combining the results reported in Table 4.2.1 with the results shown in Table 4.3.1 we can conclude without doubt that the momentum profits documented previously are not due to the size, low-price, or B/M effects.

Surprisingly, although the loser has the lowest average C/P ratio relative to other decile portfolios as documented in the last section, the average number of high-C/P firms the loser portfolio contains is not less than the average number of high-C/P firms the winner portfolio contains. Rather, the number of high-C/P firms in the winner portfolio is the smallest though there are no big differences in the average numbers of high-C/P firms in the ten decile portfolios. Panel A of Table 4.3.1 shows that the winner includes 34.45 high-C/P firms on average, which account for 8.5% of the total high-C/P firms, while the high-C/P firms in the loser portfolio account for 9.3% of the total high-C/P firms. In Panel B of Table 4.3.1, the same pattern with respect to the high-C/P firms each portfolio contains can be seen. Panel A shows that over the 42 test periods there are 14 test periods in which the winner portfolio picks up more high-C/P firms than the loser portfolio, while there are only 11 such test periods when we classify stocks according to the quintile breakpoint.[5] Therefore, results in Table 4.3.1 do not give any strong suggestion that the momentum profits are related to the C/P effect. Further investigations will be carried out in Section 4.5.

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[5] Note that the loser has the lowest average C/P ratio as presented in Table 4.2.1 and the number of high-C/P firms in the loser portfolio is not less than in the winner and other decile portfolios. This may be due to one of two reasons (or both): the high-C/P companies in the loser portfolio (L) have C/P ratios at the low end of this group; the non-high-C/P companies in L have C/P ratios at the low end of this group. Another possibility is that L has an outlier problem, containing one or two observations where C/P is extremely low.

4.4 Adjusting for Risk, Size, and Book-to-Market Factors

The portfolio performances measured in Chapter 3 and Section 4.2 are not adjusted for risk and other factors that influence security return. Although the momentum effect cannot be explained separately by systematic risk, size, and B/M as analysed previously, simultaneously adjusting for them may give different results. In this section I investigate whether the momentum profits can be explained by the Fama-French (1993) three-factor model.

Fama and French believe that the expected return on a portfolio in excess of the risk-free rate ($E[r_{P\tau}]-r_{f\tau}$) is explained by the sensitivity of its return to the three factors of market risk premium ($r_{m\tau}-r_{f\tau}$), size (SMB_τ) and book-to-market (HML_τ). The three-factor model is given by

$$r_{P\tau}-r_{f\tau}=a_P+b_P(r_{m\tau}-r_{f\tau})+s_P SMB_\tau+h_P HML_\tau+\varepsilon_{P\tau}, \qquad (4.4.1)$$

where $r_{P\tau}$ is the return on the decile portfolio P ($P = L, D2, ..., D9, W$) in month τ; $r_{f\tau}$ is the 1-month Treasury Bill rate observed at the beginning of month τ; and $r_{m\tau}$ is the value-weighted market return in month τ. SMB_τ is the return on the factor-mimicking portfolio for size; and HML_τ is the return on the factor-mimicking portfolio for B/M. The methods for constructing SMB_τ and HML_τ are the same as in Fama and French (1993, 1996), and they are described in Table 4.4.1.

Fama and French (1993, 1996) find that many anomalies that cannot be explained by the CAPM are captured by the three-factor model. In terms of the three-factor model the expected excess return on portfolio P, $E[r_{P\tau}] - r_{f\tau}$, is

$$E[r_{P\tau}] - r_{f\tau} = b_P(E[r_{m\tau}] - r_{f\tau}) + s_P E[SMB_\tau] + h_P E[HML_\tau]. \qquad (4.4.2)$$

Accordingly, if the momentum portfolio's performance is just a manifestation of size, book-to-market effects and beta/systematic risk, then the intercept, a_P, in equation (4.4.1) should not be significantly different from zero.

Panel A of Table 4.4.1 reports summary statistics for the time series regressions of the three-factor model for each decile portfolio and for the momentum portfolio on the 6×6 strategy over the full test period of 252 months from July 1977 to June 1998. As a comparison, Table 4.4.1 (in Panel B) also reports the estimates for the Shape-Lintner version of the CAPM, which is

$$r_{P\tau} - r_{f\tau} = \alpha_P + \beta_P(r_{m\tau} - r_{f\tau}) + e_{P\tau}. \qquad (4.4.3)$$

The estimate of systematic risk, β_P, is estimated using the Scholes-Williams method. That is,

$$\beta_P = \sum_{k=-1}^{1} \frac{b_k}{1+2\rho}, \qquad (4.4.4)$$

where ρ is the first-order auto-correlation of $r_{m\tau} - r_{f\tau}$, and the b_k are the slope coefficients from three separate OLS regressions,

$$r_{P\tau} - r_{f\tau} = a_k + b_k(r_{m,\tau+k} - r_{f,\tau+k}) + e_{P\tau}, \qquad k = -1,0,+1 .$$

The risk-adjusted return from the CAPM for each decile portfolio is estimated by the intercept of α_P in equation (4.4.3).[6] The momentum return from the CAPM is given by the Jensen performance index of $\alpha_W - \alpha_L$, and similarly for the Fama-French three-factor model.

Table 4.4.1 Estimates of Fama-French Three-factor Model and CAPM for the Decile Portfolios

The 6×6 strategy's decile portfolios of loser (L) through winner (W) are formed semi-annually based on 6-month past returns. The Fama-French three-factor model is

$$r_{P\tau} - r_{f\tau} = a_P + b_P(r_{m\tau} - r_{f\tau}) + s_P SMB_\tau + h_P HML_\tau + \varepsilon_{P\tau},$$

and it is estimated using the test-period monthly decile-portfolio returns, $r_{P\tau}$, with respect to the value-weighted monthly market return, $r_{m\tau}$. The average abnormal monthly portfolio returns are estimated by a_P, and $r_{f\tau}$, the risk-free rate, is the 1-month Treasury Bill rate observed at the beginning of month τ. SMB_τ is the monthly return on the factor-mimicking portfolio for size (MV); and HML_τ is the monthly return on the factor-mimicking portfolio for book-to-market (B/M), and both SMB_τ and HML_τ are constructed in the same way as in Fama and French (1993, 1996). That is, the stocks in the accounting sample are semi-annually allocated to two groups (small (s) and big (b)) based on whether their market values (MV) at the beginning of the sorting period are below or above the median MV. The stocks in the accounting sample are allocated in an independent sort to three book-to-market groups (low (l), medium (m) and high (h)) based on the breakpoints for the bottom 30%, middle 40% and top 30% of the values of B/M. Six size-B/M portfolios (s/l, s/m, s/h, b/l, b/m, b/h) are defined as the intersections of the two MV and the three B/M groups. The value-weighted monthly returns on the six size-B/M portfolios are calculated for the subsequent 6 months

[6] Repeatedly, the intercept is estimated by running Equation (4.4.3) while I restrict beta to equal the value from Equation (4.4.4).

based on each semi-annual sorting. SMB_τ is the difference, each month, between the average of the returns on the three small-stock portfolios (s/l, s/m and s/h) and the average of the returns on the three big-stock portfolios (b/l, b/m and b/h). HML_τ is the difference, each month, between the average of the returns on the two high-B/M portfolios (s/h and b/h) and the average of the returns on the two low-B/M portfolios (s/l and b/l). Panel A summarises the estimates of the three-factor model. R^2s are adjusted for degrees of freedom. Panel B gives the results estimated from the adjusted CAPM. In Panel B, β_p is given by equation (4.4.4) and α_p is derived from equation (4.4.3). Numbers shown in parentheses are t-statistics. The sample period is January 1977 to June 1998.

	L	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	W	$W-L$
			Panel A: Estimates of Fama-French Three-factor Model								
a_p	−0.0061	−0.0050	−0.0028	−0.0037	−0.0010	0.0002	0.0013	0.0024	0.0044	0.0081	0.0142
	(−3.35)	(−5.08)	(−2.75)	(−4.82)	(−1.42)	(0.27)	(1.61)	(2.80)	(5.01)	(7.06)	(6.22)
b_p	1.158	1.099	0.996	0.964	0.989	1.006	0.995	0.999	1.007	1.098	−0.060
	(27.94)	(48.72)	(43.42)	(55.66)	(61.86)	(55.77)	(52.42)	(52.04)	(49.85)	(41.89)	(−1.15)
s_p	1.061	0.935	0.755	0.700	0.687	0.641	0.643	0.707	0.692	0.894	−0.167
	(19.30)	(31.30)	(24.83)	(30.51)	(32.42)	(26.81)	(25.54)	(27.79)	(25.85)	(25.72)	(−2.42)
h_p	0.605	0.557	0.372	0.357	0.279	0.297	0.163	0.165	0.082	-0.057	−0.662
	(7.64)	(12.94)	(8.49)	(10.78)	(9.14)	(8.61)	(4.50)	(4.49)	(2.12)	(-1.14)	(−6.66)
R^2	0.779	0.912	0.887	0.928	0.940	0.926	0.917	0.917	0.911	0.884	0.153
			Panel B: Estimates of CAMP								
β_p	1.152	1.023	0.944	0.938	0.981	0.979	0.988	0.978	1.083	1.097	−0.055
α_p	−0.0044	−0.0029	−0.0013	−0.0025	−0.0002	0.0013	0.0019	0.0030	0.0040	0.0080	0.0124
	(−1.45)	(−1.26)	(−0.67)	(−1.41)	(−0.11)	(0.80)	(1.15)	(1.73)	(2.20)	(3.54)	(5.09)

Not surprisingly, the patterns of the CAPM estimates in abnormal returns (α_p) and betas (β_p) shown in Panel B of Table 4.4.1 are similar to those reported in Table 4.2.1 where the abnormal returns are market-adjusted and betas are the Scholes-Williams estimates from the market model. As expected, the abnormal returns of the decile portfolios, a_p, estimated by the three-factor model are smaller than those obtained from the CAPM. This indicates that the three-factor model does capture additional effects missed by the CAPM.

However, adjusting for size and B/M does not change the observed pattern in returns documented previously. The abnormal return (a_p) of the loser portfolio (L) is −0.61% per month (t-statistic is −3.35). From decile 8 ($D8$) to the winner portfolio (W), portfolios make significant positive abnormal returns. The momentum return, which is still mainly due to the winner portfolio, is 1.42% per month with a t-statistic of 6.22. These results are in accordance with the market-adjusted TM-month abnormal returns reported in Table 4.2.1. In addition, loser and winner portfolios still appear to have similar market risk exposures ($b_L = 1.158$, $b_W = 1.098$) with the loser portfolio being riskier than the winner portfolio. All decile portfolios load significantly positively on SMB_τ and HML_τ except for winner where h_p is negative (−0.057 with t-statistic of −1.14). These results indicate that there is indeed a small-firm effect and a high-B/M effect. Moreover, the coefficient of s_p shows that both winner and loser are heavily loaded with small firms with the loser being more so. Meanwhile, the h_p coefficients are decreasing from loser portfolio to winner portfolio with the loser portfolio concentrating most heavily on value stocks, and the winner on glamour stocks. These results are completely consistent with the facts reported in Table 4.2.1, and imply that the Fama-French three-factor model is sound. However, adjusting for the three factors cannot eliminate the significant abnormal returns earned by the momentum portfolio, rather it makes the momentum portfolio appear more profitable because the momentum portfolio is loaded significantly negatively with size and B/M.

As a further confirmation, I also estimate the three-factor model in the two 11-year sub-periods as examined in Chapter 3. These results together with the portfolios' characteristics such as MV, UP, C/P, and B/M in the sub-periods are reported in Table 4.4.2. Panel A and Panel B of Table 4.4.2 presents the results of the sub-periods of January 1977 to December 1987 and July 1987 to June 1998, respectively.

Table 4.4.2 Fama-French-Three-factor Model Estimates in Sub-periods

The 6×6 strategy's decile portfolios are formed based on 6-month past buy-and-hold returns and held for 6 months. At the beginning of each test-period, the stocks are sorted in ascending order on the basis of 6-month past returns. The equally-weighted portfolio of stocks in the lowest past return decile is designated the loser portfolio (L), the equally-weighted portfolio of stocks in the next decile is denoted as portfolio $D2$, and so on. The equally-weighted portfolio of stocks in the highest past return decile is the winner portfolio (W). The momentum portfolio is the winner portfolio minus the loser portfolio (W–L). This table reports the estimates of the Fama-French three-factor model together with portfolio characteristics such as MV, UP, C/P and B/M in two 11-year sub-periods. Panel A summarises the results of the sub-period of January 1977 to December 1987. Panel B reports the results of the sub-period of July 1987 to June 1998. The Fama-French-three-factor model is

$$r_{p\tau} - r_{f\tau} = a_p + b_p(r_{m\tau} - r_{f\tau}) + s_p SMB_\tau + h_p HML_\tau + \varepsilon_{p\tau}.$$

The constructions of the two factor-mimicking portfolios of SMB_τ and HML_τ are described in Table 4.4.1. Numbers shown in parentheses are t-statistics. F is the F-statistic (i.e., Chow test) computed under the null that for a given portfolio the coefficients (a_p, b_p, s_p, h_p) estimated in the two 11-year sub-periods are the same. $p-V$ is the p-value of F.

	L	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	W	$W-L$
	Panel A: January 1977-December 1987										
a_p	−0.0049	−0.0039	−0.0015	−0.0039	0.0003	0.0001	0.0015	0.0006	0.0032	0.0061	0.0110
	(−2.06)	(−2.71)	(−0.89)	(−3.46)	(0.26)	(0.14)	(1.08)	(0.43)	(2.30)	(3.32)	(3.56)
b_p	0.977	1.038	0.955	0.931	0.975	1.011	1.004	1.055	1.038	1.153	0.176
	(20.55)	(35.96)	(29.37)	(41.37)	(45.44)	(48.29)	(37.05)	(39.68)	(36.89)	(31.60)	(2.86)
s_p	0.806	0.848	0.654	0.648	0.665	0.650	0.646	0.822	0.787	1.023	0.217
	(11.08)	(19.20)	(13.15)	(18.83)	(20.27)	(20.30)	(15.58)	(20.23)	(18.30)	(18.33)	(2.31)
h_p	0.457	0.485	0.365	0.337	0.275	0.313	0.199	0.234	0.155	−0.049	−0.505
	(5.04)	(8.82)	(5.90)	(7.87)	(6.73)	(7.86)	(3.86)	(4.63)	(2.88)	(−0.70)	(−4.31)
R^2	0.773	0.913	0.873	0.932	0.943	0.949	0.918	0.928	0.918	0.897	0.205
UP	81.41	118.02	129.07	145.24	144.82	157.71	151.42	161.68	163.91	163.10	81.69
MV	37.80	72.98	90.01	112.25	103.32	112.70	124.72	104.04	79.29	42.90	5.11
B/M	2.8393	2.3731	2.1989	1.7357	1.7181	1.5261	1.6695	1.3619	1.4662	1.2486	−1.5907
C/P	0.0632	0.1720	0.1768	0.1725	0.2045	0.1983	0.2002	0.2019	0.2171	0.1812	0.1181
	Panel B: July 1987-June 1998										
a_p	−0.0040	−0.0049	−0.0029	−0.0028	−0.0020	0.0001	0.0011	0.0027	0.0044	0.0087	0.0126
	(−1.61)	(−3.68)	(−2.40)	(−2.68)	(−2.14)	(0.12)	(1.04)	(2.71)	(4.11)	(6.16)	(4.26)
b_p	1.423	1.177	1.045	1.017	1.003	1.004	0.986	0.941	0.992	1.030	−0.393
	(21.07)	(32.04)	(31.34)	(35.94)	(38.74)	(29.92)	(34.61)	(34.66)	(33.70)	(26.70)	(−4.83)
s_p	1.313	1.015	0.839	0.757	0.695	0.633	0.636	0.610	0.612	0.789	−0.524
	(17.74)	(25.21)	(22.94)	(24.40)	(24.49)	(17.20)	(20.35)	(20.51)	(18.95)	(18.64)	(−5.88)
h_p	0.733	0.636	0.357	0.371	0.269	0.270	0.107	0.083	−0.028	−0.034	−0.767
	(5.84)	(9.32)	(5.76)	(7.05)	(5.60)	(4.34)	(2.03)	(1.65)	(−0.52)	(−0.47)	(−5.08)
R^2	0.830	0.916	0.906	0.924	0.931	0.887	0.912	0.912	0.906	0.867	0.346
UP	86.69	154.30	204.43	204.34	251.38	280.02	282.25	258.14	272.72	260.65	176.72
MV	110.48	208.44	348.99	301.04	426.16	454.64	366.14	363.65	386.54	261.29	150.81
B/M	0.5841	0.8692	0.8258	0.7942	0.7094	0.8253	0.6600	0.6669	0.5591	0.4247	−0.1594
C/P	−0.0813	0.1002	0.1007	0.1048	0.1081	0.1147	0.1128	0.1136	0.1117	0.0803	0.1616
F	11.02	3.33	2.10	1.85	2.18	0.00	0.00	4.69	4.16	2.44	12.06
$p-V$	0.0000	0.0112	0.0810	0.1202	0.0720	1.0000	1.0000	0.0012	0.0028	0.0476	0.0000

The momentum returns realised in the two sub-periods are both statistically significantly positive. The average monthly return of the winner minus loser portfolio ($W-L$) is 1.10% with a t-statistic of 3.56 in the sub-period of January 1977 to December 1987 and it is equal to 1.26% with a t-statistic of 4.26 in the sub-period of July 1987 to June 1998. The patterns with respect to the estimates of the three-factor model and the characteristics of each portfolio in the two sub-periods are similar with the full sample period, but the factor loadings within the two sub-periods are not completely same as in the full sample period. In addition, the factor loadings from the first 11-year sub-period to the second 11-year sub-period are not same. The Chow tests show that, in general, for a given portfolio the coefficients of the three-factor model are different in the two sub-periods, especially in the loser portfolio (L) and the $W-L$ portfolio (The F-statistics of L and $W-L$ are 11.02 and 12.06, respectively.). Nevertheless, this structural change is not due to the coefficient of a_p. For instance, in the sub-period of July 1987 to June 1998, the loser portfolio is riskier and more heavily loaded with small firms than the winner portfolio, which is consistent with the full sample case, but the reverse is true in the sub-period of January 1977 to December 1987. This evidence indicates the time-varying expected security returns documented in the literature.

In addition, the portfolios' MV, UP, B/M and C/P experience big changes from the first 11-year period to the second 11-year period though their patterns remain unchanged within each sub-period across the portfolios. For each portfolio both MV and UP are sharply increasing, while B/M and C/P decrease. For example, all decile portfolios' B/M ratios are greater than 1 in the sub-period of January 1977 to December 1987, but they are less than 1 in the sub-period of July 1987 to June 1998.

This evidence indicates that stocks may be overvalued in the period of July 1987 to June 1998. The reduction in each portfolio's profitability from the first to the second 11-year periods, as documented in Table 3.6.1, may be explained by this evidence. However, this explanation is not so convincing because each portfolio's abnormal returns realised respectively in the two sub-periods are similar (comparing a_p reported in Panel A and Panel B of Table 4.4.2).

In a nutshell, the estimates of the Fama-French three-factor model in Table 4.4.1 and 4.4.2 generally confirm the earlier findings. The conclusion from these results is the same as Fama and French's (1996) findings that the three-factor model cannot explain the continuation in returns over the intermediate time horizon.

4.5 Analysis of Controlling for C/P

Because the winner portfolio's C/P is significantly greater than the loser's (see Table 4.2.1), it is possible that the extra performance available to investors from holding winner stocks and selling losers may be caused by winner stocks being high-C/P firms. To test this hypotheses I use Zarowin's (1989, 1990) technique of controlling for firm size to control for firms' C/P. The procedure of controlling for C/P is the following:

(i) For any $RM \times TM$ strategy the stocks in the sample are sorted in ascending order based on their C/P ratios at the beginning of each test period, and allocated to 5 quintile portfolios. The top quintile stocks are defined as low-C/P stocks, and the bottom quintile stocks are designated as high-C/P stocks.

(ii) Similarly, the stocks in the sample are allocated in an independent sort to another 5 quintile portfolios based on their past RM-month buy-and-hold returns at the beginning of each test period. The stocks in the top quintile are losers and the bottom quintile is referred to as the winner portfolio. Note that the definitions of loser and winner are different from previous analyses where the decile loser and winner are used. Using quintile loser and winner here is to ensure that the C/P-performance portfolios, which will be defined soon, contain a certain number of stocks.

(iii) Four C/P-performance portfolios (low-C/P loser (LL), low-C/P winner (LW), high-C/P loser (HL) and high-C/P winner (HW)) are defined as the intersections of the two extreme C/P quintiles (low-C/P and high-C/P quintiles) and the two extreme performance quintiles (loser and winner quintiles). The equally weighed TM-month returns and monthly returns on the four C/P-performance portfolios are calculated for the following TM months based on each sorting. The monthly returns are used to estimate the Fama-French three-factor model. The obvious reason is that if significant momentum returns are still evident from the Fama–French model after controlling for C/P, then we can be more confident about the presence of a momentum effect.

(iv) Five arbitrage portfolios are constructed based on the four C/P-performance portfolios formed in ***(iii)***, and they are:

(a) low-C/P winner minus low-C/P loser ($LW - LL$);

(b) high-C/P winner minus high-C/P loser ($HW - HL$);

(c) high-C/P loser minus low-C/P loser ($HL - LL$);

(d) high-C/P winner minus low-C/P winner ($HW - LW$);

(e) high-C/P winner minus low-C/P loser ($HW - LL$).

Note that (a) and (b) are C/P-matched arbitrage portfolios; (c) and (d) are performance-matched arbitrage portfolios; and (e) is a miscellaneous arbitrage portfolio. Their arbitrage TM-month returns and monthly returns are directly derived from the four performance-C/P portfolios, respectively.

It is obvious that if the C/P effect is the cause of the momentum profits documented previously then we can expect two results. First, the two arbitrage portfolios of $LW - LL$ and $HW - HL$ that are C/P-matched but characterised by disparate past RM-month performance cannot make significant profits. Second, the two arbitrage portfolios of $HL - LL$ and $HW - LW$ that are performance-matched but characterised by disparate C/P ratio should earn significant returns. If, however, the momentum effect does exist or the market under-reacts to information, especially to past returns news, we expect the opposite results to hold.

Table 4.5.1 summarises the 6×6 strategy's results after controlling for C/P ratio. In this table, P_sz shows the average number of firms in the four performance-C/P portfolios (i.e., portfolio size); ret_6 is the average 6-month return of each portfolio over the 42 test periods. In addition, Table 4.5.1 also reports the estimates of the Fama-French three-factor model for each portfolio. The notion is the same as in Equation (4.4.1), and the average monthly abnormal return of each portfolio is given by a_p.

Table 4.5.1 Results after Controlling for C/P

This table summarises the 6×6 strategy's results. At the beginning of each test period, the stocks are ranked in ascending order based on their C/P ratios. The top quintile of stocks are referred to as low-C/P firms, and the bottom quintile of stocks as high-C/P firms. At the beginning of each test period, the stocks are also independently sorted in ascending order based on their past 6-month returns. The top quintile is categorised as the loser portfolio and the bottom quintile is the winner portfolio. Four performance-C/P portfolios of low-C/P loser (LL), low-C/P winner (LW), high-C/P loser (HL) and high-C/P winner (HW) are defined as the intersections of the two extreme C/P quintiles and the two extreme performance quintiles. The portfolios are equally weighted. In this table P_sz shows the average number of stocks in the portfolios (i.e., portfolio size), and ret_6 describes the average 6-month returns the portfolios earn over the 42 test periods. This table also reports the estimates of the Fama-French three-factor model:

$$r_{p\tau} - r_{f\tau} = a_p + b_p(r_{m\tau} - r_{f\tau}) + s_p SMB_\tau + h_p HML_\tau + \varepsilon_{p\tau}.$$

a_p is the estimate of the average monthly abnormal return. The numbers shown in parentheses are t-statistics. R^2s are adjusted for degree of freedom. For detailed description of the three-factor model, see Section 4.4. The sample period is January 1977 to June 1998. $HW-LL$

	LL	LW	HL	HW	$LW-LL$	$HW-HL$	$HL-LL$	$HW-LW$	$HW-LL$
P_sz	77.83	51.29	56.10	43.86	-	-	-	-	-
C/P	−0.3157 (−8.79)	−0.0443 (−2.58)	0.4478 (12.66)	0.3482 (16.65)	0.2715 (9.00)	−0.0996 (−2.94)	0.7635 (14.12)	0.3925 (17.05)	0.6639 (17.46)
ret_6	0.0224 (0.65)	0.0887 (2.95)	0.1777 (5.81)	0.2400 (7.99)	0.0663 (2.62)	0.0622 (3.31)	0.1553 (8.46)	0.1512 (6.25)	0.2175 (11.22)
a_p	−0.0156 (−8.52)	−0.0040 (−1.99)	0.0080 (4.30)	0.0198 (14.04)	0.0116 (4.46)	0.0118 (5.02)	0.0236 (9.84)	0.0238 (9.69)	0.0354 (14.60)
b_p	1.191 (28.44)	1.134 (24.76)	1.164 (27.38)	1.056 (32.73)	−0.057 (−0.96)	−0.108 (−2.00)	−0.028 (−0.51)	−0.078 (−1.39)	−0.135 (−2.44)
s_p	1.267 (22.82)	1.051 (17.31)	1.078 (19.14)	0.836 (19.55)	−0.216 (−2.73)	−0.242 (−3.39)	−0.189 (−2.60)	−0.215 (−2.88)	−0.430 (−5.85)
h_p	0.519 (6.49)	−0.136 (−1.55)	0.756 (9.32)	0.159 (2.58)	−0.654 (−5.76)	−0.597 (−5.81)	0.237 (2.27)	0.295 (2.75)	−0.359 (−3.39)
R^2	0.797	0.738	0.776	0.818	0.126	0.137	0.037	0.054	0.138

The method used to control for C/P is not precise because the C/P ratios of both C/P-matched arbitrage portfolios ($LW - LL$ and $HW - HL$) are statistically different from zero. Even so, the results in Table 4.5.1 can still give us clear insights into the relation between C/P and momentum effects. The C/P effect is distinct. The average 6-month raw returns (ret_6) of the two high-C/P-performance portfolios of HW and HL are 24.00% and 17.77%, while they are 8.87% and 2.24% for the two low-C/P-performance portfolios of LW and LL. As a result, the two performance-matched portfolios of high-C/P loser minus low-C/P loser ($HL - LL$) and high-C/P winner minus low-C/P winner ($HW - LW$) and the miscellaneous arbitrage portfolio of high-C/P winner minus low-C/P loser ($HW - LL$) earn unusually high returns. Their average 6-month arbitrage returns are 15.53%, 15.12% and 21.75% with t-statistics of 8.46, 6.25 and 11.22, respectively.

However, the apparent C/P effect can not explain the momentum effect. The returns of the two C/P-matched zero-cost portfolios of low-C/P winner minus low-C/P loser ($LW - LL$) and high-C/P winner minus high-C/P loser ($HW - HL$) are significantly positive in spite of the C/P ratio of $HW - HL$ being significantly negative. The average 6-month arbitrage returns of $LW - LL$ and $HW - HL$ are 6.63% and 6.22% with t-statistics of 2.62 and 3.31, respectively. This implies that winner firms still significantly outperform loser firms after controlling for their C/P ratios. The results also imply that the momentum strategy does not tend to select more high-C/P firms in the winner portfolio than in the loser portfolio. These results are consistent with previous findings (see Table 4.3.1).

Finally, adjusting for the three factors of risk, MV and B/M after controlling for C/P cannot eliminate the momentum returns. The estimates of the Fama-French three-factor model generally confirm the momentum effect and other findings documented previously. The robustness test shows that the momentum returns after controlling for C/P are still significantly positive. The two C/P-matched arbitrage portfolios of $LW-LL$ and $HW-HL$ realise average monthly returns of 1.16% and 1.18% with t-statistics of 4.46 and 5.02, respectively. Additionally, the patterns of other parameters (b_p, s_p, h_p) are the same as for earlier findings. For instance, loser and winner appear to have similar risk exposures with loser being riskier than winner, and loser is more heavily loaded with small firms and high-B/M firms than winner is. Therefore, adjusting for the three factors does not influence the profitability of the momentum strategy even after controlling for the C/P effect. In fact, it makes the momentum portfolio appear to be more profitable because of the negative coefficients of b_p, s_p and h_p of the zero-cost portfolios.

In short, the results obtained after controlling for C/P show that the C/P effect does exist. However, its contribution to the momentum profits documented earlier is not strong. Combining the results with the facts that the winner portfolio does not tend to select more high-C/P firms than the loser portfolio does, we can say that to a great degree the C/P effect cannot explain the momentum profits, notwithstanding its existence in the market.

4.6 Sub-sample Analysis

This section examines portfolio performances within a number of sub-samples stratified on the basis of MV, UP, B/M and C/P, respectively. Twelve sub-samples are analysed: three size-based sub-samples (small-MV, medium-MV, and big-MV sub-samples), three price-based sub-samples (low-UP, medium-UP, and high-UP sub-samples), three B/M-based sub-samples (low-B/M, medium-B/M, and high-B/M sub-samples), and three C/P-based sub-samples (low-C/P, medium-C/P, and high-C/P sub-samples). Each sub-sample contains 1/3 of the stocks that are in the accounting sample. For example, at the beginning of each test period the 1/3 smallest stocks in the accounting sample constitute the small-MV sub-sample.

There are good reasons for carrying out the sub-sample analysis. First of all, it provides direct examinations of the size effect, low-price effect, high-B/M effect and high-C/P effect. In addition, the results obtained from the sub-samples can be compared with previous findings to see whether the conclusions made earlier are robust. Furthermore, it allows us to examine whether the profitability of the momentum strategies is confined to any particular sub-sample. More important, this analysis gives additional evidence regarding the source of the momentum profits. As demonstrated in Jegadeesh and Titman (1993), the cross-sectional variation in expected returns should be less within these sub-samples than in the full sample if size, price, B/M and C/P are related to expected stock returns. As a result, the profitability of the momentum strategy will be less pronounced when it is implemented within each sub-sample than in the full sample if cross-sectional variation in expected security returns is an important source. If, however, the momentum profits are due to serial correlation in idiosyncratic returns, they need not be reduced when the momentum strategies are implemented on these sub-samples.

Table 4.6.1 summarises the average semi-annual returns of the 6×6 strategy for each of the 12 sub-samples. Numbers in parentheses are t-statistics. $F10$ is the F-statistic computed under the hypothesis that for a given sub-sample the average semi-annual returns of the 10 decile portfolios are jointly equal. $F8$ is the F-statistic calculated under the null hypothesis that for a given sub-sample the average semi-annual returns of the second decile portfolio ($D2$) through the ninth decile portfolio ($D9$) are jointly equal. Numbers shown in square brackets are p-values of the F-statistics.

Table 4.6.1 Sub-sample Analysis

This table presents the average semi-annual returns for the decile portfolios and the momentum portfolio of the 6×6 strategy implemented on various sub-samples. Within each sub-sample, the decile portfolios are formed on the basis of 6-month past buy-and-hold security returns and held for 6 months. At the beginning of each test period, the stocks in a given sub-sample are ranked in ascending order based on their 6-month past returns. The equally-weighted portfolio of stocks in the lowest past return decile is the loser portfolio (L), the equally-weighted portfolio of stocks in the next decile is denoted as $D2$, and so on. The equally-weighted portfolio of stocks in the highest past return decile is the winner portfolio (W). The momentum portfolio is winner portfolio minus loser portfolio (W–L). Panel A summarises the results of the three-size based and three-price based sub-samples. Panel B reports the average semi-annual returns for each portfolio within the three-B/M based and the three-C/P based sub-samples. Numbers shown in parentheses are t-statistics. $F10$ is the F-statistic computed under the hypothesis that for a given sub-sample the average semi-annual returns of the 10 decile portfolios are jointly equal. $F8$ is the F-statistic calculated under the null that for a given sub-sample the average semi-annual returns of the second decile portfolio ($D2$) through the ninth decile portfolio ($D9$) are jointly equal. Numbers in the square brackets are p-values of the F-statistics. The sample period is January 1977 to June 1998.

Panel A	Small-MV	Medium-MV	Big-MV	Low-UP	Medium-UP	High-UP
L	0.1144 (2.73)	0.0369 (1.28)	0.0535 (2.48)	0.1074 (2.54)	0.0394 (1.70)	0.0664 (3.42)
$D2$	0.1219 (3.92)	0.0680 (2.65)	0.0838 (4.64)	0.1016 (2.97)	0.0797 (3.48)	0.0809 (4.84)
$D3$	0.1005 (3.65)	0.0772 (3.20)	0.0801 (4.24)	0.0969 (3.17)	0.1020 (4.35)	0.0919 (4.95)
$D4$	0.1067 (3.81)	0.0829 (3.64)	0.0938 (5.31)	0.1089 (3.63)	0.0834 (3.82)	0.0974 (5.83)
$D5$	0.0941 (3.43)	0.0858 (3.85)	0.0883 (4.95)	0.0683 (2.54)	0.0904 (4.59)	0.0933 (5.22)
$D6$	0.1277 (4.28)	0.1046 (4.16)	0.0964 (5.75)	0.1089 (3.56)	0.1085 (5.11)	0.1012 (6.06)
$D7$	0.1530 (5.39)	0.1197 (5.17)	0.0956 (4.93)	0.1230 (3.92)	0.1180 (5.16)	0.1071 (5.81)
$D8$	0.1249 (4.36)	0.1178 (5.18)	0.1134 (5.48)	0.1347 (4.27)	0.1144 (5.07)	0.1162 (6.26)
$D9$	0.1408 (5.25)	0.1343 (5.28)	0.1194 (6.11)	0.1355 (4.28)	0.1303 (5.58)	0.1341 (6.73)
W	0.1614 (5.24)	0.1575 (5.74)	0.1477 (6.66)	0.1328 (3.93)	0.1679 (7.14)	0.1622 (6.87)
$W-L$	0.0470 (1.84)	0.1207 (6.31)	0.0941 (4.81)	0.0254 (1.00)	0.1284 (7.65)	0.0958 (5.15)
$F10$ [p -value]	0.53 [0.8543]	2.02 [0.0361]	1.72 [0.0831]	0.41 [0.9291]	2.30 [0.0159]	2.12 [0.0271]
$F8$ [p -value]	0.50 [0.8366]	0.98 [0.4472]	0.54 [0.8039]	0.51 [0.8262]	0.64 [0.7231]	0.84 [0.5528]

Panel B	Low-B/M	Medium-B/M	High-B/M	Low-C/P	Medium-C/P	High-C/P
L	0.0523 (1.67)	0.0627 (2.27)	0.1171 (3.23)	0.0412 (1.07)	0.0709 (2.82)	0.1585 (4.91)
$D2$	0.0518 (2.20)	0.0837 (4.08)	0.1174 (4.17)	0.0186 (0.64)	0.0722 (3.27)	0.1550 (5.97)
$D3$	0.0740 (3.11)	0.0914 (4.39)	0.1099 (4.01)	0.0258 (0.95)	0.0907 (4.72)	0.1485 (6.15)
$D4$	0.0886 (4.21)	0.0993 (4.48)	0.1090 (4.02)	0.0082 (0.38)	0.0909 (4.28)	0.1386 (6.04)
$D5$	0.0832 (3.68)	0.0975 (4.62)	0.1111 (4.39)	0.0372 (1.67)	0.0939 (4.73)	0.1600 (6.23)
$D6$	0.0943 (4.59)	0.1154 (5.33)	0.1184 (4.83)	0.0487 (2.57)	0.1051 (5.12)	0.1604 (6.53)
$D7$	0.1181 (5.39)	0.1087 (4.95)	0.1241 (5.48)	0.0760 (3.14)	0.0958 (4.91)	0.1667 (7.03)
$D8$	0.1347 (5.55)	0.1052 (5.32)	0.1221 (5.23)	0.0721 (3.70)	0.1047 (5.03)	0.1777 (7.40)
$D9$	0.1458 (5.91)	0.1319 (5.44)	0.1349 (5.12)	0.0902 (4.30)	0.1299 (5.68)	0.1894 (6.59)
W	0.1739 (6.03)	0.1429 (5.48)	0.1324 (5.99)	0.1116 (3.94)	0.1528 (6.37)	0.2102 (7.78)
$W-L$	0.1216 (4.69)	0.0803 (4.41)	0.0153 (0.63)	0.0704 (2.41)	0.0819 (5.08)	0.0517 (2.86)
$F10$ [p -value]	2.74 [0.0041]	1.03 [0.4137]	0.11 [0.9994]	1.70 [0.0881]	1.33 [0.2206]	0.64 [0.7590]
$F8$ [p -value]	1.93 [0.0639]	0.48 [0.8482]	0.12 [0.9973]	1.64 [0.1227]	0.63 [0.7313]	0.41 [0.8951]

The results in Panel A of Table 4.6.1 show that the size effect and low-price effect are evident. The performances of the 10 decile portfolios within the small-MV and the low-UP sub-samples are apparently better than within the medium- and big-MV sub-samples, and the medium- and high-UP sub-samples, respectively. However, the momentum profits observed from the small-MV and the low-UP sub-samples are smaller than in the full sample where the average semi-annual momentum profit is 7.807%, and both are insignificant. The F-statistics show that we cannot reject the hypotheses that the average semi-annual returns of the 10 decile portfolios are jointly equal either in the small-MV sub-sample and or in the low-UP sub-sample. By contrast, the momentum profits obtained from medium- and big-MV sub-samples, and from medium- and high-UP sub-samples are considerably larger than in the full sample. For example, the average semi-annual momentum returns in the medium-MV and medium-UP sub-samples are 12.07% and 12.84% with t-statistics of 6.31 and 7.65, respectively. The F-statistics also support the large momentum profits in the two medium MV and UP sub-samples. The evidence implies that the momentum returns are not related to firm size or low-price effects. This is consistent with previous findings.

The results in Panel B of Table 4.6.1 show a similar conclusion to Panel A analysed above. The B/M and C/P effects are eye-catching. For instance, the average semi-annual returns of the winner portfolios in the high-B/M and high-C/P sub-samples are 13.24% and 21.02% with t-statistics of 5.99 and 7.78, respectively. However, the F-statistics show that there is no significant difference in the 10 decile portfolio returns either in the high-B/M sub-sample or in the high-C/P sub-sample. The average semi-annual momentum returns in both high-B/M and high-C/P sub-samples are smaller than in the entire sample and the momentum return realised in the high-B/M sub-sample is insignificant. On the other hand, the momentum returns obtained in the low- and medium-B/M sub-samples, and in the low- and medium-C/P sub-samples are statistically significant and they are generally not less than 7.807%, which is the average semi-annual momentum return of the 6×6 strategy implemented over the entire sample. This evidence means that the momentum profits are not principally due to the B/M and C/P effects. This further confirms the previous findings.

All these results in Table 4.6.1 show that the momentum profits documented earlier are not due to some particular sub-sample. Because the momentum profits are not driven by the small-MV, low-price, high-B/M and high-C/P sub-samples, and within other sub-samples they are not less than the magnitude obtained when the momentum strategy is implemented on the entire sample, these findings indicate that the momentum profits are not due to the cross-sectional variation in expected security returns.

In addition, I also examine the price reactions to common factors. As we have seen in Chapter 3 (see Table 3.4.1 and Table 3.4.2), Lehmann's weighting strategy is closely related to the decile portfolio strategy. For instance, for the 6×6 strategy the correlation between the momentum profits of Lehmann's weighting strategy and the decile portfolio strategy is 0.914. Based on Lehmann's weighting strategy, Jegadeesh and Titman (1995b) find that the expected momentum returns are related to three sources by introducing a return-generating process: the cross-sectional variation in the unconditional mean returns of the individual stocks, the serial correlation of the idiosyncratic components of security returns, and the stock price reactions to common factors. For the detailed decomposing analysis see Appendix 4A in this Chapter. Following Jegadeesh and Titman's (1993, 1995b) decompositions, when referring to the value-weighted market index constructed from the accounting sample as the common factor I find that the coefficient b in Equation (4A.2.11) is significantly negative (−1.844 with a t-statistic of −2.35, see Appendix 4A of this chapter). Additionally, I also find that the first-order auto-correlation of the semi-annual returns of the equally-weighted market index constructed from the same sample is -0.0791 with a t-statistic of −0.52 (see Equation (4A.2.15) in Appendix 4A of this chapter for its implication). These results suggest that the delayed price reactions to common factor and the serial correlation in common factor realisations are not important sources of the momentum effect. Because the evidence documented in the last chapter and this chapter shows that the momentum effect is not due to the cross-sectional variation of the mean returns, the momentum effect is likely to result from market underreaction to firm-specific information. These findings are same as for the US market as documented in Jegadeesh and Titman (1993).

4.7 Concluding Remarks

In this chapter I examine whether the momentum effect documented in Chapter 3 can be explained by systematic risk and other systematic effects such as size, low-price, C/P and B/M effects. The results show that the momentum profits cannot be explained by the systematic risk and the Fama-French three-factor model. Rather, adjusting for systematic risk gives even larger momentum profits since the loser portfolio is riskier than the winner portfolio.

Further investigations show that size, low-price, B/M and C/P effects do exist in the UK stock market. However, the momentum effect is not limited to small, low-price, high-B/M and high-C/P firms. In fact, the momentum strategies cannot even earn significant profits within the small-MV, low-price, high-B/M sub-samples. Such risk factors have little power in explaining the momentum returns.

The bulk of the evidence indicates that the profitability of the momentum strategy is not due to cross-sectional variation in the unconditional mean returns of the individual securities. In addition, following Jegadeesh and Titman's (1993, 1995b) decompositions the results show that the remarkable momentum profits can be explained neither by delayed stock price reactions to common factor realisations nor by serial correlation in common factor realisations. As a result, the profitability of the price momentum strategies should be attributed to the serial correlation in idiosyncratic components of security returns. In other words, the results, which strongly suggest a rejection of the efficient markets hypothesis, are consistent with delayed price reactions (under-reactions) to firm-specific information.

The results documented in this chapter and Chapter 3 are very similar to the findings of Jegadeesh and Titman (1993) for the US market. This evidence may reflect the generality of investors' behaviour. As we have seen, the profitability of the momentum strategies is mainly due to the winner's performance rather than the loser's, this suggests that investors may under-react to good firm-specific information while their reactions to bad news are appropriate over the intermediate time horizon of 3 to 12 months. This may imply that investors are prudent, and the risk-averse hypothesis commonly adopted in finance and economics literature is clearly acceptable. Obviously, further studies on this are needed. The next two chapters concentrate on an event study together with the tests for private information, to ascertain whether the momentum effect is the same thing as the post-earnings-announcement drift (PAD) in security returns documented in the literature.

Appendix 4A

Decomposition Analysis of Momentum Profits

As we have seen in Section 3.4 of Chapter 3 (see Table 3.4.1 and Table 3.4.2), Lehmann's weighting strategy is closely related to the decile portfolio strategy. Because of the analytic tractability of Lehmann's weighting strategy, this appendix decomposes the profits from the momentum strategy described in equation (3.3.4) into different components. The following section adopts Lehmann decomposition to obtain a general view on the momentum profits documented previously. In section 4A.2, Jegadeesh and Titman's (1993, 1995b) decomposition will be used to examine the stock price reactions to different information under a return-generating process.

4A.1 Lehmann's Decomposition

From equation (3.3.4) we know that the momentum profits in test period t is given by

$$\pi_t = \sum_{i=1}^{N_{t-1}} \frac{(R_{i,t-1} - R_{m,t-1})R_{i,t}}{\sum_{R_{i,t-1}-R_{m,t-1}>0} (R_{i,t-1} - R_{m,t-1})}. \qquad (4A.1.1)$$

For detailed description of the notation see Section 3.3 in Chapter 3. For convenience and with no loss of generality, the subsequent analyses will ignore the factor of proportionality (i.e., let $\sum_{R_{i,t-1}-R_{m,t-1}>0}(R_{i,t-1} - R_{m,t-1}) = 1$) and assume that N_{t-1}, the number of qualified stocks in the sample at the beginning of the test period, is fixed at N. Therefore, Equation (4A.1.1) becomes

$$\pi_t = \sum_{i=1}^{N}(R_{i,t-1} - R_{m,t-1})R_{i,t} . \qquad (4A.1.2)$$

In addition, denote $R_t = [R_{1,t} \;\; R_{2,t} \;\; \ldots \;\; R_{N,t}]'$ as an $N \times 1$ vector of the N security returns at t, and assume that R_t is a jointly covariance-stationary stochastic process with expectation $E[R_t]$ = μ = $[\mu_1 \;\; \mu_2 \;\; \ldots \;\; \mu_N]'$. Under these assumptions, the expected momentum portfolio return can be expressed as

$$E[\pi_t] = \sum_{i=1}^{N} Cov(R_{i,t-1}, R_{i,t}) - NCov(R_{m,t-1}, R_{m,t}) + \sum_{i=1}^{N}(\mu_i - \mu_m)^2 , \qquad (4A.1.3)$$

where μ_m is the unconditional mean return on the equally weighted within-sample market index, given by $\frac{1}{N}\sum_{i=1}^{N}\mu_i$. The derivation of equation (4A.1.3) is given at the end of this appendix. Note that the assumptions made above are maintained throughout this appendix.

Equation (4A.1.3) shows that the momentum portfolio profits depend on the auto-covariance of the returns of the individual securities, $Cov(R_{i,t-1}, R_{i,t})$, the auto-covariance of the equally weighted market index, $Cov(R_{m,t-1}, R_{m,t})$, and the cross-sectional variation of the mean returns, $\sum_{i=1}^{N}(\mu_i - \mu_m)^2$.

Obviously, if returns are both cross-sectionally and serially independent as commonly assumed in the finance literature, the first two terms of equation (4A.1.3) will equal zero. Thus, significantly positive momentum profits imply that,

$$E[\pi_t] = \sum_{i=1}^{N}(\mu_i - \mu_m)^2 > 0 .$$

This means that under the assumption of independence of stock returns the expected returns on the momentum portfolio are positive as long as there is some cross-sectional variation in expected returns. In this case, the positive momentum profits need not be an indication of market inefficiency, as the momentum profits may be attributed to compensation for bearing systematic risk.

However, previous results show that the momentum profits are not due to systematic risk. For example, the winner's Scholes-Williams beta is generally smaller than loser's. In addition, the previous evidence also shows that the momentum portfolios do not tend to pick up high-expected-return stocks such as small stocks, low-price stocks, and value stocks. These results imply that the observed momentum profits are less likely to be due to the third source of profits in expression (4A.1.3), the dispersion in expected returns. More important, because of the significant momentum profits that cannot be explained by the cross-sectional variation in the unconditional expected returns of the individual securities, the assumption that security returns are independently distributed is not tenable. Consequently, there must be serial correlation either in the returns of the individual securities or in the returns of the equally weighted market index. This deduction, however, is not new. As reviewed in Chapter 2, studies have documented significant autocorrelations of individual stock returns and of portfolio returns over different intervals. For example, Solnik (1973) finds significant negative auto-correlation of daily returns of stocks trading on exchanges in the United Kingdom and other countries. Poon and Taylor (1992) report that, in the UK, the Financial Times All Share Index (a value-weighted index) exhibited significantly positive lag-one auto-correlation in daily returns (0.19) during the period 1965–1989. In this study, the first-order auto-correlation of the monthly returns on the equal-weighted market index constructed from the accounting sample is 0.2733 (t-statistic 4.47) during the sample period of January 1977 to June 1998. The first-order auto-correlation of the monthly returns on the value-weighted market index constructed from the sample during the same period is 0.0063 (t-statistic 0.099). This phenomenon of large significant positive auto-correlation in the monthly returns of the equal-weighted market index and small insignificant positive auto-correlation in the monthly returns of the value-weighted market index is consistent with the demonstration of Cohen et al. (1986) as cited in Section 3.3 of Chapter 3.

However, the substantial question is why do the serial correlations exist? Possible microstructure explanations have been examined in the literature. For instance, Fisher (1966) documents that the observation of positive index serial correlation implies that the prices of different securities do not adjust simultaneously to common information. Cohen et al. (1986) show that frictions in the trading process such as infrequent trading, non-synchronous trading, adjustment lags in quotation prices, etc. lead to a pattern of price-adjustment delays. These delays in turn result in serial correlation in observed security and index returns. Neiderhofer and Osborne (1966) find that successive trades tend to occur alternatively at the bid and then the ask, resulting in negative serial correlation in returns at short frequencies. Nevertheless, if the serial correlations in returns of individual stocks and in returns of stock portfolios are caused by microstructure-related effects, we should not conclude that the market is inefficient. And yet such microstructure-related explanations cannot completely account for the serial correlation present in stock returns. For instance, Foerster and Keim (1992) find that 80 percent of the Dow 30 stocks, which are very liquid stocks, have significant positive autocorrelations in daily returns in the 1963–1990 period. In effect, the power of the microstructure explanations on the autocorrelations in stock returns will be rather trivial over intervals of 3 to 12 months. Therefore, stock price reactions to common factors and to firm-specific information are most likely to be the causes of the serial correlation in stock returns. As documented in the overreaction literature, overreacting to information and then correcting the overreaction in the following period will result in negative serial correlation. Naturally, if stock prices tend to under-react to information, positive serial correlation will result. To ascertain the origins of the serial correlations in stock returns over 3- to 12-month intervals, which lead to the significantly positive momentum profits, the next subsection specifies a return-generating process to identify different sources of the momentum profits.

4A.2 Decomposition of Momentum Profits Based on a Return-generating Process

Based on Lehmann's (1990) weighting strategy, Lo and Mackinlay (1990) and Jegadeesh and Titman (1995b) study the short-term (a week) overreaction hypothesis. By rearranging Lehmann's decomposition, Lo and Mackinlay show that the expected contrarian profits depend on three components: the dispersion of expected returns, the serial covariances of returns, and cross-serial covariances of returns. Lo and Mackinlay posit that the cross-serial covariances measure the contribution of the lead-lag structure to contrarian profits.[7] Lo and Mackinlay's analysis is heuristic. It makes an important point that one cannot draw definitive inferences about how stock prices react to information based on the observed profitability of contrarian strategies. Additionally, the use of the factor model in their decomposition also sheds light upon how stock prices react to information.

However, resorting to a factor-model-based decomposition, Jegadeesh and Titman (1995b) find that the Lo and Mackinlay decomposition counts the effect of delayed reactions twice. They, therefore, argue that this double counting in general leads to misleading inferences. For instance, the average cross-autocovariance may overestimate the contrarian profit due to the lead-lag effect. By comparison, the Jegadeesh and Titman decomposition ties down the importance of the different components of contrarian profits to their sources, identified from how stock prices respond to information. Their factor-model-based decomposition, hence, enables us to separately examine stock price reactions to common factors and firm-specific

[7] The pattern of cross-autocovariances documented in Lo and Mackinlay (1990) implies a size-dependent lead-lag structure. They find large positive covariances between the returns of small stocks and lagged returns of large stocks, but virtually no correlation between returns of large stocks and lagged small stock returns.

information. Because of the advantages of the Jegadeesh and Titman decomposition, this section adopts it to examine the sources of the momentum profits documented previously.

A. A Multifactor Model Describing Stock Returns

Consider a collection of K factors and denote by F_t the $K \times 1$ vector of their period t realisations $[F_{1,t} \ \ F_{2,t} \ \ \ldots \ \ F_{K,t}]'$. Let the return-generating process for $R_{i,t}$ be given by the following K-factor model:

$$R_{i,t} = \mu_i + \sum_{k=1}^{K} (\alpha_{i,k,t} F_{k,t} + \beta_{i,k,t} F_{k,t-1}) + \varepsilon_{i,t} \,, \qquad \text{(4A.2.1)}$$

$$E[F_{k,t}] = 0 \,, \quad \forall \ k$$

$$E[\varepsilon_{i,t}] = 0$$

$$Cov(F_{k,t}, \varepsilon_{i,t}) = Cov(F_{k,t-1}, \varepsilon_{i,t}) = 0 \,, \quad \forall \ k$$

$$Cov(\varepsilon_{i,t}, \varepsilon_{j,t-1}) = 0 \,, \quad \forall \ i \neq j$$

where $\alpha_{i,k,t}$ and $\beta_{i,k,t}$ are the sensitivities of stock i to the contemporaneous and lagged realisations of factor k at time t, and $\varepsilon_{i,t}$ is the firm-specific component of return at time t.[8]

Given the return-generating process, the equally weighted market return at t, $R_{m,t}$, is given by

$$R_{m,t} = \mu_m + \sum_{k=1}^{K}(\alpha_{m,k,t}F_{k,t} + \beta_{m,k,t}F_{k,t-1}), \qquad (4A.2.2)$$

where $\alpha_{m,k,t} = \frac{1}{N}\sum_{i=1}^{N}\alpha_{i,k,t}$ and $\beta_{m,k,t} = \frac{1}{N}\sum_{i=1}^{N}\beta_{i,k,t}$.

Without loss of generality let us assume that the F_t are both cross-sectionally and serially uncorrelated with $Var(F_{k,t}) = \sigma_{Fk}^2$, and that the factor sensitivities are uncorrelated with factor realisations.

Under the assumptions, substituting $R_{i,t}$ defined by equation (4A.2.1) and $R_{m,t}$ given by equation (4A.2.2) into equation (4A.1.2) and taking expectations yields,

$$E[\pi_t] = \sum_{i=1}^{N}(\mu_i - \mu_m)^2 + \sum_{i=1}^{N}Cov(\varepsilon_{i,t-1}, \varepsilon_{i,t}) +$$

$$\sum_{i=1}^{N}\sum_{k=1}^{K}\left\{\sigma_{Fk}^2 E[(\alpha_{i,k,t-1} - \alpha_{m,k,t-1})(\beta_{i,k,t} - \beta_{m,k,t})]\right\}. \qquad (4A.2.3)$$

The derivation of equation (4A.2.3) is also given at the end of this appendix.

Equation (4A.2.3) shows that the expected momentum profits are related to three sources. The first one is the cross-sectional variation in the unconditional mean returns of the individual stocks, $\sum_{i=1}^{N}(\mu_i - \mu_m)^2$. As analysed in the previous section of this appendix, this is not likely to be an important contributor to momentum profits.

[8] This multifactor model with lagged realisations of factors is used in Jegadeesh and Titman (1995b) to examine the short-term overreaction effect.

The second source is the serial covariance of the idiosyncratic components of security returns, $Cov(\varepsilon_{i,t-1}, \varepsilon_{i,t})$, which is determined by stock price reactions to firm-specific information. If stock prices under-react to firm specific information over the intermediate time horizon of 3 to 12 months, $\sum_{i=1}^{N} Cov(\varepsilon_{i,t-1}, \varepsilon_{i,t})$ will be positive. In this case, there is an indication of market inefficiency. The last source is attributable to stock price reactions to common factors. If $E[(\alpha_{i,k,t-1} - \alpha_{m,k,t-1})(\beta_{i,k,t} - \beta_{m,k,t})] > 0$, the stock price reactions to the kth-factor realisations contribute positively to momentum profits, otherwise the contribution of the price reactions to the common factor is negative.

Comparing this decomposition with equation (4A.1.3), we can find that the auto-covariance of the returns of the individual securities, $Cov(R_{i,t-1}, R_{i,t})$, can be caused by stock price reactions to common factors and to firm-specific information. The auto-covariance of the returns of the equal-weighted market index, $Cov(R_{m,t-1}, R_{m,t})$, in equation (4A.1.3) is due to reactions of stock price to common factors. That is,

$$
\begin{aligned}
Cov(R_{i,t-1}, R_{i,t}) &= E[(R_{i,t-1} - \mu_i)(R_{i,t} - \mu_i)] \\
&= E[(\alpha'_{i,t-1} F_{t-1} + \beta'_{i,t-1} F_{t-2} + \varepsilon_{i,t-1})(\alpha'_{i,t} F_t + \beta'_{i,t} F_{t-1} + \varepsilon_{i,t})] \\
&= E[\alpha'_{i,t-1} F_{t-1} \beta'_{i,t} F_{t-1}] + E[\varepsilon_{i,t-1} \varepsilon_{i,t}] \\
&= \sum_{k=1}^{K} [\sigma_{Fk}^2 E(\alpha_{i,k,t-1} \beta_{i,k,t})] + Cov(\varepsilon_{i,t-1}, \varepsilon_{i,t}), \qquad (4A.2.4)
\end{aligned}
$$

and

$$
\begin{aligned}
Cov(R_{m,t-1}, R_{m,t}) &= E[(R_{m,t-1} - \mu_m)(R_{m,t} - \mu_m)] \\
&= E[(\alpha'_{m,t-1}F_{t-1} + \beta'_{m,t-1}F_{t-2})(\alpha'_{m,t}F_t + \beta'_{m,t}F_{t-1})] \\
&= E[\alpha'_{m,t-1}F_{t-1}\beta'_{m,t}F_{t-1}] \\
&= \sum_{k=1}^{K}[\sigma^2_{Fk}E(\alpha_{m,k,t-1}\beta_{m,k,t})]. \qquad (4A.2.5)
\end{aligned}
$$

These equations imply that the introduction of the return-generating process helps to identify causes of the autocorrelations in the returns of the individual stocks and in the returns of the equal-weighted market index, which are likely sources of momentum profits.

To make matters concrete, the following analysis uses a simple one-factor model to separately examine stock price reactions to common factors and to firm-specific information. The basic idea is that if the momentum profits are due neither to stock price reactions to delayed common factor realisations nor to the serial correlation in the common factor realisations, then the significant momentum profits are most likely due to the market under-reaction to firm-specific information.

B. Delayed Price Reaction to a Common Factor and Momentum Profits: One-factor Model Analysis (I)

Let the return-generating process for R_t be given by

$$R_{i,t} = \mu_i + \alpha_i f_t + \beta_i f_{t-1} + \varepsilon_{i,t}, \qquad (4A.2.6)$$

where f_t is the common factor realisation at time t with unconditional zero mean and variance σ_f^2.

Let us assume from now that the factor sensitivities (α_i and β_i) are not time-varying. Intuitively, if stock i reacts with a delay to the common factor realisation then $\beta_i > 0$, and if it overreacts to contemporaneous factor realisations and this overreaction gets corrected in the subsequent period then $\beta_i < 0$.

Given the return-generating process defined by equation (4A.2.6), the expected momentum profits can be shown to be,

$$E[\pi_t] = \sum_{i=1}^{N}(\mu_i - \mu_m)^2 + \sum_{i=1}^{N} Cov(\varepsilon_{i,t-1}, \varepsilon_{i,t}) + \gamma\sigma_f^2 , \qquad (4A.2.7)$$

where $\sigma_f^2 = E[f_{t-1}^2]$, $\gamma = \sum_{i=1}^{N}[(\alpha_i - \alpha_m)(\beta_i - \beta_m)]$, and where $\alpha_m = \frac{1}{N}\sum_{i=1}^{N}\alpha_i$, and $\beta_m = \frac{1}{N}\sum_{i=1}^{N}\beta_i$.

By assuming that the $\varepsilon_{i,t}$ s are normally distributed, following Jegadeesh and Titman's (1995b) analysis, the expected momentum profit at t conditional on lagged common factor realisations, f_{t-1}, and on lagged firm-specific components of return, $\varepsilon_{i,t-1}$, is given by,

$$E[\pi_t | f_{t-1}, \varepsilon_{i,t-1}] = \sum_{i=1}^{N} (\mu_i - \mu_m)^2 + \gamma f_{t-1}^2 + \rho \sum_{i=1}^{N} \varepsilon_{i,t-1}^2 , \qquad (4A.2.8)$$

where ρ is the first-order auto-correlation of $\varepsilon_{i,t}$ (i.e., $\rho = Cov(\varepsilon_{i,t-1}, \varepsilon_{i,t}) / E[\varepsilon_{i,t-1}^2]$, $\forall i$).

Since here I wish to focus on delayed price reactions to a common factor as the sole source of the momentum profits, I further assume that the firm-specific component of returns are serially uncorrelated (ρ = 0). Note that this assumption is only for the current purpose, and it will be relaxed in the following analysis. Consequently, the expected momentum profit conditional on lagged common factor realisation is simplified as follows:

$$E[\pi_t | f_{t-1}] = \sum_{i=1}^{N} (\mu_i - \mu_m)^2 + \gamma f_{t-1}^2 . \qquad (4A.2.9)$$

The effect of delayed stock price reaction to a common factor can hence be examined by the following time-series regression:

$$\pi_t = a + b f_{t-1}^2 + e_{i,t} . \qquad (4A.2.10)$$

For the 6×6 strategy mainly considered in this study the length of a period, t, is 6 months. If we think of the value-weighted market index (VWI) constructed from the accounting sample as the common factor, the regression equation (4A.2.10) can be expressed as,

$$\pi_t = a + b(R_{VWI,t-1} - \mu_{VWI})^2 + e_{i,t}, \qquad (4A.2.11)$$

where $R_{VWI,t-1}$ is the return on the value-weighted market index (VWI) at time $t-1$, and μ_{VWI} is the unconditional mean return of the VWI.

The estimate of the slope coefficient, b, is -1.844 with a t-statistic of -2.35. The significantly negative coefficient of b indicates that delayed reaction to a common factor is not an important source of momentum profits. Having found this evidence we may ignore the lagged factor realisation in equation (4A.2.6) without influencing the conclusion, to further examine the sources of the momentum profits by relaxing some of assumptions made earlier.

C. Serial Correlation in Common Factor Realisations and Momentum Profits: One-factor Model Analysis (II)

Let the return-generating process for R_t be given by,

$$R_{i,t} = \mu_i + \alpha_i f_t + \varepsilon_{i,t}. \qquad (4A.2.12)$$

Here let us relax the assumption on the common factor to allow for serial correlation in the common factor realisations. Other assumptions made previously remain unchanged. Given the single-factor model described by equation (4A.2.12), the return on the equal-weighted market index at t, $R_{m,t}$, is given by,

$$R_{m,t} = \mu_m + \alpha_m f_t, \qquad (4A.2.13)$$

where $\alpha_m = \frac{1}{N}\sum_{i=1}^{N}\alpha_i$.

The expected momentum profits, therefore, can be shown to be

$$E[\pi_t] = \sum_{i=1}^{N}(\mu_i - \mu_m)^2 + Cov(f_{t-1}, f_t)\sum_{i=1}^{N}(\alpha_i - \alpha_m)^2 + \sum_{i=1}^{N}Cov(\varepsilon_{i,t-1}, \varepsilon_{i,t}). \qquad (4A.2.14)$$

Under this circumstance, equation (4A.2.14) suggests three potential sources of momentum profits. The first and the last terms in this equation have been explained earlier. The second term implies that the momentum profits are related to serial correlation of the common factor realisations. If the serial correlation is positive, it will positively contribute to the momentum profits, otherwise it reduces the momentum profits.

To examine whether there is positive serial correlation in the common factor realisations, I still concentrate on the 6×6 strategy. Because of the relation between the common factor realisations (f_t) and the equal-weighted market returns ($R_{m,t}$) described by equation (4A.2.13), it can be shown that the auto-covariance of the common factor realisations, $Cov(f_{t-1}, f_t)$, is given by,

$$Cov(f_{t-1}, f_t) = \frac{1}{\alpha_m^2}Cov(R_{m,t-1}, R_{m,t}). \qquad (4A.2.15)$$

The above expression means that serial correlation of the common factor realisations is related to the auto-correlation of the equally weighted within-sample market index returns. If serial correlation in the common factor realisations is an important source of momentum profits, the serial correlation of the equal-weighted market returns should be positive. However, I find that the first-order auto-correlation of the semi-annual returns of the equally weighted market index constructed from the accounting sample is −0.0791 with a t-statistics of −0.52 over the sample period 1977 to 1998. Accordingly, $Cov(f_{t-1}, f_t)$ will be negative, and the momentum profits are not likely to be due to serial correlation of the common factor realisations.

In a word, the one-factor model analyses indicate that stock price reaction to common factor realisations are unlikely to be the source of momentum profits.

4A.3 Derivation of Equations (4A.1.3) and (4A.2.3)

(1) Derivation of Equation (4A.1.3)

From equation (4A.1.2) of this appendix we know,

$$\pi_t = \sum_{i=1}^{N} [(R_{i,t-1} - R_{m,t-1}) R_{i,t}] .$$

Thus,

$$\pi_t = \sum_{i=1}^{N} \left\{ (R_{i,t-1} - R_{m,t-1})[(R_{i,t} - R_{m,t}) + R_{m,t}] \right\}$$

$$= \sum_{i=1}^{N} [(R_{i,t-1} - R_{m,t-1})(R_{i,t} - R_{m,t}) + R_{m,t}(R_{i,t-1} - R_{m,t-1})]$$

$$= \sum_{i=1}^{N} [(R_{i,t-1} - R_{m,t-1})(R_{i,t} - R_{m,t})] + R_{m,t} \sum_{i=1}^{N} (R_{i,t-1} - R_{m,t-1}) .$$

Because

$$R_{m,t} = \frac{1}{N} \sum_{i=1}^{N} R_{i,t} \text{ , we have } \sum_{i=1}^{N} (R_{i,t-1} - R_{m,t-1}) = 0 .$$

Substituting $\sum_{i=1}^{N} (R_{i,t-1} - R_{m,t-1}) = 0$ into π_t yields

$$\pi_t = \sum_{i=1}^{N} [(R_{i,t-1} - R_{m,t-1})(R_{i,t} - R_{m,t})] . \qquad (4A.3.1)$$

Equation (4A.3.1) can also be expressed as,

$$\pi_t = \sum_{i=1}^{N} \left\{ [(R_{i,t-1} - \mu_i) - (R_{m,t-1} - \mu_m) + (\mu_i - \mu_m)][(R_{i,t} - \mu_i) - (R_{m,t} - \mu_m) + (\mu_i - \mu_m)] \right\}$$

$$= \sum_{i=1}^{N} [(R_{i,t-1} - \mu_i)(R_{i,t} - \mu_i)] - (R_{m,t} - \mu_m) \sum_{i=1}^{N} (R_{i,t-1} - \mu_i) \; +$$

$$\sum_{i=1}^{N} [(R_{i,t-1} - \mu_i)(\mu_i - \mu_m)] - (R_{m,t-1} - \mu_m) \sum_{i=1}^{N} (R_{i,t} - \mu_i) \; +$$

$$N(R_{m,t-1}-\mu_m)(R_{m,t}-\mu_m)-(R_{m,t-1}-\mu_m)\sum_{i=1}^{N}(\mu_i-\mu_m)\ +$$

$$\sum_{i=1}^{N}[(R_{i,t}-\mu_i)(\mu_i-\mu_m)]-(R_{m,t}-\mu_m)\sum_{i=1}^{N}(\mu_i-\mu_m)+\sum_{i=1}^{N}(\mu_i-\mu_m)^2\ .$$

In the above expression, it is easy to verify that,

$$(R_{m,t}-\mu_m)\sum_{i=1}^{N}(R_{i,t-1}-\mu_i)=(R_{m,t-1}-\mu_m)\sum_{i=1}^{N}(R_{i,t}-\mu_i)=N(R_{m,t-1}-\mu_m)(R_{m,t}-\mu_m)\ ,$$

and

$$\sum_{i=1}^{N}(\mu_i-\mu_m)=0\ .$$

Hence,

$$\pi_t=\sum_{i=1}^{N}[(R_{i,t-1}-\mu_i)(R_{i,t}-\mu_i)]-N(R_{m,t-1}-\mu_m)(R_{m,t}-\mu_m)\ +$$

$$\sum_{i=1}^{N}(\mu_i-\mu_m)^2+\sum_{i=1}^{N}[(R_{i,t-1}-\mu_i)(\mu_i-\mu_m)]+\sum_{i=1}^{N}[(R_{i,t}-\mu_i)(\mu_i-\mu_m)]\ .$$

Taking expectations we have,

$$E[\pi_t]=\sum_{i=1}^{N}E[(R_{i,t-1}-\mu_i)(R_{i,t}-\mu_i)]-NE[(R_{m,t-1}-\mu_m)(R_{m,t}-\mu_m)]+\sum_{i=1}^{N}(\mu_i-\mu_m)^2\ .$$

That is,

$$E[\pi_t] = \sum_{i=1}^{N} Cov(R_{i,t-1}, R_{i,t}) - NCov(R_{m,t-1}, R_{m,t}) + \sum_{i=1}^{N} (\mu_i - \mu_m)^2 \ .$$

(2) Derivation of Equation (4A.2.3)

From equation (4A.3.1) above, the expected momentum portfolio return, $E[\pi_t]$, can be expressed as

$$E[\pi_t] = \sum_{i=1}^{N} E[(R_{i,t-1} - R_{m,t-1})(R_{i,t} - R_{m,t})] . \qquad (4A.3.2)$$

Let $\alpha_{i,t} = [\alpha_{i,1,t} \ \ \alpha_{i,2,t} \ \cdots \ \alpha_{i,K,t}]'$, $\beta_{i,t} = [\beta_{i,1,t} \ \ \beta_{i,2,t} \ \cdots \ \beta_{i,K,t}]'$,

$\alpha_{m,t} = [\alpha_{m,1,t} \ \ \alpha_{m,2,t} \ \cdots \ \alpha_{m,K,t}]'$, and $\beta_{m,t} = [\beta_{m,1,t} \ \ \beta_{m,2,t} \ \cdots \ \beta_{m,K,t}]'$.

Then equation (4A.2.1) and equation (4A.2.2) can be written as,

$$R_{i,t} = \mu_i + \alpha'_{i,t} F_t + \beta'_{i,t} F_{t-1} + \varepsilon_{i,t} , \qquad (4A.3.3)$$

and

$$R_{m,t} = \mu_m + \alpha'_{m,t} F_t + \beta'_{m,t} F_{t-1} . \qquad (4A.3.4)$$

Substituting (4A.3.3) and (4A.3.4) into equation (4A.3.2) we have

$$E[\pi_t] = \sum_{i=1}^{N} E[(\mu_i + \alpha'_{i,t-1}F_{t-1} + \beta'_{i,t-1}F_{t-2} + \varepsilon_{i,t-1} - \mu_m - \alpha'_{m,t-1}F_{t-1} - \beta'_{m,t-1}F_{t-2})$$

$$(\mu_i + \alpha'_{i,t}F_t + \beta'_{i,t}F_{t-1} + \varepsilon_{i,t} - \mu_m - \alpha'_{m,t}F_t - \beta'_{m,t}F_{t-1})]$$

$$= \sum_{i=1}^{N} E\{[(\mu_i - \mu_m) + \varepsilon_{i,t-1} + (\alpha_{i,t-1} - \alpha_{m,t-1})'F_{t-1} + (\beta_{i,t-1} - \beta_{m,t-1})'F_{t-2}]$$

$$[(\mu_i - \mu_m) + \varepsilon_{i,t} + (\alpha_{i,t} - \alpha_{m,t})'F_t + (\beta_{i,t} - \beta_{m,t})'F_{t-1}]\}$$

$$= \sum_{i=1}^{N} (\mu_i - \mu_m)^2 + \sum_{i=1}^{N} Cov(\varepsilon_{i,t-1}, \varepsilon_{i,t}) +$$

$$\sum_{i=1}^{N} \sum_{k=1}^{K} \{\sigma^2_{Fk} E[(\alpha_{i,k,t-1} - \alpha_{m,k,t-1})(\beta_{i,k,t} - \beta_{m,k,t})]\}.$$

CHAPTER 5

POST-EARNINGS-ANNOUNCEMENT DRIFT

5.1 Introduction

From the results in Chapters 3 and 4 we have seen that a significant momentum effect is present in UK stock returns, and that this effect is distinct from other systematic effects and established regularities associated with cross-sectional variation in average returns. For instance, market risk, size effect, low-price effect, value-stock effect and so forth cannot explain the significant momentum profits. However, studies have documented an important phenomenon known as post-earnings-announcement drift (PAD), and revealed substantial abnormal returns over the short- and intermediate-horizons that are positively related to the sign and magnitude of the earnings surprise. In other words, abnormal stock returns are predictable on the basis of past earnings news. Intuitively, there should be some relation between momentum profits and the PAD phenomenon (at least, this follows from the literal meanings of momentum and drift over the intermediate-horizon). It is thus worth examining the relationship between the two. Before doing so, it is clear that we need to investigate first whether the PAD effect exists in the UK. This chapter will perform the task.

The following section briefly provides a literature review of the PAD phenomenon. Section 5.3 describes the study sample, data, and research methodology. Because of the introduction of the earnings data including analysts' forecasts of earnings, the sample size and the sample period are considerably reduced compared with the samples examined in previous chapters. Also, the methods adopted to examine the PAD phenomenon are not the same as those used to test for the momentum effect described in Chapter 3. Empirical evidence on the PAD phenomenon based on three different earnings surprise variables, which are described in Section 5.3, is presented in Section 5.4. In Section 5.5 I analyse the relation between the three measures of earnings surprises to see if they contain the same information. The final section summarises this chapter.

5.2 Literature Review of the PAD Phenomenon

5.2.1 Documented Evidence on PAD

Ball and Brown (1968) first reported the post-earnings-announcement drift. They find that even after earnings are announced, estimated cumulative abnormal returns continue to drift upwards for firms with better than expected earnings results, and downwards for firms with worse than expected earnings results. In other words, the PAD effect can be described as a positive association between unexpected earnings news from the announcement and post-announcement abnormal stock returns. The drift usually continues for several months, matching the intermediate time horizon in which momentum profits are realised. The PAD phenomenon directly challenges the efficient market hypothesis, a cornerstone of modern finance, at the semi-strong form level. Lev and Ohlson (1982) describe evidence of PAD as the "most damaging to the naïve and unwavering belief in market efficiency" (p. 284).

Previous research into this area has been carried out mainly based on US data. The PAD effect has survived robustness checks as many studies following the Ball and Brown (1968) paper have documented this market anomaly including extensions to more recent data. There are at least eight studies that report evidence of the PAD phenomenon before 1978. Ball (1978), and Joy and Jones (1979) survey the early evidence on the PAD phenomenon. The earlier studies suffer from a variety of limitations such as small samples and short sample periods etc. so that the documented evidence of a PAD effect may be spurious. However, many subsequent studies reconfirm the PAD effect. For example, Rendleman, Jones and Latane (1982) report significant abnormal returns (that is a PAD effect) between high-SUE and low-SUE portfolios[1] over a longer sample period of 1971 to 1980. Their conclusion is that there is "a significant PAD effect over the entire decade of the 1970s, and there is no evidence to suggest that it has disappeared" (p. 286). Yet, not all studies find a significant PAD effect. For instance, Reinganum's (1981) examination based on a sample of 566 firms shows that the abnormal returns between two extreme SUE portfolios cannot be earned over the sample period 1975 to 1977. Rendleman, Jones and Latane (1982), however, argue that Reinganum's (1981) sample period is too

[1] SUE stands for standardised unexpected earnings, defined as unexpected earnings (the difference between actual and expected earnings) divided (or standardised) by the standard deviation of unexpected earnings. This measure is widely used in PAD examinations. Detailed procedures to compute such a measure are discussed in the following subsection.

short to properly identify high- and low-*SUE* stocks. As a result, Reinganum's (1981) results may be misleading.

There are no limitations of sample size, sample period and so forth in recent studies. Recent studies have documented a significant PAD anomaly based on more refined techniques, larger samples, and longer sample periods. Foster, Olsen and Shevlin (1984) document that an arbitrage portfolio buying the highest-*SUE* decile stocks and selling the lowest-*SUE* decile stocks short realises abnormal returns of about 6.31% over the 60 trading days subsequent to the earnings announcement. Their results are obtained based on a large sample of over 56,000 observations covering the period 1974 to 1981. Further examination shows that the PAD phenomenon is not attributable to the size effect. Although the magnitude of drift is inversely related to firm size, evidence of the PAD effect can be found in all firm size categories. Foster, Olsen and Shevlin's (1984) study is important. They comprehensively examine a number of models measuring earnings surprise, which will be discussed in the following subsection, and their study has had significant influence on subsequent research in the area.

The most extensive study of the PAD effect in the US is by Bernard and Thomas (1989, 1990). Their sample size exceeds 80,000 earnings announcements for the period 1974 to 1986. They find that the abnormal returns realised from *SUE*-grouped portfolios increase monotonically with unexpected earnings after earnings announcements. Bernard and Thomas (1989) document that the arbitrage portfolio of a long position in the highest-*SUE* decile and a short position in the lowest-*SUE* decile yields abnormal returns of 4.2% over the 60 trading days subsequent to the earnings announcement. In addition, the PAD effect is not limited to the 60 trading days subsequent to the earnings announcements; it persists for up to 180 days. Their results are also consistent with Foster, Olsen and Shevlin (1984) when analysing three size-based sub-samples. The long–short positions implemented within the small, medium and large size-based sub-samples yield abnormal returns of 5.3%, 4.5%, and 2.8% respectively over the 60 trading days after the earnings announcements. Further analyses into the firm size categories reveal that all of the drift for small firms occurs within 9 months following the earnings announcement, while it occurs within 6 months for large firms. Moreover, Bernard and Thomas (1990) develop and test a refutable alternative to the efficient market hypothesis, which states that investors do not fully anticipate the implications of current earnings surprises for future earnings announcements. The attractive feature of their development is that, for instance, if abnormal returns are not observed at the time of subsequent earnings announcements, then the alternative of market inefficiency is refuted. However, the alternative cannot be rejected as significant abnormal returns around future announcements are found based on current unexpected earnings news. In fact, Bernard and Thomas (1990) document that the sum of the three-day abnormal returns around the subsequent four quarterly announcements account for 23% to 31% of the cumulative PAD up to the fourth quarter. Finally, their results are corroborated by subsequent studies. Examples are Freeman and Tse (1989), Wiggins (1991), Bartov (1992), Abarbanell and Bernard (1992), Ball and Bartov (1995, 1996), Chan, Jegadeesh and Lakonishok (1996). Updated surveys of PAD evidence can be found in Ball (1992) and Bernard (1993).

Using UK data, Hew, Skerratt, Strong and Walker (1996) find some preliminary evidence of a PAD effect based on a sample of 206 firms over the period 1989 to

1992. An arbitrage portfolio of high-SUE quintile minus low-SUE quintile realises significant abnormal returns of 7.3% over the 180 days subsequent to earnings announcements. However, when they implement the same strategy on four size-based quartile sub-samples the PAD evidence can only be observed in the small size-based sub-sample. Hence, they conclude that there is "evidence of significant drift for the earnings announcements of small firms but not for the announcements of large firms" (p. 283) in the UK. Given their limited sample size, robustness checks using a larger sample and longer sample period may provide significant additional insights into the PAD phenomenon in the UK. Such an analysis is made in Section 5.4 of this thesis.

5.2.2 Methodology Commonly Adopted in Testing the PAD Phenomenon

The research methodology adopted to examine PAD is the event study, testing whether security prices react fully and rapidly to all publicly available information (semi-strong form of market efficiency).[2] Event studies have a long history. Perhaps the first use is in Dolley's (1933) examination of the price effects of stock splits. Ball and Brown (1968) and Fama, Fisher, Jensen, and Roll (1969) introduce the formal methodology. Event studies measure the impact of a specific event and produce useful evidence on, for instance, how stock prices respond to information. The usefulness of such studies comes from the fact that, given rationality in the marketplace, the effect of an event will be reflected immediately in security prices. Event studies have been applied to a variety of firm specific and economy wide events such as mergers and acquisitions, earnings announcements, issues of new debt or equity. In this thesis I

[2] Beaver (1981) points out that of all the public information that is available to the market, earnings are generally regarded as the most important regularly reported item. Parts of the analysis of momentum profits in this thesis could also be interpreted as a form of event study with the event here being the return over the previous 3 to 12 months.

will not discuss the event study methodology. Instead, I will focus on its application in the research of the PAD phenomenon, and relate the evidence on the PAD effect (if it does exist in the UK market) to momentum profits. A detailed description of event studies in economics and finance can be found in Mackinlay (1997).

Applying event study methods, the initial task is to define the event of interest and identify the news (good or bad) that the event carries to the market. For research of the PAD phenomenon the event is the earnings announcement, and the information content (news) of the earnings event is referred to as the earnings surprise or unexpected earnings. The earnings surprise is used to classify securities into different portfolios. In practice, approaches to measuring the earnings surprise fall into three categories. One is based on the earnings data announced on the event day (earnings-based); another looks at the reaction of security price around the event day (price-based); and the third measures the earnings surprise using analysts' forecasts of earnings (analysts-forecasts-based). The following outlines the three categories for measuring the earnings surprise.

(1) Earnings-based measure of earnings surprise

In this category the standardised unexpected earnings (SUE) usually measures the earnings surprise. As mentioned in the last subsection the SUE measure is defined as unexpected earnings (UE) scaled by the standard deviation of the UEs over the preceding estimation period. By definition, UE is given by actual earnings less its expected value. In algebraic form firm i's SUE at time t can be expressed as,

$$SUE_{it} = \frac{UE_{it}}{\sigma_{UE}}, \qquad (5.2.1)$$

where $UE_{it} = e_{it} - E[e_{it}]$, σ_{UE} is the standard deviation of UE_{it} estimated over a chosen period prior to time t, e_{it} is firm i's reported earnings at t, and $E[e_{it}]$ is the expected value of e_{it}.

Thus, to compute the SUE measure we should first have an earnings expectation model to obtain $E[e_{it}]$ so that UE and its standard error can be calculated. There are several statistical time-series earnings expectation models used in the literature.

Model 1: *The naïve expectation model*

The current literature commonly uses a seasonal version of the Ball and Brown (1968) 'naïve model', that is, a seasonal random walk model with or without a drift term. Using the naïve seasonal random walk model the expected earnings $E[e_{it}]$ is simply given by,

$$E[e_{it}] = \delta_i + e_{i,t-4}, \qquad (5.2.2)$$

where δ_i is a drift term. Note that equation (5.2.2) assumes that quarterly earnings are used, and $e_{i,t-4}$ is earnings per share 4 quarters ago.

The naïve expectation model assumes that investors are unaware of the exploitable serial correlation in the model's forecast errors that has been documented in the academic literature.[3] Foster (1977), Foster, Olsen and Shevlin (1984), and Bathke and Lorek (1984) adopt this model in their studies. Rendleman, Jones and Latane (1987) show that investors use the simple seasonal random walk model in forecasting future earnings, without incorporating serial correlation in SUE. Bernard and Thomas (1990) believe that "market prices can be modelled *partially* as reflections of naïve expectations" (p. 307). Wiggins (1991) considers that the naïve seasonal random walk model is a reasonable proxy for unsophisticated individual investors' predictions. However, Griffin (1977) argues that the quarterly earnings process cannot be adequately described as a random walk process. The recent study by Ball and Bartov (1996) shows that investors do not use the simple seasonal random walk model to forecast earnings. They show that the earnings expectations implied by stock prices shortly before earnings announcements are consistent with investors underestimating, but not completely ignoring, dependencies in seasonally differenced quarterly earnings. More recently, Rangan and Sloan (1998) interpret their evidence as corroborating Bernard and Thomas' (1990) naïve investor hypothesis (seasonal random walk model) and not supporting Ball and Bartov (1996). They conclude that the naïve investor hypothesis provides a useful framework for understanding and explaining the profitability of stock returns following earnings announcements.

Model 2: $AR(1)$ *model in seasonal earnings differences*

[3] The existence of serial correlation in seasonally-differenced quarterly earnings has been found by a number of studies in the US. See Foster (1977), Griffin (1977), Brown and Rozeff (1979), Bernard and Thomas (1990), and Bartov (1992).

Foster (1977) finds that a more accurate earnings expectations model can be obtained using a univariate first order autoregressive process, $AR(1)$, model in seasonally-differenced earnings. The expected earnings under this earnings-based model is given by,

$$E[e_{it}] = \delta_i + e_{i,t-4} + \phi_i(e_{i,t-1} - e_{i,t-5}). \qquad (5.2.3)$$

Note that the notation used in this model is the same as in equation (5.2.2), and quarterly earnings are also assumed.

The $AR(1)$ model incorporates first-order serial correlation in seasonal earnings differences. Foster (1977) finds that this $AR(1)$ model performs best out of six models for expected earnings examined in his study. He also finds that there is little difference between the results of the naïve seasonal random walk model and this $AR(1)$ model. This $AR(1)$ model in seasonal differences of earnings has been commonly adopted in the PAD literature. Foster, Olsen and Shevlin (1984) and Bernard and Thomas (1989, 1990) use this time-series $AR(1)$ model in their studies. Hew, Skerratt, Strong and Walker (1996) also use this model for PAD examinations on UK data.

Model 3: *Brown-Rozeff's earnings expectation model*

Bathke and Lorek (1984), and Bernard and Thomas (1990) suggest that the most accurate earnings expectations model is the Brown and Rozeff (1979) model. With a drift term, this expectation model is expressed as follows:[4]

$$E[e_{it}] = \delta_i + e_{i,t-4} + \phi_i(e_{i,t-1} - e_{i,t-5}) + \theta_i \varepsilon_{i,t-4}, \qquad (5.2.4)$$

where $\theta_i \varepsilon_{i,t-4}$ is a seasonal moving average term at the fourth lag assuming quarterly earnings data, used to account for the observed negative correlation in year-to-year seasonally-differenced earnings.[5] Other notation is the same as in Model 2 above.

Empirical studies (e.g., Brown and Rozeff 1979, and Bathke and Lorek 1984) show that this model fits earnings data well and generates more accurate out-of-sample earnings forecasts than other time-series models. However, both the studies of Bathke and Lorek (1984) and Bernard and Thomas (1990) find that the superiority in terms of forecast accuracy of the Brown-Rozeff model is not substantial when compared to others such as Model 1 and Model 2 discussed above. In addition, Wiggins (1991) finds that it is empirically difficult to estimate the Brown-Rozeff model because the non-linear algorithm fails to converge. As a result, this model is less commonly used in the literature. Wiggins (1991) suggests using an $AR(1,4)$ model in seasonal earnings differences to capture the negative autocorrelation noted at the fourth lag

[4] The initial Brown and Rozeff (1979) expectations model does not include the trend term, and it is given by,

$$E[e_{it}] = e_{i,t-4} + \phi_i(e_{i,t-1} - e_{i,t-5}) + \theta_i \varepsilon_{i,t-4}.$$

[5] See Griffin (1977), Brown and Rozeff (1979), and Bernard and Thomas (1990). Bernard and Thomas (1990) provide a thorough test and show that the serial correlations over four lags between seasonally-differenced quarterly earnings have a $(+,+,+,-)$ pattern. In other words, the autocorrelations over the first three lags are positive, but serial correlation at the fourth lag is negative. Ball and Bartov (1996) verify this pattern in their sample.

while maintaining the spirit of the Brown-Rozeff model (see equation (7) in Wiggins 1991).

As mentioned above the earnings-based measure of earnings surprise (SUE) can be empirically estimated from equation (5.2.1) given a proxy for market expectations of future earnings such as Model 1, 2, and 3 above.

(2) Price-based measure of earnings surprise:

Unlike the earnings-based measure of earnings surprise discussed above, the price-based measure does not resort to a sophisticated statistical model. Instead, it directly focuses on the price reaction to the earnings announcement. Foster, Olsen and Shevlin (1984) use two such measures of earnings surprise (see Model 3 and Model 4 in their paper). One focuses on the short-run market reaction to the earnings announcement, and the earnings surprise is measured by the cumulative two-day abnormal return in the day preceding and the day of the earnings announcement. Another one measures earnings surprise using the average cumulative abnormal return (CAR) over a longer period of 61 trading days up to and including the day of the earnings announcement. In their study, both past abnormal announcement returns (two-day CAR and average 61-day CAR) are deflated by the standard deviation of daily abnormal returns.

Empirical evidence shows that valuable information can be obtained from security prices in forecasting future earnings that cannot be obtained from the time series of earnings alone. Beaver, Lambert and Morse (1980) find that price-based forecasting models have significantly lower prediction errors compared with time series forecasting models. Kothari and Sloan (1992) reveal that the predictive ability of stock prices with respect to future earnings is as good if not better than the historical time series of earnings. In fact, they consider the information set reflected in stock prices as richer than the past time series of earnings because price change over a period reflects revisions in the market's expectations of future earnings as well as realised earnings over the period.

Bernard, Thomas and Wahlen (1995), and Chan, Jegadeesh and Lakonishok (1996) do find that announcement period returns help to predict future excess returns. For instance, Chan, Jegadeesh and Lakonishok's (1996) results show that the differences in returns associated with differences in past abnormal announcement returns are as large as the differences induced by ranking on the earnings-based measure of SUE. However, Foster, Olsen and Shevlin (1984) find that future returns are associated with past SUE but not with past abnormal announcement returns. Bernard, Thomas and Wahlen (1995) argue that the holding period used in Foster, Olsen and Shevlin (1984) to track returns after an earnings announcement, stops short of the next announcement. Therefore, a possible explanation for the weaker results in Foster, Olsen and Shevlin (1984) is that they miss much of the stock price reaction around subsequent announcements.

However, there might be another reason why their results by ranking on the past abnormal announcement returns differ from their results by ranking on earnings surprise. Foster, Olsen and Shevlin's (1984) past abnormal announcement returns are scaled by the standard deviation of past abnormal returns, while Chan, Jegadeesh and Lakonishok (1996) do not make this deflation. In other words, Chan, Jegadeesh and

Lakonishok (1996) use the abnormal announcement returns directly without deflating them by the standard deviation of the past abnormal returns as in Foster, Olsen and Shevlin (1984). Hence, their stock ranking might not be same. High abnormal announcement returns in Chan, Jegadeesh and Lakonishok (1996) will not be high in Foster, Olsen and Shevlin (1984) if the standard deviation of the stock's past abnormal returns is large. It seems that there is no particular reason to scale the abnormal announcement returns when using a price-based measure of earnings surprise.

(3) Analysts-forecasts-based measure of earnings surprise:

As we have seen, the earnings-based measure of earnings surprise (SUE) requires a model of expected earnings and hence runs the risk of specification error. As an alternative, investors may directly use analysts' forecasts of earnings to measure earnings surprise. On the one hand, this is because analysts provide a more direct measure of earnings expectations. Comparing with the benchmark of a time-series earnings expectation model this is because analysts are able to revise their forecasts by updating with new information. When producing their forecasts, analysts have the advantage of a broader, richer and more timely information set such as macroeconomic information, industrial financial figures, management corporate releases and so forth. Researchers (see Brown and Rozeff 1978, Fried and Givoly 1982, Brown, Griffin, Hagerman and Zmijewski 1987, and O'Brien 1988) suggest that analysts provide more accurate forecasts compared to those from time series models. In addition, analysts' forecasts of earnings are available on a more timely basis for most stocks. There is also evidence that investors use analysts' earnings forecasts. For instance, investment managers use a popular technique of tracking changes in analysts' forecasts. Mendenhall's (1991) empirical results show a significant market response to the information in analysts' earnings forecasts revisions. Nevertheless, analysts' earnings forecasts have not been as widely used in examinations of the PAD phenomenon. The extant literature concerning analysts' earnings forecasts mainly focuses on testing whether analysts' forecasts are efficient or biased, examining whether analysts under-react or overreact to information such as earnings announcements when producing their forecasts. Such tests are beyond the scope of this thesis. The remainder of this subsection outlines how analysts' earnings forecasts can be used to measure the earnings surprise for examining the PAD effect.

As opposed to constructing the SUE measure, using analysts' forecasts as a proxy for investors' expectations, the earnings forecast error (EFE), which is the difference between the actual and forecast earnings per share, can be used as a measure of earnings surprise. For cross-sectional comparability, EFEs are usually deflated by security price. Thus, EFE is defined as:

$$EFE_{it} = \frac{e_{it} - F[e_{it}]}{P_{it}}, \qquad (5.2.5)$$

where $F[e_{it}]$ is the forecast of reported earnings, e_{it}, and P_{it} is stock i's price.

In the light of the definition of PAD, future abnormal returns should be positively correlated with the most recent earnings forecast error, EFE_{it}. Freeman and Tse (1989) provide results consistent with this hypothesis. Mendenhall (1991) reports significant positive auto-correlation between EFE s, indicating that analysts seem to underweight the information that current earnings have for future earnings.

Another analysts-forecasts-based measure of earnings surprise is the earnings forecast revision (REV), which is defined as the change in analysts' forecasts of earnings deflated by stock price. Algebraically, stock i's REV at time t is expressed as,

$$REV_{it} = \frac{F_t[e_{iT}] - F_{t-1}[e_{iT}]}{P_{i,t-1}}, \qquad (5.2.6)$$

where e_{iT} is stock i's earnings at future time T; $F_t[e_{iT}]$ is e_{iT}'s forecast at t ($T > t$); and $P_{i,t-1}$ is stock i's price.

The intuition of the REV measure is that the greater the changes (positive or negative) in analysts' forecasts of earnings, the greater the changes in expectations of future dividends and, hence, the greater the earnings surprise. Under the PAD hypothesis, REV should be positively associated to future abnormal returns. Mendenhall (1991) documents a significant positive association between analysts' forecast revisions and abnormal returns around subsequent earnings announcements. He concludes "the market under-reacts to a direct signal of upcoming earnings" (p. 171).

Chan, Jegadeesh and Lakonishok (1996) use a slightly different measure of revisions in analyst earnings forecasts, which is the six-month moving average of past changes in earnings forecasts by analysts. The rationale for using the six-month moving average is that information either directly or indirectly relevant to earnings is being released gradually over time. An example of a piece of direct information about earnings is a profit warning, whose timing is unknown in advance. The six-month moving average, in a sense, cumulates earnings surprises (indirectly using the proxy of analysts' forecast revisions) over the past six months. This measure also gets around the fact that analysts' forecasts of earnings are not necessarily revised every month (Chan et al. rank stocks on a monthly basis). Moreover, the period of six months is consistent with the time horizon used in examining the momentum strategy in their study. Chan et al. (1996) document that sorting stocks on the six-month moving average REV yields the largest spread in one-year returns (9.7%) compared to other measures of earnings surprise such as earnings-based and price-based ones.

Once the earnings surprise measure is chosen (from one of the three categories outlined above) the stocks can be grouped into different portfolios based on the rankings of the earnings surprise. The PAD effect is examined by tracing the performances of the earnings-surprise-grouped portfolios. If the high earnings surprise portfolio significantly outperforms the low earnings surprise portfolio, we would refer to this as a PAD effect if we could not find convincing competing explanations for the phenomenon. The following subsection gives a brief review of the competing explanations of PAD.

5.2.3 Competing Explanations for PAD

Subsequent research on PAD has sought explanations for this phenomenon. These can be categorised into four classes, which are shortly reviewed as follows.

(i) Improper Risk Adjustment

In this class, researchers have tried to examine whether PAD is caused by a failure to fully control for risk when estimating abnormal returns. Ball, Kothari and Watts (1993) find that betas shift upward (downward) for firms with high (low) unexpected earnings. Therefore, they suggest that using betas estimated prior to earnings announcements, as in Rendleman, Jones and Latane (1982), is inappropriate, because of the positive relation between *SUE* s and changes in beta coefficients.

However, the primary focus of Ball et al.'s (1993) research is not the PAD phenomenon, and their methodology is not exactly same as those commonly adopted in PAD studies. For instance, their portfolio formation is based on annual rather than quarterly earnings. This is unlikely to capture the full magnitude of the PAD effect since empirical results (e.g., Bernard and Thomas 1989) show that most of the PAD occurs within three months of the earnings announcement. In addition, their approach could exaggerate the extent of beta shifts, particularly in the few days around subsequent earnings announcements where a significant proportion of abnormal returns appear? For very short windows it's unlikely that sophisticated controls for expected returns will make any difference at all (over a short window expected returns are very close to zero). Bernard and Thomas (1989) document that beta shifts following earnings announcements are much too small to explain the PAD anomaly. They also reveal that arbitrage pricing theory risk factors as identified by Chen, Roll and Ross (1986) are effectively uncorrelated with unexpected earnings. These results are inconsistent with the improper risk adjustment explanation.

(ii) Size Effects

In this category, studies have tried to examine whether the well-known size effect can subsume the PAD effect. This originates from the fact that the smaller (hence less visible) a firm is, the less likely factors affecting its share price such as earnings announcements are known to the market. Arbel, Carvell and Strebel's (1983) findings indicate that the earnings announcements of small firms are gradually rather than immediately impounded into their stock prices. Freeman (1987) investigates the relationship between reported earnings and stock prices for small and big firms. He shows similar results to Arbel, Carvell and Strebel's (1983) that the stock prices of small firms reflect earnings information slower than large firms' prices.

Relating size effect to PAD, Foster, Olsen and Shevlin (1984) find that firm size explains 61 per cent of the variation in PAD. Bernard and Thomas (1989, 1990) show that the magnitude of PAD is inversely related to firm size. However, Bhushan (1994) finds that firm size plays no part in explaining PAD once transaction costs are controlled for. In the UK, Hew, Skerratt, Strong and Walker (1996) document that there is only evidence of PAD for the smallest size portfolio, but none in the other size portfolios based on their limited sample size of 206 UK firms. In this chapter I will examine the association between the size effect and the PAD phenomenon.

(iii) Market-microstructure Related Effects

This explanation is based on market frictions caused by the costs of information processing and transaction. Bidwell (1979) suggests that if the information contained in earnings reports is costly to process, rational investors will be unable to fully incorporate the earnings information into their private valuations and optimal portfolio proportions in the instant following the earnings release, and prices will only gradually reflect the new information. In addition, delayed price response may also occur because specialists may attempt to smooth any price response to earnings information, in order to keep an orderly market.

Further, PAD may appear because transaction costs create sufficient trading frictions to prevent a complete and rapid response by the market to earnings when they are announced. Bernard and Thomas (1990) argue this explanation. They find that the abnormal returns generated from the PAD effect still significantly exceed transaction costs. However, Bhushan (1994) provides evidence that high trading costs can result in PAD existing up to the magnitude of transaction costs. Firms with high relative transaction costs display price delay resulting in PAD; while firms with low relative transaction costs are unlikely to be mispriced. Wiggins' (1991) empirical results show that the market microstructure explanation for PAD is incomplete, and suggests that investor misperception of the stochastic process for earnings is a contributing factor.

(iv) Naïve Investors' Misperceptions

This explanation is based on the premise that the market is unaware of the correct time-series properties of earnings. That is, the market as a whole is naïve as it misperceives the true stochastic process of earnings changes. For example, Rendleman, Jones and Latane (1987) hypothesise that the market does not realise firms' seasonally differenced earnings are serially correlated. They report evidence that supports their hypothesis and suggest that the market under-reacts to earnings when they are announced. Specifically, the market does not fully account for and exploit the information in past earnings, and subsequently makes poor predictions of future earnings.

Bernard and Thomas (1989, 1990) corroborate Rendleman, Jones and Latane's (1987) hypothesis. Bernard and Thomas assume that the market follows a seasonal random walk (i.e., naïve expectations) and is unaware of the full implications of current earnings when predicting future earnings. Bernard and Thomas' (1990) empirical results are consistent with their assumption (the naïve expectations hypothesis). They conclude that "stock prices partially reflect a naïve earnings expectation: that future earnings will be equal to earnings for the comparable quarter of the prior year" (p. 338). However, Bernard and Thomas (1990) find that the quarterly earnings, *SUE* s, and the short-term price reaction around earnings announcement all appear to follow a similar autocorrelation pattern of (+, +, +, −). That is, for the quarterly earnings the autocorrelation is positive over the first three lags, while it is negative at the fourth lag. Because stock prices fail to reflect the extent to which each firm's earnings series differs from a seasonal random walk, abnormal returns can be earned by exploiting the serial correlations of earnings. Wiggins (1991) and Bartov (1992) provide further support for the naïve expectation hypothesis.

However, Ball and Bartov (1996) criticise the naïve expectation hypothesis. They find that the market does not act as if using a naïve earnings expectation model. Their results suggest that the market is aware of the autocorrelation pattern of earnings observed by Bernard and Thomas (1990), and does exploit the serial correlations. However, the market underestimates the magnitude of these serial correlations by 50 per cent on average. Their findings rule out the 'naïve expectations' of investors as a possible explanation of the PAD effect. Consequently, Ball and Bartov (1996) suggest that alternative explanations of PAD such as possible sources of bias in investors' assessment of serial correlations should be examined. Based on their evidence, they also argue that predictable stock returns following earnings announcements remain anomalous and may be due to biases in sample selection or abnormal return measurement. As mentioned previously, however, Rangan and Sloan's (1998) findings corroborate and extend the naïve expectation hypothesis proposed by Bernard and Thomas (1990). They argue that their evidence casts doubt on Ball and Bartov's (1996) conjecture that Bernard and Thomas' original findings could be due to unspecified research design biases.

5.3 Sample Selection, Data Collection, and Research Design

5.3.1 Sample and Data

Since this study requires information on earnings, I collect the reported earnings per share and announcement date data from the Extel Equity Research database, and data on analysts' earnings forecasts are extracted from the Lynch, Jones, and Ryan Institutional Brokers Estimate System (I/B/E/S) database. In this chapter the reference point for the sample is the accounting sample examined previously. However, the stocks in the accounting sample need to simultaneously satisfy the following requirements:

(i) Each stock must have semi-annual earnings per share data and announcement dates (interim and final) available on the Extel Equity Research database from January 1988 onwards. This is because companies are required to report earnings semi-annually in the UK. This is different from the US where firms report earnings quarterly. The Extel Equity Research database starts to record semi-annual earnings per share data from January 1988.

(ii) Each stock must have at least 9 semi-annual earnings per share figures available on the Extel Equity Research database. Estimating the time-series earnings model illustrated in the following subsection requires a minimum of 9 observations. In addition, each stock must have at least one semi-annual observation reported after the end of 1991. This is due to the fact that earnings announcement dates are only available on the Extel database from the beginning of 1992.

(iii) Each stock must have analysts' earnings forecasts for the current fiscal year (FY1) on the I/B/E/S database. The I/B/E/S database used in this thesis has analysts' forecasts of earnings available from January 1987 on a monthly basis, but the forecasts end in May 1997. In addition, forecast data for the next fiscal year (FY2) on the I/B/E/S database are also required when constructing the earnings forecast revision measure described below. Further, the actual earnings per share data recorded on the I/B/E/S database are also used to construct the earnings forecast error (see below).

These restrictions result in a reduced sample of 835 stocks including dead as well as live stocks. The sample period is from January 1988 to May 1998.[6] Since this sample restricts attention to stocks for which semi-annual earnings data are available, I refer to this sample of 835 stocks as the *earnings* sample. There are 13,848 observations of semi-annual earnings per share data over the sample period. Of these there are 9,382 observations with semi-annual earnings announcements from January 1992 onwards. Note that the semi-annual Extel earnings per share data between January 1988 and December 1991 are used only for model-estimation purposes.

All data items in the accounting sample in addition to the earnings data are also included in the earnings sample. Moreover, daily returns of each stock in the earnings sample are calculated for the sample period. The calculations of the daily returns follow the same procedure described in Section 3.2 of Chapter 3 except that daily Datastream data are used in equation (3.2.1). For consistency with previous chapters weekly returns are still used in the examination of momentum and PAD effects. The daily returns are used to construct one of the earnings surprise variables, described in the next subsection. Furthermore, in this chapter I also estimate monthly Scholes-Williams betas for each individual stock based on prior 3-year monthly returns. The estimated Scholes-Williams betas are used to examine whether the momentum and

[6] For the earnings estimates issued by analysts the sample period ends in May 1997 when the analysts' earnings forecasts end in the I/B/E/S database used in this thesis. However, one more year of return, reported earnings, and announcement data are required for testing purposes after May 1997. This will be explained further in Subsection 5.3.2.

PAD effects can be explained by systematic risk. For details of the estimation of Scholes-Williams betas see footnote 20 in Chapter 3.

Finally, for each stock in the earnings sample I calculate the monthly number of I/B/E/S analysts who provide Fiscal Year 1 (FY1) earnings estimates. Where a stock has no analyst following in a particular month, I set the number of analysts to zero. The number of analysts is used to examine whether there is any relation between the number of analysts following particular companies and the strength/presence of price momentum and PAD. The reason is that more analysts mean more competition and greater informational efficiency. Hence, we might ask whether winner and loser (or high-earnings-surprise and low-earnings-surprise) companies would have lower analyst following. If this is the case we will partially confirm the conclusion of market under-reaction to firm-specific information documented in the previous two chapters. Chen, Lin and Sauer (1997) document that the stock of information, as measured by the number of financial analysts, contributes significantly to the variations in excess returns and return volatility. Hong, Lim, and Stein (1999) find that momentum strategies work better among stocks with low analyst coverage, which is measured by the number of I/B/E/S analysts, and the effect of number of analysts is greater for stocks that are past losers than for past winners. In addition, Bhushan (1989) finds that the number of analysts is very strongly correlated with firm size. Thus, it is worth examining the effect of the number of analysts using UK data.

5.3.2 Methodology and Trading Strategies

As in previous chapters, the momentum and PAD effects will be examined based on specific trading strategies. To provide consistency and comparability, in this chapter I construct similar trading strategies to Chan, Jegadeesh, and Lakonishok (1996).[7] Decile portfolios are mainly used in the examination of momentum and PAD effects. The trading strategies used to re-examine the momentum effect based on the earnings sample will be implemented using a ranking variable of past 6-months buy-and-hold returns to form ten equally-weighted decile portfolios. Then, the subsequent buy-and-hold returns for 3, 6, 9, and 12 months of the decile portfolios and the momentum portfolio are tracked. In other words, the momentum effect will be re-examined based on the 6×3, 6×6, 6×9, and 6×12 strategies examined in Chapter 3. From the results documented in Chapters 3 and 4, the four strategies are good representatives for re-examining the momentum effect.

As PAD is defined as a positive association between earnings surprise and post-announcement abnormal stock returns, similar trading strategies used to examine the momentum effect can be employed to test the PAD phenomenon. Obviously, the ranking variables to examine the PAD effect will be earnings surprises at the announcement date rather than the past returns used in the examination of the momentum effect. I use four earnings-surprise variables to examine the PAD phenomenon in this chapter. They are taken from the three categories reviewed in the last section. Specifically, the four earnings-surprise variables are as follows.

[7] Chan et al. (1996) refer to PAD as earnings momentum in their paper. Since PAD is well established in the literature, I use the conventional term of PAD rather than earnings momentum in this study. Literally, earnings momentum should be regarded as the positive relation between the most recent earnings news and future earnings news. In the US such earnings momentum over an intermediate time horizon has been documented in Bernard and Thomas (1990). In this thesis I also find that, within one year, high (low) most recent earnings surprises tend to be followed by high (low) earnings surprises in

(i) Earnings-based measure of earnings surprise—SUE :

In this study SUE is constructed based on an $AR(1)$ earnings expectations model in seasonal earnings differences. This measure is widely used in the PAD literature, and is also used in Hew et al. (1996) for the examination of the PAD phenomenon in the UK. Hence, results from this measure can be directly compared with those of Hew et al. (1996) as well as with US studies.[8] However, equation (5.2.3), the $AR(1)$ earnings expectations model in seasonal earnings differences, cannot be directly used in the UK where companies report earnings semi-annually. Hew et al. (1996) have modified this $AR(1)$ expectation model to apply to semi-annual data as follows,

$$E[e_{it}] = \delta_i + e_{i,t-2} + \phi_i(e_{i,t-1} - e_{i,t-3}), \qquad (5.3.1)$$

Note that the notation is the same as in equation (5.2.3) except that semi-annual observations are used in equation (5.3.1). This $AR(1)$ process is estimated for each stock over the sample period using at least nine semi-annual observations, and the number of observations used in the estimation increases subject to the availability of the data. The SUE s are computed for each stock over the period of January 1992 to May 1998 using equation (5.2.1). This gives 7,166 SUE s in total.

(ii) Price-based measure of earnings surprise—$AR4D$:

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the future (see subsequent empirical results). Thus, I distinguish the uses of PAD and earnings momentum in this thesis.

[8] Chan et al. (1996) construct a *SUE* measure based on the seasonal random walk model of earnings expectations without the drift term in equation (5.2.2).

The price-based measure is the 4-day buy-and-hold abnormal stock return ($AR4D$) around the earnings announcement date, given by,

$$AR4D_{it} = \prod_{d=-1}^{2}(1+r_{i,d}) - \prod_{d=-1}^{2}(1+r_{m,d}), \qquad (5.3.2)$$

where $r_{i,d}$ is stock i's daily return on day d (with the earnings being announced on day 0) and $r_{m,d}$ is the within-sample value-weighted daily market return on day d. This measure is slightly different from that of Chan et al. (1996) where they use the cumulative abnormal announcement return. The rationale for equation (5.3.2) is that if investors respond sluggishly to the news in earnings, we should expect to see a drift in future stock returns that can be predicted by the sign and magnitude of the short-term abnormal stock return around the earnings announcement date. There are 9,382 $AR4D$s constructed from the earnings sample.

(iii) Earnings-forecasts-based measures of earnings surprise — EFE and *$REV6$*

I will adopt two earnings-forecasts-based measures of earnings surprise in this chapter. One is the price-deflated earnings forecast error, EFE. The other is the cumulative price-deflated earnings forecast revision over prior six months, $REV6$.

The price-deflated earnings forecast error (EFE) is given by equation (5.2.5). In this study $F[e_{it}]$ in equation (5.2.5) is the latest earnings forecast for actual earnings of e_{it} by I/B/E/S analysts. The deflator, P_{it}, in equation (5.2.5) is stock price at the beginning of the month in which the latest earnings forecast, $F[e_{it}]$, is made. To avoid the possible asymmetric distribution in analyst's forecasts, the median analyst's forecasts are used in this study. Since there are few semi-annual earnings forecasts in the UK in the I/B/E/S database, $F[e_{it}]$ is the latest median I/B/E/S estimate of firm $i's$ earnings for the current fiscal year (FY1) before the announcement date t, and e_{it} is the annual earnings per share announced at t.[9] This absence of interim earnings forecasts results in 3,419 EFE s constructed in total from 1992 to 1997 in the earnings sample.

Similar to Chan, et al. (1996), the cumulative price-deflated revisions in analyst earnings forecasts over the previous six months, $REV6$, is defined as,

$$REV6_{it} = \sum_{j=1}^{N_{REV}} \frac{F[e_{i,t-j}] - F[e_{i,t-j-1}]}{P_{i,t-j-1}}, \qquad (5.3.3)$$

where $F[e_{i,t-j}]$ is the median I/B/E/S estimate in month $t-j$ of firm $i's$ earnings for the current fiscal year (FY1), $P_{i,t-j-1}$ is stock $i's$ price at the beginning of month $t-j-1$, and N_{REV} is the number of individual revisions in median forecasts over the previous six months. The maximum N_{REV} is 6. N_{REV} may be smaller than 6 since analyst forecasts may not be available for each month for a firm, and for a particular individual revision it is calculated from two adjacent median forecasts. Note that if two adjacent median forecasts of $F[e_{i,t-j}]$ and $F[e_{i,t-j-1}]$ are not for the same fiscal

[9] Actual annual earnings per share data, extracted from the I/B/E/S database, are adjusted for capitalisations on the same basis as the forecast data, while announcement dates used in constructing this earnings surprise measure of EFE are the Extel announcements.

year, the FY2 median forecast in month $t-j-1$ is used in constructing the individual revision.

There are many papers documenting the bias in analyst forecasts in the US and the UK. Associated tests are known as tests of analysts' rationality or efficiency. In other words, these studies try to ascertain whether analysts under-react or overreact to earnings information in producing their forecasts. The empirical findings have been conflicting and inconclusive. DeBondt and Thaler (1990) find an overreaction in analysts' forecasts. Chan et al. (1996) show that security analysts are slow to revise their expectations when the news in earnings is unfavourable. The optimistic earnings forecasts may be due to behavioural or sociological considerations such as the desire to encourage investors to trade and hence generate brokerage commissions. By contrast, Klein (1990) and Abarbanell and Bernard (1992) report results that are consistent with the hypothesis that analysts under-react to earnings information. Both Dowen (1996) and Easterwood and Nutt (1999) distinguish analysts' reactions to negative and non-negative earnings. Dowen reports that analysts display more over-optimism about negative earnings firms than they do for other firms. Easterwood and Nutt document that analysts under-react to negative information, but overreact to positive information so that their results are consistent with systematic optimism in analysts' response to information. In the UK Bhaskar and Morris (1984) find a tendency for UK analysts to underestimate future earnings, while Patz (1989) shows an opposite bias with results consistent with over-optimistic analysts' forecasts. In addition, using I/B/E/S analysts' forecasts from 1987 to 1989 O'Hanlon and Whiddett (1991) document evidence that UK analysts are prone to under-reaction. More recently, Capstaff, Paudyal and Rees (1995) reveal an optimistic bias and overreaction in I/B/E/S UK earnings forecasts by analysts for the period 1987 to 1990.

Thus, before adopting the EFE earnings surprise measure, which uses the latest analyst forecast as the benchmark for expected earnings instead of the time-series benchmark of the SUE, it is important to examine the accuracy/rationality of analysts forecasts in the earnings sample. A standard test for unbiased analyst forecasts is to run the regression (see DeBondt and Thaler 1990),

$$e_{it} - e_{i,t-1} = \alpha + \beta(F[e_{it}] - e_{i,t-1}) + \varepsilon_t , \qquad (5.3.4)$$

where e_{it} is firm i's reported annual earnings per share, and $F[e_{it}]$ is the latest median forecast of e_{it}.

If analysts forecasts are unbiased then parameter estimates are $\alpha = 0$ and $\beta = 1$. A β estimate of less than one indicates that forecast changes are too extreme (an overreaction in analysts' earnings forecasts); a β estimate of greater than one indicates the opposite (an under-reaction in analysts' forecasts of earnings). Debondt and Thaler (1990) suggest that a negative α estimate might indicate that forecasts are on average over-optimistic.

In addition, I also run the following regression equation over all observations:

$$\frac{e_{it} - e_{i,t-1}}{P_{i,t-1}} = \alpha + \beta \frac{F[e_{it}] - e_{i,t-1}}{P_{i,t-1}} + \varepsilon_t , \qquad (5.3.5)$$

where $P_{i,t-1}$ is stock i's price at the beginning of the month in which the last actual earnings per share, $e_{i,t-1}$, was announced. Other notation is same as in equation (5.3.4).

Table 5.3.1 reports the results of pooled regressions. Panel A of Table 5.3.1 summarises the results of running equation (5.3.4) and Panel B presents the results from running equation (5.3.5). Because there is no reason to assume homoscedasticity, I calculate the White heteroscedasticity-adjusted t-statistics of the coefficient estimates (White t-statistic). In addition, I also use the bootstrap approach by re-sampling 10,000 times from the total observations, each time sampling 25% of observations from the total observations. Based on each sampling, equation (5.3.4) and equation (5.3.5) are estimated. This procedure gives 10,000 estimates of β as well as α. Then, the bootstrap p-values are computed for the coefficient estimates by using the bootstrap shift method based on the 10,000 estimates either for α or β. For details of the calculation of bootstrap p-values see Appendix 3A in Chapter 3.

Table 5.3.1 Rationality test of analysts' forecasts of earnings

Analyst Forecast Efficiency Tests				
Panel A: Results of running equation (5.3.4)				
	α	β	$\beta-1$	R^2
OLS estimated coefficient	−0.1710	1.0413	0.0413	0.80
White t-statistic	−1.47	34.83	1.38	
Bootstrap p-value	0.7763	0.0000	0.2156	
Panel B: Results of running equation (5.3.5)				
	α	β	$\beta-1$	R^2
OLS estimated coefficient	−0.00382	0.90555	−0.09445	0.80
White t-statistic	−2.48	14.76	−1.54	
Bootstrap p-value	0.8925	0.0000	0.8161	

The results from running equations (5.3.4) and (5.3.5) give the same conclusion. Both White t-statistics and bootstrap p-values show that the hypothesis of β being equal to one cannot be rejected. The bootstrap p-values indicate that $\alpha = 0$ is also accepted. In addition, I also run both equations after excluding possible outliers. I identify outliers in two ways. One regards the top 1% and bottom 1% of EFE s as outliers. Another one treats the 2% highest absolute values of EFE as outliers.[10] The results from running equations (5.3.4) and (5.3.5) remain unchanged after excluding the 'outliers'. For example, from running equation (5.3.5), R^2 is equal to 0.9747, the estimate of α is −0.0011 (bootstrap p-value is 0.855) and the estimate of β is 1.004, which is insignificantly different from one (bootstrap p-value is 0.431) after excluding the top 1% and bottom 1% EFE s. The corresponding estimates of α and β are 0.0013 (bootstrap p-value is 0.049) and 1.008, which is insignificantly different from one (bootstrap p-value is 0.217) with R^2 being equal to 0.9838 after excluding the 2% highest absolute values of EFE. It is thus plausible to state that UK analysts' earnings forecasts are efficient from 1992 to 1997 in the earnings sample.

This may not be surprising because I use the median forecast, which excludes extremely high and low analysts' forecasts. This is different from the consensus mean forecast commonly used in the literature. Although I obtain the same conclusion for the analysts' rationality test including and excluding 'outliers', I do check whether 'outliers' influence the results of implementing the $REV6$-based and EFE-based

[10] I find that these 2% outliers are almost all from the negative EFE s. From inspection of the data, the obvious outliers are a small number of cases where earnings changes are massively negative and analysts fail to anticipate these. Hence, this criterion of referring to the small number of highest absolute values of EFE as outliers seems to be more reasonable than the first criterion.

trading strategies. I find that the results including 'outliers' are quite similar to the results excluding the 2% highest absolute values of EFE in the sample. For example, the EFE-based trading strategy earns semi-annual PAD profit of 3.67% ($t = 2.26$) when including 'outliers', while it is also 3.67% ($t = 2.49$) when excluding the 2% highest absolute values of EFE. Therefore, I do not delete 'outliers' when I use $REV6$ and EFE measures in this thesis.

Having defined the earnings surprises, we can rank stocks based on these variables. In this study, the earnings-surprise-ranked stocks are assigned to ten equally-weighted portfolios, and their buy-and-hold returns over 3, 6, 9 and 12 months subsequent to portfolio formation are examined.[11] The PAD phenomenon suggests that buying past high-earnings-surprise stocks and shorting past low-earnings-surprise stocks will realise significant arbitrage profits. Therefore, similar to the momentum portfolio an arbitrage portfolio of buying the most recent past highest-earnings-surprise decile stocks and selling the most recent past lowest-earnings-surprise decile stocks will also be examined. In this study I refer to this arbitrage portfolio as the *PAD portfolio*.

To increase the power of the tests in this chapter and the next chapter the various trading strategies involved include portfolios with *overlapping* ranking and holding periods on a monthly basis. Because the earnings announcements are only available from January 1992 onwards, the first test period starts at the beginning of July 1992 for each trading strategy. This also means that the first ranking period ends at the end of June 1992 for each strategy. Furthermore, for each trading strategy the final test period starts at the beginning of June 1997 since the analysts' earnings forecasts end in

May 1997 in the I/B/E/S database as mentioned in the last subsection. This results in 60 overlapping test periods (60 months from July 1992 to June 1997 inclusive) as well as 60 ranking variables for each trading strategy. For the holding period of 12 months (the longest one) the sample period ends at the end of May 1998, while it ends at the end of August 1997 for the shortest holding period of 3 months.

Note that for a particular test period the returns of some stocks are not immediately tracked following the earnings announcement by applying the designed trading strategies examining the PAD phenomenon. In other words, the timing of measuring the four earnings surprises and the prior 6-month ranking-period return, which will be defined as ret_{-6}, is different. This can be illustrated by an example. Let us assume that the beginning of the test period is 01/01/95, and firm A's financial-year end is in December. Let us further assume that firm A announces 1993's final earnings on 15/04/94, and announces 1994's interim earnings on 21/10/94. For this example, the most recent past SUE and $AR4D$ used to rank stocks on 01/01/95 (the beginning of the test period) are constructed on 21/10/94, whereas the most recent past EFE used to rank stocks on 01/01/95 is calculated on 15/04/94. The test-period return is traced from 01/01/95. It is clear that there is a time gap between earnings announcement and the starting point of the test period.[12] From the example given above, the gap is more than two months for SUE and $AR4D$ measures, and it is more than 8 months for the EFE measure. For some time points, the gap could be as large as 6 months for SUE and $AR4D$ measures, and it could be as large as 12 months for EFE measure. SUE and $AR4D$ measures will refer to earnings for the six months after the period to

[11] This is slightly different from the standard PAD examinations used in the literature where earnings-surprise-based portfolios' returns are usually tracked from several days to several months subsequent to portfolio formation. This difference is to be consistent with the examination of the momentum effect.

which EFE relates for half the observations and will refer to only the second half of the period to which EFE relates for the other half of the observations. Thus, we would not expect as strong a relation between EFE and SUE or $AR4D$ as we would expect between the latter two variables. By contrast, $REV6$ provides a timely earnings surprise measure. There would be no time gap from using the $REV6$ measure provided that there are at least two earnings forecasts over the previous 6 months with the last one being made at the beginning of the test period. The maximum length of time gap from the use of the $REV6$ measure might be 4 months, which will be trivial because of the use of cumulative earnings forecast revision over the prior 6 months.[13] This procedure might result in a downward bias to finding any PAD effect because Bernard and Thomas (1989) find that a disproportionate amount of the 60-day drift occurs in the first five days following the earnings announcement in the US. However, this possible downward bias may not be serious because of the use of a monthly overlapping strategy. In addition, Hew, Skerratt, Strong and Walker (1996) do not find a high degree of drift in the days immediately following earnings announcements in the UK.

As in previous chapters, an eligible stock must have at least six months plus one more week return data available at the beginning of each test period. This ensures that a stock can be held for at least one week, and its prior 6-month return can be traced. In addition, each stock may have return, $AR4D$, EFE, and $REV6$ data available at some time point, but its SUE data may not be available at the same time because of the data requirement in constructing SUE. Thus, a common sample referenced by the SUE data is used for all examinations of PAD and momentum effects in the

[12] This research design, however, ensures no hindsight bias is involved.

subsequent sections and the next chapter so that the results are comparable. For the t-statistics where observations are overlapping I use Newey-West, heteroscedasticity- and autocorrelation-consistent standard errors, whose calculations are given in Chapter 3 (see footnote 25 in Chapter 3).

Finally, for both momentum re-examined in the next chapter and PAD trading strategies, the earnings surprises measured by SUE and $AR4D$ for the next announcement after portfolio formation are also tracked. Bernard and Thomas (1990), and Chan, Jegadeesh and Lakonishok (1996) track four announcements after portfolio formation. However, in this chapter, for the earnings sample I find that there are insufficient observations on second announcements within one year after portfolio formation. Nevertheless, tracking the immediate announcement after portfolio formation can still help to examine whether the earnings surprise is predictable. In subsequent sections and the next chapter I will use SUE_0, $AR4D_0$, $REV6_0$ and EFE_0 to denote the most recent past earnings surprises, while SUE_1 and $AR4D_1$ denote the next earnings surprises after portfolio formation.

5.4 Empirical Evidence on the PAD Effect

This section examines the presence of the PAD phenomenon based on the four earnings surprise variables, SUE, $AR4D$, $REV6$, and EFE described in the last section. The PAD effect is tested in a similar way to the examination of the

[13] Note that there is no time gap between prior 6-month ranking-period return, which is used to re-

momentum effect performed in previous chapters. Specifically, decile (or quintile) portfolios used to examine the PAD effect are formed by ranking most recent past earnings surprises rather than prior returns as used in the examination of the momentum effect. As described in the last section, the EFE measure is often dated by implementing the designed PAD strategy and it only uses reported final earnings and earnings announcements rather than semi-annual data as used in SUE and $AR4D$, so the EFE measure may not be exactly comparable with the other three earnings surprise variables. Accordingly, I will not report the EFE-based PAD results in the main text; instead, the EFE-related PAD evidence is presented in Appendix 5A of this chapter.

In this section I also estimate the Fama-French three-factor model for the earnings surprises classified decile and PAD portfolios besides reporting their ranking- and holding-period raw returns. Detailed descriptions of the Fama-French three-factor model is provided in Section 4.4 of Chapter 4, and it is

$$r_{P\tau} - r_{f\tau} = a_P + b_P(r_{m\tau} - r_{f\tau}) + s_P SMB_\tau + h_P HML_\tau + \varepsilon_{P\tau}.$$

The three regressors used in this section are same as those adopted in Chapter 4, which are constructed based on the accounting sample. However, in this section and in the next Chapter, the three-factor model is estimated over the overlapping holding-period monthly portfolio returns, $r_{P\tau}$. Specifically, at the beginning of each test period from July 1992 to June 1997 (60 test periods) each portfolio's equally-weighted monthly return is traced for the subsequent 6 months. This procedure results in 360

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examine the momentum effect in the next chapter, and test-period return.

test-period overlapping monthly returns for each portfolio over which the Fama-French three-factor model is estimated. Because overlapping data is involved, the t-statistics of the coefficient estimates of the three-factor model are computed using Newey-West heteroscedasticity- and autocorrelation-adjusted variance-covariance matrix.

5.4.1 PAD Effect Related to the SUE Measure

Table 5.4.1 reports the performances, characteristics, and earnings surprises of decile portfolios formed on the basis of the most recent past standardised unexpected earnings (SUE_0). In Table 5.4.1 LD denotes the lowest earnings surprise decile portfolio (here LD is the lowest-SUE_0 decile portfolio), and HD is the highest one. In addition, $HD-LD$ is the costless PAD portfolio of HD minus LD.

Table 5.4.1 Performances, Characteristics, and Earnings Surprises of Decile and PAD Portfolios Classified by Standardised Unexpected Earnings

At the beginning of every month from July 1992 to June 1997, all stocks in the earnings sample are sorted in ascending order based on their most recent past standardised unexpected earnings (SUE_0) and assigned to one of ten decile portfolios. All stocks are equally-weighted in a portfolio. The lowest-earnings-surprise (i.e., lowest-SUE_0) decile is denoted as portfolio LD; the next decile is portfolio $D2$; and so on. The highest-earnings-surprise (i.e., highest-SUE_0) decile is denoted as portfolio HD; and $HD-LD$ stands for the PAD portfolio (arbitrage portfolio) of HD minus LD. Panel A reports the portfolios' performances: ret_{-6} is the average past six-month return over the 60 ranking periods; ret_n is the average n-month (n = 3, 6, 9, 12) buy-and-hold return over the 60 test periods. Panel B presents the estimates of the Fama-French three-factor model, which is

$$r_{P\tau} - r_{f\tau} = a_P + b_P(r_{m\tau} - r_{f\tau}) + s_P SMB_\tau + h_P HML_\tau + \varepsilon_{P\tau}.$$

The two factor-mimicking portfolios of SMB_τ and HML_τ, and the value-weighted market return, $r_{m\tau}$, are constructed based on the accounting sample (for detailed descriptions of the constructions of SMB_τ and HML_τ, and other notation of the 3-factor model see Section 4.4 of Chapter 4). Panel C shows the portfolios' average Scholes–Williams beta ($SW-\beta$), market value (MV), unadjusted price (UP), cash flow to price ratio (C/P), book-to-market ratio (B/M) and number of analysts (ANo) at the beginning of the holding periods. Panel D presents the portfolios' average most recent past earnings surprises as well as the next ones after portfolio formation. In Panel D, SUE_0, $AR4D_0$, and $REV6_0$ stand for the portfolios' average most recent past standardised unexpected earnings (SUE), 4-day abnormal return around earnings announcements ($AR4D$), and cumulative price-deflated earnings forecast revision over the prior 6 months ($REV6$), respectively; SUE_1 and $AR4D_1$ stand for the portfolios' average next SUE and $AR4D$ after portfolio formation, respectively. Numbers in parenthesis are t-statistics; where observations are overlapping the Newey-West heteroscedasticity- and autocorrelation-consistent standard errors are used in computing the t-statistics.

	LD	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	HD	$HD-LD$
					Panel A: Performance						
ret_{-6}	0.0189	0.0328	0.0541	0.0681	0.0912	0.1085	0.1247	0.1120	0.1197	0.1528	0.1340
	(0.82)	(1.45)	(2.40)	(2.33)	(3.26)	(3.47)	(4.74)	(3.53)	(3.48)	(4.98)	(9.43)
ret_3	0.0246	0.0299	0.0377	0.0374	0.0440	0.0472	0.0480	0.0429	0.0462	0.0537	0.0291
	(2.11)	(2.44)	(2.72)	(3.08)	(3.30)	(3.63)	(4.19)	(3.50)	(3.54)	(3.36)	(3.54)
ret_6	0.0594	0.0682	0.0825	0.0947	0.0924	0.0955	0.0963	0.0934	0.0988	0.1109	0.0516
	(3.22)	(2.75)	(2.72)	(3.44)	(3.60)	(4.02)	(4.12)	(3.70)	(3.58)	(3.22)	(2.28)
ret_9	0.0882	0.1084	0.1191	0.1426	0.1307	0.1420	0.1346	0.1376	0.1411	0.1705	0.0824
	(3.72)	(2.97)	(2.91)	(3.26)	(3.43)	(3.89)	(3.93)	(3.49)	(3.22)	(3.10)	(2.08)
ret_{12}	0.1269	0.1499	0.1575	0.1889	0.1812	0.1915	0.1811	0.1869	0.1899	0.2345	0.1076
	(4.14)	(3.27)	(3.51)	(3.19)	(3.72)	(4.44)	(4.10)	(3.57)	(3.19)	(3.27)	(1.88)
					Panel B: Estimates of the Fama-French three-factor model						
$a_P(\%)$	−0.407	−0.206	−0.204	0.038	0.031	0.083	0.154	0.060	0.037	0.195	0.603
	(−2.14)	(−1.41)	(−1.16)	(0.25)	(0.21)	(0.80)	(1.33)	(0.55)	(0.22)	(1.29)	(2.62)
b_P	1.0546	0.9685	1.0769	1.0620	1.0048	1.0782	1.0137	0.9718	1.1422	1.0964	0.0417
	(28.1)	(27.4)	(26.7)	(41.2)	(25.8)	(36.1)	(27.0)	(36.3)	(31.0)	(28.2)	(0.73)
s_P	0.6170	0.7212	0.7034	0.6873	0.7365	0.6530	0.6392	0.7087	0.7565	0.7089	0.0919
	(7.65)	(9.38)	(12.8)	(14.2)	(18.5)	(16.6)	(21.9)	(13.9)	(15.4)	(11.7)	(0.73)
h_P	0.1325	0.0351	0.2029	0.2899	0.2484	0.2232	0.2102	0.4110	0.3180	0.3271	0.1945
	(1.32)	(0.55)	(4.32)	(3.15)	(4.59)	(3.92)	(3.98)	(5.18)	(6.21)	(3.50)	(1.10)
R^2	0.7991	0.7956	0.8208	0.8147	0.8253	0.8338	0.8112	0.8185	0.8587	0.8339	0.0436
					Panel C: Characteristics						
$SW-\beta$	0.9969	0.9190	0.9716	1.0239	1.0515	1.0501	1.0553	1.0735	1.0689	1.0150	0.0181
	(27.6)	(12.4)	(29.2)	(22.2)	(35.3)	(17.8)	(23.2)	(22.6)	(17.3)	(17.3)	(0.67)
MV	574.55	403.85	778.46	528.41	666.52	554.84	651.95	559.91	586.00	518.81	−55.74
	(15.3)	(11.6)	(17.6)	(14.1)	(15.3)	(14.2)	(17.8)	(16.1)	(19.3)	(12.6)	(−0.84)
UP	253.79	243.97	246.91	231.26	226.98	256.85	257.42	236.10	254.44	284.13	30.35
	(35.1)	(57.3)	(49.8)	(71.8)	(60.8)	(39.0)	(63.7)	(53.4)	(67.7)	(21.8)	(1.88)
C/P	0.0876	0.1114	0.1083	0.1177	0.1058	0.1151	0.1139	0.1147	0.1128	0.1110	0.0234
	(24.6)	(39.9)	(49.7)	(36.4)	(28.3)	(92.1)	(71.8)	(56.4)	(44.5)	(52.7)	(7.28)
B/M	0.6122	0.6082	0.5721	0.6251	0.5128	0.5215	0.5510	0.4916	0.5496	0.5669	−0.0453
	(28.3)	(28.2)	(37.4)	(27.9)	(41.8)	(19.6)	(20.9)	(21.6)	(18.9)	(19.6)	(−1.22)
ANo	2.034	1.699	1.912	1.674	1.815	1.748	1.710	1.766	1.892	1.911	−0.123
	(18.6)	(17.9)	(19.7)	(21.8)	(21.5)	(20.0)	(24.5)	(19.9)	(17.1)	(16.7)	(−1.37)
					Panel D: Earnings Surprises						
SUE_0	−1.6017	−0.7740	−0.3523	−0.0777	0.1437	0.3338	0.5266	0.7516	1.0536	1.6281	3.2298
	(−29.8)	(−20.4)	(−11.5)	(−2.60)	(3.63)	(6.48)	(8.87)	(11.4)	(19.0)	(30.0)	(36.4)
$AR4D_0(\%)$	−1.128	−0.846	−0.597	−0.189	0.599	0.949	1.599	1.563	1.874	2.586	3.714
	(−2.40)	(−2.79)	(−2.06)	(−0.72)	(5.63)	(3.56)	(4.72)	(5.35)	(5.49)	(11.5)	(9.91)
$REV6_0(\%)$	−1.935	−1.779	−0.976	−0.970	−0.839	−0.560	−0.448	−0.559	−0.311	−0.178	1.757
	(−5.96)	(−4.28)	(−4.37)	(−3.03)	(−5.70)	(−3.83)	(−3.24)	(−2.55)	(−2.75)	(−1.95)	(5.02)
SUE_1	−0.2192	−0.1477	−0.0058	0.0810	0.1386	0.2534	0.2300	0.2628	0.3144	0.4528	0.6720
	(−3.82)	(−3.12)	(−0.09)	(2.05)	(3.71)	(4.67)	(3.88)	(6.13)	(5.02)	(15.2)	(10.2)
$AR4D_1(\%)$	0.499	0.382	0.597	0.300	1.101	1.019	0.899	1.197	1.103	1.454	0.955
	(1.43)	(1.08)	(1.72)	(1.48)	(3.76)	(4.26)	(3.07)	(4.25)	(3.63)	(3.84)	(1.89)

Examination of Panel A in Table 5.4.1 reveals the well-documented PAD effect. The PAD portfolio earns significant profits over 3- to 12-month holding periods.[14] In the first 6 months after portfolio formation, the average PAD profit is 5.16 percent ($t = 2.28$). The decile portfolios' average holding-period returns generally increase from low-SUE_0 (LD) to high-SUE_0 (HD) decile portfolios. The evident PAD phenomenon, especially the significant spread between the performances of HD and LD, can be seen from Figure 5.4.1, which plots the decile portfolios' market-adjusted holding-period abnormal returns over 3 to 12 months.[15] In addition, the past 6-month returns of the decile portfolios (ret_{-6}) are also increasing from LD to HD, indicating a possible relation between SUE_0 and prior 6-month return. In Panel B of Table 5.4.1, the estimates of the Fama-French three-factor model further confirm the SUE_0-based PAD phenomenon. The lowest-SUE_0 decile portfolio's three-factor-adjusted monthly abnormal return is lowest and significantly negative (–0.407% with a t-statistic of –2.14), while the highest-SUE_0 decile portfolio's is the highest one (0.195% with a t-statistic of 1.29). As a result, the three-factor-adjusted monthly PAD profit is 0.603% ($t = 2.62$). In addition, both LD and HD portfolios have similar loading on the three factors, which is consistent with the results reported in Panel C of Table 5.4.1 (see analysis on this below).

[14] For the 12-month PAD profits the significance level is at 6 percent.

[15] The market index used here is the within-sample equally-weighted return. As illustrated in Chapter 4, such an adjustment does not alter the PAD profits reported in Panel A of Table 5.4.1.

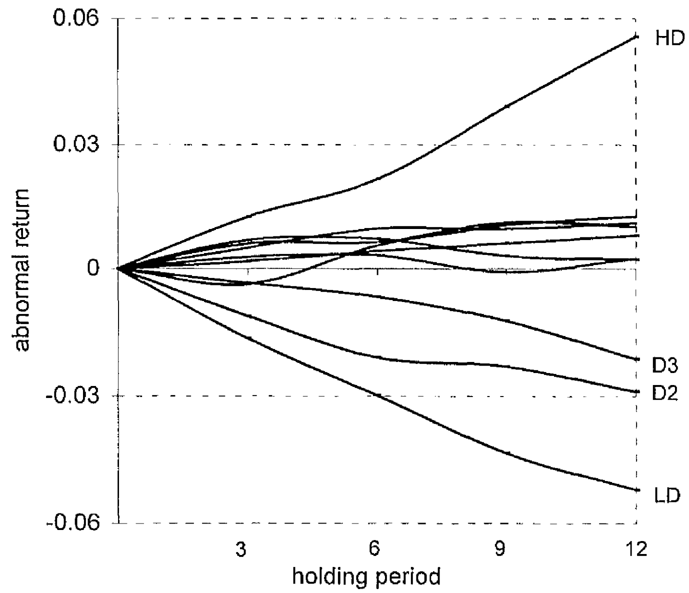

Figure 5.4.1 Holding-period abnormal returns of decile portfolios classified by most recent past standardised unexpected earnings (SUE_0)

Examining the average earnings surprises of the SUE_0-classified decile portfolios presented in Panel D of Table 5.4.1, it is easy to see that the 4-day abnormal returns around the most recent past earnings announcements ($AR4D_0$) have almost the same pattern as SUE_0s. The spread in $AR4D_0$s between highest-SUE_0 and lowest-SUE_0 decile portfolios is 3.71 percent ($t = 9.91$). Meanwhile, the portfolios' average $REV6_0$s are also generally increasing when moving from low-SUE_0 decile to high-SUE_0 decile. The evidence suggests that there might be a relation between the three earnings surprise variables of SUE_0, $AR4D_0$ and $REV6_0$.[16] The interesting feature in Panel D is that all decile portfolios' $REV6_0$s are significant negative. A potential explanation might be that analysts are overly optimistic in the early month and become less optimistic in the later month before earnings announcement. Eventually,

[16] Note that the three earnings surprise variables are not constructed at exactly the same time point, as demonstrated in the last section, although I use the 0 subscription for the three most recent past

analysts' forecasts are unbiased at the latest month immediately before earnings announcement, as tested in the last section. This seems to reflect the behavioural or sociological considerations. Analyst is less likely willing to produce unfavourable forecast as it may damage his/her firm's investment banking and underwriting relationships. In addition, encouraging investors to trade through providing favourable earnings forecasts is not only helpful to maintain good relations between management and the analyst, but it also generate brokerage commissions.

Consistent with US evidence, the earnings surprise is predictable. This can be seen by comparing the average SUE_0 s with SUE_1 s in Panel D of Table 5.4.1. Namely, high-SUE tends to be followed by high-SUE, and low-SUE by low-SUE. At the next announcement following portfolio formation the SUE_0-classified PAD portfolio's standardised unexpected earnings (SUE_1) is 0.672 ($t = 10.2$). Moreover, the 4-day abnormal returns around earnings announcements generally continue to drift in the same direction as SUE. Detailed examination of the relationships among these earnings surprise variables is presented in the following section.

Panel C of Table 5.4.1 shows that there are no significant differences between the highest-SUE_0 decile portfolio (HD) and the lowest-SUE_0 decile portfolio (LD) with respect to the various characteristics except for the C/P ratio. In fact, the differences in characteristics are not big throughout the 10 SUE_0-classified decile portfolios. In addition, both LD and HD portfolios tend to have more analysts following with LD having the highest average number of analysts. These results

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earnings surprise measures. The same notation is also adopted in the subsequent analyses and in the next chapter.

indicate that the SUE_0-based PAD profits are less likely to be due to market risk and other systematic effects. To further confirm if this is true, I conduct sub-sample analyses. In particular, I analyse 18 sub-samples stratified on MV, UP, C/P, B/M, β, and ANo. Among other benefits, sub-sample analysis provides a way of examining systematic risk and other effects as explanations of PAD or momentum profits. For a detailed description of the sub-sample style of analysis see Section 4.6 of Chapter 4.

Table 5.4.2 summarises the average 6-month holding-period returns of quintile and PAD portfolios for each of the 18 sub-samples (with t-statistics in parentheses). The quintile portfolios are formed by ranking most recent past standardised unexpected earnings (SUE_0) within each sub-sample.

Table 5.4.2 Sub-sample Analysis with Portfolios Being Classified by SUE_0

This table presents the average semi-annual holding-period returns for the quintile portfolios and the PAD portfolio within various sub-samples stratified on MV, UP, C/P, B/M, β, and ANo. Each sub-sample contains one-third of the stocks in the earnings sample at the beginning of each holding period. For instance, for the 3 MV-based sub-samples the low-MV sub-sample contains the $1/3$ lowest-MV stocks at the beginning of each holding period; the medium-MV sub-sample contains the $1/3$ medium-MV stocks at the beginning of each holding period; and the high-MV sub-sample contains the $1/3$ highest-MV stocks at the beginning of each holding period. Within each sub-sample, the quintile portfolios are formed at the beginning of each month (from July 1992 to June 1997) on the basis of most recent past standardised unexpected earnings (SUE_0) and held for 6 months. At the start of each holding period, the stocks in a given sub-sample are ranked in ascending order based on their SUE_0s. The equally-weighted portfolio of stocks in the lowest-SUE_0 quintile is the lowest earnings surprise portfolio (LQ), the equally-weighted portfolio of stocks in the next quintile is denoted as $Q2$, and so on. The equally-weighted portfolio of stocks in the highest-SUE_0 quintile is the highest earnings surprise portfolio (HQ). The PAD portfolio is the HQ portfolio minus the LQ portfolio ($HQ-LQ$). In Panel E β stands for Scholes-Williams beta, and in Panel F ANo stands for the number of analysts. Numbers in parentheses are Newey-West-standard-error-adjusted t-statistics. The test period is July 1992 to November 1997.

Sub-sample Analyses with portfolios being classified by SUE_0

	Panel A: 3 MV -based sub-samples			**Panel B**: 3 UP-based sub-samples		
	Low-MV	Medium-MV	high-MV	Low-UP	Medium-UP	high-UP
LQ	0.07901 (3.22)	0.05188 (2.10)	0.06385 (3.40)	0.07137 (2.95)	0.06389 (3.00)	0.05421 (2.77)
$Q2$	0.11258 (2.71)	0.06477 (2.18)	0.08345 (3.76)	0.11737 (2.70)	0.07060 (2.77)	0.08100 (3.46)
$Q3$	0.11764 (3.86)	0.07492 (2.89)	0.08185 (4.55)	0.11016 (3.26)	0.07995 (3.85)	0.08439 (4.38)
$Q4$	0.12317 (4.18)	0.09144 (3.14)	0.08028 (3.68)	0.12343 (3.41)	0.08494 (4.07)	0.08477 (4.35)
HQ	0.12144 (2.91)	0.11200 (3.66)	0.07989 (3.06)	0.10659 (2.81)	0.10647 (3.17)	0.09909 (3.95)
$HQ-LQ$	0.04243 (1.66)	0.06012 (3.85)	0.01605 (1.51)	0.03522 (1.33)	0.04258 (2.04)	0.04488 (4.75)

	Panel C: 3 C/P-based sub-samples			**Panel D**: 3 B/M -based sub-samples		
	Low-C/P	Medium-C/P	high-C/P	Low-B/M	Medium-B/M	high-B/M
LQ	0.03812 (1.65)	0.05290 (2.31)	0.10625 (4.19)	0.05788 (2.17)	0.06133 (2.30)	0.07787 (3.29)
$Q2$	0.04735 (2.08)	0.07905 (3.09)	0.12861 (3.28)	0.07614 (3.17)	0.07766 (2.64)	0.10322 (2.98)
$Q3$	0.06370 (3.32)	0.07858 (3.81)	0.13907 (4.30)	0.10292 (4.86)	0.07948 (3.04)	0.09866 (3.78)
$Q4$	0.06063 (2.53)	0.09450 (4.29)	0.13667 (4.38)	0.09034 (3.59)	0.08916 (3.55)	0.11263 (3.78)
HQ	0.08875 (2.78)	0.09397 (3.40)	0.12970 (3.98)	0.10149 (3.68)	0.10381 (3.31)	0.10706 (2.94)
$HQ-LQ$	0.05064 (2.54)	0.04107 (3.75)	0.02344 (1.29)	0.04361 (2.61)	0.04248 (4.16)	0.02919 (1.25)

	Panel E: 3 β-based sub-samples			**Panel F**: 3 ANo-based sub-samples		
	Low-β	Medium-β	high-β	Low-ANo	medium-ANo	high-ANo
LQ	0.08364 (3.70)	0.04796 (2.08)	0.05955 (2.45)	0.07793 (3.31)	0.05522 (2.47)	0.05767 (2.41)
$Q2$	0.07996 (2.78)	0.08676 (3.41)	0.09354 (2.81)	0.10884 (3.45)	0.08819 (2.89)	0.06539 (3.02)
$Q3$	0.10002 (4.16)	0.08876 (4.58)	0.09539 (3.02)	0.11857 (4.35)	0.08822 (3.26)	0.07306 (3.33)
$Q4$	0.10827 (4.57)	0.08810 (4.29)	0.09573 (2.97)	0.11121 (3.61)	0.09583 (3.95)	0.08719 (3.64)
HQ	0.11286 (3.76)	0.09768 (4.05)	0.09880 (2.57)	0.11803 (3.69)	0.11264 (3.13)	0.07902 (3.15)
$HQ-LQ$	0.02921 (1.52)	0.04972 (5.20)	0.03925 (1.66)	0.04010 (2.27)	0.05742 (2.80)	0.02134 (1.61)

It is evident that the size, price, C/P and B/M effects are still striking within the earnings sample. In addition, consistent with US findings the low-number-of-analysts effect is also remarkable. On average, the semi-annual returns on low-, medium-, and high-ANo stocks are 10.69%, 8.80%, and 7.25%, respectively. Further investigation of the effect of number of analysts is provided in the next chapter.

Portfolio returns within the low-β sub-sample are not less than portfolio returns within the medium- and high-β sub-samples although portfolio returns within the medium-β sub-sample are consistently less than those in the high-β sub-sample. On average, returns realised in the medium-β sub-sample are lowest, and they are highest in the low-β sub-sample. This evidence indicates that the market model does not successfully describe the relation between stock returns and market returns—a fact documented in the modern finance literature.

The crucial fact from the sub-sample analysis, however, is that the SUE_0-based PAD profits are unlikely to be related to UP, C/P, B/M, and ANo effects. For instance, the SUE_0-based PAD profits are statistically significant within the low- and medium-C/P sub-samples, but are insignificant in the high-C/P sub-sample. However, the SUE_0-based PAD profits seem to be more heavily concentrated on medium-β and medium-MV sub-samples. The average 6-month PAD profit is 6.01 percent ($t = 3.85$) within the medium-MV sub-sample, while it is 4.24 percent ($t = 1.66$) and 1.61 percent ($t = 1.51$) within the low- and high-MV sub-samples, respectively. This is different from Hew et al.'s (1996) results where they find that PAD is fairly pronounced for small firms. In this study the average medium-MV is greater than £50m (Hew et al. refer to firms within the £0-50m category as small firms.). Nevertheless, the fact of insignificant SUE_0-based PAD profits within the high-MV sub-sample is consistent with Hew et al.'s (1996) results.

5.4.2 PAD Effect Related to the $REV6$ Measure

Analysts serve an important role in ensuring the efficiency of the market by ferreting out disparate facts and offering valuable insights. Yet, the earnings forecasts issued by analysts may be coloured by other incentives. For example, analysts may attempt to protect business relationships at the cost of fair analysis in order to promote a company's prospects. Analysts can benefit from doing this because analysts' compensation is increasingly based on the profitability of their firm's corporate finance division and their contribution to the deals to which they are assigned. In the last subsection, the empirical results provided evidence supporting this conjecture (see Panel D of Table 5.4.1). Nevertheless, in the previous section I documented that UK analysts' latest earnings forecasts for the current fiscal year (FY1) are efficient over the sample period of 1992 to 1997. This subsection examines whether the cumulative earnings forecast revisions over the prior 6 months ($REV6$) predicts PAD profits.

Table 5.4.3 presents the results of $REV6_0$-based decile and PAD portfolios. Both Panel A and Panel B show a significant $REV6_0$-based PAD effect. In Panel A, the PAD portfolio of $HD-LD$ realises a 3-month holding-period profit of 3.49% ($t=3.16$), a 6-month holding-period profit of 5.27% ($t=2.59$), a 9-month holding-period profit of 6.55% ($t=1.96$), and a 12-month holding-period profit of 7.24% ($t=1.60$). Note that the PAD profits over the shorter holding periods of 3 and 6 months are striking, and they are greater than the *SUE*-based ones presented in Table 5.4.1. However, the $REV6_0$-based PAD profits tend to be less pronounced over the longer holding periods, and it is only significant at 11% significance level over 12-month holding period. In Panel B, the Fama-French three-factor-model-adjusted monthly PAD profit (i.e. the a_p estimate of the PAD portfolio of $HD-LD$) is

1.199% with a t-statistic of 5.87. The decile portfolios' average prior 6-month returns (ret_{-6}) reported in Panel A of Table 5.4.3 monotonically increase from lowest-$REV6_0$ decile (LD) to highest-$REV6_0$ decile (HD), indicating a possible relation between the two variables of $REV6_0$ and ret_{-6}, one of the variables used to test the momentum effect.[17]

Table 5.4.3 Performances, Characteristics, and Earnings Surprises of Decile and PAD Portfolios Classified by Earnings Forecast Revision ($REV6$)

At the beginning of every month from July 1992 to June 1997, all stocks in the earnings sample are sorted in ascending order based on their cumulative price-deflated earnings forecast revision over the prior 6 months ($REV6_0$) and assigned to one of ten portfolios. All stocks are equally-weighted in a portfolio. The lowest-earnings-surprise (i.e., lowest-$REV6_0$) decile is denoted as portfolio LD; the next decile is portfolio $D2$; and so on. The highest-earnings-surprise (i.e., highest-$REV6_0$) decile is denoted as portfolio HD; and $HD-LD$ stands for the PAD portfolio (arbitrage portfolio) of HD minus LD. Panel A reports the portfolios' performances: ret_{-6} is the average past six-month return over the 60 ranking periods; ret_n is the average n-month (n = 3, 6, 9, 12) buy-and-hold return over the 60 test periods; and ΔEPS is the average of the book-value-deflated change in earnings from the most recent past reported final earnings per share to the next reported final earnings per share after portfolio formation. Panel B presents the estimates of Fama-French three-factor model, which is

$$r_{P\tau} - r_{f\tau} = a_P + b_P(r_{m\tau} - r_{f\tau}) + s_P SMB_\tau + h_P HML_\tau + \varepsilon_{P\tau}.$$

The two factor-mimicking portfolios of SMB_τ and HML_τ, and the value-weighted market return, $r_{m\tau}$, are constructed based on the accounting sample (for detailed descriptions of the constructions of SMB_τ and HML_τ, and other notation of the 3-factor model see Section 4.4 of Chapter 4). Panel C shows the portfolios' average Scholes-Williams beta ($SW-\beta$), market value (MV), unadjusted price (UP), cash flow to price ratio (C/P), book-to-market ratio (B/M), and number of analysts (ANo) at the beginning of the holding periods. Panel D presents the portfolios' average most recent past earnings surprises as well as the next ones after portfolio formation. In Panel D, SUE_0, $AR4D_0$, and $REV6_0$ stand for the portfolios' average most recent past standardised unexpected earnings (SUE), the 4-day abnormal return around earnings announcements ($AR4D$), and the cumulative price-deflated earnings forecast revision over the prior 6 months ($REV6$), respectively; SUE_1 and $AR4D_1$ stand for the portfolios' average next SUE and $AR4D$ after portfolio formation, respectively. Numbers in parenthesis are t-statistics; where observations are overlapping the Newey-West heteroscedasticity- and autocorrelation-consistent standard errors are used in computing the t-statistics.

[17] I also examine the price-deflated single latest analyst forecast revision, and find similar results. The average 3-, 6-, 9-, and 12-month PAD profits are 3.20% (t = 3.73), 2.98% (t = 2.35), 2.62 (t = 1.40), and 5.33% (t = 2.25), respectively.

	LD	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	HD	$HD-LD$
Panel A: Performance											
ret_{-6}	−0.0906 (−2.43)	−0.0189 (−0.69)	0.0255 (0.98)	0.0478 (2.24)	0.0720 (3.16)	0.0870 (3.71)	0.1142 (4.85)	0.1309 (5.17)	0.1674 (6.14)	0.2422 (6.09)	0.3328 (14.7)
ret_3	0.0389 (2.13)	0.0245 (1.50)	0.0218 (1.73)	0.0293 (2.56)	0.0262 (2.32)	0.0353 (3.20)	0.0358 (3.43)	0.0394 (3.24)	0.0473 (3.81)	0.0738 (4.86)	0.0349 (3.16)
ret_6	0.0962 (2.35)	0.0696 (2.12)	0.0551 (2.26)	0.0605 (2.75)	0.0578 (2.67)	0.0617 (3.13)	0.0754 (3.56)	0.0850 (3.91)	0.0976 (4.10)	0.1489 (5.16)	0.0527 (2.59)
ret_9	0.1511 (2.33)	0.1088 (2.17)	0.0871 (2.32)	0.0848 (2.55)	0.0773 (2.54)	0.0870 (3.38)	0.1056 (3.68)	0.1226 (4.27)	0.1358 (4.08)	0.2166 (5.42)	0.0655 (1.96)
ret_{12}	0.2106 (2.53)	0.1502 (2.31)	0.1191 (2.65)	0.1218 (2.83)	0.1073 (3.03)	0.1157 (3.88)	0.1410 (4.32)	0.1598 (4.53)	0.1803 (4.56)	0.2829 (5.85)	0.0724 (1.60)
ΔEPS	−0.0838 (−2.26)	−0.0194 (−3.74)	−0.0061 (−1.44)	0.0016 (1.06)	0.0065 (3.68)	0.0069 (5.83)	0.0089 (5.69)	0.0124 (6.44)	0.0167 (3.80)	0.0195 (3.53)	0.1033 (2.69)
Panel B: Estimates of the Fama-French three-factor model											
$a_P(\%)$	−0.361 (−2.23)	−0.483 (−2.96)	−0.644 (−4.23)	−0.445 (−3.31)	−0.458 (−4.77)	−0.353 (−3.25)	−0.102 (−0.72)	−0.065 (−0.64)	0.159 (1.16)	0.838 (4.69)	1.199 (5.87)
b_P	1.3886 (23.5)	1.1518 (29.2)	1.0764 (31.4)	1.0602 (29.4)	1.0417 (25.1)	1.0144 (32.8)	0.9961 (23.8)	1.0794 (23.5)	1.0578 (16.7)	1.1480 (27.7)	−0.2406 (−2.80)
s_P	0.9653 (11.3)	0.8453 (24.0)	0.7827 (15.2)	0.5194 (15.3)	0.5009 (13.2)	0.4951 (16.6)	0.4190 (7.92)	0.4958 (10.1)	0.5735 (9.55)	0.7554 (8.94)	−0.2100 (−4.25)
h_P	0.6444 (4.87)	0.4765 (4.63)	0.4538 (8.04)	0.1760 (2.18)	0.1917 (3.11)	0.1130 (2.88)	−0.0027 (−0.04)	0.0988 (2.52)	0.1491 (2.74)	0.1801 (2.44)	−0.4643 (−3.20)
R^2	0.7583	0.7972	0.7794	0.7652	0.7928	0.7953	0.7620	0.8173	0.7582	0.7772	0.1131
Panel C: Characteristics											
$SW-\beta$	1.2089 (8.53)	1.1139 (13.8)	1.1336 (26.3)	1.0816 (31.0)	1.0802 (84.1)	1.0758 (69.4)	1.0692 (38.6)	1.0926 (51.7)	1.1583 (25.1)	1.1034 (17.0)	−0.1054 (−1.31)
MV	195.4 (15.7)	617.4 (10.9)	626.2 (16.0)	886.6 (17.6)	1009.6 (18.4)	1056.3 (16.5)	993.4 (20.6)	977.0 (15.5)	911.6 (13.5)	621.9 (12.0)	426.5 (7.61)
UP	131.4 (34.2)	201.2 (45.7)	257.1 (39.2)	305.6 (41.2)	337.2 (50.4)	344.3 (32.2)	351.3 (39.8)	332.9 (43.8)	316.3 (36.6)	262.4 (34.5)	131.0 (13.2)
C/P	0.0926 (10.2)	0.1242 (60.5)	0.1182 (55.8)	0.1107 (81.8)	0.1057 (88.4)	0.1017 (78.2)	0.0993 (59.5)	0.1043 (77.1)	0.1073 (66.4)	0.1282 (63.2)	0.0357 (3.94)
B/M	0.7139 (23.1)	0.6232 (30.3)	0.5327 (36.9)	0.5135 (21.9)	0.4449 (27.8)	0.4001 (35.4)	0.4413 (19.6)	0.4038 (29.8)	0.4370 (27.4)	0.5247 (46.0)	−0.1892 (−5.55)
ANo	1.8444 (21.1)	2.1168 (21.4)	2.1925 (25.6)	2.2946 (22.4)	2.1512 (24.7)	2.0786 (21.7)	1.9362 (19.6)	2.0235 (21.8)	2.0507 (21.1)	1.6136 (22.2)	−0.2308 (−2.86)
Panel D: Earnings Surprises											
SUE_0	−0.2132 (−3.83)	−0.0701 (−1.24)	0.0559 (1.01)	0.1044 (2.28)	0.1742 (6.14)	0.1993 (5.08)	0.2619 (7.38)	0.2875 (7.99)	0.3343 (6.72)	0.3238 (6.19)	0.5370 (9.74)
$AR4D_0(\%)$	−3.999 (−8.21)	−1.762 (−5.48)	−0.621 (−2.46)	0.310 (1.25)	0.482 (3.20)	0.780 (6.13)	1.485 (7.21)	1.838 (9.84)	2.687 (8.71)	3.905 (15.8)	7.904 (15.7)
$REV6_0(\%)$	−8.956 (−10.5)	−1.788 (−11.0)	−0.909 (−8.95)	−0.499 (−6.83)	−0.242 (−4.66)	−0.058 (−1.87)	0.090 (3.38)	0.279 (10.1)	0.618 (16.6)	2.794 (12.6)	11.750 (12.8)
SUE_1	−0.2596 (−5.49)	−0.1151 (−1.96)	−0.0294 (−0.37)	0.0847 (2.19)	0.1377 (5.30)	0.1705 (5.90)	0.2208 (8.52)	0.2770 (8.07)	0.3441 (7.87)	0.4052 (6.22)	0.6648 (13.3)
$AR4D_1(\%)$	0.575 (0.95)	0.263 (0.66)	0.255 (1.07)	0.093 (0.40)	0.049 (0.29)	0.590 (3.46)	0.547 (2.88)	1.178 (5.89)	1.223 (6.88)	1.802 (7.20)	1.227 (2.54)

Since the $REV6$ measure is constructed using earnings forecasts for the current fiscal year (FY1), Panel A of Table 5.4.3 also reports portfolio's average of book-value-deflated change in earnings from the most recent past reported final earnings per share to the next one subsequent to portfolio formation, denoted ΔEPS. For a portfolio P, its book-value-deflated change in earnings from t to $t+1$, ΔEPS_{Pt}, is given by

$$\Delta EPS_{Pt} = \frac{EPS_{P,t+1} - EPS_{Pt}}{BV_{Pt}}, \qquad (5.4.1)$$

where EPS_{Pt} is portfolio P's most recent reported final earnings per share and $EPS_{P,t+1}$ stands for the next one subsequent to portfolio formation, and BV is P's book value.

The average of portfolio P's book-value-deflated change in earnings over all test periods, ΔEPS_P is, thus, computed by,

$$\Delta EPS_P = \frac{1}{T}\sum_{t=1}^{T} \Delta EPS_{Pt}, \qquad (5.4.2)$$

where T is equal to 60, the total number of test periods.[18]

In Panel A of Table 5.4.3, the ΔEPS measure shows that portfolios' book-value-deflated earnings changes monotonically increase when moving from low-$REV6_0$ to high-$REV6_0$ portfolios. As forecast by analysts, the two extreme decile portfolios' reported final earnings experience considerable changes from ranking to holding periods. While LD experiences sharp decline in earnings (its ΔEPS is lowest and statistically negative, –8.38% with a t-statistic of –2.26), HD's earnings are significantly increasing from ranking to holding periods (its ΔEPS is highest and significantly positive at 1.95% with a t-statistic of 3.53). As a result, the earnings change from ranking to holding periods for the PAD portfolio is as high as 10.33% with a t-statistic of 2.69. This evidence is consistent with the efficiency of analysts' forecasts documented in the last section.

However, the holding-period raw returns are not monotonically increasing from LD to HD for any given holding period. Although HD realises the overwhelmingly highest average holding-period raw returns over different periods within the intermediate horizon, LD generally earns the relatively higher holding-period raw returns especially for the longer holding periods of 9 and 12 months. Specifically, LD realises the second highest average holding-period raw returns for the longer holding periods of 9 and 12 months and its average holding-period raw returns are the fourth and third highest ones for the shorter holding periods of 3 and 6 months, respectively. This U-shape pattern in decile portfolios' holding-period raw returns is plotted in Figure 5.4.2.

[18] Similar results are found when using market value rather than book value as a deflator in equation (5.4.1).

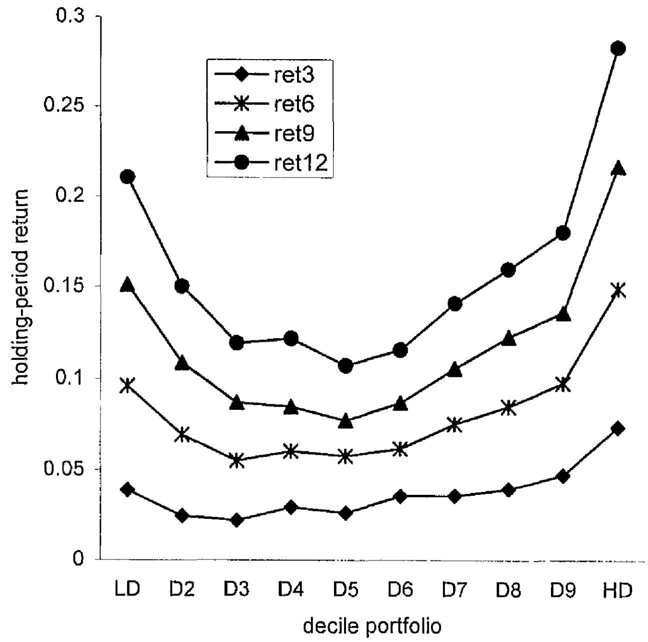

Figure 5.4.2 Holding-period returns of decile portfolios classified by $REV6_0$
In this figure, ret3, ret6, ret9, and ret12 are average holding-period returns for 3, 6, 9, and 12 months, respectively.

This pattern immediately raises a question: why does LD, which experiences a sharp decline in earnings subsequent to portfolio formation, realise a higher holding-period return than some other portfolios? This question can be answered by examining portfolio characteristics and the estimates of the Fama-French three-factor model. The results in Panel C of Table 5.4.3 show that LD's average market value, MV, is far smaller than for the other deciles, and its book-to-market ratio, B/M, is the highest. In addition, LD's average Scholes-Williams beta ($SW-\beta$) is highest, and it has the lowest average UP. Thus, higher holding-period returns earned by the lowest-$REV6_0$ decile might be caused by this decile bearing higher market risk and other risk factors such as size and book-to-market. The three-factor model estimates presented in Panel B of Table 5.4.3 confirm this explanation. After adjusting for the three factors, portfolio LD does not make any abnormal profits. Rather its adjusted return is the fifth lowest and is significantly negative (–0.361% with a t-statistic of –2.23).

Consistent with the portfolio characteristics reported in Panel C of Table 5.4.3, the three-factor model estimates show that portfolio LD is most heavily loaded on size and book-to-market, and it has the highest market risk exposure. By contrast, the highest-$REV6_0$ portfolio (HD) earns significantly positive three-factor-model-adjusted abnormal returns (0.838% with a t-statistic of 4.69). Consequently, the PAD portfolio earns unusually high average PAD profits of 1.199% (t-statistic is 5.87) per month after adjusting for the three factors. Moreover, portfolio HD has significantly less market risk and loads less heavily on size and book-to-market than portfolio LD. Furthermore, although HD's average C/P ratio is significantly greater than LD's, the ten decile portfolios' average C/P ratios are similar and there is no evident pattern. The results in Panel B and Panel C of Table 5.4.3 hence indicate that the significant $REV6_0$-based PAD effect is unlikely to be due to market risk and other risk or market microstructure factors such as size, book-to-market, etc.

The $REV6_0$-sorted portfolios' earnings surprises presented in Panel D of Table 5.4.3 generally show that the patterns of the three earnings surprise variables, $REV6$, SUE and $AR4D$, are consistent, and this is true even for the next SUE and $AR4D$ measures subsequent to portfolio formation. As documented in the last subsection, all the evidence in Panel D of Table 5.4.3 reveals possible relations among the three earnings surprise variables.

Table 5.4.4 summarises the average 6-month holding-period returns of $REV6_0$-classified quintile and PAD portfolios for each of the 18 sub-samples (with t-statistics in parentheses). The results in this table confirm the $REV6_0$-based PAD phenomenon. All the PAD profits are significant within the various sub-samples except for the high-*MV*, high-*ANo* and high-B/M sub-samoles. The U-shape of holding-period returns within various sub-samples is also striking, and the $REV6_0$-related PAD effect is not attributable to variation in expected returns or other systematic effects. In the interests of brevity, detailed analyses on the sub-sample results will not be performed. Similar analysis can be referenced from Chapter 4 and the last subsection.

Table 5.4.4 Sub-sample Analysis with Portfolios Being Classified by $REV6_0$

This table presents the average semi-annual holding-period returns for the quintile portfolios and the PAD portfolio within various sub-samples stratified on MV, UP, C/P, B/M, β, and ANo. Each sub-sample contains one-third of the stocks in the earnings sample at the beginning of each holding period. For instance, for the 3 MV-based sub-samples the low-MV sub-sample contains the $1/3$ lowest-MV stocks at the beginning of each holding period; the medium-MV sub-sample contains the $1/3$ medium-MV stocks at the beginning of each holding period; and the high-MV sub-sample contains the $1/3$ highest-MV stocks at the beginning of each holding period. Within each sub-sample, the quintile portfolios are formed at the beginning of each month (from July 1992 to June 1997) on the basis of cumulative price-deflated earnings forecast revision over the prior 6 months ($REV6_0$) and held for 6 months. At the start of each holding period, the stocks in a given sub-sample are ranked in ascending order based on their $REV6_0$s. The equally-weighted portfolio of stocks in the lowest-$REV6_0$ quintile is the lowest earnings surprise portfolio (LQ), the equally-weighted portfolio of stocks in the next quintile is denoted as $Q2$, and so on. The equally-weighted portfolio of stocks in the highest-$REV6_0$ quintile is the highest earnings surprise portfolio (HQ). The PAD portfolio is the HQ portfolio minus the LQ portfolio ($HQ-LQ$). In Panel E β stands for Scholes-Williams beta, and in Panel F ANo stands for the number of analysts. Numbers in parentheses are Newey-West-standard-error-adjusted t-statistics. The test period is July 1992 to November 1997.

Sub-sample Analyses with portfolios being classified by $REV6_0$

	Panel A: 3 MV -based sub-samples			**Panel B**: 3 UP-based sub-samples		
	Low-MV	Medium-MV	high-MV	low-UP	Medium-UP	high-UP
LQ	0.1077 (1.96)	0.0788 (2.11)	0.0979 (2.88)	0.1164 (2.03)	0.0665 (2.10)	0.0719 (3.00)
$Q2$	0.0637 (1.97)	0.0516 (1.95)	0.0646 (3.05)	0.0782 (1.97)	0.0555 (2.36)	0.0599 (3.02)
$Q3$	0.0657 (2.31)	0.0601 (2.49)	0.0710 (3.92)	0.0721 (2.08)	0.0626 (2.80)	0.0653 (3.69)
$Q4$	0.0871 (2.79)	0.0848 (3.54)	0.0732 (3.58)	0.0953 (2.92)	0.0742 (3.25)	0.0822 (4.30)
HQ	0.1629 (3.40)	0.1346 (3.94)	0.1022 (4.03)	0.1634 (3.17)	0.1178 (3.76)	0.1242 (4.71)
$HQ-LQ$	0.0552 (4.06)	0.0558 (4.49)	0.0043 (0.21)	0.0470 (3.93)	0.0512 (3.38)	0.0524 (4.15)
	Panel C: 3 C/P-based sub-samples			**Panel D**: 3 B/M-based sub-samples		
	Low-C/P	Medium-C/P	high-C/P	low-B/M	Medium-B/M	high-B/M
LQ	0.0493 (1.12)	0.0723 (2.49)	0.1377 (2.95)	0.0687 (1.90)	0.0466 (1.51)	0.1228 (2.56)
$Q2$	0.0416 (1.64)	0.0637 (2.51)	0.0928 (2.56)	0.0492 (1.98)	0.0581 (2.23)	0.0940 (2.47)
$Q3$	0.0553 (2.93)	0.0538 (2.44)	0.0900 (3.20)	0.0675 (3.33)	0.0608 (2.61)	0.0851 (2.94)
$Q4$	0.0782 (3.51)	0.0670 (2.92)	0.1046 (3.77)	0.0849 (3.52)	0.0812 (3.11)	0.0835 (3.29)
HQ	0.1105 (3.24)	0.1161 (4.60)	0.1731 (3.96)	0.1507 (4.62)	0.1224 (3.61)	0.1284 (3.28)
$HQ-LQ$	0.0612 (2.56)	0.0437 (3.61)	0.0355 (3.27)	0.0820 (5.69)	0.0758 (7.42)	0.0056 (0.39)
	Panel E: 3 β-based sub-samples			**Panel F**: 3 ANo-based sub-samples		
	Low-β	Medium-β	high-β	low-ANo	medium-ANo	high-ANo
LQ	0.0992 (2.56)	0.0787 (1.92)	0.0989 (2.03)	0.1081 (2.48)	0.0835 (1.91)	0.0858 (2.11)
$Q2$	0.0533 (2.45)	0.0561 (2.22)	0.0772 (2.23)	0.0738 (2.56)	0.0611 (2.42)	0.0619 (2.34)
$Q3$	0.0641 (3.12)	0.0607 (2.95)	0.0752 (2.58)	0.0684 (2.62)	0.0628 (2.69)	0.0594 (3.08)
$Q4$	0.0728 (3.33)	0.0836 (3.98)	0.0824 (3.03)	0.0837 (3.21)	0.0819 (3.29)	0.0761 (4.14)
HQ	0.1517 (5.05)	0.1171 (4.24)	0.1410 (3.15)	0.1543 (3.55)	0.1343 (4.03)	0.1116 (4.38)
$HQ-LQ$	0.0525 (2.96)	0.0384 (1.86)	0.0420 (2.65)	0.0462 (3.73)	0.0508 (3.07)	0.0258 (1.13)

5.4.3 PAD Effect Related to the $AR4D$ Measure

As mentioned previously, the SUE measure may suffer from model misspecification, and behavioural or sociological considerations may explain analysts' overly optimistic forecasts of earnings. Hence, PAD profits related to the two earnings surprise measures of SUE and $REV6$ may be influenced by these problems. As a comparison, the $AR4D$ measure may be a clearer, more objective measure of the earnings surprise. Table 5.4.5 provides results for portfolios formed on the basis of 4-day abnormal returns around the most recent past earnings announcement.

Table 5.4.5 Performances, Characteristics, and Earnings Surprises of Decile and PAD Portfolios Classified by 4-day Abnormal Return around Earnings Announcements ($AR4D$)

At the beginning of every month from July 1992 to June 1997, all stocks in the earnings sample are sorted in ascending order based on their most recent past 4-day abnormal return around earnings announcements ($AR4D_0$) and assigned to one of decile portfolios. Stocks are equally-weighted in a portfolio. The lowest-earnings-surprise (i.e., lowest-$AR4D_0$) decile is denoted as portfolio LD; the next decile is portfolio $D2$; and so on. The highest-earnings-surprise (i.e., highest-$AR4D_0$) decile is denoted as portfolio HD; and $HD-LD$ stands for the PAD portfolio (arbitrage portfolio) of HD minus LD. Panel A reports the portfolios' performances: ret_{-6} is the average past six-month return over the 60 ranking periods; ret_n is the average n-month (n = 3, 6, 9, 12) buy-and-hold return over the 60 test periods. Panel B presents the estimates of Fama-French three-factor model, which is

$$r_{P\tau} - r_{f\tau} = a_P + b_P(r_{m\tau} - r_{f\tau}) + s_P SMB_\tau + h_P HML_\tau + \varepsilon_{P\tau}.$$

The two factor-mimicking portfolios of SMB_τ and HML_τ, and the value-weighted market return, $r_{m\tau}$, are constructed based on the accounting sample (for detailed descriptions of the constructions of SMB_τ and HML_τ, and other notation of the 3-factor model see Section 4.4 of Chapter 4). Panel C shows the portfolios' average Scholes-Williams beta ($SW\text{-}\beta$), market value (MV), unadjusted price (UP), cash flow to price ratio (C/P), book-to-market ratio (B/M), and number of analysts (ANo) at the beginning of the holding periods. Panel D presents the portfolios' average most recent past earnings surprises as well as the next ones after portfolio formation. In Panel D, SUE_0, $AR4D_0$, and $REV6_0$ stand for the portfolios' average most recent past standardised unexpected earnings (SUE), 4-day abnormal return around earnings announcements ($AR4D$), and cumulative price-deflated earnings forecast revision over the prior 6 months ($REV6$), respectively; SUE_1 and $AR4D_1$ stand for the portfolios' average next SUE and $AR4D$ after portfolio formation, respectively. Numbers in parenthesis are t-statistics; where observations are overlapping the Newey-West heteroscedasticity- and autocorrelation-consistent standard errors are used in computing the t-statistics.

	LD	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	HD	$HD-LD$
					Panel A: Performance						
ret_{-6}	−0.1013	0.0118	0.0376	0.0580	0.0835	0.0879	0.1149	0.1367	0.1902	0.2626	0.3639
	(−3.15)	(0.52)	(1.44)	(2.85)	(3.29)	(3.33)	(4.59)	(5.11)	(6.00)	(6.25)	(19.1)
ret_3	0.0165	0.0255	0.0326	0.0366	0.0389	0.0395	0.0405	0.0532	0.0603	0.0658	0.0493
	(1.14)	(2.18)	(2.50)	(3.33)	(3.00)	(3.03)	(3.33)	(4.42)	(4.50)	(4.55)	(5.76)
ret_6	0.0510	0.0698	0.0778	0.0751	0.0920	0.0823	0.0825	0.1089	0.1115	0.1363	0.0853
	(1.86)	(2.75)	(3.28)	(3.45)	(3.16)	(3.13)	(3.91)	(4.06)	(4.26)	(4.69)	(6.31)
ret_9	0.0926	0.1070	0.1178	0.1130	0.1339	0.1196	0.1170	0.1599	0.1500	0.1990	0.1064
	(2.17)	(2.70)	(3.26)	(3.39)	(3.04)	(3.18)	(3.74)	(3.85)	(3.94)	(4.75)	(7.32)
ret_{12}	0.1368	0.1472	0.1657	0.1543	0.1741	0.1648	0.1616	0.2127	0.2017	0.2669	0.1301
	(2.55)	(2.72)	(3.32)	(3.75)	(3.20)	(3.64)	(3.76)	(4.15)	(4.52)	(5.30)	(6.40)
					Panel B: Estimates of the Fama-French three-factor model						
$a_p(\%)$	−0.787	−0.394	−0.196	−0.120	0.015	−0.078	−0.046	0.340	0.367	0.671	1.458
	(−5.55)	(−3.67)	(−1.68)	(−0.75)	(0.14)	(−0.68)	(−0.31)	(2.20)	(3.68)	(4.19)	(6.31)
b_p	1.1842	1.1983	1.0464	0.9650	1.0084	0.9560	1.0140	0.9757	1.0819	1.0266	−0.1576
	(29.1)	(22.0)	(19.1)	(23.0)	(29.0)	(28.0)	(19.8)	(28.7)	(17.9)	(20.7)	(−2.99)
s_p	0.8169	0.6803	0.6832	0.6223	0.7170	0.6348	0.5957	0.6415	0.7029	0.8323	0.0154
	(12.1)	(14.2)	(17.3)	(14.8)	(17.8)	(19.6)	(16.9)	(10.5)	(8.38)	(12.5)	(0.24)
h_p	0.3116	0.2006	0.3252	0.1698	0.2873	0.3495	0.1717	0.1369	0.1223	0.3113	−0.0003
	(5.10)	(3.18)	(5.70)	(2.69)	(4.70)	(4.34)	(3.56)	(2.30)	(1.43)	(3.73)	(−0.002)
R^2	0.8100	0.8463	0.8326	0.7786	0.8133	0.8170	0.8117	0.8251	0.8239	0.7862	0.0496
					Panel C: Characteristics						
$SW-\beta$	1.0489	1.1228	1.0428	0.9793	0.9786	0.9525	0.9534	1.0351	1.0855	1.0324	−0.0166
	(11.2)	(26.5)	(49.8)	(18.9)	(15.1)	(25.5)	(21.0)	(22.2)	(27.8)	(20.4)	(−0.33)
MV	314.70	746.83	859.64	668.60	576.13	804.34	655.01	605.30	454.35	165.10	−149.60
	(11.8)	(14.5)	(18.3)	(17.7)	(16.2)	(15.7)	(17.5)	(12.8)	(12.3)	(17.2)	(−5.01)
UP	147.71	213.11	253.84	265.78	284.51	298.66	277.81	293.06	267.49	185.60	37.90
	(34.9)	(43.0)	(61.3)	(67.5)	(39.0)	(65.7)	(48.8)	(33.5)	(40.1)	(57.2)	(8.53)
C/P	0.0898	0.1157	0.1096	0.0990	0.1164	0.1109	0.1136	0.1118	0.1129	0.1127	0.0229
	(13.4)	(44.4)	(60.4)	(36.9)	(69.6)	(58.5)	(60.0)	(58.2)	(55.1)	(50.2)	(3.69)
B/M	0.6781	0.6604	0.6020	0.4816	0.6200	0.5987	0.5065	0.4750	0.4755	0.4966	−0.1815
	(33.1)	(21.7)	(24.7)	(19.2)	(37.9)	(23.0)	(27.8)	(72.6)	(25.1)	(24.8)	(−6.37)
ANo	1.310	1.755	1.845	1.754	1.401	1.611	1.526	1.487	1.429	0.985	−0.325
	(19.6)	(20.3)	(25.4)	(20.0)	(20.1)	(21.1)	(20.3)	(19.3)	(23.5)	(14.4)	(−5.58)
					Panel D: Earnings Surprises						
SUE_0	−0.1698	0.0937	0.0885	0.1721	0.1397	0.1551	0.2276	0.2366	0.3390	0.3594	0.5293
	(−5.25)	(1.76)	(1.72)	(3.16)	(3.21)	(2.34)	(3.71)	(9.63)	(6.37)	(8.09)	(12.2)
$AR4D_0(\%)$	−14.004	−5.385	−2.737	−1.172	−0.046	1.080	2.445	4.126	6.805	15.236	29.240
	(−37.8)	(−30.9)	(−17.6)	(−10.7)	(−0.46)	(7.54)	(13.8)	(19.1)	(22.9)	(23.8)	(43.0)
$REV6_0(\%)$	−3.951	−1.423	−0.716	−0.562	−0.627	−0.416	−0.220	−0.316	0.058	−0.452	3.499
	(−6.44)	(−5.56)	(−6.72)	(−5.93)	(−6.08)	(−3.12)	(−2.38)	(−5.66)	(0.59)	(−2.42)	(7.05)
SUE_1	−0.2018	0.0230	0.0681	0.0811	0.1586	0.2382	0.2209	0.1972	0.2743	0.2992	0.5009
	(−4.13)	(0.44)	(1.67)	(1.39)	(5.05)	(4.32)	(5.38)	(3.55)	(4.08)	(6.11)	(7.77)
$AR4D_1(\%)$	0.140	0.175	1.025	0.572	0.851	1.307	0.805	1.207	1.198	1.298	1.158
	(0.30)	(0.54)	(1.97)	(1.26)	(2.29)	(4.71)	(2.33)	(6.92)	(5.21)	(5.18)	(1.79)

From Panel A of Table 5.4.5 it is clearly that the $AR4D$-based PAD effect is remarkable. The high-$AR4D_0$ decile portfolios tend to outperform the low-$AR4D_0$ decile portfolios in both holding periods and ranking period. This tendency can be seen from Figure 5.4.3, which plots the within-sample-equally-weighted-market-adjusted holding-period abnormal returns of decile portfolios classified by the most recent past 4-day abnormal return around earnings announcements. All 4 holding-period PAD profits are decisively significant. The average 3-, 6-, 9- and 12-month holding-period PAD profits are 4.93% ($t = 5.76$), 8.53% ($t = 6.31$), 10.64% ($t = 7.32$), and 13.01% ($t = 6.40$), respectively. These magnitudes are similar to those of the momentum profits documented in Chapters 3 and 4, and they are economically greater than the SUE - and $REV6$ -based PAD profits. Therefore, the earnings surprise measure of short-term price reaction around earnings announcements shows the strongest PAD effect compared with other two measures of SUE and $REV6$.[19] However, $AR4D$ measure does not show a stronger PAD effect than the momentum effect, even though it realises the strongest PAD profits. In fact, the $AR4D$-based PAD profits over the longer holding periods of 9 and 12 months are smaller than the corresponding momentum profits although they are not less than the momentum profits over the shorter holding periods of 3 and 6 months (see Table 3.4.2 and Table 3.5.1 in Chapter 3 for the 6×3, 6×6, 6×9, and 6×12 strategies). This evidence indicates that the PAD effect is relatively shorter-lived than the price momentum effect. Further evidence can been seen in the following chapter. The Fama-French three-factor-model estimates shown in Panel B of Table 5.4.5 are consistent with the stronger $AR4D$-based PAD effect. Portfolio LD's three-factor-model-adjusted monthly abnormal return is lowest and significantly negative (−0.787% with a t-statistic of −5.55), whilst HD's is highest and significantly positive (0.671% with a t-statistic of 4.19). The monthly PAD profit is thus as high as 1.458% ($t = 6.31$) after adjusting for the three factors.

[19] It might not be surprising to observe the strongest $AR4D_0$-related PAD effect because the $AR4D_0$ measure should capture all good/bad news released at the preliminary/interim announcement date, not just earnings news.

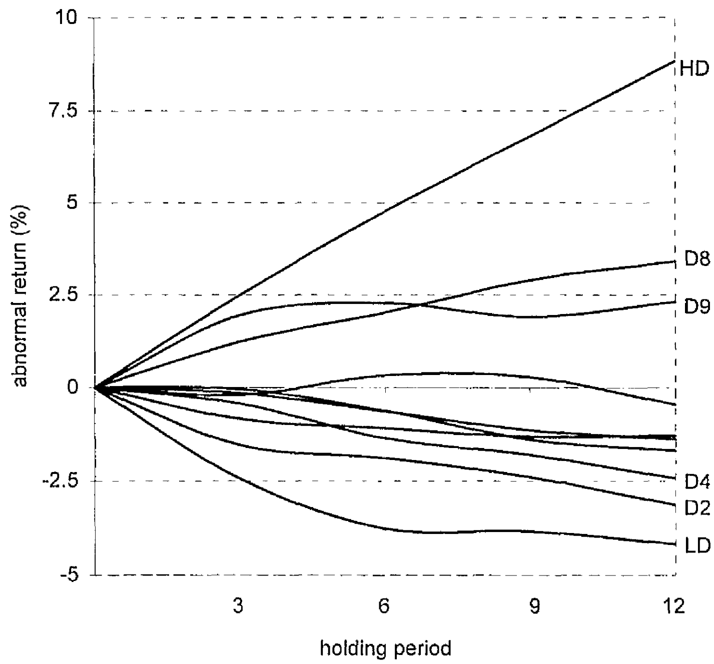

Figure 5.4.3 Holding-period abnormal returns of decile portfolios classified by $AR4D_0$

As with previous findings, the portfolios' earnings surprises reported in Panel D of Table 5.4.5 show that the three most recent earnings surprises tend to have similar patterns, indicating a possible relation among them. In addition, the momentum in earnings surprise itself is evident. High $AR4D$ tends to be followed by high $AR4D$ and high SUE measures at the next announcement subsequent to portfolio formation, and similarly for low values. The negative $REV6$s are still observed from the $AR4D$-classified decile portfolios.

Also, the $AR4D$-based decile portfolios' characteristics (see Panel C of Table 5.4.5) reveal a similar pattern to those classified by prior return, SUE, and $REV6$. These results indicate that the $AR4D$-based PAD profits are less likely to be due to systematic risk, low price, and high book-to-market effects. Because both the highest-and lowest-$AR4D_0$ decile portfolios tend to have low MV and low number of analysts (ANo) with the highest-$AR4D_0$ decile portfolio having the lowest MV and ANo, the $AR4D$-based PAD profits seem to be related to size and the number of analysts. Moreover, the highest-$AR4D_0$ decile portfolio's C/P ratio is on average significantly greater than the lowest-$AR4D_0$ decile portfolio's, resulting in a possible explanation of cash flow-to-price ratio for the PAD profits. However, all these conjectures are hard to maintain after examining the Fama-French three-factor-model estimates reported in Panel B of Table 5.4.5 and the sub-sample analysis presented in Table 5.4.6. Although the highest-$AR4D_0$ decile portfolio (HD) loads most heavily on size, which is consistent with its lowest average MV presented in Panel C of Table 5.4.5, adjusting for this does not eliminate its profitability. In fact, there is no significant difference in the loading on MV and B/M between LD and HD portfolios, and HD's three-factor-model-adjusted abnormal return remains the highest as mentioned previously, though portfolio LD appears to be riskier than portfolio HD. All the $AR4D$-based PAD profits are significant within various sub-samples except for the high-B/M sub-sample,[20] indicating that the $AR4D$-based PAD profits are unlikely to be attributable to market risk or other systematic effects.

Table 5.4.6 Sub-sample Analysis with Portfolios Being Classified by $AR4D_0$

This table presents the average semi-annual holding-period returns for the quintile portfolios and the PAD portfolio within various sub-samples stratified on MV, UP, C/P, B/M, β, and ANo. Each sub-sample contains one-third of the stocks in the earnings sample at the beginning of each holding period. For instance, for the 3 MV-based sub-samples the low-MV sub-sample contains the 1/3 lowest-MV stocks at the beginning of each holding period; the medium-MV sub-sample contains the 1/3 medium-MV stocks at the beginning of each holding period; and the high-MV sub-sample contains the 1/3 highest-MV stocks at the beginning of each holding period. Within each sub-sample, the quintile portfolios are formed at the beginning of each month (from July 1992 to June 1997) on the basis of most recent past 4-day abnormal returns around earnings announcement ($AR4D_0$) and held for 6

[20] The significance level within the medium-β sub-sample is at 6%.

months. At the start of each holding period, the stocks in a given sub-sample are ranked in ascending order based on their $AR4D_0$s. The equally-weighted portfolio of stocks in the lowest-$AR4D_0$ quintile is the lowest earnings surprise portfolio (LQ), the equally-weighted portfolio of stocks in the next quintile is denoted as $Q2$, and so on. The equally-weighted portfolio of stocks in the highest-$AR4D_0$ quintile is the highest earnings surprise portfolio (HQ). The PAD portfolio is the HQ portfolio minus the LQ portfolio ($HQ-LQ$). In Panel E β stands for Scholes-Williams beta, and in Panel F ANo stands for the number of analysts. Numbers in parentheses are Newey-West-standard-error-adjusted t-statistics. The test period is July 1992 to November 1997.

Sub-sample Analyses with portfolios being classified by $AR4D_0$

	Panel A: 3 MV-based sub-samples			**Panel B**: 3 UP-based sub-samples		
	Low-MV	Medium-MV	high-MV	low-UP	Medium-UP	high-UP
LQ	0.11230 (2.85)	0.05440 (1.70)	0.06971 (2.98)	0.10193 (2.87)	0.05997 (2.08)	0.05542 (3.02)
$Q2$	0.09647 (2.94)	0.07014 (2.50)	0.07075 (3.54)	0.11335 (2.86)	0.06461 (2.48)	0.07452 (3.75)
$Q3$	0.13605 (3.34)	0.06281 (2.28)	0.07677 (3.34)	0.11986 (2.61)	0.07703 (2.93)	0.07379 (3.21)
$Q4$	0.13396 (3.75)	0.09685 (3.37)	0.08866 (3.94)	0.12537 (3.56)	0.10364 (3.80)	0.09323 (4.06)
HQ	0.15764 (3.89)	0.12208 (3.95)	0.10486 (3.93)	0.15955 (3.60)	0.12215 (4.08)	0.10899 (4.69)
$HQ-LQ$	0.04534 (2.39)	0.06768 (8.35)	0.03515 (3.78)	0.05762 (3.00)	0.06218 (4.05)	0.05357 (5.43)
	Panel C: 3 C/P-based sub-samples			**Panel D**: 3 B/M-based sub-samples		
	Low-C/P	Medium-C/P	high-C/P	low-B/M	Medium-B/M	high-B/M
LQ	0.05953 (2.18)	0.06158 (2.32)	0.12665 (3.21)	0.06079 (2.07)	0.04960 (1.76)	0.12172 (3.36)
$Q2$	0.05801 (2.14)	0.07373 (3.32)	0.11148 (3.72)	0.07704 (3.03)	0.07744 (2.63)	0.10746 (3.27)
$Q3$	0.05264 (2.14)	0.07098 (2.89)	0.14090 (3.94)	0.08061 (2.97)	0.07157 (2.83)	0.10944 (3.30)
$Q4$	0.07066 (2.57)	0.09369 (3.48)	0.15007 (4.51)	0.10129 (3.76)	0.09091 (3.23)	0.11242 (3.79)
HQ	0.11039 (3.29)	0.11500 (3.98)	0.15885 (4.94)	0.14850 (4.16)	0.11773 (3.91)	0.12811 (4.13)
$HQ-LQ$	0.05085 (3.44)	0.05342 (5.68)	0.03220 (2.41)	0.08771 (5.31)	0.06813 (7.47)	0.00639 (0.42)
	Panel E: 3 β-based sub-samples			**Panel F**: 3 ANo-based sub-samples		
	Low-β	Medium-β	high-β	low-ANo	medium-ANo	high-ANo
LQ	0.09288 (3.51)	0.08300 (2.92)	0.06800 (1.81)	0.10925 (3.07)	0.07311 (2.24)	0.06473 (2.40)
$Q2$	0.06716 (3.00)	0.07678 (2.70)	0.10526 (2.99)	0.09895 (3.25)	0.08108 (2.97)	0.06321 (2.65)
$Q3$	0.08034 (2.82)	0.07781 (3.46)	0.08687 (3.00)	0.11656 (3.50)	0.07160 (2.50)	0.06953 (2.98)
$Q4$	0.11566 (3.79)	0.10427 (4.01)	0.09811 (3.26)	0.13546 (4.18)	0.10017 (3.19)	0.08181 (4.02)
HQ	0.15329 (4.36)	0.11342 (5.00)	0.12716 (3.33)	0.15624 (4.24)	0.12859 (4.13)	0.10353 (3.83)
$HQ-LQ$	0.06041 (3.46)	0.03042 (1.87)	0.05916 (4.45)	0.04699 (2.55)	0.05548 (5.06)	0.03880 (6.71)

5.5 Relation between the Three Earnings Surprise Measures

The results reported in the last section imply that the three measures of earnings surprise (SUE, $AR4D$, and $REV6$) may be related to each other. At the same time, the previous evidence also suggests that they may each contain different information. This section examines how closely they are associated. The methodology used in this section is similar to Zarowin's (1989, 1990) technique of controlling for size, which can be denoted a *two-dimensional analysis*. Specifically, this technique is designed to examine one effect of interest after controlling for the other. For example, we can examine the SUE-based ($AR4D$-based) PAD effect after controlling for the $AR4D$-based (SUE-based) PAD effect to see the relation between SUE and $AR4D$. I have used this method to control for stocks' C/P ratios in Chapter 4. For details of the procedure for performing this two-dimensional analysis see Section 4.5 in Chapter 4. Note that the procedure adopted in this section and in the next chapter is slightly different from Chapter 4 where the stocks are independently sorted into quintile portfolios, while in this section and the next chapter the stocks in the earnings sample are independently ranked into three portfolios. Because I will use this technique to examine different relations between different variables, specific descriptions with respect to the use of the method are demonstrated in each corresponding table.

As in the last section, I also estimate the Fama-French three-factor model for various two-dimensional portfolios in this section in addition to the reports of portfolios' raw returns. At the beginning of each test period from July 1992 to June 1997, portfolios' monthly returns are traced for 6 months. This procedure leads to 360 overlapping monthly returns for each portfolio over which the Fama-French three-factor model is estimated.

(1) Relation between SUE ***and*** $AR4D$

Table 5.5.1 summarises the results for the SUE_0- and $AR4D_0$-based portfolios. The nine $SUE_0 - AR4D_0$ portfolios' holding-period returns over 6 and 12 months reported in Panel A show that both SUE and $AR4D$ predict continued drifts in returns. For example, when we hold Ls (low-SUE_0) fixed, the returns increase from low-, to medium-, to high-$AR4D_0$ portfolios. The annual returns are 9.49%, 14.20% and 18.09% for these portfolios of low-$AR4D_0$-low-SUE_0 portfolio ($LaLs$), medium-$AR4D_0$-low-SUE_0 portfolio ($MaLs$), and high-$AR4D_0$-low-SUE_0 portfolio ($HaLs$), respectively. However, the three $AR4D_0$-matched arbitrage portfolios' returns reported in the first three columns in Panel B of Table 5.5.1 are insignificant for both holding periods of 6 and 12 months except for the high-$AR4D_0$ matched portfolio's 6-month holding-period return. By contrast, all three SUE_0-matched arbitrage portfolios ($HaLs - LaLs$, $HaMs - LaMs$, $HaHs - LaHs$) realise significant holding-period profits. These results are generally consistent with the estimates of the Fama-French three-factor model. The three SUE_0-matched arbitrage portfolios earn significantly positive abnormal monthly returns of 0.489% ($t = 3.03$), 0.853% ($t = 4.77$), and 1.067% ($t = 5.25$) respectively, whereas a significant SUE_0-based PAD profit is only observed within the high-$AR4D_0$ stocks, which is 0.603% ($t = 3.39$). In addition, the match method is successful on the whole. The three

$AR4D_0$-matched arbitrage portfolios' $AR4D_0$s tend to be insignificant, while the three SUE_0-matched arbitrage portfolios' average SUE_0s are not statistically significant with the exception of the medium-SUE_0 matched one. Accordingly, these results suggest that the $AR4D_0$ measure almost subsumes the SUE-related information, but the SUE measure cannot explain the $AR4D$-based PAD profits.

Table 5.5.1 Relationships between SUE_0- and $AR4D_0$-based PAD Effects: Examining SUE_0-based ($AR4D_0$-based) PAD Effect after Controlling for $AR4D_0$-based (SUE_0-based) PAD Effect

At the beginning of every month from July 1992 to June 1997, all stocks in the earnings sample are sorted in ascending order based on their most recent past standardised unexpected earnings (SUE_0) and assigned to one of three equally-sized portfolios. The first one is referred to as the low-SUE_0 portfolio (Ls); the middle one as the medium-SUE_0 portfolio (Ms); and the third one as the high-SUE_0 portfolio (Hs). All stocks are also independently sorted in ascending order based on their most recent past 4-day abnormal returns around earnings announcements ($AR4D_0$) and assigned to one of three equally-sized portfolios. The first portfolio including the 1/3 lowest-$AR4D_0$ stocks is denoted as low-$AR4D_0$ portfolio (La); the middle one as medium-$AR4D_0$ portfolio (Ma); and the third one containing the 1/3 highest-$AR4D_0$ stocks is referred to as high-$AR4D_0$ portfolio (Ha). The intersections of the three SUE_0-sorted portfolios (Ls, Ms, Hs) and the three $AR4D_0$-sorted portfolios (La, Ma, Ha) give nine SUE_0-$AR4D_0$ portfolios. The nine SUE_0-$AR4D_0$ portfolios are: low-$AR4D_0$-low-SUE_0 portfolio ($LaLs$), low-$AR4D_0$-medium-SUE_0 portfolio ($LaMs$), low-$AR4D_0$-high-SUE_0 portfolio ($LaHs$); medium-$AR4D_0$-low-SUE_0 portfolio ($MaLs$), medium-$AR4D_0$-medium-SUE_0 portfolio ($MaMs$), medium-$AR4D_0$-high-SUE_0 portfolio ($MaHs$); high-$AR4D_0$-low-SUE_0 portfolio ($HaLs$), high-$AR4D_0$-medium-SUE_0 portfolio ($HaMs$), and high-$AR4D_0$-high-SUE_0 portfolio ($HaHs$). All stocks are equally-weighted in a portfolio. Seven arbitrage portfolios are constructed based on the nine SUE_0-$AR4D_0$ portfolios. Three of the seven arbitrage portfolios are $AR4D_0$-matched, and they are: low-$AR4D_0$-high-SUE_0 portfolio minus low-$AR4D_0$-low-SUE_0 portfolio ($LaHs-LaLs$), medium-$AR4D_0$-high-SUE_0 portfolio minus medium-$AR4D_0$- low-SUE_0 portfolio ($MaHs-MaLs$), and high-$AR4D_0$-high-SUE_0 portfolio minus high-$AR4D_0$-low-SUE_0 portfolio ($HaHs-HaLs$). Another three of the seven arbitrage portfolios are SUE_0-matched, and they are: high-$AR4D_0$-low-SUE_0 portfolio minus low-$AR4D_0$-low-SUE_0 portfolio ($HaLs-LaLs$), high-$AR4D_0$-medium-SUE_0 portfolio minus low-$AR4D_0$-medium-SUE_0 portfolio ($HaMs-LaMs$), and high-$AR4D_0$-high-SUE_0 portfolio minus low-$AR4D_0$-high-SUE_0 portfolio ($HaHs-LaHs$). One of the seven arbitrage portfolios is miscellaneous, and it is high-$AR4D_0$-high-SUE_0 portfolio minus low-$AR4D_0$-low-SUE_0 portfolio ($HaHs-LaLs$). Panel A reports the average 6-month holding-period returns (ret_6), 12-month holding-period returns (ret_{12}), most recent past standardised unexpected earnings surprise (SUE_0), most recent past 4-day abnormal return around earnings announcement ($AR4D_0$) of the nine $AR4D_0$-SUE_0 portfolios. P_sz is the average number of stocks in a portfolio (i.e., portfolio size). a_p, b_p, s_p, and h_p are estimates of the Fama-French three-factor model, which is,

$$r_{P\tau} - r_{f\tau} = a_P + b_P(r_{m\tau} - r_{f\tau}) + s_P SMB_\tau + h_P HML_\tau + \varepsilon_{P\tau}.$$

The two factor-mimicking portfolios of SMB_τ and HML_τ, and the value-weighted market return, $r_{m\tau}$, are constructed based on the accounting sample (for detailed descriptions of the constructions of SMB_τ and HML_τ, and other notation of the 3-factor model see Section 4.4 of Chapter 4). The results of the seven arbitrage portfolios are given in Panel B. The R^2s of the regressions of the Fama-French three-factor model are reported in the bottom line of each panel. Numbers in parentheses are t-statistics relative to the autocorrelation-adjusted standard error of the mean.

Relationship between SUE_0 and $AR4D_0$

Panel A: 9 SUE_0 - $AR4D_0$ portfolios

	$LaLs$	$LaMs$	$LaHs$	$MaLs$	$MaMs$	$MaHs$	$HaLs$	$HaMs$	$HaHs$
ret_6	0.0411 (2.60)	0.0726 (2.84)	0.0732 (2.30)	0.0703 (2.63)	0.0790 (3.35)	0.0833 (2.96)	0.0848 (3.44)	0.1058 (4.91)	0.1188 (4.29)
ret_{12}	0.0949 (4.20)	0.1347 (2.75)	0.1750 (2.62)	0.1420 (2.99)	0.1668 (3.77)	0.1636 (2.91)	0.1809 (4.02)	0.1986 (5.60)	0.2143 (3.97)
SUE_0	−0.8324 (−36.6)	0.2119 (5.08)	1.0556 (17.1)	−0.8419 (−19.5)	0.2212 (5.23)	1.0718 (20.5)	−0.8343 (−20.7)	0.2489 (5.57)	1.1068 (25.4)
$AR4D_0$(%)	−7.021 (−16.4)	−5.968 (−33.5)	−5.498 (−19.6)	0.482 (3.60)	0.515 (4.08)	0.524 (4.41)	7.706 (19.5)	7.132 (22.0)	8.034 (23.9)
P_sz	61.33	53.30	40.00	49.88	51.50	54.38	43.42	50.97	60.25
a_P(%)	−0.502 (−4.07)	−0.312 (−2.64)	−0.468 (−2.32)	−0.209 (−1.30)	0.062 (0.53)	0.027 (0.16)	−0.004 (−0.02)	0.541 (4.20)	0.599 (5.82)
b_P	1.0704 (25.2)	1.1485 (33.3)	1.1217 (31.5)	1.0076 (23.5)	0.9461 (33.0)	1.0241 (37.8)	1.0195 (24.0)	1.0269 (28.5)	1.0554 (28.1)
s_P	0.6679 (9.29)	0.7049 (22.2)	0.7430 (23.5)	0.6645 (18.0)	0.6677 (27.8)	0.6561 (22.3)	0.7399 (6.57)	0.6454 (8.89)	0.7615 (17.2)
h_P	0.0792 (1.16)	0.2933 (4.77)	0.4459 (6.03)	0.2013 (3.77)	0.2107 (4.24)	0.3576 (4.34)	0.1680 (1.90)	0.1370 (2.81)	0.2769 (4.09)
R^2	0.8117	0.8481	0.8074	0.8267	0.8065	0.8475	0.7658	0.8412	0.8464

Panel B: 7 arbitrage portfolios

	$LaHs-LaLs$	$MaHs-MaLs$	$HaHs-HaLs$	$HaLs-LaLs$	$HaMs-LaMs$	$HaHs-LaHs$	$HaHs-LaLs$
ret_6	0.0321 (1.48)	0.0130 (0.87)	0.0340 (2.79)	0.0437 (4.05)	0.0332 (2.10)	0.0456 (3.53)	0.0777 (4.70)
ret_{12}	0.0800 (1.48)	0.0216 (0.95)	0.0334 (1.19)	0.0859 (3.20)	0.0639 (3.37)	0.0393 (1.67)	0.1193 (3.11)
SUE_0	1.8880 (35.0)	1.9137 (53.9)	1.9411 (36.5)	−0.0019 (−0.06)	0.0370 (3.31)	0.0512 (1.74)	1.9392 (51.5)
$AR4D_0$(%)	1.523 (3.79)	0.041 (0.67)	0.328 (1.52)	14.727 (41.4)	13.100 (43.7)	13.532 (32.9)	15.055 (34.9)
a_P(%)	0.034 (0.14)	0.235 (0.92)	0.603 (3.39)	0.498 (3.03)	0.853 (4.77)	1.067 (5.25)	1.101 (7.43)
b_P	0.0513 (1.34)	0.0166 (0.33)	0.0359 (0.68)	−0.0509 (−0.88)	−0.1216 (−2.64)	−0.0663 (−1.34)	−0.0150 (−0.30)
s_P	0.0752 (1.00)	−0.0084 (−0.22)	0.0216 (0.22)	0.0720 (0.97)	−0.0595 (−0.80)	0.0184 (0.39)	0.0936 (1.67)
h_P	0.3667 (3.42)	0.1563 (2.01)	0.1089 (0.90)	0.0888 (1.07)	−0.1563 (−2.31)	−0.1690 (−1.83)	0.1977 (2.10)
R^2	0.1014	0.0259	0.0111	0.0407	0.0482	0.0337	0.0721

(2) Relation between SUE ***and*** $REV6$

The two-dimensional analysis on SUE and $REV6$ is presented in Table 5.5.2. Consistent with previous evidence, the results in Panel A of Table 5.5.2 show that holding $REV6_0$ fixed the holding-period returns are generally higher (lower) for high (low) SUE_0-stocks, but this is not true for $REV6_0$ stocks when holding SUE_0 fixed. The low-$REV6_0$ stocks have higher holding-period returns than medium-$REV6_0$ stocks within the low-, medium- and high-SUE_0 categories. For instance, holding medium-SUE_0 fixed, the low-$REV6_0$ stocks (i.e., $LrMs$ portfolio) earn average annual returns of 17.81%, while this is 12.27% for the medium-$REV6_0$ stocks (i.e., $MrMs$ portfolio). These results are consistent with the U-shape in $REV6_0$-based holding-period returns presented in the last section. Also, the higher returns of the low-$REV6_0$ stocks seem to be caused by low-$REV6_0$ stocks being small, high-B/M, and high-risk stocks. Continuing with the above example, the estimates of the three-factor model show that $LrMs$ is more heavily loaded on MV and B/M, and it has higher risk exposure than $MrMs$. The performances of the $REV6_0$-classified stocks are generally steadily increasing from low- to high-$REV6_0$ stocks after adjusting for the three factors.

Table 5.5.2 Relationships between SUE_0- and $REV6_0$-based PAD Effects: Examining SUE_0-based ($REV6_0$-based) PAD Effect after Controlling for $REV6_0$-based (SUE_0-based) PAD Effect

At the beginning of every month from July 1992 to June 1997, all stocks in the earnings sample are sorted in ascending order based on their most recent past standardised unexpected earnings (SUE_0) and assigned to one of three equally-sized portfolios. The first one is referred to as the low-SUE_0 portfolio (Ls); the middle one as the medium-SUE_0 portfolio (Ms); and the third one as the high-SUE_0 portfolio (Hs). All stocks are also independently sorted in ascending order based on their cumulative price-deflated earnings forecast revision over prior 6 months ($REV6_0$) and assigned to one of three equally-sized portfolios. The first portfolio including the 1/3 lowest-$REV6_0$ stocks is denoted as low-$REV6_0$ portfolio (Lr); the middle one as medium-$REV6_0$ portfolio (Mr); and the third one containing the 1/3 highest- $REV6_0$ stocks is referred to as high- $REV6_0$ portfolio (Hr). The intersections of the three SUE_0-sorted portfolios (Ls, Ms, Hs) and the three $REV6_0$-sorted portfolios (Lr, Mr, Hr) give nine SUE_0- $REV6_0$ portfolios. The nine SUE_0- $REV6_0$ portfolios are: low- $REV6_0$-low- SUE_0 portfolio ($LrLs$), low- $REV6_0$-medium- SUE_0 portfolio ($LrMs$), low- $REV6_0$-high- SUE_0 portfolio ($LrHs$); medium- $REV6_0$-low- SUE_0 portfolio ($MrLs$), medium- $REV6_0$-medium- SUE_0 portfolio ($MrMs$), medium- $REV6_0$-high- SUE_0 portfolio ($MrHs$); high- $REV6_0$-low- SUE_0 portfolio ($HrLs$), high- $REV6_0$-medium- SUE_0 portfolio ($HrMs$), and high- $REV6_0$-high- SUE_0 portfolio ($HrHs$). All stocks are equally-weighted in a portfolio. Seven arbitrage portfolios are constructed based on the nine SUE_0- $REV6_0$ portfolios. Three of the seven arbitrage portfolios are $REV6_0$-matched, and they are: low- $REV6_0$-high- SUE_0 portfolio minus low- $REV6_0$-low- SUE_0 portfolio ($LrHs-LrLs$), medium- $REV6_0$-high- SUE_0 portfolio minus medium- $REV6_0$- low- SUE_0 portfolio ($MrHs-MrLs$), and high- $REV6_0$-high- SUE_0 portfolio minus high- $REV6_0$-low- SUE_0 portfolio ($HrHs-HrLs$). Another three of the seven arbitrage portfolios are SUE_0-matched, and they are: high- $REV6_0$-low- SUE_0 portfolio minus low- $REV6_0$-low- SUE_0 portfolio ($HrLs-LrLs$), high- $REV6_0$-medium- SUE_0 portfolio minus low- $REV6_0$-medium- SUE_0 portfolio ($HrMs-LrMs$), and high- $REV6_0$-high- SUE_0 portfolio minus low- $REV6_0$-high- SUE_0 portfolio ($HrHs-LrHs$). One of the seven arbitrage portfolios is miscellaneous, and it is high- $REV6_0$-high- SUE_0 portfolio minus low- $REV6_0$-low- SUE_0 portfolio ($HrHs-LrLs$). Panel A reports the average 6-month holding-period returns (ret_6), 12-month holding-period returns (ret_{12}), most recent past standardised unexpected earnings surprise (SUE_0), cumulative price-deflated earnings forecast revision over prior 6 months ($REV6_0$) of the nine SUE_0- $REV6_0$ portfolios. P_sz is the average number of stocks in a portfolio (i.e., portfolio size). a_p, b_p, s_p, and h_p are estimates of the Fama-French three-factor model, which is,

$$r_{P\tau}-r_{f\tau}=a_P+b_P(r_{m\tau}-r_{f\tau})+s_P SMB_\tau+h_P HML_\tau+\varepsilon_{P\tau}.$$

The two factor-mimicking portfolios of SMB_τ and HML_τ, and the value-weighted market return, $r_{m\tau}$, are constructed based on the accounting sample (for detailed descriptions of the constructions of SMB_τ and HML_τ, and other notation of the 3-factor model see Section 4.4 of Chapter 4). The results of the seven arbitrage portfolios are given in Panel B. The R^2s of the regressions of the Fama-French three-factor model are reported in the bottom line of each panel. Numbers in parentheses are t-statistics relative to the autocorrelation-adjusted standard error of the mean.

Relationship between SUE_0 and $REV6_0$									
Panel A: 9 SUE_0 - $REV6_0$ portfolios									
	$LrLs$	$LrMs$	$LrHs$	$MrLs$	$MrMs$	$MrHs$	$HrLs$	$HrMs$	$HrHs$
ret_6	0.0571 (2.31)	0.0847 (2.36)	0.0784 (2.17)	0.0460 (2.26)	0.0633 (3.19)	0.0778 (3.31)	0.0889 (3.77)	0.1108 (4.75)	0.1142 (4.43)
ret_{12}	0.1213 (2.85)	0.1781 (2.50)	0.1796 (2.28)	0.0902 (3.31)	0.1227 (3.20)	0.1392 (3.45)	0.1663 (4.63)	0.2019 (5.70)	0.2208 (4.78)
SUE_0	−0.9247 (−31.0)	0.1993 (4.38)	1.0767 (20.1)	−0.8160 (−23.4)	0.2378 (5.44)	1.0745 (20.7)	−0.8250 (−20.7)	0.2362 (5.11)	1.0934 (21.1)
$REV6_0$(%)	−4.192 (−7.91)	−3.380 (−7.36)	−2.749 (−11.7)	−0.185 (−3.98)	−0.164 (−3.81)	−0.156 (−3.62)	1.353 (10.9)	1.036 (8.63)	1.024 (17.8)
P_sz	59.82	42.03	35.55	42.22	49.58	46.53	35.37	46.72	55.32
a_P(%)	−0.572 (−4.47)	−0.371 (−1.82)	−0.492 (−2.54)	−0.606 (−4.83)	−0.356 (−3.52)	−0.145 (−1.44)	0.042 (0.24)	0.353 (2.93)	0.332 (2.55)
b_P	1.0993 (19.6)	1.2287 (23.9)	1.2194 (26.2)	0.9837 (23.1)	1.0444 (41.1)	1.0541 (18.4)	1.0826 (23.7)	1.0789 (36.0)	1.0890 (29.7)
s_P	0.7538 (7.00)	0.8030 (16.0)	0.9852 (17.3)	0.4957 (12.0)	0.4775 (12.7)	0.4634 (11.3)	0.6138 (6.61)	0.5781 (11.4)	0.5781 (11.6)
h_P	0.2640 (4.84)	0.5474 (4.80)	0.7237 (5.89)	0.1706 (3.00)	0.1072 (1.80)	0.1577 (2.15)	−0.0019 (−0.02)	0.0768 (1.28)	0.2293 (4.72)
R^2	0.8112	0.8053	0.7887	0.7459	0.8364	0.7597	0.7542	0.7888	0.8236

Panel B: 7 arbitrage portfolios							
	$LrHs-LrLs$	$MrHs-MrLs$	$HrHs-HrLs$	$HrLs-LrLs$	$HrMs-LrMs$	$HrHs-LrHs$	$HrHs-LrLs$
ret_6	0.0214 (1.16)	0.0318 (4.53)	0.0253 (2.25)	0.0319 (2.47)	0.0261 (1.19)	0.0357 (1.94)	0.0571 (7.13)
ret_{12}	0.0583 (1.26)	0.0490 (2.20)	0.0545 (2.54)	0.0450 (1.69)	0.0238 (0.61)	0.0412 (0.92)	0.0995 (6.28)
SUE_0	2.0013 (37.2)	1.8905 (45.6)	1.9184 (37.4)	0.0997 (4.16)	0.0369 (5.05)	0.0167 (0.47)	2.0181 (41.5)
$REV6_0$(%)	1.442 (3.06)	0.028 (3.90)	−0.329 (−3.21)	5.545 (10.0)	4.416 (10.0)	3.774 (17.8)	5.216 (9.83)
a_P(%)	0.080 (0.40)	0.461 (4.59)	0.290 (1.85)	0.614 (4.59)	0.724 (3.05)	0.823 (4.61)	0.903 (6.51)
b_P	0.1201 (1.86)	0.0704 (1.53)	0.0064 (0.15)	−0.0167 (−0.26)	−0.1498 (−2.97)	−0.1304 (−1.97)	−0.0103 (−0.15)
s_P	0.2314 (1.64)	−0.0323 (−0.87)	−0.0357 (−0.65)	−0.1400 (−3.40)	−0.2249 (−4.01)	−0.4071 (−5.29)	−0.1757 (−2.38)
h_P	0.4597 (3.40)	−0.0129 (−0.18)	0.2312 (1.68)	−0.2659 (−2.29)	−0.4706 (−3.38)	−0.4945 (−4.11)	−0.0347 (−0.66)
R^2	0.1683	0.0284	0.0484	0.0898	0.1824	0.2910	0.0944

The results in Panel B of Table 5.5.2 show that the significant SUE_0-based PAD effect is generally observed within the median- and high-$REV6_0$ categories. The estimates of the Fama-French three-factor model also confirm the significant SUE_0-based PAD profits within the medium- and high-$REV6_0$ stocks, and the SUE_0-based PAD profit also tends to be insignificant within the low-$REV6_0$ stocks after adjusting for the three factors. This evidence indicates that $REV6_0$ does have some power in explaining the SUE_0-based PAD profits, but it cannot completely account for the SUE measure. Because of the observed U-shape in $REV6_0$-based holding-period returns and the shorter-lived $REV6_0$-related PAD effect, the holding-period returns of the medium- or high-SUE_0 matched portfolios ($HrMs - LrMs$, $HrHs - LrHs$) tend to be insignificant especially for 12-month holding periods. As noticed above, however, the estimates of the Fama-French three-factor model show that the low-$REV6_0$ portfolios are more heavily loaded on small and value stocks than high-$REV6_0$ portfolios. This is indicated by the significantly negative coefficient estimates of s_p and h_p of the three SUE_0-matched portfolios reported in Panel B of Table 5.5.2. As a result, all three SUE_0-matched portfolios earn significantly positive three-factor-adjusted $REV6_0$-related PAD profits, and the magnitudes are greater than the corresponding SUE_0-based PAD profits. The evidence presented in Table 5.5.2 indicates that the SUE_0-based ($REV6_0$-based) PAD effect can not subsume the $REV6_0$-based (SUE_0-based) PAD effect, and the two earnings surprise variables seem to contain different pieces of information. Nonetheless, the SUE_0 ($REV6_0$) measure does have some limited power to explain the $REV6_0$ (SUE_0) measure. Both controlled PAD profits are smaller than uncontrolled ones (see the empirical results in the last section).

(3) Relation between $AR4D$ ***and*** $REV6$

The results of examining the relation between the two earnings surprise measures of $AR4D$ and $REV6$ are reported in Table 5.5.3. Both Panels A and B reveal significant $AR4D$-based PAD effects. The $AR4D$ measure predicts post-earnings-announcement drift in returns over 6 and 12 months. The Fama-French-three-factor-adjusted $AR4D$-based PAD profits are also highly significantly positive after controlling for the $REV6$-based PAD effect. On the other hand, the $REV6$-related PAD is also pronounced within the high-$AR4D$ category over the holding period of 6 months, which realises an average semi-annual $REV6$-based PAD profit of 3.80% ($t = 3.21$). However, the $REV6$-based PAD effect is insignificant within the low-$AR4D$ category. Within the medium-$AR4D$ stocks, the $REV6$-based PAD profit is only observed for the shorter holding period of 6 months at the 8% significant level (3.36% with a t-statistic of 1.75). Similar to previous findings, medium- and high-$AR4D$-matched portfolios realise significantly positive $REV6$-based PAD profits after adjusting for the three factors. Nevertheless, the magnitudes of the $REV6$-based PAD profits are on average smaller than the $AR4D$-based ones, and within the low-$AR4D$ category (portfolio *HrLa–LrLa*) the three-factor-adjusted $REV6$-based PAD profit is insignificant. These results suggest that the $AR4D$-linked PAD is stronger than the $REV6$-based PAD. The $REV6$-based PAD cannot explain the $AR4D$-classified PAD and the stronger $AR4D$-classified PAD can only partially account for the $REV6$-related PAD.

Table 5.5.3 Relationships between $AR4D_0$- and $REV6_0$-based PAD Effects: Examining $AR4D_0$-based ($REV6_0$-based) PAD Effect after Controlling for $REV6_0$-based ($AR4D_0$-based) PAD Effect

At the beginning of every month from July 1992 to June 1997, all stocks in the earnings sample are sorted in ascending order based on their most recent past 4-day abnormal returns around earnings announcements ($AR4D_0$) and assigned to one of three equally-sized portfolios. The first one is referred to as the low-$AR4D_0$ portfolio (La); the middle one as the medium-$AR4D_0$ portfolio (Ma); and the third one as the high-$AR4D_0$ portfolio (Ha). All stocks are also independently sorted in ascending order based on their cumulative price-deflated earnings forecast revision over prior 6 months ($REV6_0$) and assigned to one of three equally-sized portfolios. The first portfolio including the 1/3 lowest-$REV6_0$ stocks is denoted as low-$REV6_0$ portfolio (Lr); the middle one as medium-$REV6_0$ portfolio (Mr); and the third one containing the 1/3 highest-$REV6_0$ stocks is referred to as high-$REV6_0$ portfolio (Hr). The intersections of the three $AR4D_0$-sorted portfolios (La, Ma, Ha) and the three $REV6_0$-sorted portfolios (Lr, Mr, Hr) give nine $AR4D_0$-$REV6_0$ portfolios. The nine $AR4D_0$-$REV6_0$ portfolios are: low-$REV6_0$-low-$AR4D_0$ portfolio ($LrLa$), low-$REV6_0$-medium-$AR4D_0$ portfolio ($LrMa$), low-$REV6_0$-high-$AR4D_0$ portfolio ($LrHa$); medium-$REV6_0$-low-$AR4D_0$ portfolio ($MrLa$), medium-$REV6_0$-medium-$AR4D_0$ portfolio ($MrMa$), medium-$REV6_0$-high-$AR4D_0$ portfolio ($MrHa$); high-$REV6_0$-low-$AR4D_0$ portfolio ($HrLa$), high-$REV6_0$-medium-$AR4D_0$ portfolio ($HrMa$), and high-$REV6_0$-high-$AR4D_0$ portfolio ($HrHa$). All stocks are equally-weighted in a portfolio. Seven arbitrage portfolios are constructed based on the nine $AR4D_0$-$REV6_0$ portfolios. Three of the seven arbitrage portfolios are $REV6_0$-matched, and they are: low-$REV6_0$-high-$AR4D_0$ portfolio minus low-$REV6_0$-low-$AR4D_0$ portfolio ($LrHa-LrLa$), medium-$REV6_0$-high-$AR4D_0$ portfolio minus medium-$REV6_0$-low-$AR4D_0$ portfolio ($MrHa-MrLa$), and high-$REV6_0$-high-$AR4D_0$ portfolio minus high-$REV6_0$-low-$AR4D_0$ portfolio ($HrHa-HrLa$). Another three of the seven arbitrage portfolios are $AR4D_0$-matched, and they are: high-$REV6_0$-low-$AR4D_0$ portfolio minus low-$REV6_0$-low-$AR4D_0$ portfolio ($HrLa-LrLa$), high-$REV6_0$-medium-$AR4D_0$ portfolio minus low-$REV6_0$-medium-$AR4D_0$ portfolio ($HrMa-LrMa$), and high-$REV6_0$-high-$AR4D_0$ portfolio minus low-$REV6_0$-high-$AR4D_0$ portfolio ($HrHa-LrHa$). One of the seven arbitrage portfolios is miscellaneous, and it is high-$REV6_0$-high-$AR4D_0$ portfolio minus low-$REV6_0$-low-$AR4D_0$ portfolio ($HrHa-LrLa$). Panel A reports the average 6-month holding-period returns (ret_6), 12-month holding-period returns (ret_{12}), most recent past 4-day abnormal returns around earnings announcements ($AR4D_0$), cumulative price-deflated earnings forecast revision over prior 6 months ($REV6_0$) of the nine $AR4D_0$-$REV6_0$ portfolios. P_sz is the average number of stocks in a portfolio (i.e., portfolio size). a_p, b_p, s_p, and h_p are estimates of the Fama-French three-factor model, which is,

$$r_{p\tau} - r_{f\tau} = a_p + b_p(r_{m\tau} - r_{f\tau}) + s_p SMB_\tau + h_p HML_\tau + \varepsilon_{p\tau}.$$

The two factor-mimicking portfolios of SMB_τ and HML_τ, and the value-weighted market return, $r_{m\tau}$, are constructed based on the accounting sample (for detailed descriptions of the constructions of SMB_τ and HML_τ, and other notation of the 3-factor model see Section 4.4 of Chapter 4). The results of the seven arbitrage portfolios are given in Panel B. The R^2s of the regressions of the Fama-French three-factor model are reported in the bottom line of each panel. Numbers in parentheses are t-statistics relative to the autocorrelation-adjusted standard error of the mean.

Relationship between $AR4D_0$ and $REV6_0$									
Panel A: 9 $AR4D_0$ - $REV6_0$ portfolios									
	$LrLa$	$LrMa$	$LrHa$	$MrLa$	$MrMa$	$MrHa$	$HrLa$	$HrMa$	$HrHa$
ret_6	0.0618 (2.04)	0.0680 (2.03)	0.0939 (3.09)	0.0525 (2.68)	0.0564 (2.63)	0.0795 (3.57)	0.0602 (2.82)	0.1017 (3.96)	0.1319 (5.13)
ret_{12}	0.1346 (2.22)	0.1567 (2.48)	0.1908 (3.25)	0.1060 (3.04)	0.1054 (3.10)	0.1446 (4.17)	0.1395 (4.29)	0.1894 (4.56)	0.2388 (5.39)
$AR4D_0$(%)	−8.110 (−26.2)	0.357 (2.76)	8.164 (19.1)	−4.786 (−33.9)	0.443 (3.87)	6.493 (24.7)	−4.779 (−24.0)	0.572 (4.88)	7.674 (27.7)
$REV6_0$(%)	−4.361 (−9.14)	−2.581 (−9.40)	−3.101 (−10.9)	−0.190 (−4.20)	−0.161 (−3.69)	−0.153 (−3.48)	1.179 (9.45)	0.996 (16.0)	1.190 (8.59)
P_sz	65.65	39.93	31.82	44.25	50.28	43.80	27.50	48.12	61.78
a_P(%)	−0.688 (−4.93)	−0.540 (−3.00)	−0.075 (−0.37)	−0.555 (−4.81)	−0.444 (−3.82)	−0.094 (−0.96)	−0.522 (−3.39)	0.268 (1.80)	0.606 (5.00)
b_P	1.2460 (31.1)	1.1009 (16.8)	1.1142 (17.7)	1.0736 (25.4)	1.0045 (35.1)	1.0194 (22.6)	1.1675 (24.3)	1.0166 (28.5)	1.1023 (33.3)
s_P	0.8343 (16.0)	0.8541 (17.7)	0.8340 (8.11)	0.4520 (16.0)	0.4830 (15.7)	0.5021 (7.49)	0.5390 (7.80)	0.5381 (12.9)	0.6373 (8.48)
h_P	0.4588 (5.65)	0.5723 (7.02)	0.4560 (3.54)	0.1723 (3.17)	0.1131 (2.20)	0.1315 (1.49)	0.1275 (1.88)	0.0547 (1.31)	0.1910 (2.98)
R^2	0.8269	0.7967	0.7061	0.7825	0.8032	0.7862	0.7291	0.8061	0.8189

Panel B: 7 arbitrage portfolios							
	$LrHa-LrLa$	$MrHa-MrLa$	$HrHa-HrLa$	$HrLa-LrLa$	$HrMa-LrMa$	$HrHa-LrHa$	$HrHa-LrLa$
ret_6	0.0322 (3.33)	0.0271 (3.63)	0.0717 (6.28)	−0.0015 (−0.08)	0.0336 (1.75)	0.0380 (3.21)	0.0701 (5.31)
ret_{12}	0.0563 (3.13)	0.0385 (5.39)	0.0992 (4.26)	0.0050 (0.13)	0.0328 (0.92)	0.0479 (1.63)	0.1042 (4.22)
$AR4D_0$(%)	16.274 (29.9)	11.279 (40.8)	12.453 (37.5)	3.330 (10.8)	0.215 (6.07)	−0.491 (−1.50)	15.783 (36.9)
$REV6_0$(%)	1.259 (3.24)	0.037 (5.17)	0.011 (0.07)	5.540 (12.3)	3.577 (13.6)	4.292 (12.4)	5.551 (11.8)
a_P(%)	0.613 (2.91)	0.460 (4.06)	1.127 (8.88)	0.166 (0.84)	0.808 (4.54)	0.680 (4.01)	1.294 (8.17)
b_P	−0.1318 (−2.00)	−0.0542 (−2.19)	−0.0652 (−1.69)	−0.0785 (−1.28)	−0.0844 (−1.04)	−0.0119 (−0.20)	−0.1437 (−2.69)
s_P	−0.0003 (−0.003)	0.0500 (0.83)	0.0983 (2.39)	−0.2952 (−5.71)	−0.3160 (−5.50)	−0.1967 (−3.15)	−0.1969 (−3.66)
h_P	−0.0027 (−0.02)	−0.0408 (−0.44)	0.0636 (0.70)	−0.3313 (−2.93)	−0.5177 (−6.56)	−0.2650 (−1.71)	−0.2677 (−2.14)
R^2	0.0250	0.0309	0.0595	0.1672	0.2899	0.0982	0.1183

To summarise, the results presented in this section echo the evidence documented in the last section. Amongst the three earnings surprises (SUE, $AR4D$, and $REV6$), the $AR4D$ measure shows the strongest PAD effect. However, the $AR4D$ measure cannot subsume other two measures of SUE and $REV6$ completely, and the latter two cannot account for each other. The evidence suggests that the three earnings surprise measures contain common information, but they do not reflect exactly the same information.

5.6 General Conclusions

All three earnings surprise variables of SUE, $REV6$, and $AR4D$ confirm the systematic post-earnings-announcement drift in security returns. Generally, the more positive the unexpected earnings news, the greater the post-announcement returns, while the more negative the unexpected earnings information, the smaller the post-announcement returns. Further investigation via sub-sample analysis shows that the presence of PAD profits are unlikely to be related to systematic risk and various effects such as size, price, cash flow-to-price ratio, market-to-book ratio, and the number of analysts. The empirical results obtained from examination of the PAD phenomenon in this chapter support previous research—investors underweight earnings-related information.

However, these three earnings surprise measures do not reflect exactly the same information. On the one hand, this can be seen from the returns of portfolios sorted on the basis of the three variables. Among these, the earnings surprise measure of the 4-day abnormal return around earnings announcements shows the strongest post-announcement drift. On the other hand, the two-dimensional analysis reveals that the SUE_0- and $REV6$-related PAD profits can partially be explained by the $AR4D$

measure, and the SUE ($REV6$) measure cannot account for the $REV6$-based (SUE-based) PAD effect.

Further, high (low) earnings surprise portfolios also tend to have high (low) prior 6-month returns, indicating a possible association between the pronounced PAD and momentum effects. Detailed investigation of this is carried out in the following chapter.

APPENDIX 5A

PAD EFFECT RELATED to the *EFE* MEASURE

In this appendix I examine the PAD phenomenon based on the EFE measure in which the unexpected earnings (earnings forecast error) is measured using the latest median analyst forecast as the benchmark for expected earnings. Table 5A.1 reports the performances, characteristics, and earnings surprises of decile and PAD portfolios classified by the most recent past earnings forecast error, EFE_0.

Table 5A.1 Performances, Characteristics, and Earnings Surprises of Decile and PAD Portfolios Classified by Earnings Forecast Error (EFE)

At the beginning of every month from July 1992 to June 1997, all stocks in the earnings sample are sorted in ascending order based on their most recent past price-deflated earnings forecast errors (EFE_0) and assigned to one of ten portfolios. All stocks are equally-weighted in a portfolio. The lowest-earnings-surprise (i.e., lowest-EFE_0) decile is denoted as portfolio LD; the next decile is portfolio $D2$; and so on. The highest-earnings-surprise (i.e., highest-EFE_0) decile is denoted as portfolio HD; and $HD-LD$ stands for the PAD portfolio (arbitrage portfolio) of HD minus LD. Panel A reports the portfolios' performances: ret_{-6} is the average past six-month return over the 60 ranking periods; ret_n is the average n-month (n = 3, 6, 9, 12) buy-and-hold return over the 60 test periods; EPS_0 is the average most recent past reported final earnings per share; and EPS_1 is the average next reported final earnings per share subsequent to portfolio formation. Panel B presents the estimates of Fama-French three-factor model, which is,

$$r_{p\tau} - r_{f\tau} = a_p + b_p(r_{m\tau} - r_{f\tau}) + s_p SMB_\tau + h_p HML_\tau + \varepsilon_{p\tau}.$$

The two factor-mimicking portfolios of SMB_τ and HML_τ, and the value-weighted market return, $r_{m\tau}$, are constructed based on the accounting sample (for detailed descriptions of the constructions of SMB_τ and HML_τ, and other notation of the 3-factor model see Section 4.4 of Chapter 4). Panel C shows the portfolios' average Scholes-Williams beta ($SW-\beta$), market value (MV), unadjusted price (UP), cash flow to price ratio (C/P), book-to-market ratio (B/M), and number of analysts (ANo) at the beginning of the holding periods. Panel D presents the portfolios' average most recent past earnings surprises as well as the next ones after portfolio formation. In Panel D, SUE_0, $AR4D_0$, $REV6_0$ and EFE_0 stand for the portfolios' average most recent past standardised unexpected earnings (SUE), 4-day abnormal return around earnings announcements ($AR4D$), cumulative price-deflated earnings forecast revision over the prior 6 months ($REV6$), and price-deflated earnings forecast error (EFE), respectively; SUE_1 and $AR4D_1$ stand for the portfolios' average next SUE and $AR4D$ after portfolio formation, respectively. Numbers in parenthesis are t-statistics; where observations are overlapping the Newey-West heteroscedasticity- and autocorrelation-consistent standard errors are used in computing the t-statistics.

	LD	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	HD	$HD-LD$
Panel A: Performance											
ret_{-6}	0.0633	0.0482	0.0440	0.0541	0.0646	0.0820	0.0998	0.1086	0.1075	0.1439	0.0807
	(1.55)	(1.75)	(1.91)	(2.22)	(3.10)	(3.62)	(3.33)	(4.30)	(3.44)	(3.65)	(5.87)
ret_3	0.0406	0.0307	0.0205	0.0212	0.0253	0.0358	0.0443	0.0462	0.0529	0.0616	0.0210
	(2.51)	(2.51)	(1.82)	(1.70)	(2.53)	(3.10)	(3.24)	(3.67)	(4.28)	(3.88)	(2.77)
ret_6	0.0967	0.0651	0.0453	0.0457	0.0540	0.0743	0.0916	0.0948	0.1108	0.1334	0.0367
	(3.00)	(2.92)	(2.29)	(1.97)	(2.83)	(3.31)	(3.24)	(3.32)	(4.24)	(4.17)	(2.26)
ret_9	0.1535	0.0912	0.0646	0.0661	0.0811	0.1048	0.1311	0.1369	0.1609	0.2012	0.0477
	(3.17)	(3.26)	(2.36)	(2.03)	(2.75)	(3.52)	(3.22)	(3.16)	(3.83)	(4.15)	(2.46)
ret_{12}	0.2092	0.1276	0.0957	0.0911	0.1213	0.1417	0.1727	0.1804	0.2290	0.2689	0.0597
	(3.39)	(3.60)	(2.74)	(2.32)	(3.11)	(4.02)	(3.35)	(3.47)	(3.83)	(4.47)	(3.24)
EPS_0	−2.059	11.622	17.707	17.130	17.221	18.471	17.646	17.047	14.434	12.489	14.547
	(−0.90)	(9.81)	(19.6)	(29.4)	(18.5)	(15.3)	(20.5)	(22.5)	(20.9)	(12.1)	(6.35)
EPS_1	1.122	8.375	16.867	17.762	19.158	19.753	19.924	19.175	14.545	12.934	11.812
	(1.08)	(4.88)	(12.4)	(28.6)	(21.2)	(17.2)	(15.4)	(19.7)	(18.6)	(11.0)	(41.4)
Panel B: Estimates of the Fama-French three-factor model											
$a_P(\%)$	−0.098	−0.297	−0.527	−0.721	−0.493	−0.263	0.026	0.071	0.420	0.573	0.671
	(−0.41)	(−1.66)	(−3.58)	(−4.09)	(−3.20)	(−1.67)	(0.15)	(0.44)	(2.85)	(4.04)	(3.26)
b_P	1.2114	1.0394	0.9690	1.0534	1.0544	1.0423	1.0498	1.0264	0.9112	1.0551	−0.1563
	(11.5)	(32.5)	(20.3)	(29.3)	(21.2)	(28.5)	(24.9)	(38.1)	(13.1)	(21.0)	(−1.49)
s_P	0.8728	0.7327	0.6406	0.6084	0.4972	0.4236	0.5487	0.5039	0.6977	0.8563	−0.0165
	(9.96)	(8.65)	(15.5)	(12.1)	(6.11)	(6.42)	(13.0)	(9.08)	(11.2)	(11.5)	(−0.22)
h_P	0.3962	0.0311	0.0902	0.3054	0.1076	0.2026	0.2077	0.2599	0.2246	0.4315	0.0353
	(5.11)	(0.34)	(1.34)	(2.89)	(1.78)	(3.34)	(3.85)	(1.88)	(1.95)	(11.2)	(0.50)
R^2	0.7669	0.8100	0.7577	0.7938	0.7574	0.7976	0.8249	0.7711	0.7246	0.7876	0.0334
Panel C: Characteristics											
$SW-\beta$	1.1602	0.9927	1.0045	1.1119	1.0652	1.1288	1.1140	1.0786	0.9751	1.0861	−0.0740
	(10.7)	(13.3)	(57.5)	(34.6)	(23.2)	(56.4)	(33.7)	(21.5)	(12.3)	(15.4)	(−1.89)
MV	171.63	614.38	1128.8	745.41	959.19	1137.2	918.61	650.76	301.81	342.47	170.84
	(15.1)	(13.1)	(14.0)	(20.0)	(20.2)	(19.0)	(13.5)	(21.2)	(17.0)	(16.4)	(7.87)
UP	127.28	248.50	308.72	304.78	329.36	325.27	319.63	295.96	235.49	202.30	75.02
	(25.0)	(23.2)	(69.5)	(57.1)	(55.3)	(59.7)	(53.2)	(58.7)	(50.1)	(52.8)	(10.2)
C/P	0.0931	0.1014	0.1095	0.1061	0.1017	0.1028	0.1069	0.1107	0.1185	0.1347	0.0415
	(16.9)	(44.6)	(61.9)	(60.1)	(76.1)	(88.2)	(64.7)	(106)	(40.1)	(80.0)	(7.88)
B/M	0.8128	0.6090	0.4604	0.4679	0.3918	0.4081	0.3999	0.4465	0.5542	0.5669	−0.2459
	(16.2)	(34.2)	(83.2)	(33.4)	(48.0)	(39.5)	(50.6)	(54.2)	(39.2)	(34.4)	(−4.60)
ANo	1.0981	1.4662	1.9999	2.0447	2.2556	2.4890	2.1644	1.8382	1.3798	1.3217	0.2236
	(15.3)	(16.9)	(19.5)	(21.3)	(19.3)	(21.0)	(22.2)	(20.7)	(18.8)	(22.8)	(3.91)
Panel D: Earnings Surprises											
SUE_0	−0.0600	0.0198	−0.0193	0.1208	0.1495	0.2232	0.2283	0.3209	0.2836	0.2370	0.2969
	(−1.61)	(0.31)	(−0.45)	(3.44)	(6.94)	(3.80)	(5.61)	(6.45)	(5.08)	(5.62)	(7.57)
$AR4D_0(\%)$	0.281	−0.627	−0.787	0.121	0.125	0.632	1.288	1.466	1.366	2.373	2.092
	(0.40)	(−2.22)	(−2.95)	(0.60)	(0.44)	(2.81)	(2.43)	(6.53)	(2.79)	(6.14)	(4.22)
$REV6_0(\%)$	−3.320	−1.387	−0.573	−0.648	−0.286	−0.330	−0.213	−0.261	−0.357	−0.679	2.641
	(−6.70)	(−6.19)	(−10.5)	(−5.27)	(−7.50)	(−3.60)	(−5.36)	(−3.14)	(−1.87)	(−2.31)	(4.67)
$EFE_0(\%)$	−16.782	−0.805	−0.237	−0.044	0.059	0.167	0.296	0.490	0.876	3.243	20.025
	(−5.15)	(−9.20)	(−8.32)	(−4.81)	(7.77)	(16.0)	(24.0)	(25.2)	(28.7)	(34.6)	(6.05)
SUE_1	0.3187	0.1042	0.0106	0.1225	0.1548	0.1359	0.0897	0.1110	0.1024	0.1333	−0.1854
	(3.68)	(1.52)	(0.38)	(2.37)	(5.68)	(2.61)	(2.43)	(3.39)	(2.07)	(3.39)	(−2.55)
$AR4D_1(\%)$	1.112	−0.209	−0.413	0.215	0.040	0.405	0.842	1.084	1.709	1.498	0.386
	(2.08)	(−0.58)	(−1.28)	(0.99)	(0.10)	(2.18)	(2.64)	(3.98)	(5.56)	(6.45)	(0.76)

The performances presented in Panel A of Table 5A.1 show that the average holding-period returns of all the PAD portfolios of the highest- EFE_0 decile minus the lowest- EFE_0 decile are statistically significant. The annual PAD profit is 6.0 percent with a Newey-West standard-error-adjusted t-statistic of 3.24. However, the n-month ($n = 3$, 6, 9, or 12) holding-period returns of the 10 EFE_0-based portfolios are not strictly increasing through the lowest- EFE_0 decile (LD) to the highest- EFE_0 decile (HD). In fact, the decile portfolios' holding-period returns appear to give a U-shape from LD to HD for a given holding period. In particular, the highest- EFE_0 decile portfolio has the highest return, while the lowest- EFE_0 decile realises the third highest holding-period return for the 6-, 9- and 12-month holding periods, and it is the fifth highest one for the 3-month holding period. The third or fourth decile generally has the lowest average holding-period returns. From the fourth- EFE_0 decile to HD the holding-period returns are monotonically increasing. This asymmetric U-shape pattern is plotted in Figure 5A.1. This pattern is also observed from the estimates of the Fama-French three-factor model reported in Panel B of Table 5A.1. The LD portfolio realises the fifth highest abnormal return (–0.098% per month with a t-statistic of –0.41) after adjusting for the three factors, and the HD portfolio earns the highest significant abnormal return (0.573% per month with a t-statistic of 4.04) after adjusting for the three factors. Consequently, the three-factor-adjusted PAD profit is statistically significant (0.671% per month with a t-statistic of 3.26).

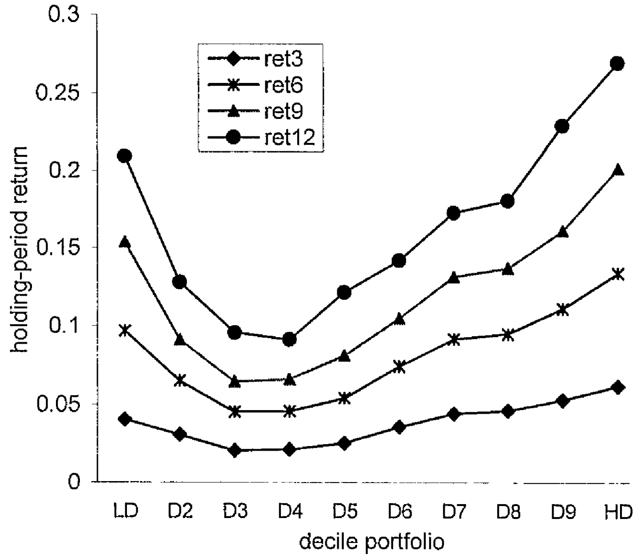

Figure 5A.1 Holding-period returns of decile portfolios classified by most recent past price-deflated earnings forecast error (EFE_0). In this figure, ret3, ret6, ret9, and ret12 are average holding-period returns for 3, 6, 9, and 12 months, respectively.

One possible explanation for the asymmetric U-shape in the portfolios' holding-period returns might be the generally accepted accounting practices that require accounts to recognise wealth losses as they occur, but only to recognise wealth gains as and when they are realised. This phenomenon is referred to as accounting earnings conservatism. Basu (1997), Ball, Kothari and Robin (1997), and Pope and Walker (1999) have presented empirical evidence of asymmetric responses of reported earnings to good and bad news. For instance, Basu (1997), and Pope and Walker (1999) document that reported earnings are much more sensitive to current bad news than to current good news. Specifically, bad (good) news tends to be over-recognised (under-recognised) in reported earnings, and in particular many bad news events are reflected in reported earnings as large, but transitory, shocks. Because of the conservative fashion in reported earnings companies that report large losses and therefore generate low forecast errors bounce back even more sharply next period, resulting in the higher holding-period return of the lowest-EFE_0 portfolio (LD). The empirical results generally confirm this inference. First of all, the lowest earnings forecast error is indeed caused by the reported large losses. The average most recent reported final earnings per share (EPS_0) of the lowest-EFE_0 portfolio (LD) presented in Panel A of Table 5A.1 is lowest and negative (–2.059 with a t-statistic of –0.90), while other decile portfolios' average EPS_0s are all largely positive. Subsequent to portfolio formation, although LD's average reported final earnings per share (EPS_1) is still the lowest, it is no longer negative (it is equal to 1.122 with a t-statistic of 1.08). Other decile portfolios' EPS_1s are similar to the corresponding EPS_0s. Secondly, the next earnings news subsequent to portfolio formation (see the analysis below) does support the fact that the previous large negative transitory earnings are not being repeated. On the other hand, for the highest-EFE_0 decile (HD) the reported earnings clearly exceed analyst forecasts. However, a story consistent with the previous results is that investors do not fully react immediately to the positive earnings surprise, and high positive returns persist over the next 3 to 12 months. Therefore, the EFE_0-based PAD effect is still pronounced despite the asymmetric U-shape in the portfolios' holding-period returns and the fact that the earnings surprise used here is often very dated. Moreover, the dated EFE_0 measure may also be responsible for the asymmetric U-shape pattern in holding-period returns. The reason is that the EFE_0-classified dated bad/good news may not be accurate at the beginning of the test period.

The EFE_0-based portfolios' earnings surprises reported in Panel D of Table 5A.1 show that the patterns in most recent past earnings surprises measured by SUE_0,

EFE_0, $REV6_0$, and $AR4D_0$ are generally consistent, but the order of the portfolios' SUE_0, $REV6_0$, and $AR4D_0$ does not completely match the EFE_0 sorting. This confirms the previous findings that the four earnings surprise variables contain common information sources, but they do not reflect completely the same information. More interestingly, at the next announcement after portfolio formation the lowest-EFE_0 decile portfolio has the highest standardised unexpected earnings (SUE_1). The next average 4-day abnormal return around earnings announcements subsequent to portfolio formation ($AR4D_1$) of the lowest-EFE_0 decile also generally confirms the higher average return of the lowest-EFE_0 portfolio since its $AR4D_1$ is the third highest one. These results are consistent with the above explanations for the asymmetric U-shape pattern in holding-period returns.

The EFE_0-based portfolios' characteristics presented in Panel C of Table 5A.1 reveal a very similar pattern to those of the prior-return-based portfolios documented in previous chapters and in Section 5.4 of this chapter. For brevity, I do not provide detailed analysis of this. Similar analyses to Chapter 4 and Section 5.4 of this chapter can be conducted. The general conclusion is that the EFE_0-based PAD profits are not seriously related to market risk and various effects such as size, price, cash earnings-to-price, book-to-market, and number of analysts. The EFE_0-based PAD trading strategy implemented within a number of sub-samples also confirms the fact (see Table 5A.2).

Table 5A.2 Sub-sample Analysis with Portfolios Being Classified by EFE_0

This table presents the average semi-annual holding-period returns for the quintile portfolios and the PAD portfolio within various sub-samples stratified on MV, UP, C/P, B/M, β, and ANo. Each sub-sample contains one-third of the stocks in the earnings sample at the beginning of each holding period. For instance, for the 3 MV-based sub-samples the low-MV sub-sample contains the 1/3 lowest-MV stocks at the beginning of each holding period; the medium-MV sub-sample contains the 1/3 medium-MV stocks at the beginning of each holding period; and the high-MV sub-sample contains the 1/3 highest-MV stocks at the beginning of each holding period. Within each sub-sample, the quintile portfolios are formed at the beginning of each month (from July 1992 to June 1997) on the basis of most recent past price-deflated earnings forecast error (EFE_0) and held for 6 months. At the start of each holding period, the stocks in a given sub-sample are ranked in ascending order based on their EFE_0s. The equally-weighted portfolio of stocks in the lowest-EFE_0 quintile is the lowest earnings surprise portfolio (LQ), the equally-weighted portfolio of stocks in the next quintile is denoted as $Q2$, and so on. The equally-weighted portfolio of stocks in the highest-EFE_0 quintile is the highest earnings surprise portfolio (HQ). The PAD portfolio is the HQ portfolio minus the LQ portfolio ($HQ-LQ$). In Panel E β stands for Scholes-Williams beta, and in Panel F ANo stands for the number of analysts. Numbers in parentheses are Newey-West-standard-error-adjusted t-statistics. The test period is July 1992 to November 1997.

Sub-sample Analyses with portfolios being classified by EFE_0

Panel A: 3 MV-based sub-samples

	Low-MV	Medium-MV	high-MV
LQ	0.1185 (3.32)	0.0593 (2.22)	0.0707 (3.05)
$Q2$	0.0682 (2.61)	0.0499 (2.41)	0.0585 (2.76)
$Q3$	0.0702 (2.06)	0.0610 (2.85)	0.0627 (3.88)
$Q4$	0.1064 (3.09)	0.0828 (3.07)	0.0959 (3.86)
HQ	0.1216 (3.08)	0.1245 (3.43)	0.1063 (4.05)
$HQ-LQ$	0.0030 (0.14)	0.0652 (4.24)	0.0357 (4.36)

Panel B: 3 UP-based sub-samples

	Low-UP	Medium-UP	high-UP
LQ	0.1127 (3.00)	0.0511 (2.17)	0.0697 (3.44)
$Q2$	0.0853 (2.87)	0.0476 (2.63)	0.0582 (2.59)
$Q3$	0.0768 (2.15)	0.0502 (2.58)	0.0627 (3.90)
$Q4$	0.1073 (3.00)	0.0878 (3.01)	0.0867 (3.66)
HQ	0.1202 (2.77)	0.1259 (4.06)	0.1141 (4.82)
$HQ-LQ$	0.0075 (0.33)	0.0748 (5.56)	0.0444 (4.26)

Panel C: 3 C/P-based sub-samples

	Low-C/P	Medium-C/P	high-C/P
LQ	0.0438 (1.45)	0.0725 (3.35)	0.1341 (4.45)
$Q2$	0.0202 (0.88)	0.0609 (2.81)	0.0828 (3.22)
$Q3$	0.0500 (3.04)	0.0509 (2.31)	0.1043 (3.57)
$Q4$	0.0765 (3.21)	0.0776 (2.85)	0.1242 (3.67)
HQ	0.0899 (2.89)	0.1103 (4.12)	0.1580 (3.74)
$HQ-LQ$	0.0461 (3.38)	0.0377 (3.27)	0.0239 (1.13)

Panel D: 3 B/M-based sub-samples

	low-B/M	Medium-B/M	high-B/M
LQ	0.0763 (2.23)	0.0546 (2.34)	0.1139 (3.30)
$Q2$	0.0446 (2.13)	0.0543 (2.45)	0.0693 (2.94)
$Q3$	0.0601 (3.71)	0.0590 (2.35)	0.0823 (2.74)
$Q4$	0.0794 (3.04)	0.0880 (2.99)	0.0941 (3.33)
HQ	0.1495 (3.82)	0.1134 (3.70)	0.1163 (3.32)
$HQ-LQ$	0.0732 (2.79)	0.0589 (5.34)	0.0024 (0.13)

Panel E: 3 β-based sub-samples

	Low-β	Medium-β	high-β
LQ	0.0941 (3.26)	0.0843 (2.71)	0.0779 (2.47)
$Q2$	0.0589 (2.93)	0.0597 (2.37)	0.0560 (2.15)
$Q3$	0.0385 (2.47)	0.0547 (2.83)	0.0866 (3.23)
$Q4$	0.0856 (3.45)	0.0949 (3.64)	0.0918 (2.73)
HQ	0.1456 (4.10)	0.1068 (4.74)	0.1204 (2.72)
$HQ-LQ$	0.0515 (2.20)	0.0225 (1.57)	0.0425 (1.57)

Panel F: 3 ANo-based sub-samples

	low-ANo	medium-ANo	high-ANo
LQ	0.1071 (3.45)	0.0841 (2.73)	0.0619 (2.67)
$Q2$	0.0743 (3.01)	0.0427 (1.92)	0.0498 (2.42)
$Q3$	0.0760 (2.81)	0.0590 (2.78)	0.0639 (3.55)
$Q4$	0.0987 (3.47)	0.0904 (3.19)	0.0857 (3.58)
HQ	0.1344 (3.66)	0.1189 (3.29)	0.1095 (3.76)
$HQ-LQ$	0.0272 (1.74)	0.0348 (2.67)	0.0476 (4.09)

CHAPTER 6

THE MOMENTUM EFFECT AND POST-EARNINGS-ANNOUNCEMENT DRIFT

6.1 Introduction

The previous chapter documents a significant post-earnings-announcement drift (PAD) in UK stock returns. Further investigation shows that this PAD effect is unlikely to be related to market risk and other factors such as the size effect, low-price effect, and value-stock effect. Among the three earnings surprise variables examined in the last chapter, the short-term stock price reaction around earnings announcement ($AR4D$) reveals the strongest PAD effect, and the magnitude of the $AR4D$-based PAD profits is nearly the same as those of the momentum profits documented in Chapters 3 and 4. This immediately raises a question: can the pronounced PAD effect account for the presence of the momentum effect? In fact, the evidence in Chapter 5 implies a possible relationship between the two. For instance, the backward drift in security returns can also be found at earnings announcements: high (low) earnings surprises tend to follow high (low) past 6-month returns, which is one of the variables used in examining the momentum effect. It is thus worth examining the relationship between momentum and PAD. This is the objective of this chapter: to trace the sources of the momentum profits documented in previous chapters by taking into account the PAD effect. At the same time, as a by-product, this chapter also provides evidence on whether momentum can explain PAD.

This chapter is organised as follows. The following section re-examines the momentum effect based on the earnings sample in which the PAD phenomenon is tested in the previous chapter. Because of the introduction of the earnings data including analysts' forecasts of earnings, the sample size and the sample period are considerably reduced compared with the samples examined in Chapters 3 and 4. Thus, a re-examination of momentum is necessary based on the same sample and sample period as the examination of PAD. The re-examination also helps further to see whether the momentum effect is sample and period specific by implementing the momentum strategy on the earnings sample. The two-dimensional analysis described and employed in the last chapter will be used in Section 6.3 to analyse the relationship between momentum and PAD effects by controlling for one effect to examine the other. As another way of disentangling the two effects, analyses of cross-sectional and time-series regressions are reported in Section 6.4. The final section summarises this chapter.

6.2 Re-examination of the Momentum Effect

This section re-examines the momentum effect based on the earnings sample. The following subsection examines if the momentum effect documented in Chapters 3 and

4 exists in the earnings sample. The re-examination is implemented based on the 6×3, 6×6, 6×9, and 6×12 momentum strategies. In other words, the ranking variable used to group stocks into different portfolios is the prior 6-month buy-and-hold security return, and the holding-period buy-and-hold returns are traced for n months ($n = 3, 6, 9, 12$). To be consistent with the PAD tests conducted in the last chapter, these four momentum strategies include portfolios with *overlapping* ranking and holding periods on a monthly basis. All data items, test periods, and data requirements involved in Chapter 5 are also required in this chapter. For detailed descriptions see Section 5.3 in Chapter 5. If the momentum effect does exist within the earnings sample, Subsection 6.2.2 investigates whether it can be explained by market beta or various effects such as small firm, low-price, high-C/P, high-B/M, and number of analysts.

6.2.1 Evidence of a Momentum Effect based on the Earnings Sample

Based on the earnings sample, Table 6.2.1 reports the portfolios' average returns, other characteristics, and earnings surprises over the sample period. In Panel A of Table 6.2.1, ret_{-6} is the average 6-month ranking-period return, and ret_n is the average n-month ($n = 3, 6, 9, 12$) holding-period return. In Panel B of Table 6.2.1, $SW\text{-}\beta$, MV, UP, C/P, B/M, and ANo are a portfolio's average Scholes-Williams beta, market value, unadjusted price, cash flow to price ratio, book-to-market ratio, and number of I/B/E/S analysts at the beginning of the holding periods, respectively. In Panel C of Table 6.2.1, SUE_0, $AR4D_0$ and $REV6_0$ are a portfolios' average most recent past earnings surprise; and SUE_1 and $AR4D_1$ are the next earnings surprises after portfolio formation. Numbers in parentheses are t-statistics.[1]

Table 6.2.1 Performances, Characteristics and Earnings Surprises of Decile and Momentum Portfolios Classified by Prior 6-Month Returns (ret_{-6})

At the beginning of every month from July 1992 to June 1997, all stocks in the earnings sample are sorted in ascending order based on their prior 6-month buy-and-hold returns and assigned to one of ten portfolios. The equally-weighted portfolio of stocks in the lowest past return decile is the loser portfolio (L); the equally-weighted portfolio of stocks in the next decile is portfolio $D2$; and so on. The equally-weighted portfolio of stocks in the highest past return decile is the winner portfolio (W); and $W-L$ stands for the momentum portfolio (arbitrage portfolio) of winner minus loser. Panel A reports each portfolio's performance: ret_{-6} is the average past six-month return over the 60 ranking periods; ret_n is the average n-month ($n = 3, 6, 9, 12$) buy-and-hold return over the 60 test periods. Panel B shows each portfolio's average Scholes-Williams beta ($SW-\beta$), market value (MV), unadjusted price (UP), cash flow to price ratio (C/P), book-to-market ratio (B/M), and number of analysts (ANo) at the beginning of the holding period. Panel C presents for each portfolio the average of the most recent earnings surprise and of the next earnings surprise after portfolio formation. In Panel C SUE_0, $AR4D_0$, and $REV6_0$ stand for a portfolio's average most recent standardised unexpected earnings, the 4-day abnormal return around the earnings announcement, and the price-deflated cumulative earnings forecast revision over the prior 6 months; SUE_1 and $AR4D_1$ stand for a portfolio's average next standardised unexpected earnings and the 4-day abnormal return around the next earnings announcement after portfolio formation. Numbers in parenthesis are t-statistics where if observations are overlapping Newey-West heteroscedasticity- and autocorrelation-consistent standard errors are used in computing the t-statistics.

[1] The t-statistics for MV, UP, C/P, B/M and ANo are standard ones, but for others Newey-West heteroscedasticity- and autocorrelation-consistent standard error are used in calculating the t-statistics. The number of lags in computing the Newey-West standard errors varies depending on the overlapping periods. Specifically, the number of lags in computing the t-statistics for ret_{-6}, ret_6, $AR4D_0$, $AR4D_1$ and $REV6_0$ is 5; and it is 2, 8, 11, 35, 8, and 8 for ret_3, ret_9, ret_{12}, $SW\text{-}\beta$, SUE_0, and SUE_1, respectively.

	L	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	W	$W-L$
					Panel A: Performance						
ret_{-6}	−0.3200	−0.1353	−0.0591	−0.0030	0.0486	0.0994	0.1493	0.2095	0.2983	0.5993	0.9193
	(−15.5)	(−6.47)	(−2.79)	(−0.14)	(2.11)	(4.01)	(5.53)	(7.07)	(8.65)	(11.5)	(24.9)
ret_3	0.0206	0.0283	0.0361	0.0335	0.0398	0.0388	0.0446	0.0434	0.0603	0.0666	0.0461
	(1.14)	(1.77)	(2.82)	(3.05)	(3.44)	(3.19)	(3.86)	(3.83)	(4.88)	(5.17)	(3.40)
ret_6	0.0585	0.0685	0.0746	0.0739	0.0775	0.0832	0.0924	0.0933	0.1270	0.1446	0.0861
	(1.52)	(2.31)	(3.01)	(3.44)	(3.43)	(3.57)	(3.79)	(3.95)	(4.60)	(5.67)	(3.02)
ret_9	0.0999	0.0941	0.1035	0.1078	0.1122	0.1182	0.1353	0.1434	0.1790	0.2236	0.1237
	(1.66)	(2.17)	(2.77)	(3.16)	(3.46)	(3.51)	(3.85)	(3.84)	(4.57)	(5.56)	(3.05)
ret_{12}	0.1425	0.1351	0.1456	0.1495	0.1544	0.1608	0.1861	0.1864	0.2384	0.2941	0.1516
	(1.94)	(2.48)	(2.86)	(3.17)	(3.73)	(3.73)	(4.15)	(4.21)	(4.90)	(6.25)	(3.39)
					Panel B: Characteristics						
$SW\text{-}\beta$	1.0128	1.0051	1.0066	0.9962	1.0402	1.0145	1.0397	1.0474	0.9976	1.0644	0.0516
	(9.56)	(16.5)	(27.9)	(21.7)	(25.6)	(38.9)	(24.6)	(24.6)	(20.4)	(17.0)	(0.58)
MV	278.08	418.93	596.75	627.47	663.36	786.78	836.17	727.23	641.65	272.16	−5.91
	(5.84)	(10.2)	(12.6)	(13.7)	(18.4)	(16.6)	(14.2)	(13.3)	(10.5)	(6.46)	(−0.08)
UP	124.41	188.55	238.47	258.36	274.81	293.80	296.88	293.43	273.58	245.75	121.33
	(21.7)	(35.6)	(33.2)	(42.9)	(33.2)	(52.5)	(45.8)	(43.1)	(48.2)	(30.7)	(9.95)
C/P	0.0805	0.1220	0.1222	0.1158	0.1129	0.1100	0.1088	0.1082	0.1100	0.1070	0.0265
	(9.87)	(36.0)	(51.2)	(52.0)	(77.0)	(65.8)	(64.2)	(63.0)	(66.2)	(45.2)	(3.16)
B/M	0.7662	0.7179	0.6485	0.5701	0.5202	0.5344	0.5208	0.4735	0.4770	0.3883	−0.3779
	(19.2)	(23.4)	(32.0)	(40.7)	(40.6)	(26.3)	(25.2)	(33.9)	(28.8)	(18.0)	(−8.40)
ANo	1.394	1.565	1.670	1.713	1.635	1.679	1.679	1.555	1.313	0.911	−0.483
	(13.6)	(17.9)	(18.3)	(17.1)	(23.7)	(21.6)	(20.9)	(19.3)	(19.7)	(13.2)	(−4.31)
					Panel C: Earnings Surprises						
SUE_0	−0.1352	0.0062	0.0644	0.1264	0.1664	0.2065	0.2422	0.2879	0.3288	0.3392	0.4744
	(−2.29)	(0.14)	(1.57)	(3.82)	(4.53)	(5.40)	(9.16)	(7.23)	(7.11)	(8.11)	(8.44)
$AR4D_0$(%)	−6.094	−2.480	−1.063	−0.139	0.836	1.342	1.986	2.495	3.579	5.798	11.892
	(−11.6)	(−16.0)	(−5.61)	(−0.86)	(4.61)	(8.75)	(10.6)	(10.8)	(13.4)	(12.4)	(17.1)
$REV6_0$(%)	−4.702	−1.396	−0.750	−0.593	−0.339	−0.228	−0.233	−0.122	−0.066	−0.234	4.467
	(−7.69)	(−6.79)	(−8.07)	(−4.57)	(−5.01)	(−4.21)	(−2.80)	(−1.51)	(−0.85)	(−1.08)	(7.49)
SUE_1	−0.4038	−0.0735	0.0406	0.0816	0.1713	0.1976	0.2758	0.3275	0.3740	0.3708	0.7746
	(−8.83)	(−1.86)	(1.04)	(1.53)	(4.09)	(6.56)	(6.65)	(7.52)	(6.60)	(6.28)	(11.3)
$AR4D_1$(%)	0.019	0.659	0.578	0.645	0.600	0.649	1.128	1.104	1.417	1.798	1.780
	(0.04)	(1.44)	(1.53)	(2.62)	(3.09)	(2.61)	(4.81)	(6.45)	(6.91)	(6.73)	(2.62)

From the results reported in Panel A of Table 6.2.1 it is clear that the momentum effect is pronounced and the results are consistent with previous findings documented in Chapters 3 and 4. The average holding-period returns of 3, 6, 9 and 12 months monotonically increase from loser portfolio (L) to winner portfolio (W). All momentum portfolio ($W-L$) returns are significantly positive. The average 3-, 6-, 9-, and 12-month holding-period momentum profits are 4.61%, 8.61%, 12.37% and 15.16% with t-statistics of 3.40, 3.02, 3.05 and 3.39, respectively. These figures are quite similar to the results obtained from the full sample of 4,182 stocks and the accounting sample (see Table 3.4.2 and Table 3.5.1 in Chapter 3). This clear evidence of a momentum effect can be seen from Figure 6.2.1, which plots the decile portfolios' average 3-, 6-, 9-, and 12-month holding-period returns.

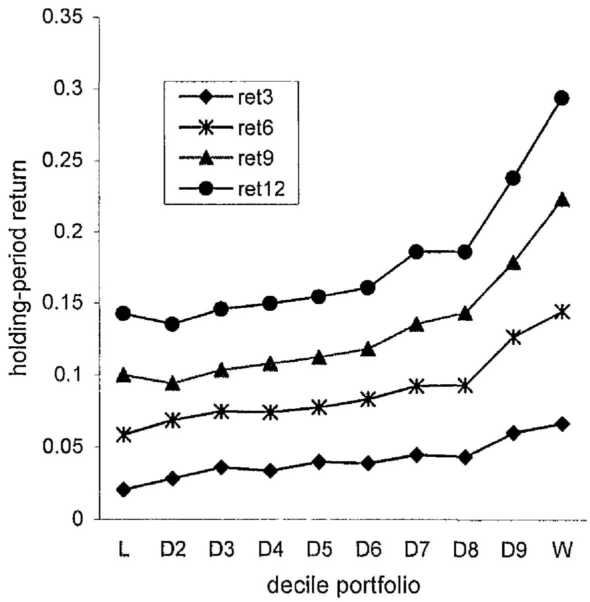

Figure 6.2.1 Performances of the Decile Portfolios Classified by Prior Six-month Return. In this figure, ret3, ret6, ret9, and ret12 are average holding-period returns of 3, 6, 9, and 12 months, respectively.

Panel B of Table 6.2.1 shows that the patterns of each portfolio's UP, C/P, and B/M for the earnings sample are the same as those in Table 4.2.1 of Chapter 4 for the accounting sample. The loser portfolio has the lowest UP and the winner portfolio's UP is significant greater than the loser portfolio's. In addition, the loser portfolio's B/M is the highest one while the winner portfolio's B/M is the lowest. As with previous findings these results suggest that momentum profits are unlikely to be due to low-price or high-B/M effects. Moreover, the loser portfolio has the lowest C/P and the winner portfolio's C/P is the second lowest one with the winner portfolio's C/P being significant greater than the loser portfolio's. This suggests that there might be a relation between momentum profits and the C/P effect, but the relation might be weak since the winner portfolio's C/P is the second lowest one. Further investigation is carried out in the following subsection.

Looking at the average Scholes-Williams beta and MV in Panel B of Table 6.2.1, although the patterns are similar to previous findings documented in Chapters 3 and 4, the results are slightly different. Loser and winner portfolios still have similar risk exposures with the winner portfolio's average Scholes-Williams beta being the highest,[2] but the winner portfolio's Scholes-Williams beta is not significantly greater than the loser portfolio's. This indicates that there is no significant evidence to support the market risk explanation of the momentum profits. Again, both loser and winner portfolios tend to select smaller firms. Yet, in this earnings sample loser and winner portfolios' average MV s are almost the same. The winner portfolio's average MV is lowest and the loser portfolio's is the second lowest, and their difference is insignificant. This evidence also seems to eliminate the size explanation of the momentum effect. Further examination of whether systematic risk or size can account for the momentum profits is carried out in the following subsection and sections.

In panel B of Table 6.2.1 the portfolios' average numbers of analysts show a striking pattern. Both winner and loser portfolios tend to have fewer analyst following with the winner portfolio's average number of analysts being lowest and the loser portfolio's being the third lowest, with the difference being statistically significant (−0.483 with a t-statistic of −4.31). As mentioned in the last chapter, more analysts mean greater informational efficiency, with information being more quickly impounded into price. Hong, Lim and Stein (1999) believe that firm-specific information will move more slowly across the investing public if stocks have lower analyst following. They hence regard the number of analysts as a proxy for the rate of firm-specific information flow. They show that the momentum strategy works particularly well among stocks that have lower analyst following. The fact that winners and losers have fewer analysts seems to be consistent with Hong et al.'s (1999) evidence, and it also seems to support the overall conclusion of Chapters 3 and 4 that momentum is attributable to the market's under-reaction to firm-specific information.

Because of this intriguing finding of both losers and winners having low analyst following, I investigate whether there is a 'number of analysts' effect in the UK.[3] In addition, I examine the relationship between firm size and the number of analysts. The empirical results strongly confirm the conjectures. The effect of the number of analysts is very pronounced, and the size effect is closely related to it. In fact, further analyses reveal that size and analyst numbers effects tend to be the same thing. The effect of number of analysts can explain the size effect, and it is also almost explained by size. However, in the finance literature the size effect has been regarded as an empirical fact and there are few further explanations of it. The results obtained from the examination of size and the number of analysts suggest that the size effect can be attributed to informational inefficiency. This story fits well with the Arbel-Carvell-Strebel neglected firm hypothesis. Arbel, Carvell and Strebel (1983), Arbel and Strebel (1982), Arbel (1985), and Strebel and Carvell (1987), refer to stocks that are

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[2] This is not exactly the same as previous findings where the loser portfolio usually has the highest Scholes-Williams beta.

[3] The number of analysts effect can be described as a negative association between stock return (or return momentum) and the number of analysts. Given a link between the effect of analyst numbers and price momentum, we would expect that stocks with fewer analysts would exhibit more pronounced momentum.

not followed by large numbers of analysts on a regular basis as neglected stocks. The idea in their model is that a stock with fewer analysts following will be one where the quality of information available on the stock is relatively low. They deduce that, all else equals, equilibrium expected returns on neglected stocks would be larger than on those stocks that are widely followed by analysts. The empirical evidence and the detailed analyses regarding the effect of number of analysts and the relationship between it and size are presented in Appendix 6A. It is clear from the results reported in Table 6A.1 of Appendix 6A that small (big) firms tend to be followed by fewer (more) analysts. Thus, small firms fit the neglected firm hypothesis. The following subsection examines whether price momentum is due to the effect of the number of analysts.

Panel C of Table 6.2.1 provides clues as to whether price momentum is driven by the PAD phenomenon. Consistent with previous conjectures, the patterns of the portfolios' earnings surprises in both ranking and holding periods coincide well with those of the portfolios' return performance. The loser portfolio has the lowest most recent earnings surprises (SUE_0, $AR4D_0$, $REV6_0$), while the winner portfolio has the highest earnings surprises except for the $REV6_0$ measure. All winner portfolios' three most recent earnings surprises are significantly greater than those of the loser portfolios at all conventional levels of significance. The differences of the three most recent earnings surprises between winner and loser portfolios are 0.474 ($t = 8.44$), 11.892% ($t = 17.1$) and 4.467% ($t = 7.49$) for SUE_0, $AR4D_0$ and $REV6_0$, respectively. These imply that stocks with high (low) prior 6-month returns have relatively high (low) most recent and next earnings surprises. This evidence can be seen more intuitively from Figure 6.2.2, which plots the most recent earnings surprises (SUE_0, $AR4D_0$, $REV6_0$) as well as the next ones (SUE_1, $AR4D_1$) subsequent to portfolio formation for the decile portfolios classified by prior 6-month return.

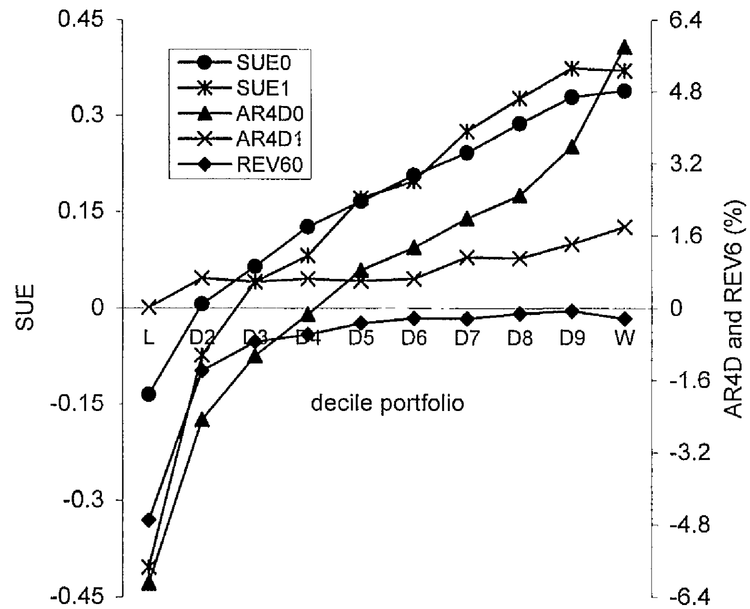

Figure 6.2.2 Average Earnings surprises of the ten-decile portfolios classified by prior 6-month returns. SUE0 and AR4D0 are the most recent past standardised unexpected earnings, and the most recent past 4-day abnormal return around earnings announcement, respectively. SUE1 and AR4D1 are the average next standardised unexpected earnings and 4-day abnormal returns around earnings announcements subsequent to portfolio formations, respectively. REV60 is the cumulative price-deflated earnings forecast revision over the prior 6 months.

A much more surprising finding is that the patterns of earnings surprises continue in the period after portfolio formation. The average next earnings surprises of SUE and $AR4D$ subsequent to portfolio formation also increase almost monotonically from loser to winner portfolios (see Figure 6.2.2). The differences between the average next earnings surprises subsequent to portfolio formation (SUE_1, $AR4D_1$) of the winner and loser portfolios are significantly positive with the SUE_1 difference (0.7746) being even greater than the SUE_0 difference (0.4744).[4] The 4-day abnormal return around the next announcement subsequent to portfolio formation is higher by 1.78 percent ($t = 2.62$) on average for the winner portfolio compared to the loser portfolio, accounting for 21 percent of the 6-month momentum profit of 8.61 percent.

In brief, the evidence in Panel C of Table 6.2.1 reveals a possible association between prior returns and most recent earnings surprises. In Chapter 5 the empirical results also show that stocks with most recent past good (bad) earnings news tend to have good (poor) past 6-month performance. Therefore, momentum profits may be due to the market under-reacting to earnings news. Before examining whether this is the case I first perform a sub-sample analysis to examine the power of market beta and various effects such as size, book-to-market, and so forth to explain momentum profits for the earnings sample.

6.2.2 Sub-sample Analysis

The results in Panel B of Table 6.2.1 show that the winner portfolio has the highest Scholes-Williams beta, the lowest MV and the lowest number of analysts, and the winner portfolio's C/P is significantly greater than the loser portfolio's. As a result, the momentum profits reported in Panel A of Table 6.2.1 may be related to market beta, firm size, number of analysts, or high C/P effects. This subsection examines if this conjecture is tenable by performing various sub-sample analyses. Similar to Chapter 5, I will analyse 18 sub-samples stratified on MV, UP, C/P, B/M, β, and

[4] This finding is the same as that of Chan et al. (1996), indicating that the model of expected earnings used to compute the SUE measure may be mis-specified.

ANo. For detailed description of the sub-sample analysis see Section 5.4 of Chapter 5 and Table 6.2.2 reported below.

Table 6.2.2 summarises the average 6-month holding-period returns of quintile and momentum portfolios for each of the 18 sub-samples (with t-statistics in parentheses).[5] The quintile portfolios are formed by ranking past 6-month stock returns within each sub-sample. The results in Panel A to Panel D of Table 6.2.2 are similar to the results documented in Chapter 4 (see Table 4.6.1 in Chapter 4), indicating that momentum profits are unlikely to be related to size, price, cash flow-to-price, and book-to-market effects.

Table 6.2.2 Sub-sample Analysis with Portfolios Being Classified by Prior 6-month Returns

This table presents the average semi-annual holding-period returns for quintile portfolios and the momentum portfolio within various sub-samples stratified on MV, UP, C/P, B/M, β, and ANo. Each sub-sample contains one-third of the stocks in the earnings sample at the beginning of each holding period. For instance, for the 3 MV-based sub-samples, the low-MV sub-sample contains the 1/3 lowest-MV stocks at the beginning of each holding period; the medium-MV sub-sample contains the 1/3 medium-MV stocks at the beginning of each holding period; and the high-MV sub-sample contains the 1/3 highest-MV stocks at the beginning of each holding period. Within each sub-sample, the quintile portfolios are formed at the beginning of each month (from July 1992 to June 1997) on the basis of 6-month past buy-and-hold returns and held for 6 months. At the start of each holding period, the stocks in a given sub-sample are ranked in ascending order based on their 6-month past returns. The equally-weighted portfolio of stocks in the lowest past return quintile is the loser portfolio (L), the equally-weighted portfolio of stocks in the next quintile is denoted as $Q2$, and so on. The equally-weighted portfolio of stocks in the highest past return quintile is the winner portfolio (W). The momentum portfolio is the winner minus the loser portfolio ($W-L$). In Panel E β stands for Scholes-Williams beta, and in Panel F ANo stands for the number of analysts. Numbers in parentheses are Newey-West-standard-error-adjusted t-statistics. The test period is July 1992 to November 1997.

[5] Holding-period returns of decile and momentum portfolios are also calculated with similar results.

Sub-sample Analyses with portfolios being classified by prior 6-month returns						
	Panel A: 3 MV-based sub-samples			**Panel B**: 3 UP-based sub-samples		
	Low-MV	medium-MV	high-MV	low-UP	Medium-UP	high-UP
L	0.1319 (2.32)	0.0374 (1.01)	0.0778 (2.58)	0.13296 (2.18)	0.0436 (1.29)	0.0602 (2.53)
$Q2$	0.1038 (2.49)	0.0668 (2.59)	0.0688 (3.22)	0.1079 (2.39)	0.0694 (2.79)	0.0643 (3.42)
$Q3$	0.1190 (3.43)	0.0714 (2.55)	0.0712 (3.61)	0.1156 (3.11)	0.0822 (3.21)	0.0745 (3.67)
$Q4$	0.1345 (3.90)	0.0982 (3.18)	0.0863 (3.87)	0.1289 (3.62)	0.0940 (3.03)	0.0889 (3.98)
W	0.1829 (4.46)	0.1517 (4.20)	0.1115 (4.19)	0.1825 (4.08)	0.1507 (4.59)	0.1165 (4.94)
$W-L$	0.0510 (1.86)	0.1143 (8.19)	0.0337 (1.74)	0.0496 (1.93)	0.1072 (5.89)	0.0562 (3.10)
	Panel C: 3 C/P-based sub-samples			**Panel D**: 3 B/M-based sub-samples		
	Low-C/P	medium-C/P	high-C/P	low-B/M	Medium-B/M	high-B/M
L	0.0449 (0.99)	0.0608 (2.10)	0.1396 (2.58)	0.0557 (1.34)	0.0549 (1.70)	0.1221 (2.57)
$Q2$	0.0504 (1.59)	0.0666 (2.96)	0.1249 (3.57)	0.0587 (2.36)	0.0718 (2.66)	0.1251 (3.10)
$Q3$	0.0683 (2.70)	0.0743 (3.31)	0.1294 (4.21)	0.0823 (3.10)	0.0736 (2.74)	0.1111 (3.33)
$Q4$	0.0864 (3.24)	0.0773 (3.17)	0.1312 (4.27)	0.1126 (4.12)	0.0844 (3.29)	0.1173 (3.70)
W	0.1299 (4.42)	0.1377 (4.40)	0.1912 (5.32)	0.1762 (4.85)	0.1312 (3.81)	0.1339 (4.81)
$W-L$	0.0850 (2.64)	0.0769 (5.38)	0.0516 (2.19)	0.1205 (5.97)	0.0763 (5.28)	0.0118 (0.45)
	Panel E: 3 β-based sub-samples			**Panel F**: 3 ANo-based sub-samples		
	Low-β	medium-β	high-β	low-ANo	medium-ANo	high-ANo
L	0.0762 (2.15)	0.0986 (2.37)	0.0886 (1.64)	0.1189 (2.61)	0.0809 (1.66)	0.0623 (1.63)
$Q2$	0.0749 (2.85)	0.0769 (3.17)	0.0947 (2.44)	0.0959 (2.86)	0.0713 (2.46)	0.0692 (2.83)
$Q3$	0.0848 (3.61)	0.0744 (3.41)	0.0973 (3.02)	0.1110 (3.53)	0.0787 (3.00)	0.0735 (3.52)
$Q4$	0.1066 (3.98)	0.0917 (4.00)	0.0962 (3.06)	0.1295 (4.10)	0.1014 (3.55)	0.0791 (3.56)
W	0.1658 (5.15)	0.1299 (4.26)	0.1539 (4.26)	0.1743 (4.90)	0.1548 (4.35)	0.1122 (4.19)
$W-L$	0.0896 (5.16)	0.0314 (1.04)	0.0652 (2.48)	0.0554 (2.37)	0.0739 (3.40)	0.0499 (1.99)

The results in Panel E of Table 6.2.2 show that the momentum profit realised in the medium-β sub-sample is insignificant (3.14% with a t-statistic of 1.04). However, it is statistically significant in the low- and high-β sub-samples with the highest average semi-annual momentum profit of 8.96% ($t = 5.16$) being realised within the low-β sub-sample. To a certain extent, these results rule out the possibility of market-risk-based explanations of the profitability of momentum strategies. Yet, we can not entirely rule out risk-based explanations because the market model may not provide an accurate risk measure as mentioned in Chapter 5.

The effect of low number of analysts is evident in Panel F of Table 6.2.2. All portfolio returns are highest within the low-*ANo* sub-sample compared with the other two *ANo*-based sub-samples, while they are lowest in the high-*ANo* based sub-sample. These results are consistent with those reported in Appendix 6A. However, the striking effect of low number of analysts does not explain momentum profits. The momentum profits earned within all three *ANo*-based sub-samples are significantly positive with the highest one of 7.39 percent ($t = 3.40$) being realised within the medium-*ANo* sub-sample. If low number of analysts reflects lower informational efficiency, this suggests that momentum profits are less likely to be due to informational inefficiency.[6]

However, I do not wish to over-emphasise the possibility that momentum profits are not due to informational inefficiency. This conclusion is conditional on the assumption that low number of analysts means lower informational efficiency. The assumption appears reasonable, and the empirical evidence also supports it (e.g., the momentum profit within the high-*ANo* sub-sample is the lowest compared with the low- and medium-*ANo* sub-samples as documented in Table 6.2.2.). However, a reasonable objection might be that the number of analysts is too one-dimensional to capture whether the market is informationally efficient or not. In other words, there

[6] The results are not exactly same as Hong et al.'s (1999) where momentum strategies work better among stocks with low analyst coverage. This might be due to the slightly different research designs. In this study, I directly use the raw number of analysts, whereas Hong et al. (1999) adopt residual analyst coverage.

may be a proxy problem that the number of analysts only partially reflects the degree of informational efficiency. On the other hand, it could be that there are simply problems in interpreting the effect of analyst numbers. For example, herding may offset the competitive pressures of more analysts and there may be a non-monotonic relation between the degree of informational efficiency and the number of analysts. As a result, there is still room for a lot more research on this. However, this is not the immediate concern of this study. In the following section I will focus on the examination of the relations between momentum and PAD.

6.3 Relation between Momentum and PAD Effects: Two-dimensional Analysis

The empirical results documented in the last section reveal that momentum effects are still pronounced within the earnings sample. Consistent with previous chapters' findings the momentum effect cannot be attributed to market beta or various effects such as size, price, cash-flow-to-price, book-to-market, and the number of analysts. In addition, the evidence in the last section and in Chapter 5 shows that there might be a possible relation between momentum and PAD effects. For instance, a portfolio of high (low) past returns (most recent past earnings surprises), on average, has high (low) most recent past earnings surprises (past return). This section examines how closely they are related and whether they can explain each other by using the two-dimensional analysis of controlling for one effect to examine the other. For detailed descriptions on implementing the two-dimensional analysis see Section 5.5 in Chapter

5, and the illustrations presented in the corresponding tables reported below. Before doing so, I first compute the correlation coefficients between the four variables, ret_{-6}, SUE_0, $AR4D_0$, and $REV6_0$. Table 6.3.1 reports the results.

Table 6.3.1 Correlation Coefficients between Prior 6-Month Returns and Most Recent past Earnings Surprises

This table presents the correlation coefficients between prior 6-month returns, ret_{-6}, and the three earnings surprise variables, SUE_0, $REV6_0$ and $AR4D_0$. These correlation coefficients are calculated over all months from the beginning of July 1992 to June 1997 and over all individual stocks in the earnings sample.

	Correlation Coefficients			
	ret_{-6}	SUE_0	$AR4D_0$	$REV6_0$
ret_{-6}	1			
SUE_0	0.1068	1		
$AR4D_0$	0.3953	0.1196	1	
$REV6_0$	0.1809	0.1247	0.1580	1

The results in Table 6.3.1 show that the four variables adopted to examine momentum and PAD are positively correlated with one another. However, the correlations are not strong. The largest correlation coefficient between momentum and PAD is 0.3953, which is the one between prior 6-month return (ret_{-6}) and the short-term price reaction around earnings announcement ($AR4D_0$), while the correlation coefficient of 0.1068 between ret_{-6} and SUE_0 is the smallest one. The relative high correlation between ret_{-6} and $AR4D_0$ might be due to the fact that the latter is actually part of the former. Whether they can explain each other is analysed below. Among the three earnings surprise variables the highest correlation is between $REV6_0$ and $AR4D_0$, at 0.158. These positive correlations are consistent with previous findings. However, the weak correlations suggest that the four different variables do not entirely reflect the same information. The trivial correlations among the three earnings surprise variables generally confirm previous findings (see Section 5.5 in Chapter 5.). Consequently, we may expect that the PAD (momentum) effect might only partially explain the momentum (PAD) effect.

(1) Momentum and SUE-based PAD

Table 6.3.2 reports the results of the two-dimensional analysis on ret_{-6}-based momentum and SUE_0-based PAD. Consistent with previous findings the results of the nine $ret_{-6} - SUE_0$ portfolios presented in Panel A of Table 6.3.2 reveal evident momentum and PAD phenomena. Holding SUE_0 (ret_{-6}) fixed, the holding-period returns increase from low-ret_{-6} (low-SUE_0) portfolio to high-ret_{-6} (high-SUE_0) portfolio. For instance, holding medium SUE_0 fixed the low-, medium-, and high-ret_{-6} portfolios' average annual returns are 15.49%, 16.45%, and 25.28%, respectively. Holding medium ret_{-6} fixed the low-, medium- and high-SUE_0 portfolios' average annual returns are 13.78%, 16.45% and 17.60%. The SUE_0-related PAD effect is weaker after controlling for performance than is the momentum effect after controlling for SUE_0. This is confirmed statistically by the results of ret_{-6}- and SUE_0-matched portfolios presented in Panel B of Table 6.3.2. All three SUE_0-matched portfolios of $LSGP - LSPP$, $MSGP - MSPP$, and $HSGP - HSPP$ earn significant momentum profits over 6- and 12-month holding periods. Their average annual returns are 9.26% ($t = 7.26$), 9.79% ($t = 1.92$), and 7.73% ($t = 2.66$), respectively. By contrast, the SUE_0-based PAD profits tend to be insignificant after controlling for price momentum. The average annual returns of the three ret_{-6}-matched portfolios ($HSPP - LSPP$, $HSMP - LSMP$, and $HSGP - LSGP$) are 5.65%

($t = 1.27$), 3.82% ($t = 1.19$), and 4.12% ($t = 2.36$). Although the SUE_0-based PAD profits are significant within the high-ret_{-6} matched portfolio ($HSGP-LSGP$), the magnitudes are smaller than the SUE_0-controlled momentum profits. These results suggest that price momentum cannot be explained by the SUE_0-related PAD effect. In contrast, the momentum effect almost fully explains the SUE_0-related PAD phenomenon.

Table 6.3.2 Relationships between Momentum Classified by prior 6-month Return (ret_{-6}) and PAD Classified by Most Recent Past Standardised Unexpected Earnings Surprise (SUE_0): Examining the Momentum (PAD) Effect after Controlling for the PAD (Momentum) Effect

At the beginning of every month from July 1992 to June 1997, all stocks in the earnings sample are sorted in ascending order based on their buy-and-hold return over the prior six months (ret_{-6}) and assigned to one of three equally-sized portfolios. The first one is referred to as the poor-performance portfolio (PP); the middle one as the medium-performance portfolio (MP); and the third one as the good-performance portfolio (GP). All stocks are also independently sorted in ascending order based on their most recent past standardised unexpected earnings (SUE_0) and assigned to one of three equally-sized portfolios. The first portfolio including the 1/3 lowest-SUE_0 stocks is denoted as the low-earning-surprise portfolio (LS); the middle one as the medium-earning-surprise portfolio (MS); and the third one containing 1/3 highest-SUE_0 stocks is referred to as the high-earnings-surprise portfolio (HS). The intersections of the three ret_{-6}-sorted portfolios (PP, MP, GP) and the three SUE_0-sorted portfolios (LS, MS, HS) give nine earnings-surprise-performance portfolios. The nine earnings-surprise-performance portfolios are: low-earnings-surprise-poor-performance portfolio ($LSPP$), low-earnings-surprise-medium-performance portfolio ($LSMP$), low-earnings-surprise-good-performance portfolio ($LSGP$); medium-earnings-surprise-poor-performance portfolio ($MSPP$), medium-earnings-surprise-medium-performance portfolio ($MSMP$), medium-earnings-surprise-good-performance portfolio ($MSGP$); high-earnings-surprise-poor-performance portfolio ($HSPP$), high-earnings-surprise-medium-performance portfolio ($HSMP$), and high-earnings-surprise-good-performance portfolio ($HSGP$). All stocks are equally-weighted in a portfolio. Seven arbitrage portfolios are constructed based on the nine earnings-surprise-performance portfolios. Three of the seven arbitrage portfolios are earnings-surprise-matched, and they are: low-earnings-surprise-good-performance portfolio minus low-earnings-surprise-poor-performance portfolio ($LSGP-LSPP$), medium-earnings-surprise-good-performance portfolio minus medium-earnings-surprise-poor-performance portfolio ($MSGP-MSPP$), and high-earnings-surprise-good-performance portfolio minus high-earnings-surprise-poor-performance portfolio ($HSGP-HSPP$). Another three of the seven arbitrage portfolios are performance-matched, and they are: high-earnings-surprise-poor-performance portfolio minus low-earnings-surprise-poor-performance portfolio ($HSPP-LSPP$), high-earnings-surprise-medium-performance portfolio minus low-earnings-surprise-medium-performance portfolio ($HSMP-LSMP$), and high-earnings-surprise-good-performance portfolio minus low-earnings-surprise-good-performance portfolio ($HSGP-LSGP$). One of the seven arbitrage portfolios is miscellaneous, and it is high-earnings-surprise-good-performance portfolio minus low-earnings-surprise-poor-performance portfolio ($HSGP-LSPP$). Panel A reports the average 6-month holding-period returns (ret_6), 12-month holding-period returns (ret_{12}), 6-month ranking-period returns (ret_{-6}), most recent past standardised unexpected earnings (SUE_0) of the nine earnings-surprise-performance portfolios. P_sz is the average number of stocks in a portfolio (i.e., portfolio size). The results of the seven arbitrage portfolios are given in Panel B. Numbers in parentheses are t-statistics relative to the autocorrelation-adjusted standard error of the mean.

Relationship Between Momentum and PAD: Classifications of ret_{-6} and SUE_0

Panel A: 9 performance-SUE_0 portfolios

	LSPP	*LSMP*	*LSGP*	*MSPP*	*MSMP*	*MSGP*	*HSPP*	*HSMP*	*HSGP*
ret_6	0.0524 (2.04)	0.0656 (2.97)	0.1006 (3.88)	0.0729 (2.18)	0.0840 (4.07)	0.1279 (5.55)	0.0788 (2.52)	0.0935 (3.32)	0.1227 (4.42)
ret_{12}	0.1099 (2.66)	0.1378 (3.85)	0.2025 (4.37)	0.1549 (2.19)	0.1645 (4.21)	0.2528 (5.60)	0.1663 (2.40)	0.1760 (3.07)	0.2437 (4.68)
ret_{-6}	−0.1691 (−8.48)	0.0710 (2.92)	0.3355 (9.20)	−0.1497 (−6.70)	0.0724 (2.97)	0.3424 (9.27)	−0.1387 (−6.32)	0.0751 (3.22)	0.3590 (9.21)
SUE_0	−0.8613 (−29.4)	−0.7917 (−25.5)	−0.8164 (−23.2)	0.2173 (4.93)	0.2306 (5.50)	0.2487 (5.45)	1.0609 (23.7)	1.0717 (22.2)	1.1149 (22.3)
P_sz	80.28	60.30	49.77	58.95	67.12	65.13	51.12	63.78	75.45

Panel B: 7 arbitrage portfolios

	LSGP−LSPP	*MSGP−MSPP*	*HSGP−HSPP*	*HSPP−LSPP*	*HSMP−LSMP*	*HSGP−LSGP*	*HSGP−LSPP*
ret_6	0.0482 (5.06)	0.0550 (2.24)	0.0439 (2.69)	0.0263 (1.66)	0.0278 (1.92)	0.0221 (2.41)	0.0703 (6.37)
ret_{12}	0.0926 (7.26)	0.0979 (1.92)	0.0773 (2.66)	0.0565 (1.27)	0.0382 (1.19)	0.0412 (2.36)	0.1338 (5.46)
ret_{-6}	0.5046 (24.4)	0.4920 (25.5)	0.4977 (22.3)	0.0304 (5.17)	0.0041 (2.56)	0.0235 (1.81)	0.5281 (23.5)
SUE_0	0.0449 (2.02)	0.0315 (4.99)	0.0539 (3.55)	1.9222 (44.6)	1.8634 (51.0)	1.9313 (38.3)	1.9762 (46.5)

(2) Momentum and $REV6$*-based PAD*

The two-dimensional analysis of the association between momentum and $REV6$-based PAD is summarised in Table 6.3.3. Similar to previous analyses it is easy to distinguish the momentum and $REV6$-based PAD effects. For example, the high-$REV6$-good-performance portfolio ($HSGP$) earns unusually high annual returns of 24.74% on average, while the low-$REV6$-poor-performance portfolio ($LSPP$) earns average holding-period return of 12.36% per annum. The results in Panel B of Table 6.3.3 show that the three $REV6_0$-matched portfolios realise significantly positive momentum profits over 6- and 12-month holding periods. The three average annual momentum profits are 11.17% ($t = 4.22$), 7.78% ($t = 4.00$), and 8.48% ($t = 3.49$) after controlling for the $REV6_0$-based PAD effect. However, the average PAD profits of the three ret_{-6}-matched portfolios are much weaker and tend to be insignificant within the medium- and high-ret_{-6} stocks. The evidence in Table 6.3.3 indicates that the momentum effect is not due to a $REV6_0$-related PAD effect. Rather, momentum can nearly account for $REV6_0$-based PAD.

Table 6.3.3 Relationships between Momentum Classified by prior 6-month Return (ret_{-6}) and PAD Classified by Cumulative Price-deflated Earnings Forecast Revision over prior 6 Months ($REV6_0$): Examining the Momentum (PAD) Effect after Controlling for the PAD (Momentum) Effect

At the beginning of every month from July 1992 to June 1997, all stocks in the earnings sample are sorted in ascending order based on their buy-and-hold return over the prior six months (ret_{-6}) and assigned to one of three equally-sized portfolios. The first one is referred to as the poor-performance portfolio (PP); the middle one as the medium-performance portfolio (MP); and the third one as the good-performance portfolio (GP). All stocks are also independently sorted in ascending order based on the cumulative price-deflated earnings forecast revision over prior 6 months ($REV6_0$) and assigned to one of three equally-sized portfolios. The first portfolio including the 1/3 lowest-$REV6_0$ stocks is denoted as the low-earning-surprise portfolio (LS); the middle one as the medium-earning-surprise portfolio (MS); and the third one containing 1/3 highest-$REV6_0$ stocks is referred to as the high-earnings-surprise portfolio (HS). The intersections of the three ret_{-6}-sorted portfolios (PP, MP, GP) and the three $REV6_0$-sorted portfolios (LS, MS, HS) give nine earnings-surprise-performance portfolios. The nine earnings-surprise-performance portfolios are: low-earnings-surprise-poor-performance portfolio ($LSPP$), low-earnings-surprise-medium-performance portfolio ($LSMP$), low-earnings-surprise-good-performance portfolio ($LSGP$); medium-earnings-surprise-poor-performance portfolio ($MSPP$), medium-earnings-surprise-medium-performance portfolio ($MSMP$), medium-earnings-surprise-good-performance portfolio ($MSGP$); high-earnings-surprise-poor-performance portfolio ($HSPP$), high-earnings-surprise-medium-performance portfolio ($HSMP$), and high-earnings-surprise-good-performance portfolio ($HSGP$). All stocks are equally-weighted in a portfolio. Seven arbitrage portfolios are constructed based on the nine earnings-surprise-performance portfolios. Three of the seven arbitrage portfolios are earnings-surprise-matched, and they are: low-earnings-surprise-good-performance portfolio minus low-earnings-surprise-poor-performance portfolio ($LSGP-LSPP$), medium-earnings-surprise-good-performance portfolio minus medium-earnings-surprise-poor-performance portfolio ($MSGP-MSPP$), and high-earnings-surprise-good-performance portfolio minus high-earnings-surprise-poor-performance portfolio ($HSGP-HSPP$). Another three of the seven arbitrage portfolios are performance-matched, and they are: high-earnings-surprise-poor-performance portfolio minus low-earnings-surprise-poor-performance portfolio ($HSPP-LSPP$), high-earnings-surprise-medium-performance portfolio minus low-earnings-surprise-medium-performance portfolio ($HSMP-LSMP$), and high-earnings-surprise-good-performance portfolio minus low-earnings-surprise-good-performance portfolio ($HSGP-LSGP$). One of the seven arbitrage portfolios is miscellaneous, and it is high-earnings-surprise-good-performance portfolio minus low-earnings-surprise-poor-performance portfolio ($HSGP-LSPP$). Panel A reports the average 6-month holding-period returns (ret_6), 12-month holding-period returns (ret_{12}), 6-month ranking-period returns (ret_{-6}), the cumulative price-deflated earnings forecast revision over prior 6 months ($REV6_0$) of the nine earnings-surprise-performance portfolios. P_sz is the average number of stocks in a portfolio (i.e., portfolio size). The results of the seven arbitrage portfolios are given in Panel B. Numbers in parentheses are t-statistics relative to the autocorrelation-adjusted standard error of the mean.

Relationship between Momentum and PAD: Classifications of ret_{-6} and $REV6_0$

Panel A: 9 performance-$REV6_0$ portfolios									
	LSPP	*LSMP*	*LSGP*	*MSPP*	*MSMP*	*MSGP*	*HSPP*	*HSMP*	*HSGP*
ret_6	0.0533 (1.55)	0.0703 (2.71)	0.1160 (4.25)	0.0484 (2.37)	0.0601 (2.95)	0.0802 (3.48)	0.0871 (2.79)	0.0840 (3.67)	0.1314 (5.36)
ret_{12}	0.1236 (1.84)	0.1533 (2.88)	0.2353 (4.29)	0.0813 (2.23)	0.1121 (3.35)	0.1591 (4.32)	0.1626 (2.99)	0.1583 (4.13)	0.2474 (6.44)
ret_{-6}	−0.1902 (−9.25)	0.0640 (2.62)	0.3336 (8.90)	−0.0995 (−5.08)	0.0671 (2.89)	0.2699 (8.37)	−0.1109 (−5.34)	0.0766 (3.29)	0.3334 (8.94)
$REV6_0$(%)	−4.133 (−9.95)	−2.073 (−14.5)	−3.726 (−6.35)	−0.202 (−4.02)	−0.167 (−3.65)	−0.138 (−3.70)	1.232 (11.4)	0.783 (13.1)	1.305 (9.73)
P_sz	74.82	34.78	27.98	39.90	57.23	41.38	22.87	46.50	68.22

Panel B: 7 arbitrage portfolios							
	LSGP−LSPP	*MSGP−MSPP*	*HSGP−HSPP*	*HSPP−LSPP*	*HSMP−LSMP*	*HSGP−LSGP*	*HSGP−LSPP*
ret_6	0.0627 (3.06)	0.0318 (2.99)	0.0443 (2.73)	0.0338 (2.41)	0.0136 (1.09)	0.0154 (1.17)	0.0781 (3.85)
ret_{12}	0.1117 (4.22)	0.0778 (4.00)	0.0848 (3.49)	0.0389 (1.49)	0.0050 (0.18)	0.0121 (0.59)	0.1237 (3.21)
ret_{-6}	0.5238 (22.5)	0.3694 (23.9)	0.4443 (20.6)	0.0793 (25.8)	0.0126 (5.52)	−0.0002 (−0.04)	0.5236 (22.9)
$REV6_0$(%)	0.407 (0.71)	0.064 (4.27)	0.072 (0.40)	5.365 (13.1)	2.856 (23.0)	5.031 (7.62)	5.437 (12.3)

(3) Momentum and $AR4D$*-based PAD*

As mentioned in Chapter 5, the two earnings surprise measures, SUE and $REV6$, both have potential problems. In comparison, the short-term price reaction around the earnings announcement ($AR4D$) is a cleaner measure. Furthermore, we have seen that the correlation coefficient is highest between ret_{-6} and $AR4D_0$, and the $AR4D_0$-based PAD effect is the strongest relative to the other two earnings surprise measures. Examining the relationship between momentum and $AR4D$-based PAD could, therefore, provide convincing evidence on whether momentum (PAD) is the same thing as PAD (momentum). The results of the two-dimensional analysis are reported in Table 6.3.4.

Table 6.3.4 Relationships between Momentum Classified by prior 6-month Return (ret_{-6}) and PAD Classified by Most Recent Past 4-day Abnormal Return around Earnings Announcement ($AR4D_0$): Examining the Momentum (PAD) Effect after Controlling for the PAD (Momentum) Effect

At the beginning of every month from July 1992 to June 1997, all stocks in the earnings sample are sorted in ascending order based on their buy-and-hold return over the prior six months (ret_{-6}) and assigned to one of three equally-sized portfolios. The first one is referred to as the poor-performance portfolio (PP); the middle one as the medium-performance portfolio (MP); and the third one as the good-performance portfolio (GP). All stocks are also independently sorted in ascending order based on the 4-day abnormal return around their most recent past earnings announcement ($AR4D_0$) and assigned to one of three equally-sized portfolios. The first portfolio including the 1/3 lowest-$AR4D_0$ stocks is denoted as the low-earning-surprise portfolio (LS); the middle one as the medium-earning-surprise portfolio (MS); and the third one containing 1/3 highest-$AR4D_0$ stocks is referred to as the high-earnings-surprise portfolio (HS). The intersections of the three ret_{-6}-sorted portfolios (PP, MP, GP) and the three $AR4D_0$-sorted portfolios (LS, MS, HS) give nine earnings-surprise-performance portfolios. The nine earnings-surprise-performance portfolios are: low-earnings-surprise-poor-performance portfolio ($LSPP$), low-earnings-surprise-medium-performance portfolio ($LSMP$), low-earnings-surprise-good-performance portfolio ($LSGP$); medium-earnings-surprise-poor-performance portfolio ($MSPP$), medium-earnings-surprise-medium-performance portfolio ($MSMP$), medium-earnings-surprise-good-performance portfolio ($MSGP$); high-earnings-surprise-poor-performance portfolio ($HSPP$), high-earnings-surprise-medium-performance portfolio ($HSMP$), and high-earnings-surprise-good-performance portfolio ($HSGP$). All stocks are equally-weighted in a portfolio. Seven arbitrage portfolios are constructed based on the nine earnings-surprise-performance portfolios. Three of the seven arbitrage portfolios are earnings-surprise-matched, and they are: low-earnings-surprise-good-performance portfolio minus low-earnings-surprise-poor-performance portfolio ($LSGP-LSPP$), medium-earnings-surprise-good-performance portfolio minus medium-earnings-surprise-poor-performance portfolio ($MSGP-MSPP$), and high-earnings-surprise-good-performance portfolio minus high-earnings-surprise-poor-performance portfolio ($HSGP-HSPP$). Another three of the seven arbitrage portfolios are performance-matched, and they are: high-earnings-surprise-poor-performance portfolio minus low-earnings-surprise-poor-performance portfolio ($HSPP-LSPP$), high-earnings-surprise-medium-performance portfolio minus low-earnings-surprise-medium-performance portfolio ($HSMP-LSMP$), and high-earnings-surprise-good-performance portfolio minus low-earnings-surprise-good-performance portfolio ($HSGP-LSGP$). One of the seven arbitrage portfolios is miscellaneous, and it is high-earnings-surprise-good-performance portfolio minus low-earnings-surprise-poor-performance portfolio ($HSGP-LSPP$). Panel A reports the average 6-month holding-period returns (ret_6), 12-month holding-period returns (ret_{12}), 6-month ranking-period returns (ret_6), and the 4-day abnormal returns around the most recent past earnings announcements ($AR4D_0$) of the nine earnings-surprise-performance portfolios. P_sz is the average number of stocks in a portfolio (i.e., portfolio size). The results of the seven arbitrage portfolios are given in Panel B. Numbers in parentheses are t-statistics relative to the autocorrelation-adjusted standard error of the mean.

Relationship between Momentum and PAD: Classifications of ret_{-6} and $AR4D_0$									
Panel A: 9 performance-$AR4D_0$ portfolios									
	LSPP	*LSMP*	*LSGP*	*MSPP*	*MSMP*	*MSGP*	*HSPP*	*HSMP*	*HSGP*
ret_6	0.0578 (2.00)	0.0640 (3.19)	0.0835 (3.50)	0.0718 (2.41)	0.0750 (3.22)	0.1097 (4.21)	0.0775 (2.44)	0.1055 (4.25)	0.1368 (5.33)
ret_{12}	0.1346 (2.29)	0.1437 (3.50)	0.1896 (3.94)	0.1292 (2.37)	0.1471 (3.49)	0.2217 (4.62)	0.1647 (2.77)	0.1897 (4.34)	0.2629 (5.64)
ret_{-6}	−0.1786 (−8.49)	0.0661 (2.74)	0.3325 (8.34)	−0.1272 (−6.12)	0.0730 (3.06)	0.3137 (9.36)	−0.1314 (−6.61)	0.0792 (3.27)	0.3706 (9.49)
$AR4D_0$(%)	−8.403 (−28.6)	−4.783 (−25.9)	−5.222 (−22.0)	0.376 (3.24)	0.551 (4.68)	0.668 (5.58)	7.644 (16.9)	6.873 (21.9)	9.046 (22.1)
P_sz	97.68	55.57	37.10	57.87	75.33	58.00	34.80	60.30	95.25

Panel B: 7 arbitrage portfolios							
	LSGP−LSPP	*MSGP−MSPP*	*HSGP−HSPP*	*HSPP−LSPP*	*HSMP−LSMP*	*HSGP−LSGP*	*HSGP−LSPP*
ret_6	0.0257 (1.33)	0.0379 (2.75)	0.0593 (3.36)	0.0197 (2.12)	0.0415 (4.73)	0.0533 (4.48)	0.0790 (4.53)
ret_{12}	0.0550 (2.12)	0.0925 (3.36)	0.0983 (3.73)	0.0301 (2.55)	0.0460 (4.05)	0.0733 (3.91)	0.1283 (4.53)
ret_{-6}	0.5112 (22.3)	0.4409 (25.8)	0.5019 (21.8)	0.0473 (11.0)	0.0131 (9.84)	0.0380 (3.60)	0.5492 (24.5)
$AR4D_0$(%)	3.180 (8.06)	0.291 (7.00)	1.402 (3.36)	16.046 (30.9)	11.656 (37.2)	14.268 (30.2)	17.448 (51.2)

Both Panels A and B of Table 6.3.4 show apparent momentum and PAD effects. The three $AR4D_0$-matched portfolios ($LSGP-LSPP$, $MSGP-MSPP$, and $HSGP-HSPP$) realise significant momentum profits over 6- and 12-month holding periods except for the half-year case within the low-$AR4D_0$ matched portfolio. The $AR4D_0$-related PAD profits are also significant within the three performance-matched portfolios of $HSPP-LSPP$, $HSMP-LSMP$, and $HSGP-LSGP$ over 6- and 12-month holding periods. These results indicate that the $AR4D$-related PAD effect does not subsume the momentum effect, and vice versa. In addition, these results also confirm the last chapter's findings that the PAD effect tends to be shorter-lived than the momentum effect. For example, the three average annual momentum profits are 5.50% ($t=2.12$), 9.25% ($t=3.36$), and 9.83% ($t=3.73$) after controlling for the $AR4D_0$-based PAD effect, while the three average annual PAD profits are 3.01% ($t=2.55$), 4.60% ($t=4.05$), and 7.33% ($t=3.91$) after controlling for the momentum effect. This is similar to the US evidence documented in Chan et al. (1996). The shorter-lived PAD effect might partially be due to the possible downward bias in estimating PAD profits as mentioned in the last chapter. Namely, for any given time point at which a holding period starts, there may be a time lag between it and the earnings announcement since the PAD trading strategy is based on the most recent past earnings surprise. However, this possible bias may not be serious, as also mentioned in the last chapter, because of Hew et al.'s (1996) finding and the monthly overlapping strategy implemented in this study. Further, both momentum and $AR4D_0$-based PAD do have marginal explanatory power because the controlled momentum and PAD profits are smaller than the uncontrolled ones (comparing Table 6.3.4 with the results reported in the last section and the last chapter).

To state the results succinctly, the two-dimensional analysis conducted in this section shows that the PAD effect does not subsume the momentum effect. Momentum can not account for the $AR4D_0$-based PAD effects, but it can almost explain SUE_0- and $REV6_0$-based PAD profits. In Chapter 5, the evidence shows that $AR4D_0$-based PAD can nearly explain SUE_0- and $REV6_0$-based PAD. Thus, it seems appropriate to conclude that the PAD effect is not entirely attributable to the momentum effect.

6.4 Regression Analysis

The empirical results documented in Chapter 5 and the previous two sections in this chapter show that both PAD and momentum effects are pronounced within the earnings sample, and neither PAD nor momentum can subsume the other. In this section I will adopt a different method of regression analysis to examine whether the previous results are robust.

6.4.1 Cross-sectional Regression Analysis

This sub-section examines whether the positive associations between holding- and ranking-period returns, and between holding-period returns and most recent earnings surprise hold. The method adopted here is the Fama-MacBeth (1973) cross-sectional regression. The regression equation is as follows:

$$ret_6 = \alpha_0 + \alpha_1 ret_{-6} + \alpha_2 SUE_0 + \alpha_3 AR4D_0 + \alpha_4 REV6_0 + \varepsilon, \qquad (6.4.1)$$

where ret_6 is the 6-month holding-period return, ret_{-6} is the 6-month ranking-period return, and SUE_0, $AR4D_0$, and $REV6_0$ are three most recent earnings surprise variables described in the last chapter. At the beginning of each month from July 1992 to June 1997 I fit regression equation (6.4.1) across individual stocks in the earnings sample. This procedure results in 60 estimates for each slope coefficient. The average of the 60 estimates for each coefficient is reported in Table 6.4.1. In addition, I also regress ret_6 on different combinations of the four independent variables, ret_{-6}, SUE_0, $AR4D_0$, and $REV6_0$, and present the results in Table 6.4.1. Numbers in parentheses are t-statistics relative to the autocorrelation-adjusted standard errors of the time-series average of the slope coefficients.

Table 6.4.1 Analysis of Cross-sectional Regression

This table presents the results of cross-sectional regressions. The regression equation is as follows:

$$ret_6 = \alpha_0 + \alpha_1 ret_{-6} + \alpha_2 SUE_0 + \alpha_3 AR4D_0 + \alpha_4 REV6_0 + \varepsilon .$$

The regression equation is estimated across individual stocks in the earnings sample at the beginning of each month from July 1992 to June 1997 (60 months). The dependent variable, ret_6, is an individual stock's buy-and-hold return over the subsequent six months. The independent variable, ret_{-6}, is an individual stock's buy-and-hold return over the prior six months. The other three regressors are an individual stock's most recent past standardised unexpected earnings (SUE_0), the 4-day abnormal return around an individual stock's most recent past earnings announcement ($AR4D_0$), and the most recent past cumulative price-deflated earnings forecast revision over prior 6 months ($REV6_0$). In order to examine each regressor's explanatory power for future performance, various cross-sectional regressions are also implemented by choosing different combinations of the 4 independent variables. The reported statistics are the means of the time series of coefficients from the month-by-month regressions. For instance, $\overline{\hat{\alpha}}_1$ is the average of the 60 estimates of α_1. $\overline{R^2}$ is the mean value of the regression R^2s over the 60 regressions. Numbers in parentheses are t-statistics relative to the autocorrelation-adjusted standard errors of the means.

$\overline{\hat{\alpha}}_0$	$\overline{\hat{\alpha}}_1$	$\overline{\hat{\alpha}}_2$	$\overline{\hat{\alpha}}_3$	$\overline{\hat{\alpha}}_4$	$\overline{R^2}$
0.09017 (3.11)	0.07366 (3.14)				0.0164
0.08748 (3.62)		0.01499 (2.61)			0.0065
0.09493 (3.42)			0.20250 (3.70)		0.0074
0.08742 (3.15)				0.25565 (2.16)	0.0091
0.07653 (3.46)		0.01184 (2.11)	0.28258 (5.33)	0.09546 (0.52)	0.0344
0.06543 (3.16)	0.10478 (3.48)	0.00940 (1.66)	0.14010 (2.45)	0.01246 (0.08)	0.0581

The first four rows in Table 6.4.1 show that prior 6-month return and most recent earnings surprise, taken separately, are positively related to future 6-month returns, and the relations are statistically significant. This is consistent with previous findings: momentum, and SUE-, $AR4D$-, $REV6$-based PAD are significant. The regressions with all three measures of earnings surprise, and with all four independent variables generally further confirm the momentum and PAD effects, but the coefficient for $REV6_0$, $\overline{\hat{\alpha}}_4$, tends to be insignificant. This coincides with the findings documented in Chapter 5 that the relation between ret_6 and $REV6_0$ is relatively weak and non-monotonic. The last row in Table 6.4.1 shows that the coefficient for SUE_0 is also less significant (0.0094 with a t-statistics of 1.66) when the momentum variable, ret_{-6}, is included. These results conform the last section's evidence that the momentum effect can almost account for the SUE_0- and $REV6_0$-related PAD effects.

6.4.2 Time-series Regression Analysis

The evidence concerning the momentum effect documented in Sections 6.2 and 6.3 in this chapter does not directly adjust for systematic risk and other factors such as size and book-to-market ratio. This subsection examines portfolios' abnormal returns rather than raw returns as implemented previously to ascertain whether the earlier results are confounded by systematic risk, and the effects of size and book-to-market ratio. The abnormal returns are obtained by performing time series regressions of the Fama-French (1993) three-factor model. The Fama-French three-factor model is,

$$r_{P\tau} - r_{f\tau} = a_P + b_P(r_{m\tau} - r_{f\tau}) + s_P SMB_\tau + h_P HML_\tau + \varepsilon_{P\tau}.$$

The two factor-mimicking portfolios of SMB_τ and HML_τ, and the value-weighted market return, $r_{m\tau}$, are constructed based on the accounting sample (for detailed descriptions of the constructions of SMB_τ and HML_τ, and other notation for the 3-factor model see Table 4.4.1 in Chapter 4).

I do not repeat every analysis conducted previously. Instead, the three-factor model is estimated only based on the two-dimensional portfolios as constructed in the last section. Therefore, the portfolios that will be examined in this subsection are exactly the same as those reported in the last section. For details of the construction of the two-dimensional portfolios see the corresponding tables in the last section. Focusing on the estimates of the two-dimensional portfolios not only helps to examine the relation between momentum and PAD, it is also helpful to investigate, in isolation, momentum and PAD after adjusting for systematic risk and size and book-to-market effects.

Note that the 3-factor model is estimated using overlapping monthly observations. Specifically, at the beginning of each month from July 1992 to June 1997 each portfolio's monthly returns (r_{p_τ}) are subsequently traced for 6 months. This gives 360 overlapping monthly holding-period returns for each portfolio from July 1992 to November 1997, over which the Fama-French 3-factor model is estimated.

(1) Two-dimensional Portfolios Classified by ret_{-6} and SUE_0

Table 6.4.2 reports the estimates of the Fama-French three-factor model for the two-dimensional portfolios classified by ret_{-6} and SUE_0. Clearly, all nine performance-SUE_0 portfolios load significantly on size and book-to-market factors. However, adjusting for these does not alter the previous findings. Holding SUE_0 fixed, the three momentum portfolios of $LSGP - LSPP$, $MSGP - MSPP$ and $HSGP - HSPP$ earn significantly positive momentum profits, and their monthly profits are 0.932% ($t = 6.69$), 1.209% ($t = 6.00$), and 0.935% ($t = 3.78$), respectively. In addition, the loser portfolios are riskier than the winners with losers being more heavily loaded on small and value stocks. This indicates that the momentum effect cannot be explained by SUE-based PAD, size, and book-to-market effects. However, the three SUE-based PAD portfolios' returns tend to be insignificant after controlling for the momentum effect. The evidence in Table 6.4.2 is consistent with previous findings.

Table 6.4.2 Time-series Regressions of the Fama-French 3-factor Model with Portfolios Classified by ret_{-6} and SUE_0

This table summarises regression results of the Fama-French three-factor model for the portfolios from a two-dimension classification by prior 6-month return (ret_{-6}) and most recent past standardised unexpected earnings (SUE_0). Thus, the 9 performance-SUE_0 portfolios shown in Panel A and the 7 arbitrage portfolios shown in Panel B in this table are exactly the same as those reported in Table 6.3.2 (for the formation of the 16 portfolios see Table 6.3.2). The Fama-French three-factor model is,

$$r_{P\tau} - r_{f\tau} = a_P + b_P(r_{m\tau} - r_{f\tau}) + s_P SMB_\tau + h_P HML_\tau + \varepsilon_{P\tau}.$$

The two factor-mimicking portfolios of SMB_τ and HML_τ, and the value-weighted market return, $r_{m\tau}$, are constructed based on the accounting sample (for detailed descriptions of the constructions of SMB_τ and HML_τ, and other notation for the 3-factor model see Table 4.4.1 in Chapter 4). The 3-factor model is estimated using overlapping monthly observations. Specifically, at the beginning of each month from July 1992 to June 1997 these portfolios' monthly returns ($r_{P\tau}$) are subsequently traced for 6 months. This gives 360 overlapping monthly holding-period returns for each portfolio from July 1992 to November 1997, over which the Fama-French 3-factor model is estimated. Numbers in parentheses are t-statistics computed using Newey-West heteroscedasticity- and autocorrelation-consistent variance-covariance matrix.

Relationship Between Momentum and PAD: Classifications of ret_{-6} and SUE_0

Panel A: 9 performance-SUE_0 portfolios

	$LSPP$	$LSMP$	$LSGP$	$MSPP$	$MSMP$	$MSGP$	$HSPP$	$HSMP$	$HSGP$
a_P (%)	−0.659 (−5.65)	−0.251 (−1.67)	0.273 (1.89)	−0.485 (−3.75)	−0.005 (−0.05)	0.724 (4.76)	−0.364 (−1.55)	−0.022 (−0.21)	0.571 (4.47)
b_P	1.114 (31.1)	0.965 (32.2)	1.008 (25.1)	1.209 (24.2)	0.974 (32.5)	0.955 (26.1)	1.157 (35.7)	1.050 (35.6)	0.996 (23.7)
s_P	0.753 (10.3)	0.627 (11.6)	0.651 (9.93)	0.825 (18.0)	0.575 (24.4)	0.620 (8.88)	0.839 (20.0)	0.650 (25.2)	0.698 (14.9)
h_P	0.255 (4.23)	0.099 (1.88)	0.061 (1.28)	0.496 (8.15)	0.148 (3.25)	0.032 (0.43)	0.558 (5.94)	0.360 (3.48)	0.175 (3.87)
R^2	0.8348	0.8050	0.8051	0.8311	0.8062	0.8083	0.7872	0.8392	0.8302

Panel B: 7 arbitrage portfolios

	$LSGP-LSPP$	$MSGP-MSPP$	$HSGP-HSPP$	$HSPP-LSPP$	$HSMP-LSMP$	$HSGP-LSGP$	$HSGP-LSPP$
a_P (%)	0.932 (6.69)	1.209 (6.00)	0.935 (3.78)	0.295 (1.22)	0.229 (1.33)	0.298 (2.15)	1.229 (7.36)
b_P	−0.106 (−1.94)	−0.254 (−3.43)	−0.162 (−3.28)	0.043 (1.06)	0.085 (2.30)	−0.013 (−0.30)	−0.118 (−2.18)
s_P	−0.102 (−2.24)	−0.205 (−2.61)	−0.141 (−2.39)	0.086 (1.25)	0.023 (0.41)	0.047 (0.96)	−0.055 (−0.80)
h_P	−0.194 (−2.87)	−0.464 (−4.60)	−0.382 (−3.80)	0.303 (2.35)	0.261 (1.99)	0.114 (2.90)	−0.079 (−1.00)
R^2	0.0618	0.2016	0.1157	0.0708	0.0783	0.0278	0.0323

(2) Two-dimensional Portfolios Classified by ret_{-6} and $REV6_0$

The estimates of the Fama-French three-factor model for the two-dimensional portfolios classified by ret_{-6} and $REV6_0$ are presented in Table 6.4.3. The momentum profits of the three $REV6_0$-matched portfolios of $LSGP - LSPP$, $MSGP - MSPP$, and $HSGP - HSPP$ are statistically positive, and the loadings on the three factors are similar to those on portfolios classified by ret_{-6} and SUE_0 reported above. The ret_{-6}-matched $REV6_0$-related PAD portfolios also realise significant profits within the poor- and medium-performers, but the magnitudes are smaller than the corresponding momentum profits. Consistent with the results presented in Table 6.3.3 of the last section, momentum is stronger than the $REV6_0$-based PAD. In addition, the U-shape in holding-period returns of $REV6_0$-classified portfolios almost disappears after adjusting for the three factors, and when holding ret_{-6} fixed the low-$REV6_0$ portfolios generally have the worst performance. For instance, holding low-ret_{-6} fixed, the three-factor-adjusted abnormal returns of the low-$REV6_0$ ($LSPP$), medium-$REV6_0$ ($MSPP$) and high-$REV6_0$ ($HSPP$) portfolios are −0.880% ($t = -6.25$), −0.732% ($t = -5.58$), and −0.222 ($t = -1.60$), respectively. These coincide with the results documented in the last chapter.

Table 6.4.3 Time-series Regressions of the Fama-French 3-factor Model with Portfolios Classified by ret_{-6} and $REV6_0$

This table summarises regression results of the Fama-French three-factor model for the portfolios from a two-dimension classification by prior 6-month return (ret_{-6}) and price-deflated cumulative earnings forecast revision ($REV6_0$). Thus, the 9 performance-$REV6_0$ portfolios shown in Panel A and the 7 arbitrage portfolios shown in Panel B in this table are exactly the same as those reported in Table 6.3.3 (for the formation of the 16 portfolios see Table 6.3.3). The Fama-French three-factor model is,

$$r_{P\tau} - r_{f\tau} = a_P + b_P(r_{m\tau} - r_{f\tau}) + s_P SMB_\tau + h_P HML_\tau + \varepsilon_{P\tau}.$$

The two factor-mimicking portfolios of SMB_τ and HML_τ, and the value-weighted market return, $r_{m\tau}$, are constructed based on the accounting sample (for detailed descriptions of the constructions of SMB_τ and HML_τ, and other notation for the 3-factor model see Table 4.4.1 in Chapter 4). The 3-factor model is estimated using overlapping monthly observations. Specifically, at the beginning of each month from July 1992 to June 1997 these portfolios' monthly returns ($r_{P\tau}$) are subsequently traced for 6 months. This gives 360 overlapping monthly holding-period returns for each portfolio from July 1992 to November 1997, over which the Fama-French 3-factor model is estimated. Numbers in parentheses are t-statistics computed using Newey-West heteroscedasticity- and autocorrelation-consistent variance-covariance matrix.

Relationship Between Momentum and PAD: Classifications of ret_{-6} and $REV6_0$

Panel A: 9 performance-$REV6_0$ portfolios

	LSPP	*LSMP*	*LSGP*	*MSPP*	*MSMP*	*MSGP*	*HSPP*	*HSMP*	*HSGP*
a_P (%)	−0.880 (−6.25)	−0.391 (−2.32)	0.422 (1.93)	−0.732 (−5.58)	−0.371 (−4.18)	0.008 (0.06)	−0.222 (−1.60)	−0.067 (−0.49)	0.703 (4.85)
b_P	1.2824 (30.3)	1.0888 (18.9)	1.0118 (11.7)	1.1476 (22.7)	0.9959 (30.4)	0.9463 (17.7)	1.2629 (13.6)	1.0604 (35.2)	1.0440 (26.7)
s_P	0.9289 (19.6)	0.7063 (16.3)	0.6689 (6.09)	0.5361 (13.1)	0.4590 (14.1)	0.4476 (9.35)	0.6897 (9.65)	0.5301 (14.3)	0.6057 (7.42)
h_P	0.5413 (7.44)	0.4443 (4.79)	0.2727 (1.59)	0.3112 (4.85)	0.1240 (2.21)	0.0194 (0.35)	0.2251 (2.16)	0.0908 (2.25)	0.0907 (1.67)
R^2	0.8425	0.7276	0.6243	0.7511	0.8242	0.7424	0.6726	0.8009	0.8126

Panel B: 7 arbitrage portfolios

	LSGP−LSPP	*MSGP−MSPP*	*HSGP−HSPP*	*HSPP−LSPP*	*HSMP−LSMP*	*HSGP−LSGP*	*HSGP−LSPP*
a_P (%)	1.302 (5.89)	0.740 (3.98)	0.925 (5.45)	0.658 (5.41)	0.324 (2.27)	0.281 (1.28)	1.583 (8.15)
b_P	−0.2706 (−2.75)	−0.2013 (−4.43)	−0.2189 (−2.29)	−0.0196 (−0.19)	−0.0285 (−0.56)	0.0322 (0.40)	−0.2384 (−3.35)
s_P	−0.2599 (−2.85)	−0.0885 (−2.00)	−0.0841 (−1.03)	−0.2391 (−4.97)	−0.1761 (−4.57)	−0.0633 (−1.06)	−0.3232 (−5.42)
h_P	−0.2686 (−1.62)	−0.2919 (−3.94)	−0.1345 (−1.09)	−0.3161 (−3.13)	−0.3535 (−3.94)	−0.1820 (−0.92)	−0.4506 (−4.34)
R^2	0.1266	0.1086	0.0537	0.1064	0.1345	0.0308	0.2472

(3) Two-dimensional Portfolios Classified by ret_{-6} *and* $AR4D_0$

Table 6.4.4 summarises the results of time series regressions of the Fama-French three-factor model for the two-dimensional portfolios classified by prior 6-month return (ret_{-6}) and 4-day abnormal return around the most recent past earnings announcement ($AR4D_0$). The positive loading on the three factors is apparent from the nine ret_{-6} - $AR4D_0$ portfolios reported in Panel A of Table 6.4.4. Again, adjusting for the Fama-French three factors after controlling for $AR4D_0$-based PAD effect does not eliminate the momentum profits. The three average monthly momentum profits after controlling for $AR4D_0$-based PAD effect are 0.697% ($t = 3.49$), 0.834% ($t = 8.02$), and 1.154% ($t = 4.95$) with the loser portfolios being riskier and more heavily loaded on size and value stocks than the winner portfolios. Adjusting for the three factors thus accentuates the momentum profits because of the negative coefficients of b_P, s_P, and h_P of the three $AR4D_0$-matched portfolios. The momentum strategy seems to do especially well within those firms with high $AR4D_0$ s (i.e., good news firms).

The $AR4D_0$-related PAD effect is also striking. The three average monthly $AR4D_0$-based PAD profits after controlling for momentum are 0.334% ($t = 2.54$), 0.582% ($t = 4.89$), and 0.790% ($t = 5.10$). However, the magnitudes of the three PAD profits are smaller than the corresponding momentum profits, indicating that the PAD effect is relatively weaker than the momentum effect. The high- and low-$AR4D_0$ portfolios have very similar market risk exposures (b_P), and their loading on size (s_P) and book-to-market (h_P) factors is also similar. The PAD trading strategy seems to work well within good past performers.

The results in Table 6.4.4 echo the results presented in Table 6.3.4 of the last section. A significant $AR4D_0$-based PAD effect cannot subsume the momentum effect, and vice versa.

Table 6.4.4 Time-series Regressions of the Fama-French 3-factor Model with Portfolios Classified by ret_{-6} and $AR4D_0$

This table summarises regression results of the Fama-French three-factor model for the portfolios from a two-dimension classification by prior 6-month return (ret_{-6}) and most recent past 4-day abnormal return around earnings announcement ($AR4D_0$). Thus, the 9 performance-$AR4D_0$ portfolios shown in Panel A and the 7 arbitrage portfolios shown in Panel B in this table are exactly the same as those reported in Table 6.3.4 (for the formations of the 16 portfolios see Table 6.3.4). The Fama-French three-factor model is,

$$r_{P\tau} - r_{f\tau} = a_P + b_P(r_{m\tau} - r_{f\tau}) + s_P SMB_\tau + h_P HML_\tau + \varepsilon_{P\tau}.$$

The two factor-mimicking portfolios of SMB_τ and HML_τ, and the value-weighted market return, $r_{m\tau}$, are constructed based on the accounting sample (for detailed descriptions of the constructions of SMB_τ and HML_τ, and other notation for the 3-factor model see Table 4.4.1 in Chapter 4). The 3-factor model is estimated using overlapping monthly observations. Specifically, at the beginning of each month from July 1992 to June 1997 these portfolios' monthly returns ($r_{P\tau}$) are subsequently traced for 6 months. This gives 360 overlapping monthly holding-period returns for each portfolio from July 1992 to November 1997, over which the Fama-French 3-factor model is estimated. Numbers in parentheses are t-statistics computed using Newey-West heteroscedasticity- and autocorrelation-consistent variance-covariance matrix.

Relationship Between Momentum and PAD: Classifications of ret_{-6} and $AR4D_0$

Panel A: 9 performance-$AR4D_0$ portfolios

	LSPP	*LSMP*	*LSGP*	*MSPP*	*MSMP*	*MSGP*	*HSPP*	*HSMP*	*HSGP*
a_P (%)	−0.681 (−5.43)	−0.346 (−3.03)	0.017 (0.10)	−0.402 (−3.64)	−0.150 (−1.47)	0.432 (3.30)	−0.347 (−1.91)	0.236 (1.99)	0.807 (6.16)
b_P	1.181 (25.9)	1.051 (36.5)	1.008 (22.2)	1.095 (24.5)	0.943 (31.0)	0.952 (26.1)	1.168 (26.2)	1.023 (27.9)	0.989 (31.0)
s_P	0.786 (17.1)	0.591 (18.7)	0.658 (13.5)	0.826 (29.1)	0.578 (28.9)	0.624 (11.1)	0.850 (8.52)	0.674 (11.4)	0.680 (9.52)
h_P	0.438 (8.19)	0.119 (2.50)	0.038 (0.42)	0.496 (7.44)	0.222 (3.85)	0.096 (1.81)	0.305 (2.76)	0.230 (4.04)	0.122 (2.40)
R^2	0.8528	0.8187	0.7116	0.8207	0.8199	0.7965	0.7132	0.8170	0.8425

Panel B: 7 arbitrage portfolios

	LSGP−LSPP	*MSGP−MSPP*	*HSGP−HSPP*	*HSPP−LSPP*	*HSMP−LSMP*	*HSGP−LSGP*	*HSGP−LSPP*
a_P (%)	0.697 (3.49)	0.834 (8.02)	1.154 (4.95)	0.334 (2.54)	0.582 (4.89)	0.790 (5.10)	1.488 (7.77)
b_P	−0.173 (−2.42)	−0.142 (−2.25)	−0.179 (−3.62)	−0.013 (−0.21)	−0.028 (−0.76)	−0.019 (−0.53)	−0.193 (−3.40)
s_P	−0.128 (−1.87)	−0.202 (−3.28)	−0.170 (−2.07)	0.064 (0.88)	0.083 (1.31)	0.021 (0.27)	−0.107 (−2.24)
h_P	−0.400 (−3.39)	−0.400 (−5.49)	−0.184 (−1.52)	−0.133 (−1.35)	0.111 (2.08)	0.083 (0.90)	−0.316 (−3.59)
R^2	0.1070	0.1610	0.0621	0.0200	0.0483	0.0075	0.1404

In short, the regression analyses implemented in this section generally confirm the previous evidence. The positive associations between future return and past return, and between future return and most recent past earnings surprises are confirmed by the cross-sectional regression analysis. The time series regressions show that adjusting for the Fama-French three factors does not change earlier conclusions. For example, neither the $AR4D_0$-based PAD effect nor the momentum effect can subsume the other. In fact, adjusting for the three factors always enhances the momentum profits because of the negative loading of the momentum portfolios on these factors.

6.5 Summary and Conclusion

In this chapter I first re-examine the momentum effect based on the earnings sample that was selected for the PAD examinations conducted in Chapter 5. Consistent with the previous findings documented in Chapters 3 and 4, the momentum effect is still pronounced within the earnings sample. Sorting stocks on the basis of prior six-month return yields semi-annual momentum profit of 8.61% ($t = 3.02$). The momentum portfolios' characteristics and the sub-sample analysis suggest that momentum is less likely due to market beta and other effects such as size, price, book-to-market ratio, cash earnings-to-price ratio, and number of analysts.

The two-dimensional analysis shows that the PAD effect documented in Chapter 5 cannot account for momentum. In fact, price momentum tends to be stronger and longer-lived than PAD, and it can almost separately explain the SUE- and $REV6$-based PAD profits although it cannot explain the $AR4D$-based PAD effect.[7] Because the $AR4D$ measure has less problems compared with the SUE and $REV6$ measures, the general conclusion from the two-dimensional analysis performed in Section 6.3 is that price momentum is not attributable to PAD, while neither can it subsume PAD. The regression analyses in the last section generally confirm the momentum and PAD effects, and other findings documented in previous chapters. Further, the general conclusions drawn from the two-dimensional analysis of Section 6.3 remain unchanged after adjusting for the Fama-French three factors. The empirical evidence in this chapter is similar to the US market as documented in Chan et al. (1996).

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[7] After adjusting for the Fama-French three-factor model, price momentum cannot account for the

APPENDIX 6A

Size and the Number of Analysts

In this appendix I examine the effects of number of analysts and size to see whether they are the same. The examinations are conducted based on the earnings sample. For detailed description of this sample and data items used in this appendix see Chapter 5.

1. Analysts Number Effect

Table 6A.1 reports the performances and characteristics of decile portfolios classified by the number of analysts (ANo). The bottom line in Panel B of Table 6A.1 shows that the average ANo s of LD, $D2$ and $D3$ are the same (i.e., zero). We should thus refer to these three portfolios together as the lowest-ANo portfolios.

Table 6A.1 Performances and Characteristics of Decile and Decile Arbitrage Portfolios Classified by the Number of Analysts (ANo)

At the beginning of every month from July 1992 to June 1997, all stocks in the earnings sample are sorted in ascending order based on each stock's analysts number (ANo) and assigned to one of ten decile portfolios. All stocks are equally-weighted in a portfolio. The lowest-number-of-analysts (i.e., lowest-ANo) decile is denoted as portfolio LD; the next decile is portfolio $D2$; and so on. The highest-number-of-analysts (i.e., highest-ANo) decile is denoted as portfolio HD. The decile arbitrage portfolio is constructed as LD minus HD (i.e., $LD-HD$). Panel A reports the portfolios' performances: ret_{-6} is the average past six-month return over the 60 ranking periods; ret_n is the average n-month (n = 3, 6, 9, 12) buy-and-hold return over the 60 test periods. Panel B shows the portfolios' average Scholes-Williams beta ($SW-\beta$), market value (MV), unadjusted price (UP), cash

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$REV6$ -based PAD profits, but $REV6$ -based PAD is weaker than momentum.

flow to price ratio (C/P), book-to-market ratio (B/M) and number of analysts (ANo) at the beginning of the holding period. Numbers in parenthesis are t-statistics; where observations are overlapping the Newey-West heteroscedasticity- and autocorrelation-consistent standard errors are used in computing the t-statistics.

	LD	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	HD	$LD-HD$
					Panel A: Performance						
ret_{-6}	0.1141	0.1318	0.1280	0.0870	0.1017	0.0862	0.0817	0.0851	0.0705	0.0613	0.0528
	(3.64)	(3.20)	(3.21)	(2.85)	(2.98)	(2.81)	(2.82)	(2.68)	(2.46)	(2.53)	(3.21)
ret_3	0.0569	0.0640	0.0588	0.0497	0.0489	0.0417	0.0338	0.0401	0.0340	0.0353	0.0216
	(3.93)	(3.46)	(3.20)	(3.45)	(3.00)	(2.65)	(2.39)	(2.93)	(2.62)	(3.21)	(1.91)
ret_6	0.1279	0.1414	0.1189	0.1004	0.1019	0.0959	0.0817	0.0841	0.0757	0.0793	0.0486
	(4.67)	(3.29)	(3.31)	(3.31)	(3.02)	(2.76)	(2.70)	(3.15)	(2.95)	(3.42)	(3.08)
ret_9	0.1987	0.2159	0.1715	0.1515	0.1601	0.1458	0.1228	0.1248	0.1102	0.1120	0.0867
	(4.19)	(2.90)	(3.14)	(3.01)	(3.00)	(2.79)	(2.51)	(3.11)	(2.88)	(3.36)	(3.55)
ret_{12}	0.2759	0.2867	0.2216	0.1990	0.2134	0.1978	0.1696	0.1672	0.1528	0.1580	0.1179
	(4.22)	(2.89)	(3.16)	(2.90)	(2.94)	(2.99)	(2.68)	(3.37)	(3.21)	(3.88)	(2.99)
					Panel B: Characteristics						
$SW-\beta$	0.7396	1.0014	1.0431	0.9579	0.9569	1.0058	1.0871	1.1995	1.2667	1.2526	−0.5130
	(8.51)	(11.7)	(16.2)	(12.0)	(14.9)	(17.0)	(26.5)	(28.4)	(24.7)	(34.5)	(−9.77)
MV	148.90	81.34	75.42	100.17	115.80	144.49	254.39	574.10	990.92	2980.1	−2831.2
	(10.2)	(7.05)	(15.2)	(17.3)	(11.3)	(15.0)	(17.9)	(21.2)	(31.2)	(36.4)	(−38.0)
UP	162.37	155.65	181.55	202.95	209.00	213.52	249.43	293.24	315.94	369.22	−206.85
	(24.6)	(46.4)	(38.8)	(50.5)	(42.9)	(42.9)	(45.0)	(39.1)	(46.3)	(59.8)	(−43.9)
C/P	0.0837	0.0583	0.1017	0.0984	0.1011	0.1084	0.1061	0.1058	0.1074	0.1103	−0.0266
	(22.6)	(7.37)	(51.9)	(35.9)	(30.8)	(50.5)	(50.5)	(51.7)	(58.7)	(85.8)	(−7.66)
B/M	0.6037	0.6840	0.7749	0.5969	0.6040	0.5960	0.5741	0.4818	0.4856	0.4820	0.1217
	(26.4)	(14.4)	(30.5)	(20.8)	(22.8)	(25.8)	(27.3)	(30.0)	(32.7)	(27.8)	(6.13)
ANo	0.0000	0.0000	0.0000	0.0064	0.1360	0.6473	1.1266	1.8216	3.1510	6.9330	−6.9330

The results in Panel A of Table 6A.1 reveal a striking effect of number of analysts. The three lowest-ANo portfolios' average holding- and ranking-period returns are highest, while the highest-ANo portfolio's average ranking-period return (ret_{-6}) is lowest and its average holding-period returns over 3 to 12 months are generally the second lowest ones. The arbitrage portfolio of the lowest-ANo portfolio minus the highest-ANo portfolio realises average annual profits of 11.79% ($t = 2.99$).

Panel B of Table 6A.1 suggests that market beta cannot explain the effect of number of analysts because high-ANo stocks tend to have high Scholes-Williams betas ($SW-\beta$). The portfolios' average market values (MV) are consistent with the number of analysts (ANo). High-ANo portfolios tend to have high average MVs and vice versa, indicating a possible relation between size and the number of analysts. A similar pattern can be found by examining portfolios' average UP s. In addition, low-ANo (high-ANo) stocks tend to be value (glamour) stocks, but the pattern of ANo-classified portfolios' C/P s is not clear (if anything, the low-ANo portfolios seem to have low C/P s).

These results in Table 6A.1 raise an interesting question why neglected firms (i.e., low-ANo firms), which tend to be small firms and realise high holding-period returns, appear to be less risky than high-ANo firms, which tend to be blue chips and earn relatively low holding-period returns. For instance, LD's average annual holding-period return is 27.59% with average MV and market beta being 148.90 and 0.74, respectively, while HD's average annual holding-period return is 15.80% with average MV and market beta being 2980.10 and 1.25, respectively. One possible explanation is that the market model is not a good measure of risk. In addition, Scholes-Williams betas do not entirely adjust for price-adjustment delays. As Cohen et al. (1986) point out, the greater the expected price-adjustment delay of a security, the more seriously the observed beta will underestimate a positive true beta. Conversely, securities with positive betas and relatively short price-adjustment delays are likely to have their betas overestimated.[8] Because low-ANo (high-ANo) stocks tend to be small (big) firms, the low-ANo (high-ANo) portfolio's beta may be underestimated (overestimated).

2. Size Effect

[8] Cohen et al. (1986) suggest that the expected magnitude of a security's price-adjustment delays should be inversely related to its market value. In other words, a stock of relatively low market value will have greater price-adjustment delays than a stock of relatively high market value.

Similar to Table 6A.1's structure Table 6A.2 reports the MV-classified portfolios' results. The holding-period returns of portfolios presented in Panel A of Table 6A.2 show that a positive size effect is apparent. The lowest-MV decile portfolio (LD) earns the highest holding-period returns over 3 to 12 months, while the highest-MV decile portfolio (HD) realises the second or third lowest holding-period returns. As a result, the average profits of the arbitrage portfolio of $LD-HD$ are all statistically significant over 3- to 12-month holding periods. For the 6-month case, the average semi-annual arbitrage profit is 10.13% ($t = 2.56$). However, the size effect is not apparent when tracing returns backwards. The average past 6-month return of the lowest-MV decile portfolio (LD) is lowest, and it is the fourth lowest one for the highest-MV decile portfolio (HD). The highest-MV decile portfolio (HD) actually outperforms the lowest-MV decile portfolio (LD) at the significance level of 6% over the past 6 months. This evidence reveals an evident mean reversion in small firms' performances.

Table 6A.2 Performances and Characteristics of Decile and Decile Arbitrage Portfolios Classified by Market Value (MV)

At the beginning of every month from July 1992 to June 1997, all stocks in the earnings sample are sorted in ascending order based on their market value (MV) and assigned to one of ten portfolios. All stocks are equally-weighted in a portfolio. The lowest-market-value (i.e., lowest-MV) decile is denoted as portfolio LD; the next decile is portfolio $D2$; and so on. The highest-market-value (i.e., highest-MV) decile is denoted as portfolio HD. The decile arbitrage portfolio is constructed as LD minus HD (i.e., $LD-HD$). Panel A reports the portfolios' performances: ret_{-6} is the average past six-month return over the 60 ranking periods; ret_n is the average n-month (n = 3, 6, 9, 12) buy-and-hold return over the 60 test periods. Panel B shows the portfolios' average Scholes-Williams beta ($SW-\beta$), market value (MV), unadjusted price (UP), cash flow to price ratio (C/P), book-to-market ratio (B/M) and number of analysts (ANo) at the beginning of holding period. Numbers in parenthesis are t-statistics; where observations are overlapping the Newey-West heteroscedasticity- and autocorrelation-consistent standard errors are used in computing the t-statistics.

	LD	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	HD	$LD-HD$
					Panel A: Performance						
ret_{-6}	0.0293	0.0798	0.0866	0.1190	0.1113	0.1037	0.1174	0.1043	0.0973	0.0893	−0.0600
	(0.73)	(1.93)	(2.29)	(2.98)	(3.27)	(3.13)	(4.00)	(3.36)	(3.55)	(4.40)	(−1.86)
ret_3	0.0826	0.0566	0.0481	0.0314	0.0431	0.0375	0.0407	0.0419	0.0424	0.0390	0.0436
	(4.11)	(3.36)	(2.76)	(1.85)	(2.64)	(2.44)	(2.82)	(3.18)	(3.10)	(4.02)	(2.34)
ret_6	0.1782	0.1296	0.1117	0.0762	0.0967	0.0819	0.0866	0.0863	0.0832	0.0770	0.1013
	(3.73)	(3.31)	(3.02)	(2.23)	(2.84)	(2.64)	(3.26)	(3.38)	(3.06)	(4.34)	(2.56)
ret_9	0.2815	0.2059	0.1732	0.1164	0.1415	0.1215	0.1278	0.1219	0.1116	0.1128	0.1687
	(3.18)	(3.18)	(2.97)	(2.10)	(2.59)	(2.61)	(3.36)	(3.22)	(2.90)	(4.53)	(2.31)
ret_{12}	0.3882	0.2791	0.2316	0.1588	0.1840	0.1697	0.1690	0.1620	0.1462	0.1552	0.2330
	(2.91)	(3.34)	(3.05)	(2.16)	(2.56)	(2.89)	(3.65)	(3.46)	(3.16)	(4.84)	(2.02)
					Panel B: Characteristics						
$SW-\beta$	0.762	0.933	0.886	1.028	1.042	0.981	1.074	1.232	1.372	1.196	−0.434
	(7.94)	(12.6)	(13.2)	(11.0)	(13.3)	(20.0)	(18.2)	(30.0)	(30.1)	(78.3)	(−4.89)
MV	4.58	10.63	18.91	30.59	50.59	81.62	136.06	248.49	587.22	4348.68	−4344.1
	(29.5)	(30.2)	(31.7)	(32.1)	(32.6)	(39.8)	(38.7)	(36.6)	(41.3)	(42.8)	(−42.8)
UP	49.47	78.21	112.34	137.57	193.37	281.59	318.46	323.64	408.17	450.61	−401.15
	(47.6)	(56.5)	(51.1)	(51.4)	(45.0)	(69.1)	(90.2)	(49.5)	(63.5)	(59.2)	(−56.6)
C/P	0.0216	0.1009	0.1155	0.1183	0.1081	0.1070	0.1055	0.0951	0.1011	0.1071	−0.0855
	(1.70)	(23.7)	(34.1)	(50.8)	(58.6)	(67.4)	(62.3)	(70.1)	(106.9)	(97.1)	(−6.37)
B/M	1.147	0.901	0.651	0.590	0.477	0.458	0.452	0.411	0.405	0.397	0.750
	(19.6)	(20.7)	(22.8)	(23.1)	(57.0)	(53.6)	(23.7)	(26.4)	(32.9)	(48.5)	(14.5)
ANo	0.1069	0.2035	0.2930	0.4191	0.5913	0.8957	1.2345	1.7978	2.9164	4.9622	−4.8553
	(14.3)	(22.7)	(22.6)	(21.9)	(22.2)	(25.0)	(23.8)	(25.8)	(24.8)	(30.1)	(−29.8)

Again, Panel B of Table 6A.2 shows that the pattern of decile portfolios' number of analysts (ANo) matches well with the decile portfolios' market value (MV), suggesting a likely relation between size and the number of analysts. This relation can also be seen by looking at the MV-sorted decile portfolios' other characteristics such as Scholes-Williams beta ($SW-\beta$), unadjusted price (UP), cash flow to price ratio (C/P), and book-to-market ratio (B/M) since their patterns coincide with those of ANo-based decile portfolios as reported in Panel B of Table 6A.1.

3. Sub-sample Analysis

The results in Section 1 of this appendix suggest that the effect of number of analysts might be due to informational inefficiency since fewer analysts following a stock is likely to mean less informational efficiency in compounding information into the stock.[9] Because the last two sections in this appendix also show a possible relation between size and the number of analysts, this section examines how closely they are related. Here, I focus on an examination of whether the size effect can be subsumed by a number of analysts effect.

Table 6A.3 reports MV-classified portfolio performances within three ANo-stratified sub-samples. Within the low-ANo sub-sample, the results seem to support the size effect since the quintile portfolios' average semi-annual returns decrease monotonically from lowest-MV quintile (Lmv) to highest-MV quintile (Hmv). As a result, the arbitrage portfolio of Lmv minus Hmv ($Lmv - Hmv$) earns average semi-annual profits of 9.63% with a t-statistic of 2.46. However, the size effect disappears when moving to the medium- and high-ANo sub-samples in which we believe the market is more informationally efficient. Especially, within the high-ANo sub-sample the lowest-MV quintile portfolio (Lmv) realises the second lowest average holding-period return, and the average arbitrage profits of $Lmv - Hmv$ is negative (–0.1% with a t-statistic of –0.04). Consequently, the evidence in Table 6A.3 suggests that the size effect, to a great extent, may indeed be due to informational inefficiency.

[9] As mentioned previously, the number of analysts may not be an accurate measure of informational efficiency. If the degree of informational efficiency is determined by the importance of informed investors, then presumably the degree of informational efficiency is simultaneously determined with the number/size of institutional investors and the number of analysts. In addition, other factors may also affect this, such as the complexity of the business. Companies with several lines of business will be more difficult to value, as will companies in high-technology/new markets.

Table 6A.3 Sub-sample Analysis

This table presents the average semi-annual holding-period returns for MV-classified quintile portfolios and arbitrage portfolios within 3 sub-samples stratified on ANo. Each sub-sample contains one-third of the stocks in the earnings sample at the beginning of each holding period. Namely, the low-ANo sub-sample contains the 1/3 lowest-ANo stocks at the beginning of each holding period; the medium-ANo sub-sample contains the 1/3 medium-ANo stocks at the beginning of each holding period; and the high-ANo sub-sample contains the 1/3 highest-ANo stocks at the beginning of each holding period. At the beginning of each holding period from July 1992 to June 1997, the stocks in a given ANo-based sub-sample are ranked in ascending order based on their market values (MV). The equally-weighted portfolio of stocks in the lowest-MV quintile is the low-MV portfolio (Lmv), the equally-weighted portfolio of stocks in the next quintile is denoted as $Q2$, and so on. The equally-weighted portfolio of stocks in the highest-MV quintile is the high-MV portfolio (Hmv). An arbitrage portfolio of Lmv minus Hmv is denoted as $Lmv-Hmv$. Numbers in parentheses are Newey-West-standard-error-adjusted t-statistics. The test period is July 1992 to November 1997.

Average 6-month returns of MV-classified portfolios within 3 ANo-based sub-samples						
	Lmv	$Q2$	$Q3$	$Q4$	Hmv	$Lmv-Hmv$
low-ANo-based sub-sample	0.18859 (4.03)	0.13956 (3.68)	0.11116 (2.95)	0.09752 (2.80)	0.09231 (3.59)	0.09628 (2.46)
Medium-ANo-based sub-sample	0.13611 (2.85)	0.08304 (2.31)	0.08826 (2.94)	0.08720 (2.97)	0.09200 (3.55)	0.04411 (1.42)
high-ANo-based sub-sample	0.07952 (2.14)	0.07109 (2.80)	0.08352 (2.96)	0.08127 (3.08)	0.08063 (5.01)	−0.00111 (−0.04)

As further confirmation of the relationship between size and the number of analysts, I also examine the number of stocks that are matched within the equivalent MV- and ANo-stratified groups. Specifically, similar to the two-dimensional analysis performed in Chapter 5 and this chapter, stocks in the earnings sample are independently sorted into three equal-sized groups according to ANo and MV respectively at the beginning of each month from July 1992 to June 1997. Thus, there are six groups at the beginning of each month: three are ANo-based (low-, medium-, and high-ANo groups) and three are MV-based (low-, medium-, and high-MV groups). Then, I calculate the matched number of stocks from two MV- and ANo-matched groups. I find that on average there are 215 stocks that are matched between the low-ANo and low-MV groups; 177 stocks that are matched between the medium-ANo and medium-MV groups; and 198 stocks that are matched between the high-ANo and high-MV groups. In total, there are 590 matched stocks within the three equivalent MV- and ANo-classified groups, which accounts for 73% of stocks in the earnings sample. This evidence clearly supports the previous findings that the size effect is closely related to the effect of number of analysts, and the size effect may be attributable to informational inefficiency.

CHAPTER 7

SUMMARY AND COCLUSIONS

At any moment there is a most-studied anomaly. At the time of writing, momentum is that anomaly. In this thesis, I have tested the price momentum effect based in the UK stock market. This chapter summarises previous results and concludes this thesis.

In Chapter 3, I test for the presence of momentum profits using the approaches of both Lehmann (1990) and Jegadeesh and Titman (1993). I conduct this analysis for the period 1977 to 1998 on both a comprehensive sample (the *full sample* including 4,182 stocks) and on a restricted sample of stocks with suitable accounting data available such as cash earnings and book value (the *accounting sample* including 2,434 stocks). The empirical results in Chapter 3 show that significant momentum profits are available in the UK over the sample period of more than 20 years, and the results for the accounting sample mirror the results for the full sample. The decile momentum portfolio (i.e. the arbitrage portfolio of decile winner minus decile loser) of the 6×6 strategy yields a significant average semi-annual momentum profit of 7.41% from the full sample, and 7.81% from the accounting sample. An analysis of sub-period results, seasonal effects, and the persistence of momentum profits confirms the robustness of the results. Momentum profits in two 11-year sub-periods are both statistically positive; seasonal effects do not explain momentum profits (in fact, the strong January effect contributes negatively to the momentum profits); and the momentum effect does not persist beyond one year.

Because of the pronounced momentum effect documented in Chapter 3, in Chapter 4 I examine the sources of momentum profits by investigating the relation between momentum profits and factors known to be associated with differential average returns. The factors I control for are equity capitalisation (MV), stock price (UP), book-to-market ratio (B/M), and cash earnings-to-price ratio (C/P). A series of analyses are conducted for this purpose in Chapter 4. As part of the analysis I apply the Fama-French three-factor model to control for expected returns. In addition, I adopt Zarowin's (1989, 1990) technique of controlling for firm size to control for firms' cash earnings-to-price ratios. Moreover, I also use a decomposition method to examine the sources of momentum profits. As an alternative way of examining the effects of size, price, C/P, and B/M on portfolio returns, I investigate the numbers of small, low-price, high B/M, and high C/P stocks in decile portfolios. Detailed analyses on portfolio returns within several sub-samples stratified on MV, UP, C/P, and B/M are also carried out in Chapter 4.

The empirical evidence in Chapter 4 confirms the presence of size, price, book-to-market, and cash earnings-to-price effects in UK stock returns. However, these effects cannot explain momentum profits. Controlling separately for systematic risk, size, price, book-to-market ratio, or cash earnings-to-price ratio does not eliminate significant momentum effect. The bulk of evidence shows that momentum profits are not due to cross-sectional variation in unconditional mean returns of individual stocks. As in the US, the Fama-French three-factor model, which simultaneously controls for systematic risk, size, and book-to-market, leaves momentum profits intact even after controlling for the C/P ratio. Indeed, because of the momentum portfolio's loading on size and book-to-market its profits are enhanced after adjusting for the three factors. A decomposition analysis indicates that neither serial correlation in common factor realisations nor delayed price reaction to common factor realisations can explain momentum profits.

These findings documented in Chapters 3 and 4 are similar to findings on US stocks. The momentum effect is an important, independent phenomenon in UK stock returns, and the profitability of momentum strategies is likely attributable to serial correlation in idiosyncratic components of stock returns: stock prices show a delayed reaction to firm-specific information. The work in the two chapters can be regarded as tests for return profitability, and the results suggest that the efficient market hypothesis (EMH) does not hold in the weak form sense. Because there is no clear and definite conclusion drawn from Chapters 3 and 4 to explain the momentum effect in the UK stock market, I go on to further examine the momentum effect by taking into account the well-known PAD phenomenon. This task is performed in Chapters 5 and 6, with the results summarised below.

In a first attempt to establish whether momentum is due to market reaction to firm-specific events (splits, earnings announcements, etc.), I examine the presence of a PAD effect in Chapter 5. Because of the use of earnings and earnings forecast data, the sample size and sample period used in Chapters 5 and 6 (the *earnings sample* including 835 stocks) are considerably smaller than the full and accounting samples examined in Chapters 3 and 4. I mainly use three earnings surprise variables: one is the standardised unexpected earnings (SUE), a second is the cumulative price-deflated earnings forecast revision over prior 6 months ($REV6$), and the third is the 4-day abnormal return around the earnings announcement ($AR4D$). In addition, I examine the price-deflated earnings forecast error, and the price-deflated single latest analyst forecast revision. The results documented in Chapter 5 show that all these earnings surprise measures predict significant PAD profits over 3 to 12 months in the earnings sample. Further investigations show that adjusting for the Fama-French three-factor model does not eliminate the significant PAD profits. The analyses of various sub-samples stratified on MV, UP, C/P, B/M, $SW\text{-}\beta$ (Scholes-Williams beta), and ANo (number of analysts) indicate that systematic risk and other systematic effects cannot account for the PAD effect in isolation. Amongst the three earnings surprise measures of SUE, $REV6$, and $AR4D$, $AR4D$ shows the strongest PAD effect and it can partially explain the other two measures. Meanwhile, SUE and $REV6$ cannot subsume each other. As a result, the general conclusion drawn from Chapter 5 is that the three earnings surprise measures contain common information, but they do not carry completely the same information.

Since the PAD effect does exist in the UK stock market, in Chapter 6 I test whether price momentum tends to be the same as the PAD phenomenon. This test is carried out based on the earnings sample used to examine the PAD effect in Chapter 5. The momentum effect is still pronounced within the earnings sample, suggesting that evidence of momentum profits is not crucially dependent on the particular study samples. However, the studies performed in Chapter 6 show that the remarkable momentum effect in the UK stock market cannot be attributed to the PAD effect (even the strongest $AR4D$-based PAD effect). Rather, price momentum can partially account for the $REV6$-related PAD, and it can almost explain the SUE-based PAD. In addition, although momentum cannot subsume the $AR4D$-associated PAD, it tends to be stronger than the strongest $AR4D$-linked PAD. Further, the momentum effect appears to be longer-lived than PAD. All these results are confirmed by the analyses of cross-sectional and time-series regressions. Because the $AR4D$ measure seems to have less problems than other two measures of SUE and $REV6$, the general conclusion from Chapter 6 is that neither momentum nor PAD can subsume the other. Consequently, event studies conducted in the last two chapters to explore the relation between PAD and momentum do not provide persuasive evidence to support the market efficiency hypothesis.

However, the question why a stock's prior return over the intermediate-time horizon helps to predict future return in the same direction remains unanswered. The apparent consistency of the momentum profits across different national stock markets documented by Rouwenhorst (1998) reduces the likelihood that the momentum effect is due to data snooping. The fact that results in this thesis closely resemble findings for US stocks points to some generality in investor behaviour as one possible explanation. In Chapter 2 I have reviewed behavioural finance theories that predict medium-term price momentum as a result of systematic departures from the full model of investor rationality. The evidence documented in this thesis lends some support to these behavioural theories. For example, in Chapter 4 I infer that momentum is likely due to market under-reaction to firm-specific information. The event studies carried out in Chapter 5 do indicate that investors respond only gradually to new information. Although PAD, a firm-specific-event-related anomaly, cannot subsume momentum, it would be too early to claim that market irrationality cannot be put forward to interpret momentum. After all, the earnings announcement examined in this thesis is only one type of firm-specific event. The PAD effect does have marginal power in explaining momentum. In previous chapters we have seen that the semi-annual momentum profit is about 8%, but it is reduced to less than 5% on average after controlling for the $AR4D$-based PAD effect. In the US, Moskowitz and Grinblatt (1999) find that an industry momentum effect is stronger than a price momentum effect and it can, to a great extent, explain price momentum. Hong, Lim and Stein (1999) report evidence that firm-specific information, especially negative information, diffuses only gradually across the investing public. Their findings support the hypothesis that if momentum comes from gradual information flow, then there should be more momentum in those stocks for which information gets out more slowly. Hong, Lim and Stein (1999) also argue that the profitability of momentum strategies is not driven by Moskowitz and Grinblatt's (1999) industry factors. In addition, Michaely, Thaler and Womack (1995) document a post-dividend initiation/omission price drift in the same direction in the year following the announcements, and show that this drift is distinct from and more pronounced than PAD. It might therefore be helpful to gain additional insights into understanding the momentum effect by taking these US findings into account. Examining whether industries explain momentum may shed light on: (i) how diversified momentum strategies are; and (ii) the interaction between momentum and the research and investment activities of analysts and investors. To the extent that price momentum is not subsumed by PAD, dividend initiation and omission may be helpful in explaining the momentum effect.

An alternative, rational explanation for medium-term return continuation, as pointed out by Fama and French (1996), is that the momentum effect indicates a previously undiscovered risk factor. In the world of informational efficiency, this is certainly a logical possibility, and Conrad and Kaul (1998) have also suggested such an interpretation of momentum. However, in this thesis I have examined a number of factors including size, price, book-to-market ratio, cash earnings-to-price ratio, PAD, and number of analysts in explaining momentum. As summarised above, systematic risk, size, price, book-to-market ratio, cash earnings-to-price ratio, PAD, or number of analysts cannot, in isolation, explain momentum profits. In addition, adjusting for the Fama-French three-factor model after controlling for cash earnings-to-price ratio or PAD still leaves momentum profits intact. This seems to pose a challenge for the undiscovered-risk-factor-based explanations of the profitability of momentum strategies. Yet, saying this is not to conclude that the examinations in previous chapters have exhausted the analysis of the risks of momentum strategies. In fact, there is still room for studying in this area, which should provide fruitful outcomes in helping to understand the price momentum and asset pricing issues.[1] The empirical findings presented in previous chapters also illustrate bad-model problems. For example, low-Scholes-Williams-beta stocks tend to have relatively higher average returns than medium-Scholes-Williams-beta stocks. The empirical results also support Cohen et al.'s (1986) argument that small (big) firms' betas may be underestimated (overestimated). Even the Fama-French three-factor model gives an incomplete description of average returns. As shown by Fama and French (1993), the three-factor

[1] Berk, Green and Naik (1999) develop a dynamic model and analyse the behaviour of (expected) returns when firms have growth options. They argue that traditional asset pricing models ignore the dynamics and induce biased results. For their particular model they find that the presence of growth options can give the appearance of momentum profits (due to particular time-variation in expected returns). However, in their model the time period over which momentum profits should manifest themselves is longer than the 3–12 month period over which I, and other studies, find evidence of

model does not provide a full explanation of average returns on portfolios formed on size and book-to-market, the dimensions of average returns that the model's risk factors are designed to capture. Therefore, some researchers have used macroeconomic variables as factors in order to examine stock performance directly. For example, Jagannathan and Wang (1996) use labour income; and Cochrane (1996) looks at investment growth. They find that these factors are important in understanding cross-sectional variation in average returns, but none explains the book-to-market and size factors. Linking these more fundamentally determined factors with the size and value factors may well help to explain stock performance. However, a perfect asset pricing model may never be established. As Fama (1998) points out, "any asset pricing model is just a model and so does not completely describe expected returns" (p.292). In addition, spurious results can also arise even with risk adjustment using the true asset pricing model if an event sample is tilted toward sample-specific patterns in average returns. Therefore, it would be worth exploring to what extent momentum can be accounted for by behavioural theories and to what extent it can be explained by undiscovered risk.

Further, microstructure issues such as transaction costs, thin trading, high short sale costs and so on may have some power in accounting for momentum profits. When analysing the persistence in mutual fund performance, Carhart (1997) calculates transactions costs and finds that momentum has failed to yield exploitable profits after transaction costs are taken into account. Although transaction costs of 0.5% do not affect momentum profits as reported in Chapter 3 where the momentum strategies are implemented using non-overlapping test-period returns, they may influence the

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momentum. However, if their model could predict momentum over shorter periods, this would offer a rational explanation of momentum.

profitability of momentum strategies performed in Chapter 6 where frequent trading is required since portfolios are reformed every month. Transactions costs of 0.5% may seriously underestimate actual costs, especially for smaller stocks. Moreover, the evidence reported in this thesis shows that loser stocks, the short positions of implementing the momentum strategies, tend to be small, illiquid stocks. This not only increases the difficulty of short selling, but the high short sale costs will also reduce the momentum profits.

Finally, an out-of-sample test is needed. Although I have tested the momentum effect based on the full sample including 4,182 LSPD stocks from 1977 to 1998, the earnings sample used to examine the relation between momentum and PAD contains only 835 stocks and the test period is restricted to July 1992 to May 1998. An extensive study would shed more light on understanding the UK stock market. For instance, based on the earnings sample the U-shape in holding-period returns of the $REV6$-classified decile portfolios is not observed in the US. With the smaller sample size and shorter sample period (compared to the one studied by Chan, Jegadeesh and Lakonishok, 1996) it is not possible to say anything definitive about the difference. In the US, Conrad and Kaul (1998) have found that momentum profits are insignificant during the earlier 1926–1947 sub-period.

Here I have come to the end of *Price Momentum in the UK Stock Market*. In this thesis I have found a significant momentum effect in the UK, which cannot be accounted for by known risk or other systematic factors. I have further documented a clear PAD effect. However, this only partially accounts for the momentum effect.

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