The Impact of Time-Varying Idiosyncratic Risk and Trading Costs on Momentum and Value Strategies

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This thesis is dedicated to my family. To my father and mother for all they have done for me throughout my life, to my husband for his understanding and to my son for his tolerance, all of which made this thesis possible.

DECLARATION

This thesis is a result of the work done wholly by me during my candidature as a registered postgraduate student in Cass Business School, City University, United Kingdom.

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Abstract

Recent research has discussed the possible role of idiosyncratic risk in explaining equity returns. Simultaneously, but somehow independently, numerous other studies have documented the failure of the static and conditional capital asset pricing models to explain momentum profits and the value premium The first and second parts of this study assess whether the widely documented momentum profits and post-1963 value premium can be attributed to time-varying idiosyncratic risk as described by a GJR-GARCH(1,1)-M model.

In accordance with existing studies, we find that the static CAPM has no explanatory power for momentum profits and the value premium, and that firm size has only a limited role to play. The results show that momentum profits are a compensation for time-varying idiosyncratic risk. In addition, negative return shocks increase the volatility of losers, more than they increase that of winners, and the volatility of the losers responds to news more slowly, but eventually to a greater extent, than that of the winners.

The post-1963 value premium can be fully captured by the conditional variance specification incorporating time-varying idiosyncratic risk as well. The value premium is a compensation for exposure to time-varying risk. This conclusion is robust to different characteristics of value and growth stocks and to the countries under review (US and UK).

The third part of this study analyses the impact of trading costs on the profitability of momentum strategies in the UK. It finds that losers are more expensive to trade than winners due to the high selling cost of loser stocks that can be characterized as small size and low trading volume stocks. It proposes a new low-cost momentum strategy by selecting winner and loser stocks with the lowest total transaction costs. While the study severely questions the profitability of standard momentum strategies, it shows that there is still room for momentum-based return enhancement, should asset managers decide to adopt low-cost momentum strategies.

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Table of Contents

List of Tables

List of Figures

Abbreviations

AIC	Akaike information criterion
AIM	Alternative Investment Market
AMEX	American Stock Exchange
ARCH	Autoregressive conditional heteroskedasticity
ARCH-M	ARCH-in -mean
B/M	Book-to-market equity
CAPM	Capital asset pricing model
C/P	Cash flow to price
CRSP	Centre for Research in Security Prices
D/P	Dividend to price
EMH	Efficient Market Hypothesis
E/P	Earning to price
FFM	Fama and French three factor model
FTSE	Financial Times Stock Exchange
GARCH	Generalized autoregressive conditional heteroskedasticity
GJR	Glosten, Jagannathan and Runkle
GS	Growth in sale
HML	High minus low
LDV	Limited Dependent Variable
LM	Lagrange Multiplier
LSPD	London Share Price Database
MM	Market model
NASDAQ	National Association of Securities Dealers Automated Quotations
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
SD or Std Dev	Standard deviation
SMB	Small minus big
S&P	Standard & Poor's
UMD	Up minus down
V	Variance

Symbols

α	the abnormal return of portfolio
γ	the parameter of the lagged squared error term
h	the book-to-market value factor
η	the parameter of asymmetric effect
I_{t-1}	dummy variable
θ	the parameter of the lagged conditional volatility
R^2	the goodness of fit of a model
R_{ft}	the risk-free rate
R_{Mt}	the value-weighted market return
R_t	the excess return of portfolios
s *and* β_{smb}	the size factor
w	the constant term
β *and* β_m	the market risk factor
δ	the time-varying risk premium coefficient
ε_{t-1}	the unpredictable return at time t-1
v	the time-varying risk premium
σ_t	the conditional standard deviation
σ_t^2	the conditional variance

Chapter 1. Introduction

The efficient market hypothesis (EMH), which states that security prices fully reflect all available information (Fama, 1970), has been the central proposition of finance for over thirty years. The hypothesis implies that security prices are correctly set by rational agents and incorporate their true value. Therefore, no investment strategy can earn excess risk-adjusted returns in an efficient market. The problem is how to measure the risk for a particular investment strategy. It requires a model to capture the fair relationship between risk and return.

The Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) is built on the early work of Markowitz (1952) on diversification and modern portfolio theory. It is used to determine a theoretically appropriate rate of return as compensation to investors for taking on additional risk. The central principle of the CAPM is that only systematic risk, as measured by beta, should be incorporated into asset prices for a completely diversified investor. In addition, expected asset returns are positively related to market beta.

The EMH and the CAPM are internally consistent and connected in the sense that the latter provides an approach for testing the former. A large number of early studies show the success of either or both the EMH and the CAPM. However, after the late 1970s, researchers report a series of "anomalies" that are difficult to explain by the EMH and the CAPM, such as the size effect, the overreaction effect, the momentum effect and the value premium. Of these, the momentum effect and the value premium are regarded as the most important anomalies.

Jegadeesh and Titman (1993) first document the momentum effect that stocks with the best (winner stocks) or the worst (loser stocks) past performance over the 3 to 12 months tend to continue to perform well or poorly respectively over the following 3 to 12 month holding periods. They also find that winner stocks appear to be no more risky than loser stocks.

Evidence for the value premium has been reported by a number of US studies, such as Basu (1977), Fama and French (1992, 1993, 1995 and 1996) and Lakonishok, Shleifer and Vishny (1994). They find that stocks with high ratios of book-to-market equity (B/M), cash flow to price (C/P) or earnings to price (E/P) (value stocks) earn higher average returns than stocks with low ratios of B/M, C/P and E/P (growth stocks).

Momentum and value strategies involve buying winner and value stocks and short selling loser and growth stocks. These strategies have received considerable attention because financial economists fail to reach an agreement on the reasons behind the profitability of these strategies. Two explanations have been put forward. One explanation concerns the financial implication of the psychological investment decision process for irrational traders. Behavioural economists attribute momentum profits and the value premium to systematic mistakes that investors make in the way they process information. For example, investors may overvalue stocks with a long record of good news and undervalue stocks with a long record of bad news due to the representativeness heuristic bias; and they may underreact to the latest earnings news, due to the conservatism bias (see, for example, Barberis, Shleifer and Vishny, 1998; Daniel, Hirshleifer and Subrahmanyam, 1998; Hong and Stein, 1999; Haugen, 1995;

Lakonishok, Shleifer and Vishny, 1994 and La Porta, Lakonishok, Shleifer and Vishny, 1997).

The second explanation is based on the EMH. Rational economists relate the profits of momentum and value strategies to their increased risk and/or trading costs. Fama and French (1993, 1995 and 1996) and Chen and Zhang (1998) argue that the superior returns on value stocks are compensation for common variation in the returns on distressed stocks. Lesmond, Schill and Zhou (2004) point out that firm size and the price level are associated with trading costs, which have been underestimated by previous momentum studies. They conclude that after taking account of trading costs, momentum profit opportunities disappear.

1.1. Motivation

The academic work on momentum and value strategies has a strong impact on professional investment management. Momentum, value and growth are now the major investment styles for fund managers. These investment styles are the important drivers of risk and return and allow fund managers to organize and simplify their portfolio allocation decisions, as well as evaluate their performance against specified style benchmarks. Issues on how to identify momentum, value and growth styles and to design the style-specific benchmark indices for performance evaluation have pushed ongoing analysis in the academic literature.

Despite the large amount of attention that momentum and value strategies have attracted from both finance researchers and fund mangers, momentum profits and the value premium still remain puzzles. The purpose of this study is to examine the profitability of momentum and value strategies. It is particularly interested in the potential explanatory power of time-varying idiosyncratic risk and trading costs for four reasons. First, systematic risk cannot explain momentum profits and the value premium, since these profits are hard to rationalize using the CAPM. Jegadeesh and Titman (1993) use the CAPM to adjust momentum strategies for risk. They find that both winners and losers have about the same betas. Therefore, the cross-sectional differences in expected returns under the CAPM cannot explain momentum profits. Fama and French (1996) show that their three-factor model fails to capture the returns of momentum strategies. Two recent studies by Fama and French (2006) and Ang and Chen (2007) report that the CAPM is able to explain the US value premium of 1926-1963, but cannot explain it for the post-1963 period.

Second, the debates surrounding the use of time-varying market beta as modeled by the conditional CAPM to explain the profits of momentum and value strategies are still ongoing. Jagannathan and Wang (1996), Lettau and Ludvigson (2001), Wang (2003), Ang and Chen (2007) and Adrian and Franzoni (2005) argue that one of the major problems of the traditional CAPM is that it is originally derived from a static framework. They find that the conditional CAPM, with time-varying betas, performs well in explaining cross-sectional expected returns. By contrast, Lewellen and Nagel (2006), Fama and French (2006) and Petkova and Zhang (2005) report that even allowing betas to vary over time, the conditional CAPM still fails to capture momentum profits and the post-1963 value premium.

Third, an increasing literature concerns the relationship between idiosyncratic risk and stock returns. The traditional CAPM implies that all idiosyncratic risk (unsystematic risk) can be diversified away when investors hold a market portfolio. However, Levy (1978), Merton (1987) and Malkiel and Xu (2001) introduce the extensions of the CAPM and find that idiosyncratic risk can also be priced if investors do not hold the market portfolio. The winner, loser, value and growth portfolios are sorted by past performance and book-to-market equity of stocks. These portfolios may not be perfectly diversified in terms of market portfolio although they consist of large numbers of stocks. For example, Chen and Zhang (1998) report that value portfolios tend to pick up firms which experience high likelihoods of financial distress with high earnings uncertainty. Lakonishok, Shleifer and Vishny (1994) show that growth portfolios concentrate on firms which experience strong growth with high earnings. Therefore, firm-level idiosyncratic risk, driven by the specific characteristics of these stocks, may be a potentially important factor in explaining the profits of momentum and value strategies.

Fourth, trading costs play an important role in assessing investment performance. But existing studies cannot agree on the estimated trading costs for momentum strategies. Most of the previous studies, such as Jegadeesh and Titman (1993), Rouwenhorst (1998) and Liu, Strong and Xu (1999), suggest that transaction costs are sufficiently small to allow large profit opportunities for momentum investors. However, Lesmond, Schill and Zhou (2004) argue that the majority of momentum profits are produced by loser stocks, which can be characterized by small size, illiquidity and low price with high trading cost stocks. After taking account of trading costs, the greater momentum profit opportunities do not exist.

1.2. Contributions

The contributions of this study to the literature can be further specified as follows. First, this study examines whether momentum profits and the post-1963 value premium can be explained by time-varying idiosyncratic risk. It is distinguished from existing studies in the way that it assumes that the variance of stock returns follows a generalized autoregressive conditional heteroskedastic (GARCH) process (see Engle, 1982 and Bollerslev, 1986). It is the first to employ a GARCH framework to formulate a set of conditional models to examine momentum profits and the value premium. These models can capture the impact of new information on the conditional variance through the most recent squared error. Additionally, they allow expected stock returns, the variances and the covariance of stock returns to vary over time. They estimate the CAPM and GARCH-in-mean (GARCH-M) model simultaneously and enable us to solve the problem of conditional heteroskedasticity in previous studies that arises when using the static and conditional versions of the CAPM.

Second, this study adds the conditional standard deviation or variance of asset returns to the mean equation. This is able to capture the time-varying relationship between total risk and return. It also uses the GJR (stands for Glosten, Jaganathan and Runkle, 1993) variant to the standard GARCH model in order to allow good news (measured by positive return shocks) and bad news (measured by negative return shocks) to have an asymmetric impact on the volatility of the winner, loser, value and growth portfolios.

Third, this study estimates the magnitude of trading costs for 9 momentum strategies with different ranking and holding periods in the UK. It also further examines the asymmetric trading costs of the winners and losers and breaks down each round-trip trade into buyer-initiated or seller-initiated trades[1] for the winners and losers. This approach enables us to explore the reasons behind the relatively high trading costs of the losers.

Fourth, this study proposes a new type of momentum strategy. It is defined as a low-cost momentum strategy. This strategy ranks all winner and loser stocks based on their total trading costs at the end of ranking periods, then, buys L% (L = 10, 20, 50, 80 and 90) of winner stocks and sells L% of loser stocks with the lowest total trading costs, and holds the long-short portfolio over the next K months (K = 3, 6 and 12 months). These strategies show the existence of significant and positive net momentum profit opportunities if asset managers adopt low-cost momentum strategies.

The remainder of this study is outlined as follows. Chapter 2 attempts to review a large amount of related literature on momentum and value strategies. It begins by providing a brief summary of the theoretical and the empirical foundations of both the EMH and the CAPM, and then highlights some of the challenges that have been reported concerning these foundations. It surveys the evidence on the momentum effect and the value premium in the US and international markets. In addition, it explores the different types of the momentum effect and provides an overview of the various explanations for the returns on momentum and value strategies. Next, it updates recent literature on the conditional CAPM and time-varying idiosyncratic risk in explaining the cross-section of expected returns and the returns on momentum

[1] A number of US studies report that stock prices respond differently between buyer- and seller-initiated trades (see Kraus and Stoll, 1972; Holthausen, Leftwich and Mayers, 1987; Chan and Lakonoshok, 1993 and Keim and Madhavan, 1996).

and value strategies. Finally, it briefly reviews the components, estimation methods and determinants of trading costs.

Chapter 3 examines the relationship between time-varying idiosyncratic risk and momentum profits. It first runs time-series tests of the static CAPM and Fama and French three factor model (FFM) for the winner, loser and momentum portfolios. In accordance with previous research (see, for example, Jegadeesh and Titman, 1993; Fama and French, 1996 and Karolyi and Kho, 2004), the results indicate that traditional versions of the CAPM and the FFM fail to explain momentum profits. It then tests the hypothesis that momentum profits are a compensation for time-varying idiosyncratic risk, as modeled by the conditional models with a GJR-GARCH-M[2] specification. After ignoring the transaction costs and illiquidity issues, the results are in support of the hypothesis. Finally, it explores momentum profits through the GJR-GARCH(1,1) and the GARCH(1,1)-M specifications, and the results reveal neither of them could capture the abnormal performance of momentum strategies.

Chapter 4 follows a similar methodology as applied in Chapter 3 and analyzes the US post-1963 value premium. The results show that the market beta has strong explanatory power for the value and growth portfolio returns, but it cannot explain the post-1963 value premium. However, the value premium can be fully captured by a GARCH-M specification and the premium is a compensation for time-varying idiosyncratic risk. This chapter also examines the value premium based on different definitions of value and growth stocks, such as B/M, C/P and E/P ratios, and UK stocks. The results from robustness tests totally support the US findings. In order to

[2] GJR-GARCH(1,1)-M stands for Glosten, Jaganathan and Runkle (1993), Generalized Autoregressive Conditional Heteroskedasticity of order 1,1 with a Mean term that models the conditional risk premium.

investigate whether the size effect could explain the value premium, this chapter adds a size factor to the model. The results show that the size effect can explain part of the value premium when it is defined using B/M, but it does not account for the value premium defined by C/P and E/P.

Chapter 5 investigates the impact of trading costs on momentum strategies. It begins by examining the characteristics of the winners and losers. In line with the findings of Lesmond, Schill and Zhou (2004) for the US, it shows that the loser portfolio in the UK also consists mainly of stocks with low capitalization, low price and low trading volume, compared to the winner portfolio. As a result, the average round-trip quoted spreads for the losers are much higher than those for the winners. This chapter further analyzes the reasons behind the relatively high trading costs of losers. The results reveal that the losers with low capitalization and low trading volume are particularly expensive to sell. Finally, it proposes low-cost momentum strategies and finds that a shortlist comprising the 10% and 20% of winner and loser stocks with the lowest effective spreads based on actual turnover can generate positive and significant net average annual returns of 19.10% and 15.53%, respectively. After taking account of market risk and Fama and French three risk factors, low-cost momentum strategies with L = 10% and L = 20% still can generate positive and significant net abnormal returns at the 5% level based on both full and actual turnover.

Chapter 6 summarizes the whole study and suggests directions for future research.

Chapter 2. Literature Review

2.1. Efficient Market Hypothesis

The efficient market hypothesis (EMH) has been one of the dominant themes in the academic literature for over thirty years. Fama (1970) defines an efficient capital market as one in which security prices fully reflect all available information. This hypothesis relies on three assumptions. First, investors are rational and hence value securities rationally. Second, even if some investors are irrational, their trades are random and the effects of their actions cancel each other out without affecting the price of securities. Third, if the majority of investors are irrational in similar ways, rational arbitrageurs will counter this and eliminate the influence on prices (Shleifer, 2000).

According to the type of information which is reflected in prices, Fama (1970) also defines three different levels of efficiency. W*eak-form efficiency* states that share prices fully reflect all information contained in past price movements. It indicates that future returns cannot be predicted using past data. S*emi-strong form efficiency* suggests that share prices fully reflect all the relevant publicly available information. It implies that investors cannot earn superior risk-adjusted returns using this information. S*trong-form efficiency* states that all relevant information, including public and private, is reflected in the share price. Therefore, even insider information is unable to yield abnormal profits.

Under the EMH, rational investors value each security using the discounted sum of expected future cash flows, where the discount rate is consistent with a common acceptable preference specification. When new information is announced about a firm, investors quickly and rationally respond to this information. As a result, share prices incorporate the news almost immediately and correctly. Therefore, it is impossible to earn superior risk-adjusted returns through investment strategies. The ways for investors to beat the market are to take a higher risk or to be lucky. The problem is that measuring the risk of a particular investment strategy is difficult and controversial, and requires a model of the fair relationship between risk and return. The next section reviews the risk and one of the most widely used models for assessing the risk of investment strategies.

2.2. Risk and the Capital Asset Pricing Model

2.2.1. Risk

Risk plays an important role in making investment decisions. In finance, it is often defined as the variability or volatility of returns, measured by the standard deviation or variance. Most investors are risk-averse, preferring less risk to more risk for a given return Therefore, the identification, measurement and the possibility of reduction of risk should be a central feature in the decision-making process. Markowitz (1952) first develops a portfolio theory that allows investors using diversification to reduce risk by spreading investments across a range of assets, which are not perfectly correlated. As a result, investors are able to optimize their portfolios with the highest return for a particular level of risk. After the work of Markowitz (1952), the measurement of risk does not only rely on standard deviation, since one type of risk factor will be eliminated when a large portfolio is formed. The other type of non-diversified risk is often measured by the CAPM.

2.2.2. The CAPM

Based on diversification and modern portfolio theory, Sharpe (1964) and Lintner (1965) first introduce the CAPM to determine an appropriate required rate of return for taking on additional risk. It breaks down total risk into two components: systematic risk and unsystematic risk. Systematic risk is also known as non-diversifiable, non-specific or market risk. It refers to the common risk to all securities, including macroeconomic movements such as economic growth, inflation and exchange rate changes. Systematic risk cannot be avoided by diversification. Unsystematic risk is also known as diversifiable, specific or idiosyncratic risk. It affects a very specific group of securities or an individual security. Unsystematic risk can be reduced by holding a large number of different securities.

According to the CAPM, systematic risk, as measured by beta (determined by the covariance between the expected return on an asset with the return on market portfolio), is the only factor required to explain the expected return on an asset for a completely diversified investor and the relationship between expected asset return and market beta is linear. The CAPM relies on a number of assumptions about the behaviour of investors and the operation of capital markets. These assumptions have been progressively criticized as being unrealistic in the real world. Here are some of them:

1. The CAPM assumes that asset returns are normally distributed random variables and that the variances of the error terms are constant through time. However, a number of studies, such as French, Schwert and Stambaugh (1987), Schwert and Seguin (1990) and Mandelbrot (1963), have documented that the variances of the

error terms change over time and exhibit volatility clustering, where high (low) volatility tends to be followed by high (low) volatility.

2. The CAPM assumes that market beta is an adequate measure for expected asset returns and that market beta is constant over time. It is, however, frequently observed that betas tend to change from one period to another and play a weak role in explaining the cross-section of average returns (see, for example, Blume, 1971; Levy, 1971; Fama and French, 1992 and1993). Apart from the market risk, a firm's size, the ratios of B/M, C/P and E/P, dividend yield, leverage and the past performance of stocks have also been identified and have explanatory power in expected asset returns (see, for example, Banz, 1981; Reinganum, 1981, 1983; Basu, 1977, 1983; Bhandari, 1988; Keim, 1990; Litzenberger and Ramaswamy, 1979; De Bondt and Thaler, 1985; Fama and French, 1992, 1993; Lakonishok, Shleifer and Vishny, 1994; Jegadeesh and Titman, 1993 and 2001),.

3. The CAPM assumes that all investors have access to the same information and agree about the risk and expected return of all assets for any given time period. However, in the real world, investors may hold private information and update their expectations each period according to new information. This leads to conditional expectations, which are stochastic rather than constant.

4. The CAPM assumes that there are no taxes or transaction costs. In the real world, transaction cost is one of the important elements in markets for trading and it has a non-negligible impact on stock returns.

The central CAPM theory of the positive relationship between expected asset returns and market risk is consistent with the EMH. This allows researchers to test the validation of both the EMH and the CAPM. A large number of earlier empirical studies, such as Fama (1965), Jensen (1978) and Black, Jensen and Scholes (1972), find that neither of them can be rejected, based on the data that is available at the time. However, after the late 1970s, a series of findings known as "anomalies" has been reported to challenge the EMH and the CAPM. For example, Banz (1981) and Reinganum (1981) document that the CAPM understates the cross-sectional average returns of NYSE and AMEX-listed firms with low market values, and it overstates those of firms with high market values. Basu (1977) shows that excess returns are positively related to the firm's E/P ratio, when using the CAPM to measure expected stock returns. De Bondt and Thaler (1985) report that past loser stocks significantly outperform past winner stocks over the following 3- to 5-year test period. The differences in returns of the losers over the winners are not explained by the greater risk of the losers under the CAPM. Their results imply weak-form market inefficiency since stocks returns are predictable from past returns.

However, Fama (1991) states that empirical anomalies are always joint evidence on the EMH and the CAPM. These tests may suffer from the joint hypothesis problem since researchers cannot conclude whether such anomalies result from the mis-specified CAPM or market inefficiency. He believes that evidence of the size and book-to-market equity effects is due to the weak role of the market beta in explaining the cross-section of average returns; therefore, they are anomalies of the CAPM instead of market efficiency.

A large number of anomalies can be grouped by size, seasonality or book-to-market equity and so on. In any comparison of their relative significance, momentum and value strategies are regarded as the most important anomalies. The next two sections review evidence, types and explanations for the profitability of momentum and value strategies.

2.3. Momentum Strategies

Momentum is one of the major unresolved puzzles in the finance academic literature. The momentum effect is defined as evidence that stocks with high past returns tend to continue outperforming stocks with low past returns over of the following 3 to 12 months. Momentum strategies exploit this effect by buying stocks with the highest past returns and short selling stocks with the lowest past returns.

2.3.1. Momentum Evidence

Jegadeesh and Titman (1993) were the first to report momentum evidence. Using data from the Centre for Research in Security Prices (CRSP) returns file over the 1965 to 1989 period, they form ten portfolios that result from equally weighting all stocks based on their returns over the past 3 to 12 months. The portfolio with the lowest return over the rank period is called the 'loser' and with the highest return is called the 'winner'. Then, they examine the profitability of relative strength trading strategies of buying the winners and selling the losers. They find these strategies yield significant positive returns over the next 3 to 12 months. The best momentum strategy that selects stocks based on their returns over the past 12 months and holds the portfolio for 3 month (hereafter the 12-3 strategy) generates a significant profit of 1.31% per month. In order to avoid some of the bid-ask spread, price pressure and lead-lag effect addressed by Jegadeesh (1990) and Lehmann (1990), they also examine the performance of these strategies by skipping a week between the portfolio formation period and the holding period. They find that the 12-3 strategy yields a profit of 1.49% per month. They attribute momentum profits to delayed reaction to firm-specific information rather than a compensation for systematic risk.

Several later studies find that momentum strategies are also profitable in markets around the world. Rouwenhorst (1998), Chui, Titman and Wei (2001) and Griffin, Ji and Martin (2003) report that momentum profits are large in many European and Asian stock markets. They attribute the profitability of momentum strategies to macroeconomic risk instead of conventional risk factors, such as size and the market. Chan, Hameed and Tong (2000) test 23 national indices and find that significant momentum profits mainly arise from price continuations in individual stock indices rather than non-synchronous trading.

Using UK data, Liu, Strong and Xu (1999) report that momentum strategies are profitable even after taking account of risk factors. Their results suggest that momentum profits are due to market underreaction to firm-specific information. Hon and Tonks (2003) test a large sample from the London Stock Exchange and find that momentum profits are positive and significant over short and medium horizons up to 24 months. They show that momentum profits are high for the 1977 to 1996 period, but little evidence is found for momentum profits over the period of 1955 to 1976, suggesting that the momentum effect in the UK depends on the sample period. Ellis and Thomas (2003) show that momentum strategies earn significant and positive returns with an average profit of 1.4% per month for FTSE 350 stocks.

2.3.2. Other Types of Momentum

The momentum effect documented by Jegadeesh and Titman (1993) is also referred to as price momentum or individual momentum in the finance literature. After their finding, a large number of studies have discovered other momentum effects associated with industry, earnings and style. This section reviews the evidence of each type of momentum effect.

Industry momentum

Industry momentum refers to the fact that investing in previously winning industry portfolios and selling previously losing industry portfolios can generate significant returns. Moskowitz and Grinblatt (1999) find that the industry momentum effect is strong and persistent even after controlling for size, book-to-market equity and microstructure influences; the profitability of individual momentum strategies can be fully captured by industry momentum and the profits are mainly driven by the long position.

Grundy and Martin (2001) however argue that the results reported by Moskowitz and Grinblatt (1999) are because their strategies do not skip a month between the formation period and the holding period. They provide evidence that individual stock momentum can be explained by the stock-specific component of returns and is different from industry momentum. Chordia and Shivakumar (2002) attribute industry-based momentum to macroeconomic variations rather than industry-specific returns. They show that industry momentum and individual stock momentum are distinct and independent effects, with each strategy being profitable on its own.

Earnings momentum

Earnings momentum is based on past earnings and has been examined by Chan, Jegadeesh and Lakonishok (1996). They report that earnings momentum and price momentum strategies yield large differences in future returns. Earnings momentum strategies tend to be smaller and persist for a shorter period of time than price momentum strategies. Using a two-way analysis, they find that both past returns and earning surprises contribute to some improved predictive power for future returns. This indicates that earnings momentum and price momentum reflect different pieces of information and cannot subsume each other. They also show that the profitability of momentum strategies is not a compensation for risk; instead, it is driven by an underreaction of stock prices to the information in past returns and earnings.

Style momentum

Investment styles are clusters of stocks with similar characteristics, such as large capitalization or small capitalization. Style momentum strategies involve buying a style portfolio with the best past returns and selling a style portfolio with the worst past returns. Chen and De Bondt (2004) form style portfolios based on annual dividend yields, market value of equity and the book-to-market ratio for large US companies in the S&P 500 index. They find that style momentum strategies generate significant profits over the following 3 to 12 months. The most successful strategy that selects stocks based on their past 12 month returns and holds for the following 6 month yields a profit of 0.5% per month. They also show that style momentum differs from price momentum and industry momentum.

2.3.3. Explanations for Momentum Profits

Explanations for momentum profits have been subject to considerable debate, as the profits remain inexplicable from the Fama and French three-factor model (Fama and

French, 1996). In this section, the different views are put forward to explain the profitability of momentum strategies.

Behavioural models

Several studies develop behavioural models to take account of the investment behaviour of investors and the momentum effect. De Long, Shleifer, Summers and Waldmann (1990) propose a model of positive feedback trading where investors buy stocks with prices rising and sell stocks with prices falling. The most common form of positive feedback trading is extrapolative expectations where investors assume that future stock prices will follow past prices. This judgment bias may result in momentum profits.

Barberis, Shleifer and Vishny (1998) build a model motivated by two important psychological biases: conservatism and the representativeness heuristic. Conservatism bias leads investors to change their beliefs insufficiently when news arrives and underweight the new information. As a result, investors tend to underreact to firm-specific news, producing a momentum effect. The representativeness heuristic bias leads investors to misestimate future growth of companies since they use past history as the representativeness of an underlying earnings growth potential. As a result, investors tend to overvalue stocks with a record of good news and undervalue stocks with a record of bad news.

A model to reconcile long-term reversal and short-run momentum is constructed by Daniel, Hirshleifer and Subrahmanyam (1998), Their model is based on two psychological biases: overconfidence and biased self-attribution. Overconfidence leads investors to overestimate their ability to assess information and underestimate their forecast error. As a result, investors overweight private signals, resulting in overreaction and underweight the public signal causing underreaction. If an investor trades on private information, self-attribution bias leads his confidence to increase when public information confirms his belief. Therefore, increasing overconfidence further accelerates the initial overreaction to the past private signal and continuing correction causes prices changes to be positively correlated to public signal. This suggests that momentum arises because public news pushes a continuing underrreaction to the public signal and causes market mis-pricing. However, momentum is eventually reversed as further public information slowly drags the price back towards its true value.

Another behavioural model, developed by Hong and Stein (1999), is based on two different trading groups: news watchers and momentum traders. They assume that private information diffuses gradually across the news watchers who trade on private signals about future fundamentals rather than past prices. As a result, prices adjust slowly to new information and generate momentum profits. By trading based on past price movements, momentum traders explore momentum profits by pushing up short-run prices of past winners. Eventually, prices will overshoot their fundamentals in the long–run, when more and more momentum traders enter the market to earn profits.

Behavioural models suggest that any large momentum effect should be followed by a large price reversal. Moskowitz and Grinblatt (1999) provide evidence that industry momentum is the strongest at the 1-month horizon; then, tends to disperse after 12 months and eventually reverses over long-term holding periods. Similar evidence has also been reported by Jegadeesh and Titman (2001) and Bhojraj and Swaminathan

(2006). Their findings appear to support the key prediction of the behavioural models. However, Fama (1998) criticizes that the behavioural models suffer from a "bad model problem", as they perform well on the anomalies that they are designed to explain, but fail to predict long-term return reversal. He attributes short-term return continuation and long-term return reversal to chance.

Compensations for risk

Rational expectations proponents show that the profitability of momentum strategies is a compensation for risk. The following section reviews different types of risk that have been addressed by momentum studies, which include cross-sectional variation in mean returns, business cycle risk, time-varying risk, liquidity risk, skewness risk and stochastic growth rates.

Cross-sectional variation in mean returns

A number of studies have examined the argument that momentum profits can be explained by cross-sectional differences in mean returns. Following the methodology of Lehmann (1990) and Lo and MacKinlay (1990), Conrad and Kaul (1998) evaluate two possible sources of profit from long-term contrarian and short-term momentum strategies: time-series predictability in asset returns and cross-sectional variation in mean returns of securities. They find that rather than the time-series patterns in stock returns, the cross-sectional dispersion in mean returns plays an important role in determining the profitability of momentum strategies because stocks with high (low) realized returns tend to be stocks with high (low) expected returns.

Under the Conrad and Kaul's hypothesis, momentum profits should be persistent in the future period. By contrast, Jegadeesh and Titman (2001) provide evidence that the positive momentum profits are not permanent; instead, they only exist over the following 12 months (except for the first month) and become negative from 13 to 60 months following portfolio formation. The losers are more sensitive to the size and book-to-market equity factors than the winners, suggesting that momentum profits cannot be captured by the cross-sectional differences in expected returns under the FFM. However, they can be partially explained by the behavioural models. Similar findings have been reported by Grundy and Martin (2001). They confirm that the profitability of momentum strategies is neither fully explained by the cross-sectional variations in expected returns nor as a compensation for dynamic exposure to the FFM. Moskowitz and Grinblatt (1999) also provide evidence that industry momentum profits have the same magnitude as individual stock momentum profits, indicating that the cross-sectional dispersion in unconditional mean returns does not drive momentum profits.

Time-varying risk

Chordia and Shivakumar (2002), Wu (2002), Wang (2003) and Karolyi and Kho (2004) find that the models which add conditioning information into the traditional CAPM or FFM perform well in explaining momentum profits. Therefore, time-varying risk and time-varying expected return may contribute to momentum profits. By contrast, Grundy and Martin (2001), Griffin, Ji and Martin (2003) and Lewellen and Nagel (2006) argue that time-varying risks are not large enough to account for the momentum returns.

Business cycle risk

Business cycle risk is another potential explanation for momentum profits. Chordia and Shivakumar (2002) report that a set of macroeconomic variables which are related to the business cycle can explain momentum profits. Using a one-step-ahead forecasting model to predict the returns associated with macroeconomic variables, they find that momentum profits are positive only during expansions and are negative during recessions. However, Griffin, Ji and Martin (2003) attribute momentum profits to country specific risk. They show that both macroeconomic factors documented by Chen, Roll and Ross (1986) and a conditional forecasting model of Chordia and Shivakumar (2002) fail to capture momentum profits across 40 countries.

Liquidity risk

Liquidity risk has also been documented as a potential factor to explain momentum returns. Sadka (2006) tests a large cross-section of NYSE-listed firms and finds that the average total cost per share is higher for large trades; both the winners and losers are initially less liquid. His results suggest that based on the frequency of trading, superior returns from momentum strategies are related to high trading costs, a low level of liquidity and limits to arbitrage. By examining the liquidity-based factors, he finds that half of the returns on the relative-strength portfolios can be explained by a liquidity-risk premium. Furthermore, the unexplained momentum profits are due to low liquidity.

Skewness risk

Fuertes, Miffre and Tan (2008) use a sample free of survivorship bias, which consists of all stocks listed on the Amex, NYSE and NASDAQ exchanges during the period 1973 to 2004. They extend the CAPM and the FFM by adding skewness and kurtosis factors and find that skewness risk can explain approximately 0.65% of the annual abnormal returns of momentum strategies and the performance of momentum strategies falls after controlling for skewness risk.

Stochastic growth rates

Johnson (2002) argues that stochastic growth rates may account for momentum profits. His model suggests that a large stock return depends on a persistent growth rate shock, since positive growth rate shocks are more likely among companies with good performance, while negative growth rate shocks are more likely among companies with poor performance, when other things are equal. Therefore, momentum profits might be attributed to growth rate risk.

Other contributions to momentum profits

Momentum profits are also found to be the result of other contributions in a number of studies, such as gradual diffusion of information, transaction costs, trading volume and data mining. The following section reviews the potential determinants of momentum profits.

Slow diffusion of information

Hong, Lim and Stein (2000) use size and coverage as proxies for information diffusion speed and find that higher momentum profits are limited to smaller sized stocks with low analyst coverage. After controlling for size or low analyst coverage, stocks exhibit higher momentum. Their results are consistent with the model of Hong and Stein (1999). However, Lesmond, Schill and Zhou (2004) argue that the results reported by Hong, Lim and Stein (2000) are due to the fact that their information diffusion speed proxies exclude trading costs. After controlling for trading costs, analyst coverage provides a little explanatory power for the momentum returns. Sadka (2006) also argues that although small stocks, with low analyst coverage, earn high momentum returns, these returns cannot be exploited because small stocks have a low level of liquidity and higher liquidity costs.

Transaction costs

Transaction costs are regarded as one of the most important factors in explaining momentum profits. Carhart (1997) argues that the apparent profitability of momentum strategies in mutual funds is due to the omission of transaction costs. Grundy and Martin (2001) confirm that the level of round-trip transaction costs will offset the returns of momentum strategies. Lesmond, Schill and Zhou (2004) find that the momentum returns are mainly produced by stocks with the characteristics of small size, high beta and low liquidity, which have large trading costs. After taking account of trading costs, the greater momentum returns cannot be exploited by arbitrageurs.

An alternative finding is reported by Hanna and Ready (2005). They report that both equally-weighted and value-weighted momentum strategies earn significantly excess returns after trading costs. Korajczyk and Sadka (2004) discover that momentum strategies remain profitable when transaction costs equal effective and quoted spreads. However, after considering price impact costs, the profitability of equally-weighted momentum strategies is eliminated whereas value-weighted momentum strategies earn substantial abnormal returns until the market value of the investment is slightly less than $1 billion. Ellis and Thomas (2003) estimate a cost of 5.8% for a momentum strategy over a 12 month holding period for FTSE 350 stocks. They find thet momentum profits are still significant in their sample after transaction costs.

Trading volume

Trading volume is also reported as having a strong ability to predict future price momentum. Lee and Swaminathan (2000) find that past low volume stocks earn higher future returns than high volume stocks. Additionally, trading volume provides an important link to reconcile underreaction and overreaction since two winner-minus-loser strategies exhibit long-term price reversals and price continuations based on past volume. They show that stocks with low (high) past volume behave more like value (growth) stocks, which are under- (over) valued by the market. Therefore, the evidence of low (high) volume firms earning high (low) future returns is due to market misestimate of firms' future earnings. In contrast to their results, using UK data, Ellis and Thomas (2003) report that high-volume momentum portfolios generate higher returns than low-volume momentum portfolios.

Chan, Hameed and Tong (2000) also find that portfolios with high lagged trading volumes earn higher momentum profits than those of low lagged trading volumes.

Data mining

Data mining involves sorting through large amounts of data and picking out the relevant information through chance correlations or patterns. Jegadeesh and Titman (2001) re-examine the trading strategies in the time period subsequent to their original study (Jegadeesh and Titman, 1993). They find that past winners continue to outperform past losers by the same amount as in the earlier period. Momentum strategies earn a profit of 1.17% per month over the 1965 to 1989 sample period and yield a profit of 1.39% over the period 1990 to 1998. Apart from the US stock market, a number of studies have discovered that the momentum effect exists in other markets, such as international equity markets (Rouwenhorst, 1998), foreign currency markets (Okunev and White, 2003) and commodity futures markets (Miffre and Rallis, 2007). All their findings confirm that momentum evidence is not merely due to data mining.

2.4. Value Strategies

Having reviewed the literature on momentum, I now turn my attention to the other anomaly that is the focus of this PhD: the value premium. Lakonishok, Shleifer and Vishny (1994) define value stocks as those with high ratios of B/M, C/P, E/P and high growth in sale (GS); while growth stocks are those with low ratios of B/M, C/P, E/P and low GS. Value strategies are referred to as those investing in value stocks and selling growth stocks.

2.4.1. The Value Premium Evidence

The value premium is known as the difference in return between a portfolio of value stocks and a portfolio of growth stocks. Lakonishok, Shleifer and Vishny (1994) examine the performance of portfolios based on the ratios of B/M. E/P, C/P and GS. From a one-way classification, they report that high B/M (value) stocks outperform low B/M (growth) stocks by an average of 10.5 % per year. The difference of size-adjusted average return between value stocks and growth stocks is about 7.8% per year. From a two-way classification, they find that the value portfolios significantly outperform the growth portfolios and the higher returns of the value portfolios are not due to fundamental risk. They attribute the evidence of higher standard deviations of the value portfolios to the size effect, since the value portfolios largely consist of small stocks. They conjecture that the value premium arises from expectation errors made by investors who irrationally extrapolate future growth based on past growth. As a result, they are too optimistic and overvalue growth stocks, and too pessimistic and undervalue value stocks. Fama and French (1992, 1993, 1995 and 1996) and Chan and Lakonishok (2004) also report similar results.

The performance of the value and growth portfolios is examined in world markets. Fama and French (1998) study the value and growth portfolios for the US and twelve major EAFE (Europe, Australia, and the Far East) countries and find that there is strong evidence of value stocks outperforming growth stocks in markets around the world. Using the ratio of E/P, 12 out of 13 value-growth premiums are positive. There are similar value premiums when portfolios are sorted on the ratios of B/M, C/P and dividend to price (D/P), suggesting that the higher average returns on value stocks are a global phenomenon.

Dimson, Nagel and Quigley (2003) examine the value premium across all stocks listed on the London Stock Exchange during the period of 1955 to 2001. They find that the value premium exists within small capitalization, as well as large capitalization universe. However, they argue that implementation of value strategies to capture the value premium is potentially costly, particularly within the small capitalization segment. Gregory, Harris and Michou (2001 and 2003) investigate value strategies in the UK market. From both one-variable and two-variable analyses, they find that value stocks significantly outperform growth stocks. Both the FFM and the multi-factor asset pricing model fail to entirely explain the superior returns of value strategies from two-way classification.

2.4.2. Explanations for the Value Premium

The existence of the value premium goes largely undisputed, interpreting the premium and identifying its causes has been more controversial. The main debate focuses on a behavioural-based explanation, a risk-based explanation or bias related to the original study of Lakonishok, Shleifer and Vishny (1994).

Behavioural–based explanation

Behavioural economists explain that the value premium is driven by the judgmental bias of investors. Haugen (1995) interprets that investors are too pessimistic concerning value stocks and too optimistic concerning growth stocks; therefore, they undervalue value stocks and overvalue growth stocks. La Porta, Lakonishok, Shleifer and Vishny (1997) suggest that expectation errors about future earnings prospects are an important determinant of the superior performance of value stocks. They find that earnings announcement returns are substantially higher for value stocks than for growth stocks after formation. Additionally, announcement returns for growth stocks are significantly lower than growth returns on an average day, which is against the risk premium explanation. However, Levis and Liodakis (2001) test this extrapolation hypothesis using UK data. They find that the market does not extrapolate from either past earnings growth or past price performance. They show an asymmetric impact of good news and bad news on the returns of value and growth stocks. Good news has a stronger positive impact on returns of value stocks than other stocks; while bad news has a minor impact on the returns of value stocks but has a significantly more negative impact on the performance of growth stocks.

Risk-based explanation

Fama and French (1992, 1995 and 1996) and Chen and Zhang (1998) argue that the superior returns on the value portfolios are a compensation for high risk driven by their characteristics of financial distress and low earnings. They find that the value portfolios have strong positive loadings on SMB[3] and HML[4]. By contrast, growth stocks have strong negative loadings on HML. They conclude that the value premium can be explained by their three-factor model. However, the problem with their prediction is that they use the HML factor to explain the expected returns of the

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[3] SMB stands for small minus big, which is the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks.

[4] HML stands for high minus low, which is the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks.

value and growth portfolios, in other words, the explanatory and explained variables measuring the same thing.

Data snooping

The view that data snooping relates to the superior returns of value stocks has been documented by Conrad, Cooper and Kaul (2003). Conducting both one-way and two-way sorts on 15 characteristics, they find that nearly 50% of in-sample profits reported in one-way-sort studies can be explained by data snooping and about 80% to 100% of the profits to strategies of 10×10 two-way-sort portfolios are attributed to data snooping. Their results suggest that the greater potential for data snooping bias in two-way sorts arises because the two-way-sort procedure uses the prior familiarity data of firm characteristics; these firm characteristics are highly correlated. As a result, the two-way-sort procedure generates spurious superior returns for value stocks.

Selection bias

Using Compustat data, the average performance of high B/M portfolios may be enlarged by survivorship bias. Kothari, Shanken and Sloan (1995) point out that high B/M firms experience relatively high financial distress and they may not be included in Compustat database. By contrast, Chan, Jegadeesh and Lakonishok (1995) argue that the selection bias in the Compustat data is overstated by Kothari, Shanken and Sloan (1995). They find that only 3.1 % of CRSP company-years can be widely interpreted as financially distressed companies, which are omitted from the Compustat database. Also, the returns on the NYSE-AMEX domestic primary companies are only slightly different from the returns on the corresponding firms with the Compustat data.

2.5. Time-Varying Risk and the Conditional CAPM

Although many financial researchers have tried to determine the reasons behind the profits of momentum and value strategies, the debate on explanations is still ongoing. In recent years, a growing literature has attempted to use time-varying risk and the conditional CAPM to capture a cross-section of average returns and the returns of anomalies. This section reviews time-varying risk, idiosyncratic risk and the conditional CAPM.

2.5.1. Time-Varying Risk and Idiosyncratic Risk

One of the key features of financial time series is that volatility (as measured by variances) changes over time. It shows that large volatility changes tend to be followed by large volatility changes and small volatility changes tend to be followed by small volatility changes (see, for example, Mandelbrot, 1963; French, Schwert and Stambaugh, 1987 and Schwert and Seguin, 1990). Engle (1982) first introduces the Autoregressive Conditional Heteroskedastic (ARCH) process to explicitly model time-varying risk (as measured by the conditional variance) as a linear function of past squared innovations. Bollerslev (1986) extends Engle's work to the Generalized-ARCH (GARCH) process. The GARCH model provides a more flexible framework to capture various dynamic structures of volatility. It measures the conditional variance as dependent not only on past shocks but also on its previous lags. Another important extension of the ARCH model is the ARCH-in-mean (ARCH-M) model developed by Engle, Lillien and Robbins (1987), where the conditional standard deviation of asset returns is added into the mean equation. Therefore, changing time-varying risk directly affects the expected return on a portfolio.

The traditional CAPM of Sharpe (1964) and Lintner (1965) implies that only systematic risk should be incorporated into asset prices and that idiosyncratic risk can be diversified away when investors hold a market portfolio in equilibrium. However, Levy (1978), Merton (1987) and Malkiel and Xu (2001) extend the CAPM and find that idiosyncratic risk can also be priced to compensate rational investors if they do not hold the market portfolio. Campbell, Lettau, Malkie and Xu (2001), Goyal and Santa-Clara (2003), Ghysels, Santa-Clara and Valkanov (2005), Fu (2005), Diavatopoulos, Doran and Peterson (2006), and Jiang and Lee (2006) further investigate time-varying idiosyncratic risk in explaining stock returns. They find that there is a positive relationship between idiosyncratic volatility and stock market returns. However, Bali, Cakici, Yan and Zhang (2005) and Bali and Cakici (2007) argue that the relationship is in part driven by a illiquidity premium. In contrast to above studies, Ang, Hodrick, Xing and Zhang (2006) report the puzzling results whereby stocks with high past idiosyncratic volatility earn low returns and the low returns of stocks with high idiosyncratic volatility cannot be explained by size, book-to-market, momentum and liquidity effects.

2.5.2. The Conditional CAPM

The traditional CAPM is derived from a static framework. It assumes a static variance-covariance matrix for asset returns and predicts that market beta is constant over time. The conditional CAPM attempts to capture the impact of conditional information on the volatility of asset returns and the expected asset returns. It imposes the restriction that conditional expected returns on assets are linearly related to the conditional expected return on a market-wide portfolio in excess of the risk-free return. The coefficient in the linear relation is the asset's beta or the ratio of the conditional covariance of the asset's return with the market to the conditional variance of the market. Bollerslev, Engle and Wooldridge (1988), Bodurtha and Mark (1991) and Ng (1988) carry out tests of the conditional CAPM by allowing time variation in the expected asset returns, asset variance, and covariance. They assume that covariance matrix of asset returns and market risk premium to follow a multivariate GARCH process[5]. Their results suggest that time-varying systematic risk might be a better measure for the expected return on the stock market. Harvey (1989 and 1995) and Ferson and Harvey (1991 and 1993) develop the conditional CAPM by allowing for both time-varying market betas and time-varying expected returns. They find that estimated betas exhibit statistically significant time variation. Therefore, the conditional CAPM with time-varying beta performs substantially better than the static CAPM.

Recently, a number of studies have used the conditional CAPM to examine the cross-sectional variations in expected asset returns and the returns of anomalies. Jagannathan and Wang (1996), Lettau and Ludvigson (2001), and Adrian and Franzoni (2005) report that this model with time-varying beta works well in explaining the cross-sectional variation in expected returns on size and B/M portfolios. Wang (2003), Ang and Chen (2007) and Zhang (2005) show that it can also capture the profitability of momentum and value strategies. However, Lewellen

[5] Bodurtha and Mark (1988) model market risk premium as an autoregression.

and Nagel (2006) cast doubt on the empirical success of the conditional CAPM. They argue that betas vary substantially but these variations are not large enough to explain the value premium and the momentum effect. Fama and French (2006) and Petkova and Zhang (2005) confirm that even allowing betas to vary annually, this model still fails to explain the post-1963 value premium.

2.6. Trading Costs

Although many studies have reported that momentum and value strategies can generate significant gross profits, to implement these strategies, investors are also likely to face significant trading costs. The third objective of this study is to investigate the impact of trading costs on momentum strategies. With this in mind, this section reviews the components, estimation methods and determinants of trading costs.

2.6.1. Components of Trading Costs

Trading costs of implementing an investment strategy is an integral part of the investment process, having a direct impact on investment performance. According to Keim and Madhavan (1998), total trading costs can be categorised into two major components: explicit costs and implicit costs.

Explicit trading costs

Explicit trading costs include the commission charged by brokers, taxes, short selling costs and other regulatory charges, depending on the particular country and exchange. Keim and Madhavan (1997) found that commission costs are relatively low, at about

0.2% of trade value. In addition, commission paid by investors has declined over time. Stoll (1995) reports that commission in 1982 is 0.58% of market value for institutional investors, which is more than double the commission in 1992. The decline in commission may be due to an increased institutional presence in the market, a more competitive environment for trading services, and technological innovations. A short selling cost is charged by the brokerage firm for borrowing the security. When investors believe that the future price of a security will fall, they can borrow this security from a brokerage firm and sell it if they do not own it.

Implicit trading costs

Implicit trading costs are the main area of interests for researchers as they are difficult to measure. Implicit trading costs contain bid-ask spreads, price impact costs and opportunity costs.

Bid-ask spread

Early studies show that the bid-ask spread is the major part of implicit trading costs. It includes a quoted bid-ask spread and an effective bid-ask spread. The quoted bid-ask spread is the difference between the quoted ask price and the quoted bid price. Stoll (1989) first concluded that the quoted spread can be decomposed into three components: order processing costs; inventory costs; and adverse information costs. Lee and Ready (1991) argue that the measurement of the quoted bid-ask spreads may overstate the actual spread since trades are often executed inside the quoted spread.

The effective bid-ask spread provides a more accurate measure of actual trading costs than the quoted spread. Roll (1984) first shows that the effective spread can be inferred from first-order serial covariance of price changes when the market is efficient. He finds that these serial covariance estimators of the effective spread tend to be smaller than the quoted bid-ask spread. Another way to measure the effective bid-ask spread is the difference between the transaction price and bid-ask midpoint. This can account for potential price improvement when market orders are crossed, or the specialist "stops" an order before trade.

Price impact cost

Bid-ask spread estimates fail to capture the fact that large trades may move price away from the true "equilibrium" price. The price impact measures the deviation of the transaction price from the true "equilibrium" price. Berkowitz, Logue and Noser (1988) estimate the price impact cost of executing a trade as the difference between a trade price and the volume-weighted average price. They find that price impact costs on the NYSE tend to be small in relation to commissions. Knez and Ready (1996) use all market orders in the Trades, Orders, Reports, and Quotes database measuring price impact costs for listed firms on the NYSE. They find that the price impact cost is strongly related to the difference between quoted depth and order size.

Opportunity costs

Keim and Madhavan (1998) state that opportunity costs are associated with missed trading opportunities. The costs represent the difference between the performance of the desired investment and the actual investment after adjustment for execution costs and commissions. The opportunity costs are also referred to as the "hidden" costs of trading. They are not directly recorded and are therefore difficult to estimate.

2.6.2. Total Trading Costs

The previous section introduces the individual components of trading costs. The measurement of total trading costs by simply adding up the isolated cost components can lead to misleading results since implicit and explicit costs are sometimes correlated and jointly determined at a certain order level. The following section reviews the estimation methods of total trading costs.

Spread plus commission

The most direct estimate of total trading cost is spread plus commission. This is the sum of the proportional bid-ask spread and a representative commission. The proportional bid-ask spread is calculated using current specialist quotes. The commission is a proportion of the transaction value based on price per share and the number of shares traded. Stoll and Whaley (1983) investigate the small firm effect on the NYSE. They estimate the trading costs by directly calculating quoted market bid-ask spread data plus prevailing commission schedules. They report that trading costs can partially account for the small size effect. Bhardwaj and Brooks (1992) use a similar method to estimate trading costs for the January effect. They find that there is no positive abnormal return in January after taking account of transaction costs.

Price impact plus commission

Total transaction costs are also estimated by commissions plus price impact costs. Berkowitz, Logue and Noser (1988) find that price impact costs on the NYSE tend to be small in relation to commissions although total transaction costs can be very large due to large commissions. They report that total transaction costs are for their sample, on average, 0.23% of the principal value. Commissions are, on average, 0.18% of the principal value, suggesting that commissions dominate total transaction costs. Chan and Lakonishok (1997) also use the same approach to estimate the total transaction costs between issues listed on the NYSE and the NASDAQ for institutional investors. They find that institutional trading costs for relatively smaller firms are lower on the NASDAQ, while costs for the larger firms are lower on the NYSE.

Limited dependent variable (LDV) model

The limited dependent variable (LDV) model is proposed by Lesmond, Ogden and Trzcinka (1999). This model uses daily security returns to measure the effect of transaction costs through the incidence of zero returns. It assumes that if the value of accumulated information exceeds the costs of trading, the marginal investor will either reduce trading or not trade, causing a zero return. Therefore, the estimates from this model are marginal trader's effective transaction costs. They find that transaction costs, estimated by their model, are highly correlated (85%) with those estimated from the most commonly used method of spreads plus commissions.

2.6.3. Determinants of Trading Costs

Previous theoretical and empirical research suggests that trading costs are affected by a number of factors. Of these, the market capitalization of firms, the size of the transaction and the investment style, have been identified as the most important determinants of trading costs.

Market capitalization

Market capitalization has been reported as negatively associated with trading costs. Since market capitalization relates to market liquidity, stocks with large capitalization are more liquid than those with small capitalization. Therefore, they have lower implicit and explicit costs than small stocks. Chan and Lakonishok (1997) examine all trades on the NYSE and NASDAQ using 33 institutions from 1989 to 1991. They find that an average round-trip execution cost is 0.9% for large stocks and 3.31% for small stocks on the NYSE; while an average round-trip execution cost is 1.23% for large stocks and 2.22% for small stocks on the NASDAQ. Stoll and Whaley (1983), Chan and Lakonishok (1995), Bessembinder and Kaufman (1997) and Keim and Madhavan (1997) also report that there is a negative relationship between the market capitalization of stocks and trading cost.

Trade size

Trade size has been found to be positively related to trading cost. Large trades are generally more difficult to execute without high impact costs. Chan and Lakonishok (1997) report that "easy" packages, which include packages ranked below the median when sorted by relative package size, incur an average round-trip cost of

0.25%. The corresponding round-trip cost is 2.35% for "difficult" packages that is the largest 5% of packages when ranked by relative size. Loeb (1983), Chan and Lakonishok (1993 and 1995) and Keim and Madhavan (1996 and 1998) also provide evidence to show a similar relationship between trading cost and trade size.

Style investment

The market impact of a transaction can vary with different investment styles. Chan and Lakonishok (1993 and 1995) identify that the dominant influence on the market impact of a trade is investment style. They find that institutional investors, trading in growth stocks, incur a round-trip cost of 0.7%, while those trading in value stocks experience a benefit of 0.4%. Keim and Madhavan (1997) also analyze the relationship between investment style and trading costs. They find that there is a considerable variation in costs between markets and across investment styles. In particular, value traders have substantially lower trading costs than those whose trading strategies demand more immediacy.

Chapter 3. Momentum Profits and Time-Varying Idiosyncratic Risk

3.1. Introduction

Momentum strategies that buy recent winners and sell recent losers are profitable over short horizons of 3 to 12 months (Jegadeesh and Titman, 1993). Price continuation has prevailed over time (Jegadeesh and Titman, 2001), across countries (Griffin, Ji and Martin, 2003; Liu, Strong and Xu, 1999 and Ellis and Thomas, 2003), across industries (Moskowitz and Grinblatt, 1999), across equity styles (Chen and De Bondt, 2004) and across asset classes (Okunev and White, 2003). While the profitability of relative-strength portfolios is not disputed, there is still a lot of controversy as to why these abnormal returns occur. Two explanations have been put forward.

The first is based on psychology and market inefficiency. Behavioural proponents relate price under- and over-reaction to cognitive errors that investors make when incorporating information into prices. For example, investors may be too quick to draw the conclusion that a given stock follows a particular "ideal type" (the representativeness heuristic), and they may be too slow to update their beliefs when confronted with new, especially contradictory, evidence (the conservatism bias). These behavioural attributes lead first to momentum as stock prices react with delay to firm-specific information and, once deviations from equilibrium are acknowledged, to subsequent mean reversion (Barberis, Shleifer and Vishny, 1998; Daniel, Hirshleifer and Subrahmanyam, 1998 and Hong and Stein, 1999).[6] This suggests that the irrationality from which agents suffer may push prices away from fundamentals and allow profitable mis-pricings to survive.

The second explanation relies on the notion of market efficiency and argues that the returns of the relative-strength portfolios are a fair compensation for the risk and/or trading costs of implementing the strategies. On balance, however, the evidence suggests that the profitability of the relative-strength portfolios is not solely a compensation for exposure to higher risks (Jegadeesh and Titman, 1993; Chan, Jegadeesh and Lakonishok, 1996; Fama and French, 1996; Griffin, Ji and Martin, 2003; Karolyi and Kho, 2004 and Sadka, 2006)[7]. Studies that allow for time-variation in systematic risks reach conflicting conclusions. While Chordia and Shivakumar (2002), Wu (2002) and Wang (2003) explain the profitability of momentum strategies through time-variation in expected returns, Grundy and Martin (2001), Griffin, Ji and Martin (2003) and Lewellen and Nagel (2006) argue that the momentum returns are too large to be accounted for in terms of time-varying risks. It is important to note also that a rationale related to transaction costs has been put forward as an explanation for momentum profits. Lesmond, Schill and Zhou (2004)

[6] Other behavioral deficiencies that investors may suffer from include biased self-attribution and overconfidence (Daniel, Hirshleifer and Subrahmanyam, 1998) , and bounded rationality (Hong and Stein, 1999).

[7] Jegadeesh and Titman (1993) estimate a market model, to which Chan Jegadeesh and Lakonishok (1996) and Fama and French (1996) add the return of portfolios sorted on size and book-to-market value. Griffin, Ji and Martin (2003) look at macroeconomic and financial factors that are in the spirit of the model of Chen, Roll and Ross (1986). Sadka (2006) looks at the role of liquidity risk. Karolyi and Kho (2004) use bootstrap experiments and a wide range of return-generating processes.

indeed argue that momentum profits have little to do with risk as they are simply an illusion induced by trading costs.[8]

The contribution of this chapter to the literature on momentum is twofold. The first contribution is with regards to the time-varying idiosyncratic risk of the winners and the losers and to the role it may have in explaining the abnormal returns of momentum strategies. While several studies look at variations in systematic risk (Grundy and Martin, 2001; Chordia and Shivakumar, 2002; Wu, 2002; Griffin, Ji and Martin, 2003; Wang, 2003 and Lewellen and Nagel, 2006), this chapter is the first to look at variations in the idiosyncratic risks of the winner and loser portfolios. We do this within a GJR-GARCH(1,1)-M framework[9].

The rationale for choosing a GARCH(1,1)-M model stems from the idea that in rational markets, volatility is often viewed as being commensurate with news or information flow, and indeed, the autocorrelation in information arrival ("news events happen in bunches") is one of the primary rationalizations of the volatility clustering that is almost universally observed in asset returns. The conditional standard deviation term in the mean equation captures the time-varying relationship between total risk and returns, and thus our contribution is to link momentum profits with the impact of news on returns. We use the GJR variant of the basic GARCH model in order to allow for a possible asymmetry in the relationship between the

[8] Lesmond, Schill and Zhou (2004) show that momentum strategies are highly trading intensive and pick up stocks that are expensive and risky (small, high beta, illiquid, off-NYSE extreme performers). Besides, the momentum profits are mainly driven by the losers (Hong, Lim and Stein, 2000) and thus short-sale costs also need to be taken into account.

[9] GJR-GARCH(1,1)-M stands for Glosten et al. (1993) Generalized Autoregressive Conditional Heteroscedasticity of order 1,1 with a Mean term that models the conditional risk premium. A number of studies (Nelson, 1991; Glosten et al., 1993; Rabemananjara and Zakoian, 1993) show that good news (measured by positive return shocks) and bad news (measured by negative return shocks) have an asymmetric impact on the conditional variance of stock returns.

returns to the winner and loser portfolios and the volatility. By using a conditional model, we are able to capture the possibility that the risks of the winners and the losers may change in a predictable, but different, way over time. This suggests that a model explicitly allowing for risk to be time-dependent might explain the abnormal returns of the momentum strategies. Our approach is an alternative to one where pre-specified conditional variables, such as macroeconomic or firm-specific influences, are used as the risk factors in a conditional pricing model. Most such models have largely failed to explain the profitability of relative strength portfolios, and thus an advantage of the method that we employ is that it does not require any *a priori* specification of the set of risk factors in order to allow for time-varying risk.

The second contribution of this chapter to the momentum literature is to look at the impact of recent, old and bad news on the volatility of the winners and losers. As the losers are more likely to sit on bad news than the winners, managers are more likely to withhold information. On the other hand, as the winners are more likely to receive good news than the losers, managers are more eager to disclose information. Therefore, the winners and losers may respond to recent, old and bad news in different ways.

We draw the following two conclusions from our analysis. First, we identify some clear patterns in the volatility of the winner and loser portfolios. The volatility of the winners is found to be more sensitive to recent news than that of the losers, whereas by contrast, the volatility of the losers is found to be more sensitive to distant news than that of the winners. Besides, the volatility of the losers (with an average volatility half-life of 24 months and 13 days) shows a higher level of persistence than that of the winners (whose volatility half-life only equals 3 months and 5 days on average).

The second conclusion of this chapter is with regards to the hypothesis that the momentum returns are a compensation for time-varying unsystematic risk as modeled by the GJR-GARCH(1,1)-M model. We show that the GJR-GARCH(1,1)-M terms, when are added to the traditional market and Fama and French models, explain the abnormal performance of the momentum strategies without the need to resort to the transactions cost and illiquidity issues. Interestingly, neither the GJR-GARCH(1,1) nor the GARCH(1,1)-M specifications alone could account for the abnormal return of the relative-strength portfolios. It is therefore both the asymmetric response of the losers to good and bad news and the conditional risk premium embedded in the GARCH(1,1)-M model that explain the profitability of momentum strategies.

The remainder of this chapter is organized as follows. Section 3.2 introduces the dataset, the methodology employed to construct the momentum portfolios and the models used to adjust for risk. Section 3.3 examines the performance of momentum strategies and analyzes how recent news, distant news and negative return shocks impact the volatility of the winners and losers. It also tests whether momentum profits are a compensation for time-varying idiosyncratic risk common to the winners and losers. Finally, section 3.4 concludes this chapter with a summary of our findings.

3.2. Data and Methodology

Monthly UK stock prices adjusted for dividends are obtained from the London Share Price Database (LSPD) over the period 28 February 1975 to 31 December 2001.[10] To address problems of survivorship bias, we also include stocks that are delisted due to merger, acquisition or bankruptcy. The sample includes all companies with at least 3 months of available returns. A total of 6,155 companies are considered.

All stocks are ranked and sorted into 10 equally-weighted portfolios based on their past J-month cumulative returns ($J = 3, 6, 12$ months). The decile portfolio with the highest cumulative return is termed the "winner" portfolio, while the decile portfolio with the lowest cumulative return is called the "loser" portfolio. The return on the momentum portfolio is then measured as the return difference between the winner and loser portfolios over the next K months ($K = 3, 6, 12$ months). The resulting portfolio is referred to as the J-K momentum portfolio. The procedure is rolled forward at the end of each holding period to produce new winner, loser and momentum portfolios. The formation of the relative-strength portfolios is therefore non-overlapping, thus reducing the trading frequency and transaction costs incurred in portfolio construction and ensuring that statistical tests are valid without requiring modification of the standard errors. Our framework is also more realistic in terms of the behaviour of investors than one based on overlapping portfolios where they would presumably have to vary the amount of wealth devoted to the strategies over time.

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[10] The returns to the Fama-French factor portfolios that we employ subsequently are only available to December 2001, which necessitates this truncation of our sample period.

Traditionally, performance has been measured by regressed a portfolio's returns on a set of systematic risk factors emanating from the CAPM of Sharpe (1964) or the three-factor model of Fama and French (1993), which can be expressed respectively as

$$R_t = \alpha + \beta(R_{Mt} - R_{ft}) + \varepsilon_t \qquad (1)$$

$$R_t = \alpha + \beta(R_{Mt} - R_{ft}) + sSMB_t + hHML_t + \varepsilon_t \qquad (2)$$

where R_t is either the return on the momentum portfolio or the return of the winner and loser portfolios in excess of the risk-free rate, R_{ft} is the three-month Treasury bill rate, R_{Mt} is the value-weighted market return on all stocks quoted on the London Stock Exchange, SMB_t and HML_t are the UK-based returns from the Fama and French (1993) size and book-to-market value portfolios as provided by Nagel[11] and ε_t is a white noise error term. The performance of the portfolios is then evaluated by testing the statistical significance of the α coefficient in (1) and (2).[12]

Embedded in equations (1) and (2) is the assumption that $\varepsilon_t \sim N(0, \sigma^2)$ and, thus, that there is no conditional volatility in the market. Since Engle (1982), numerous studies have been written on the family of GARCH models (Poon and Granger, 2003; Andersen, Bollerslev, Christoffersen and Diebold, 2005 and Bauwens, Laurent and

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[11] These data are available at http://faculty-gsb.stanford.edu/nagel/data/UK_FFFact.csv

[12] The Carhart (1997) four-factor version of the Fama-French model is often used in performance attribution for mutual funds. The fourth factor, known as UMD ("up-minus-down") is a measure of the return to momentum portfolios. The key distinction between this approach and what we propose here is that we are trying to explain the profitability of momentum portfolios using a previously unexamined measure of risk, whereas the UMD term uses momentum to explain the returns from other strategies. Thus, in our study, momentum is the explained variable whereas in the Carhart model, it is an explanatory variable.

Rombouts, 2006). The attractiveness of the GARCH family models stems from the fact that they model the conditional variance of asset returns by taking into account persistence in volatility (where volatility shocks today influence expected volatility many months from now) and "leverage effects" (where negative return shocks impact volatility more than positive return shocks of the same magnitude). These two features are central to our hypotheses that the losers' volatilities show more persistence and asymmetry than those of the winners.

We investigate whether momentum profits in the UK are a compensation for time-varying risk within GJR-GARCH(1,1)-M versions of the market and Fama and French models:

$$\begin{aligned} R_t &= \alpha + \beta\left(R_{Mt} - R_{ft}\right) + \delta\sigma_t + \varepsilon_t \\ \sigma_t^2 &= \omega + \gamma\varepsilon_{t-1}^2 + \eta I_{t-1}\varepsilon_{t-1}^2 + \theta\sigma_{t-1}^2 \end{aligned} \tag{3}$$

$$\begin{aligned} R_t &= \alpha + \beta\left(R_{Mt} - R_{ft}\right) + sSMB_t + hHML_t + \delta\sigma_t + \varepsilon_t \\ \sigma_t^2 &= \omega + \gamma\varepsilon_{t-1}^2 + \eta I_{t-1}\varepsilon_{t-1}^2 + \theta\sigma_{t-1}^2 \end{aligned} \tag{4}$$

where σ_t^2 is the conditional variance of the winner, loser and momentum portfolios, δ measures the time-varying risk premium, γ. η relate to the lagged squared error term and measure the impact of recent news on volatility, η also measures any asymmetric response of volatility to bad and good news (commonly attributed to as leverage effect), $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$ (bad news, also called negative return shock) and $I_{t-1} = 0$ otherwise, θ relates to the lagged conditional volatility and measures the impact of old news on volatility.

Within the framework of systems (3) and (4), the following two hypotheses can be tested. First, the coefficients on conditional volatility indicate how news impacts the volatility of the winners and of the losers. In particular, we analyze the speed of the response of the winners and losers to news and test for the presence of any asymmetry in the response of the winners' and losers' volatilities to good and bad news. Second, the sign and significance of α in the mean equations of systems (3) and (4) indicate whether the momentum returns are a compensation for market risk, the risks associated with size and book-to-market value and time-varying, idiosyncratic risk.

We also test whether momentum profits can be explained by a simplified version of the above models in the standard GARCH(1,1)-M framework. This specification models the time-varying risk premium as in (3) and (4) but does not allow for asymmetric response of volatility to good and bad news. Practically, this breaks down to estimating the following systems of equations

$$\begin{aligned} R_t &= \alpha + \beta(R_{Mt} - R_{ft}) + \delta\sigma_t + \varepsilon_t \\ \sigma_t^2 &= \omega + \gamma\varepsilon_{t-1}^2 + \theta\sigma_{t-1}^2 \end{aligned} \qquad (5)$$

$$\begin{aligned} R_t &= \alpha + \beta(R_{Mt} - R_{ft}) + sSMB_t + hHML_t + \delta\sigma_t + \varepsilon_t \\ \sigma_t^2 &= \omega + \gamma\varepsilon_{t-1}^2 + \theta\sigma_{t-1}^2 \end{aligned} \qquad (6)$$

Our hypothesis is to test whether momentum profits are a compensation for time-varying idiosyncratic risk. If this hypothesis is true, then the α coefficients of momentum portfolios should be statistically indistinguishable from zero, and therefore, a two-sided test is more appropriate for assessing parameter significance in GARCH model.

3.3. Empirical Results

Table 3.1 presents summary statistics for the winner, loser and momentum portfolios. The rows represent the ranking periods (J = 3, 6 and 12 months) and the columns represent the holding periods (K = 3, 6 and 12 months). It is clear from this table that the winners systematically outperform the losers at the 1% level. Across strategies, the momentum portfolios earn an average return of 0.0151 a month, with a range from 0.0093 for the 3-3 strategy to 0.0193 for the 6-6 strategy.[13] These results corroborate those of Liu, Strong and Xu (1999) and Ellis and Thomas (2003) for the UK.

Table 3.1 also reports the monthly standard deviations and reward-to-risk ratios of each portfolio return. Consistent with rational expectations, the momentum portfolios with higher returns also have more risk. For instance, the 6-6 strategy earns the highest average return (0.0193) and, with a standard deviation of 0.0511, it is also the second most volatile strategy. With a reward-to-risk ratio of 0.3856, the 12-6 strategy generates the highest average return in risk-adjusted terms, while the 3-3 strategy offers the lowest risk-adjusted return (0.1925).

The contribution of this chapter is with regards to the time-varying idiosyncratic risk of the winner and loser portfolios and the impact that it may have on momentum profits. With this in mind, we first analyze the performance of the winner, loser and momentum portfolios within the standard market and Fama and French models and then allow for time-varying idiosyncratic risk through different specifications of the

[13] Note that all figures in this chapter refer to monthly proportion returns rather than percentage returns, unless otherwise stated.

Table 3.1. Summary statistics of the returns of the winner, loser and momentum portfolios

Winner (Loser) is an equally-weighted non-overlapping portfolio containing the 10% of stocks that performed the best (worst) over a given ranking period. Momentum is a portfolio that buys the winner portfolio and sells the loser portfolio short. Returns are measured as proportions rather than percentages. Reward-to-risk ratio is the ratio of the monthly mean to the monthly standard deviation. The *p*-values in parentheses are for the significance of the mean. They are based on heteroskedasticity and autocorrelation robust (Newey-West) standard errors. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels for a two-sided test.

	Holding period of 3 months			Holding period of 6 months			Holding period of 12 months		
	Winner	Loser	Momentum	Winner	Loser	Momentum	Winner	Loser	Momentum
Panel A: Ranking period of 3 months									
Mean	0.0063	-0.0030	0.0093	0.0084	-0.0055	0.0139	0.0077	-0.0048	0.0125
	(0.02) [b]	(0.22)	(0.04) [b]	(0.01) [a]	(0.08) [c]	(0.00) [a]	(0.01) [a]	(0.09) [c]	(0.01) [a]
Standard deviation	0.0555	0.0699	0.0485	0.0573	0.0689	0.0506	0.0608	0.0639	0.0474
Reward-to-risk ratio	0.1137	-0.0433	0.1925	0.1468	-0.0792	0.2740	0.1265	-0.0751	0.2634
Panel B: Ranking period of 6 months									
Mean	0.0107	-0.0064	0.0171	0.0113	-0.0080	0.0193	0.0085	-0.0053	0.0139
	(0.00) [a]	(0.05) [c]	(0.00) [a]	(0.00) [a]	(0.02) [b]	(0.00) [a]	(0.00) [a]	(0.08) [c]	(0.00) [a]
Standard deviation	0.0554	0.0707	0.0535	0.0562	0.0682	0.0511	0.0578	0.0654	0.0497
Reward-to-risk ratio	0.1933	-0.0911	0.3203	0.2006	-0.1170	0.3769	0.1478	-0.0815	0.2792
Panel C: Ranking period of 12 months									
Mean	0.0121	-0.0041	0.0162	0.0128	-0.0063	0.0191	0.0098	-0.0045	0.0143
	(0.00) [a]	(0.13)	(0.00) [a]	(0.00) [a]	(0.04) [b]	(0.00) [a]	(0.00) [a]	(0.11)	(0.00) [a]
Standard deviation	0.0571	0.0638	0.0501	0.0571	0.0653	0.0496	0.0568	0.0635	0.0456
Reward-to-risk ratio	0.2121	-0.0645	0.3242	0.2243	-0.0966	0.3856	0.1728	-0.0704	0.3133

GARCH(1,1) model. While doing this, we will also analyze the impact of recent news, old news and bad news on the volatility of the winners and losers.

3.3.1. Static Market and Fama and French Models

Table 3.2 reports the ordinary least squares (OLS) estimates of the market and Fama and French models (1) and (2) for the winner, loser and momentum portfolios.[14] In line with previous research (Jegadeesh and Titman, 1993; Fama and French, 1996 and Karolyi and Kho, 2004), the results indicate that traditional versions of the market and Fama and French models fail to explain momentum profits. Regardless of the model, of the ranking period, and of the holding period, the α coefficients of the momentum strategies in equations (1) and (2) are positive and significant at the 1% level. The momentum returns estimated from the market model range from 0.0095 (3-3 strategy) to 0.0194 (6-6 strategy), with an average return at 0.0151 a month. According to the Fama and French model, the winners outperform the losers by 0.0177 on average, with a range of 0.0110 (3-3 strategy) to 0.0222 (12-6 strategy). While systematic risk explains most of the over-performance of the winners, it fails to account for the under-performance of the losers. Irrespective of the ranking period, of the holding period and of the risk model considered, the losers indeed have negative alphas that are significant at the 1% level. As in Hong, Lim and Stein (2000), the momentum profits are therefore driven by the losers.

The factor loadings on R_{Mt}, SMB_t and HML_t in (1) and (2) suggest that the winner and loser portfolios tend to pick small capitalization stocks (s>0) and the losers have

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[14] Engle (1982)'s ARCH-LM test provides strong evidence of Heteroskedasticity in the OLS residuals of the market and Fama-French models. Hence, we use White's Heteroskedasticity-robust standard errors.

higher market risk than the winners($\beta_L > \beta_W$). The winners have growth characteristics ($h<0$) and the losers have value characteristics ($h>0$). The momentum strategies are predominantly market-neutral ($\beta=0$) and size-neutral ($s=0$) and have negative loadings on HML_t. These results are consistent with those previously reported, including the studies by Chan, Jegadeesh and Lakonishok (1996) and Liu, Strong and Xu (1999).

Table 3.3 reports the ARCH LM test statistics and p-values. The results show that there is substantial evidence of ARCH effects since all the LM statistics of the market and the Fama and French models are significant at the 5% level for the winner, loser and momentum portfolios. These results indicate that the static market and the Fama and French models fail to capture the problems of heteroskedasticity (and autocorrelation) contained in the returns on the winner, loser and momentum portfolio.

3.3.2. GARCH(1,1) Versions of Market and Fama and French Models

Table 3.4 presents the results of normality test for the residuals of the conditional market (MM) and Fama and French models (FFM) (3) and (4) that include a GJR-GARCH(1,1)-M term. With only a few exceptions (the 3-3 loser of the MM, the 6-3 loser of the FFM, the 6-6 loser of the FFM and 3-12 momentum of FFM), Jarque-Bera (JB) statistics are significant at the 5% level, suggesting the rejection of the hypothesis that the residuals are normal distributed. Following the argument of the central limit theorem, the sample sizes that we have in chapter 3 are quite large; therefore, non-normality will have less impact on inference than that would be the case for small samples. The studies of Brooks, Cerny and Miffre (2008) and Fuertes,

Table 3.2. Static market and Fama and French models

The table reports coefficient estimates for equations (1) and (2) for the winner, loser and momentum portfolios. Winner (Loser) is an equally-weighted non-overlapping portfolio containing the 10% of stocks that performed the best (worst) over a given ranking period. Momentum is a portfolio that buys the winner portfolio and short sells the loser portfolio. α measures the portfolio's abnormal performance, β measures the market risk of the portfolio, s and h are the portfolio loadings on the size and book-to-market value factors as measured by Fama and French (1993). MM refers to the market model and FFM refers to the Fama and French model. White's heteroskedasticity robust t-statistics are in parentheses. Significance is denoted by superscripts at the 1% (^{a}), 5% (^{b}) and 10% (^{c}) levels for a two-sided test.

	Holding period of 3 months						Holding period of 6 months						Holding period of 12 months					
	Winner		Loser		Momentum		Winner		Loser		Momentum		Winner		Loser		Momentum	
	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM
Panel A: Ranking period of 3 months																		
α	-0.0020	-0.0031	-0.0115	-0.0141	0.0095	0.0110	0.0001	-0.0009	-0.0139	-0.0170	0.0140	0.0161	-0.0007	-0.0014	-0.0132	-0.0166	0.0125	0.0152
	(-0.87)	(-2.33)^{b}	(-3.81)^{a}	(-6.24)^{a}	(3.46)^{a}	(4.11)^{a}	(0.03)	(-0.71)	(-4.59)^{a}	(-7.80)^{a}	(4.82)^{a}	(6.05)^{a}	(-0.28)	(-1.01)	(-4.68)^{a}	(-8.49)^{a}	(4.60)^{a}	(6.47)^{a}
β	0.7662	0.9660	0.9155	1.1528	-0.1493	-0.1868	0.7833	0.9856	0.8858	1.1360	-0.1025	-0.1505	0.8358	1.0392	0.8237	1.0707	0.0121	-0.0314
	(11.79)^{a}	(26.08)^{a}	(12.15)^{a}	(13.64)^{a}	(-1.62)	(-1.73)^{c}	(11.35)^{a}	(22.83)^{a}	(12.06)^{a}	(13.77)^{a}	(-1.11)	(-1.39)	(16.03)^{a}	(29.46)^{a}	(12.24)^{a}	(17.58)^{a}	(0.23)	(-0.49)
s	—	1.0001	—	1.1143	—	-0.1142	—	1.0195	—	1.1563	—	-0.1368	—	1.0439	—	1.1184	—	-0.0745
		(17.45)^{a}		(11.98)^{a}		(-0.89)		(16.45)^{a}		(12.72)^{a}		(-1.05)		(17.23)^{a}		(14.98)^{a}		(-0.69)
h	—	-0.1160	—	0.2598	—	-0.3759	—	-0.1529	—	0.3770	—	-0.5300	—	-0.2563	—	0.4934	—	-0.7497
		(-1.43)		(1.69)^{c}		(-2.05)^{b}		(-1.58)		(2.23)^{b}		(-2.36)^{b}		(-2.10)^{b}		(4.32)^{a}		(-4.04)^{a}
Panel B: Ranking period of 6 months																		
α	0.0024	0.0017	-0.0149	-0.0182	0.0173	0.0200	0.0029	0.0021	-0.0164	-0.0198	0.0194	0.0219	0.0002	-0.0005	-0.0138	-0.0173	0.0139	0.0169
	(1.05)	(1.34)	(-4.78)^{a}	(-7.89)^{a}	(5.67)^{a}	(7.03)^{a}	(1.28)	(1.75)^{c}	(-5.42)^{a}	(-9.03)^{a}	(6.60)^{a}	(8.13)^{a}	(0.07)	(-0.39)	(-4.77)^{a}	(-8.32)^{a}	(4.89)^{a}	(6.64)^{a}
β	0.7751	0.9601	0.9017	1.1525	-0.1266	-0.1924	0.7936	0.9846	0.8677	1.1181	-0.0742	-0.1334	0.8188	1.0099	0.8451	1.0899	-0.0263	-0.0800
	(11.28)^{a}	(22.13)^{a}	(11.78)^{a}	(13.31)^{a}	(-1.29)	(-1.64)	(11.87)^{a}	(22.39)^{a}	(11.77)^{a}	(13.77)^{a}	(-0.80)	(-1.21)	(15.39)^{a}	(31.08)^{a}	(12.09)^{a}	(15.50)^{a}	(-0.39)	(-0.94)
s	—	0.9475	—	1.1450	—	-0.1975	—	0.9716	—	1.1375	—	-0.1659	—	0.9807	—	1.0960	—	-0.1153
		(16.84)^{a}		(12.04)^{a}		(-1.49)		(17.19)^{a}		(12.87)^{a}		(-1.31)		(17.65)^{a}		(13.59)^{a}		(-0.99)
h	—	-0.2210	—	0.4528	—	-0.6738	—	-0.1910	—	0.4799	—	-0.6709	—	-0.2395	—	0.5575	—	-0.7971
		(-2.47)^{b}		(2.57)^{b}		(-2.89)^{a}		(-2.26)^{b}		(2.79)^{a}		(-3.03)^{a}		(-2.21)^{b}		(4.27)^{a}		(-3.92)^{a}
Panel C: Ranking period of 12 months																		
α	0.0037	0.0033	-0.0125	-0.0155	0.0162	0.0188	0.0044	0.0039	-0.0147	-0.0183	0.0191	0.0222	0.0014	0.0008	-0.0129	-0.0165	0.0142	0.0174
	(1.69)^{c}	(2.68)^{a}	(-4.46)^{a}	(-7.06)^{a}	(5.63)^{a}	(7.02)^{a}	(2.00)^{b}	(3.32)^{a}	(-5.01)^{a}	(-8.66)^{a}	(6.68)^{a}	(8.69)^{a}	(0.64)	(0.76)	(-4.59)^{a}	(-8.53)^{a}	(5.48)^{a}	(7.73)^{a}
β	0.8525	1.0210	0.8270	1.0435	0.0255	-0.0225	0.8480	1.0232	0.8214	1.0707	0.0265	-0.0475	0.8468	1.0259	0.8164	1.0599	0.0304	-0.0340
	(13.71)^{a}	(24.79)^{a}	(10.89)^{a}	(11.54)^{a}	(0.27)	(-0.19)	(13.62)^{a}	(24.14)^{a}	(10.48)^{a}	(11.58)^{a}	(0.27)	(-0.40)	(16.15)^{a}	(35.74)^{a}	(12.47)^{a}	(16.48)^{a}	(0.51)	(-0.46)
s	—	0.8763	—	0.9803	—	-0.1040	—	0.9036	—	1.1168	—	-0.2132	—	0.9200	—	1.0835	—	-0.1635
		(16.97)^{a}		(10.73)^{a}		(-0.84)		(17.08)^{a}		(12.35)^{a}		(-1.73)^{c}		(18.87)^{a}		(14.96)^{a}		(-1.71)^{c}
h	—	-0.2726	—	0.4346	—	-0.7072	—	-0.2434	—	0.5625	—	-0.8059	—	-0.2283	—	0.5925	—	-0.8208
		(-2.97)^{a}		(3.35)^{a}		(-4.07)^{a}		(-2.57)^{b}		(4.56)^{a}		(-4.71)^{a}		(-2.43)^{b}		(5.13)^{a}		(-4.91)^{a}

Table 3.3. LM tests for ARCH in the residuals of the static market and the Fama and French models

The table reports autoregressive conditional heteroskedasticity (ARCH) Lagrange Multiplier (LM) test statistics, which are asymptotically distributed as $\chi^2(5)$-variants under the null hypothesis that there is no ARCH up to order 5 in the residuals of the static market and Fama and French models. Winner (Loser) is an equally-weighted non-overlapping portfolio containing the 10% of stocks that performed the best (worst) over a given ranking period. Momentum is a portfolio that buys the winner portfolio and short sells the loser portfolio. MM refers to the market model and FFM refers to the Fama and French model. p-values are presented in parentheses.

	Holding period of 3 months						Holding period of 6 months						Holding period of 12 months					
	Winner		Loser		Momentum		Winner		Loser		Momentum		Winner		Loser		Momentum	
	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM
Panel A: Ranking period of 3 months																		
LM test statistic	123.75	50.24	42.25	61.38	50.19	44.94	130.84	38.98	20.93	48.47	88.57	63.76	127.75	112.22	15.29	26.47	93.32	80.42
p-vaue	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Panel B: Ranking period of 6 months																		
LM test statistic	158.69	78.15	42.03	66.68	100.86	66.97	129.57	35.65	25.15	43.85	110.87	75.46	143.15	73.65	19.08	32.51	77.46	73.48
p-vaue	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Panel C: Ranking period of 12 months																		
LM test statistic	122.50	44.70	34.91	50.83	73.91	53.11	96.49	20.61	22.20	44.18	67.88	55.26	101.89	45.38	23.34	46.85	47.34	61.54
p-vaue	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 3.4. Jarque-Bera test for normality of the conditional market and Fama and French models

The table reports the Jarque-Bera (JB) test statistics and p-values for normality of the conditional market and Fama and French models (3) and (4) that include a GJR-GARCH(1,1)-M term. Winner (Loser) is an equally-weighted non-overlapping portfolio containing the 10% of stocks that performed the best (worst) over a given ranking period. Momentum is a portfolio that buys the winner portfolio and short sells the loser portfolio. MM refers to the market model and FFM refers to the Fama and French model. p-values are presented in parentheses.

	Holding period of 3 months						Holding period of 6 months						Holding period of 12 months					
	Winner		Loser		Momentum		Winner		Loser		Momentum		Winner		Loser		Momentum	
	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM
Panel A: Ranking period of 3 months																		
JB test statistic	59.24	155.81	1.49	12.94	63.36	99.00	45.17	49.84	35.62	14.63	40.66	39.13	42.85	156.46	36.20	51.14	7.19	5.48
p-vaue	(0.00)	(0.00)	(0.48)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.06)
Panel B: Ranking period of 6 months																		
JB test statistic	278.45	114.55	8.76	1.90	21.79	18.64	53.90	25.90	8.01	2.50	67.33	66.77	11.87	33.37	20.14	10.06	181.32	42.58
p-vaue	(0.00)	(0.00)	(0.01)	(0.39)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.29)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Panel C: Ranking period of 12 months																		
JB test statistic	127.42	186.26	21.58	10.79	68.25	59.66	25.64	13.51	32.77	32.70	29.28	37.58	15.89	19.19	30.08	50.18	42.21	52.61
p-vaue	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Miffre and Tan (2008) also report that the departure from normality of return distributions has little to no impact on performance or on asset allocation/hedging decisions.

Table 3.5 reports the estimates of the MM and FFM that include a GJR-GARCH(1,1)-M term. Table 3.6 reports the average coefficient estimates across 9 strategies. As the non-normality of residuals reported in table 3.4, we estimate GARCH family model in the rest of this chapter using quasi-maximum likelihood covariance and standard errors introduced by Bollerslev and Wooldridge (1992). The rational for employing this method is because Bollerslev-Wooldridge robust standard errors combine unbiased and consistent maximum likelihood parameter estimates together with non-normality robust standard errors, which solve the problem of the biased maximum likelihood parameter standard errors. We first analyze how news, whether it is recent, distant or negative, impacts the volatility of the winners and the losers. We subsequently test for whether the time-varying idiosyncratic risk common to the winners and losers explains the profitability of momentum strategies.

The pattern of conditional volatility

The coefficients γ and η in systems (3) and (4) relate to the lagged squared error term and, therefore, to the impact of recent news on volatility. In Table 3.6, the average $\gamma+\eta/2$ of the conditional market model equals 0.2554 for the winners and 0.1262 for the losers.[15] The average $\gamma+\eta/2$ of the conditional Fama and French model is 0.2867

[15] While the parameters in the conditional variance equation of a symmetric GARCH model are usually required to be positive, when the GJR form of the model is used, it is possible for the parameter on the asymmetry term (η in our notation) to be negative. More specifically, if $E(I_t)$ = ½, then provided that $\gamma+\eta/2>0$, the negative parameter would not lead the conditional variance to be negative. We have checked this condition and it is satisfied for all models estimated in this study.

for the winners and 0.1551 for the losers. Clearly, recent news impacts on the volatility of the winners more than it impacts on that of the losers. With only one exception (the 3-3 winner in the Fama and French model), the conclusion holds throughout in Table 3.5, irrespective of the ranking period, of the holding period and of the model considered.

The coefficient θ in systems (3) and (4) reflects the effect of lagged conditional variance and captures the impact of "old news" on volatility. The results of the conditional market model in Table 3.6 indicate that the average θ coefficient of the winners (0.5785) is lower than that of the losers (0.7911). The same conclusion applies to the conditional Fama and French model, for which the winners have an average θ coefficient of 0.5017 and the losers have an average θ coefficient of 0.8072. It is clear therefore that "old news" has more impact on the volatility of the losers than on the volatility of the winners. Looking at the estimates of θ in Table 3.5, it appears that the conclusion holds for the vast majority of the portfolios, the 12-12 winner in the market model being the only exception.

The asymmetric coefficients (η) in Tables 3.5 and 3.6 suggest that bad news has different impacts on the volatility of the winners and of the losers. For the losers, the mean of the η coefficients in Table 3.6 is 0.3028 for the conditional market model and 0.2203 for the conditional Fama and French model. With only a few exceptions, these coefficients are significant at the 5% level in Table 3.5. Clearly, therefore, bad news increases the volatility of the losers. For the winner portfolios, however, the

Table 3.5. Conditional market and Fama and French models with a GJR-GARCH (1, 1)-M term

The table reports coefficient estimates for systems (3) and (4) for the winner, loser and momentum portfolios. Winner (Loser) is an equally-weighted non-overlapping portfolio containing the 10% of stocks that performed the best (worst) over a given ranking period. Momentum is a portfolio that buys the winner portfolio and short sells the loser portfolio. α measures the portfolio's abnormal performance, β measures the market risk of the portfolio, s and h are the portfolio loadings on the size and book-to-market value factors as measured by Fama and French (1993), $\delta\sigma_t$ is the time-varying risk exposure. The conditional variance of the portfolio returns follows a GJR-GARCH(1,1) structure as $\sigma_t^2 = \omega + \gamma\varepsilon_{t-1}^2 + \eta I_{t-1}\varepsilon_{t-1}^2 + \theta\sigma_{t-1}^2$, where ω, γ, η and θ are estimated parameters and I_{t-1} takes a value of 1, when ε_{t-1} is negative and a value of 0, otherwise. MM refers to the market model and FFM refers to the Fama and French model. Bollerslev-Wooldridge robust t-statistics are in parentheses. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels for a two-sided test.

	Holding period of 3 months						Holding period of 6 months						Holding period of 12 months					
	Winner		Loser		Momentum		Winner		Loser		Momentum		Winner		Loser		Momentum	
	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM
Panel A: Ranking period of 3 months																		
α	-0.0015	0.0164	-0.0090	0.0106	-0.0028	-0.0007	0.0094	0.0073	0.0501	0.0084	-0.0013	0.0027	0.0016	0.0215	0.0514	0.0178	0.0011	0.0024
	(-0.17)	(2.48) [b]	(-1.41)	(1.67)	(-0.44)	(-0.10)	(1.55)	(2.15) [b]	(2.64) [a]	(1.74) [c]	(-0.19)	(0.48)	(0.27)	(3.11) [a]	(10.02) [a]	(2.14) [b]	(0.21)	(0.45)
β	0.7049	0.9410	0.7786	1.0329	-0.0633	-0.1510	0.6659	0.8707	0.7589	1.0316	-0.0436	-0.1760	0.7367	1.0186	0.6933	0.9444	0.0664	0.0191
	(14.87) [a]	(34.29) [a]	(15.71) [a]	(15.89) [a]	(-1.67)	(-3.61) [a]	(22.31) [a]	(28.14) [a]	(19.30) [a]	(21.94) [a]	(-0.90)	(-4.22) [a]	(24.08) [a]	(27.37) [a]	(45.65) [a]	(38.61) [a]	(2.19) [b]	(0.61)
s	—	0.8956	—	1.0740	—	-0.2388	—	0.8066	—	1.1024	—	-0.3119		0.9423		1.0383	—	-0.1345
		(21.85) [a]		(18.48) [a]		(-3.56) [a]		(21.36) [a]		(22.51) [a]		(-4.91) [a]		(25.19) [a]		(23.53) [a]		(-2.38) [b]
h	—	0.0682	—	0.3588	—	-0.2807	—	0.1173	—	0.4939	—	-0.4083		0.1296		0.4544	—	-0.2687
		(1.07)		(4.43) [a]		(-3.23) [a]		(2.42) [b]		(6.92) [a]		(-4.34) [a]		(2.10) [b]		(8.39) [a]		(-3.87) [a]
δ	-0.0232	-0.9622	-0.0102	-0.6502	0.3038	0.2897	-0.2304	-0.3971	-1.3282	-0.7437	0.3280	0.3141	-0.0387	-1.1028	-1.3747	-1.1255	0.3497	0.3437
	(-0.08)	(-2.66) [a]	(-0.07)	(-3.31) [a]	(1.65)	(1.49)	(-1.11)	(-2.05) [b]	(-3.34) [a]	(-4.33) [a]	(1.63)	(1.78) [c]	(-0.20)	(-3.17) [a]	(-7.91) [a]	(-3.39) [a]	(2.09) [b]	(1.91) [c]
ω	0.0003	0.0001	0.0001	0.0001	0.0001	0.0001	0.0003	0.0001	0.0001	0.0000	0.0001	0.0001	0.0001	0.0001	0.0000	0.0001	0.0001	0.0001
	(2.90) [a]	(2.42) [b]	(1.12)	(1.45)	(1.63)	(1.42)	(3.02) [a]	(3.48) [a]	(1.69)	(1.48)	(1.64)	(1.51)	(2.00) [b]	(1.58)	(-0.12)	(2.27) [b]	(1.48)	(1.42)
γ	0.3542	0.1560	0.1181	0.1048	0.5210	0.4146	0.4488	0.4621	-0.0353	0.0822	0.4492	0.4765	0.3051	0.2451	-0.0062	-0.0193	0.3628	0.2953
	(3.09) [a]	(2.49) [b]	(1.73) [c]	(1.24)	(2.75) [a]	(2.56) [b]	(2.52) [b]	(2.65) [a]	(-2.63) [a]	(1.32)	(3.45) [a]	(3.97) [a]	(2.72) [a]	(2.15) [b]	(-0.53)	(-0.56)	(2.89) [a]	(2.94) [a]
η	-0.2856	0.0013	0.0789	0.1789	-0.4254	-0.3469	-0.0749	-0.1226	0.2155	0.2714	-0.2984	-0.3134	-0.0899	-0.1568	0.4319	0.3321	-0.2407	-0.1710
	(-2.15) [b]	(0.02)	(1.11)	(2.06) [b]	(-2.41) [b]	(-2.26) [b]	(-0.41)	(-0.42)	(3.24) [a]	(2.63) [a]	(-2.46) [b]	(-2.60) [a]	(-0.83)	(-1.31)	(6.97) [a]	(3.12) [a]	(-2.23) [b]	(-1.88) [c]
θ	0.5871	0.7288	0.8325	0.7560	0.6846	0.7443	0.4310	0.4042	0.8770	0.7762	0.6603	0.6657	0.6786	0.6443	0.7715	0.7870	0.7445	0.7709
	(5.71) [a]	(10.06) [a]	(12.84) [a]	(7.88) [a]	(6.79) [a]	(7.84) [a]	(4.21) [a]	(3.18) [a]	(16.21) [a]	(12.95) [a]	(5.72) [a]	(7.39) [a]	(8.68) [a]	(4.02) [a]	(31.56) [a]	(11.98) [a]	(8.44) [a]	(10.03) [a]
$\gamma+\eta/2+\theta$	0.7986	0.8854	0.9901	0.9502	0.9929	0.9854	0.8423	0.8050	0.9495	0.9942	0.9604	0.9855	0.9388	0.8110	0.9813	0.9338	0.9870	0.9806

	Holding period of 3 months						Holding period of 6 months						Holding period of 12 months					
	Winner		Loser		Momentum		Winner		Loser		Momentum		Winner		Loser		Momentum	
	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM
Panel B: Ranking period of 6 months																		
α	0.0238	0.0171	0.0665	0.0124	-0.0089	0.0011	0.0083	0.0120	0.0556	0.0077	0.0053	0.0093	0.0021	0.0147	0.0683	0.0116	-0.0014	-0.0044
	(2.37) ^{b}	(2.95) ^{a}	(3.25) ^{a}	(2.05) ^{b}	(-1.44)	(0.19)	(1.29)	(3.54) ^{a}	(4.21) ^{a}	(1.53)	(0.98)	(1.73) ^{c}	(0.34)	(3.24) ^{a}	(2.86) ^{a}	(1.83) ^{c}	(-0.22)	(-0.72)
β	0.7121	0.9063	0.7599	1.0016	-0.0088	-0.1286	0.6508	0.8930	0.7179	0.9755	-0.0357	-0.1303	0.6970	0.9290	0.6563	1.0114	0.0297	-0.0403
	(18.76) ^{a}	(48.31) ^{a}	(17.51) ^{a}	(23.82) ^{a}	(-0.35)	(-3.26) ^{a}	(23.41) ^{a}	(35.16) ^{a}	(15.53) ^{a}	(22.16) ^{a}	(-1.11)	(-3.55) ^{a}	(24.31) ^{a}	(30.72) ^{a}	(10.99) ^{a}	(19.72) ^{a}	(0.89)	(-1.03)
s	—	0.7554	—	1.0790	—	-0.3684	—	0.8613	—	1.0353	—	-0.2423		0.8999		1.0516	—	-0.1348
		(25.08) ^{a}		(18.44) ^{a}		(-6.06) ^{a}		(25.52) ^{a}		(19.26) ^{a}		(-4.04) ^{a}		(22.71) ^{a}		(18.81) ^{a}		(-2.27) ^{b}
h	—	0.0351	—	0.5217	—	-0.5132	—	-0.0762	—	0.6217	—	-0.6183		-0.0099		0.5414	—	-0.4616
		(0.88)		(5.88) ^{a}		(-5.55) ^{a}		(-1.16)		(7.07) ^{a}		(-7.92) ^{a}		(-0.14)		(5.17) ^{a}		(-6.11) ^{a}
δ	-0.6727	-0.8283	-1.6774	-0.8451	0.7616	0.4445	-0.1124	-0.4970	-1.4994	-0.7812	0.3538	0.3369	-0.0118	-0.7783	-1.7612	-0.8700	0.4165	0.5464
	(-2.11) ^{b}	(-2.55) ^{b}	(-3.66) ^{a}	(-4.37) ^{a}	(5.85) ^{a}	(2.56) ^{b}	(-0.51)	(-2.43) ^{b}	(-4.74) ^{a}	(-4.48) ^{a}	(2.28) ^{b}	(2.02) ^{b}	(-0.06)	(-2.95) ^{a}	(-3.32) ^{a}	(-3.96) ^{a}	(2.28) ^{b}	(3.02) ^{a}
ω	0.0003	0.0001	0.0003	0.0000	0.0000	0.0002	0.0003	0.0001	0.0003	0.0000	0.0001	0.0001	0.0001	0.0001	0.0003	0.0001	0.0001	0.0001
	(3.20) ^{a}	(3.40) ^{a}	(2.99) ^{a}	(1.38)	(1.74) ^{c}	(2.06) ^{b}	(2.39) ^{b}	(3.29) ^{a}	(2.81) ^{a}	(1.29)	(1.31)	(1.53)	(2.45) ^{b}	(1.76) ^{c}	(2.01) ^{b}	(1.71) ^{c}	(1.53)	(1.37)
γ	0.3669	0.2077	-0.0872	0.0337	0.6100	0.6568	0.5312	0.3356	-0.0775	0.0729	0.4646	0.4326	0.3751	0.2097	-0.0169	0.0894	0.2988	0.2407
	(2.66) ^{a}	(1.91) ^{c}	(-8.10) ^{a}	(1.21)	(6.11) ^{a}	(3.13) ^{a}	(2.16) ^{b}	(2.34) ^{b}	(-3.69) ^{a}	(1.49)	(2.69) ^{a}	(2.61) ^{a}	(3.39) ^{a}	(1.96) ^{c}	(-0.70)	(1.62)	(2.20) ^{b}	(2.32) ^{b}
η	-0.1478	0.2377	0.3757	0.2300	-0.5096	-0.6385	-0.3465	0.1933	0.3698	0.1661	-0.4266	-0.3755	-0.2771	0.2078	0.4085	0.1604	-0.2044	-0.1316
	(-0.82)	(1.26)	(4.08) ^{a}	(3.20) ^{a}	(-5.38) ^{a}	(-3.13) ^{a}	(-1.55)	(0.78)	(3.17) ^{a}	(2.08) ^{b}	(-2.49) ^{b}	(-2.29) ^{b}	(-2.00) ^{b}	(1.01)	(2.96) ^{a}	(1.65)	(-1.67)	(-1.37)
θ	0.4155	0.3368	0.7780	0.8498	0.6198	0.6158	0.4885	0.2825	0.8030	0.8409	0.7403	0.7534	0.6475	0.4660	0.7060	0.8029	0.7768	0.8062
	(2.34) ^{b}	(2.46) ^{b}	(10.88) ^{a}	(19.40) ^{a}	(12.93) ^{a}	(5.97) ^{a}	(3.47) ^{a}	(2.32) ^{b}	(13.39) ^{a}	(18.17) ^{a}	(9.74) ^{a}	(9.26) ^{a}	(6.63) ^{a}	(2.41) ^{b}	(6.73) ^{a}	(11.64) ^{a}	(8.99) ^{a}	(11.49) ^{a}
$\gamma+\eta/2+\theta$	0.7085	0.6634	0.8787	0.9985	0.9750	0.9533	0.8465	0.7147	0.9105	0.9969	0.9916	0.9983	0.8840	0.7795	0.8933	0.9725	0.9734	0.9811
Panel C: Ranking period of 12 months																		
α	0.0086	0.0240	0.0683	0.0179	-0.0103	-0.0085	0.0172	0.0171	0.0452	0.0113	0.0093	0.0038	0.0011	0.0150	0.0548	0.0208	-0.0053	-0.0025
	(1.35)	(3.36) ^{a}	(3.21) ^{a}	(2.72) ^{a}	(-1.58)	(-1.31)	(2.21) ^{b}	(4.68) ^{a}	(2.29) ^{b}	(1.32)	(1.52)	(0.52)	(0.18)	(2.87) ^{a}	(2.52) ^{b}	(1.38)	(-0.72)	(-0.32)
β	0.7515	0.9605	0.6929	0.9120	0.1299	0.0736	0.7431	0.9438	0.6810	0.9959	0.0282	-0.0366	0.7285	0.9593	0.6872	0.9881	0.0902	-0.0151
	(26.31) ^{a}	(31.43) ^{a}	(16.53) ^{a}	(18.75) ^{a}	(2.38) ^{b}	(1.32)	(16.12) ^{a}	(34.33) ^{a}	(14.93) ^{a}	(29.14) ^{a}	(0.68)	(-0.85)	(26.61) ^{a}	(69.71) ^{a}	(14.87) ^{a}	(34.46) ^{a}	(2.68) ^{a}	(-0.43)
s		0.7941	—	0.8258	—	-0.0873	—	0.8290	—	1.0513	—	-0.2256		0.8769		1.0448	—	-0.1735
		(18.67) ^{a}		(15.29) ^{a}		(-1.19)		(22.31) ^{a}		(19.40) ^{a}		(-3.64) ^{a}		(35.00) ^{a}		(20.56) ^{a}		(-3.12) ^{a}
h		-0.0816	—	0.5744	—	-0.5398	—	-0.0317	—	0.6272	—	-0.7148		0.0108		0.6901	—	-0.6555
		(-0.95)		(8.25) ^{a}		(-4.68) ^{a}		(-0.55)		(9.70) ^{a}		(-9.42) ^{a}		(0.31)		(11.33) ^{a}		(-8.74) ^{a}
δ	-0.1314	-1.0132	-1.8889	-0.9683	0.5879	0.6233	-0.3595	-0.6839	-1.2735	-0.8920	0.2718	0.4790	0.0539	-0.7640	-1.4360	-1.1617	0.5327	0.5535
	(-0.56)	(-3.14) ^{a}	(-3.56) ^{a}	(-4.45) ^{a}	(3.72) ^{a}	(3.23) ^{a}	(-1.43)	(-3.58) ^{a}	(-2.99) ^{a}	(-3.10) ^{a}	(1.64)	(2.36) ^{b}	(0.25)	(-2.33) ^{b}	(-2.79) ^{a}	(-2.26) ^{b}	(2.64) ^{a}	(2.35) ^{b}
ω	0.0001	0.0001	0.0003	0.0000	0.0001	0.0000	0.0003	0.0001	0.0001	0.0001	0.0000	0.0001	0.0001	0.0001	0.0005	0.0002	0.0001	0.0001
	(2.25) ^{b}	(2.42) ^{b}	(2.30) ^{b}	(1.58)	(1.77) ^{c}	(1.15)	(1.72) ^{c}	(2.44) ^{b}	(1.80) ^{c}	(1.43)	(0.94)	(1.22)	(2.12) ^{b}	(3.79) ^{a}	(2.78) ^{a}	(2.29) ^{b}	(1.26)	(1.90) ^{c}
γ	0.2372	0.2298	-0.0634	0.0150	0.4103	0.2702	0.2945	0.2168	-0.0269	-0.0081	0.3080	0.2646	0.2193	0.0907	-0.0318	0.0339	0.2863	0.2002
	(2.57) ^{b}	(2.39) ^{b}	(-3.75) ^{a}	(0.41)	(4.24) ^{a}	(4.00) ^{a}	(2.48) ^{b}	(1.78) ^{c}	(-1.88) ^{c}	(-0.31)	(2.45) ^{b}	(2.60) ^{a}	(3.15) ^{a}	(1.51)	(-1.53)	(1.09)	(2.33) ^{b}	(2.17) ^{b}
η	-0.2343	-0.0053	0.3392	0.2111	-0.3914	-0.3132	-0.0585	0.2030	0.1757	0.2346	-0.2691	-0.1370	-0.1521	0.2957	0.3299	0.1980	-0.2352	-0.0478
	(-1.89) ^{c}	(-0.04)	(3.50) ^{a}	(2.92) ^{a}	(-3.06) ^{a}	(-2.58) ^{a}	(-0.39)	(0.92)	(2.12) ^{b}	(2.65) ^{a}	(-2.25) ^{b}	(-1.46)	(-2.36) ^{b}	(2.43) ^{b}	(2.32) ^{b}	(2.42) ^{b}	(-2.03) ^{b}	(-0.53)
θ	0.7386	0.5574	0.7608	0.8732	0.7772	0.8642	0.5113	0.5054	0.9130	0.8770	0.7880	0.7816	0.7083	0.5904	0.6777	0.7013	0.8298	0.7385
	(8.51) ^{a}	(3.74) ^{a}	(8.13) ^{a}	(21.44) ^{a}	(14.61) ^{a}	(23.23) ^{a}	(2.58) ^{b}	(3.66) ^{a}	(18.37) ^{a}	(16.64) ^{a}	(12.77) ^{a}	(10.95) ^{a}	(6.09) ^{a}	(9.69) ^{a}	(7.22) ^{a}	(7.30) ^{a}	(12.26) ^{a}	(8.86) ^{a}
$\gamma+\eta/2+\theta$	0.8587	0.7845	0.8671	0.9937	0.9918	0.9778	0.7766	0.8238	0.9739	0.9862	0.9614	0.9777	0.8515	0.8290	0.8108	0.8343	0.9985	0.9148

Table 3.6. Average coefficient estimates of conditional market and Fama and French models with a GJR-GARCH (1, 1)-M term across nine strategies

The table reports average coefficient estimates across 9 strategies for systems (3) and (4) for the winner, loser and momentum portfolios. α measures the portfolio abnormal performance, β measures the market risk, s and h are the portfolio loadings on the size and book-to-market value factors as measured by Fama and French (1993), $\delta\sigma_t$ is the time-varying risk exposure. The conditional variance of the portfolio returns follows a GJR-GARCH(1,1) structure as $\sigma_t^2 = \omega + \gamma\varepsilon_{t-1}^2 + \eta I_{t-1}\varepsilon_{t-1}^2 + \theta\sigma_{t-1}^2$, where ω, γ, η and θ are estimated parameters and I_{t-1} takes a value of 1, when ε_{t-1} is negative and a value of 0, otherwise. MM refers to the market model and FFM refers to the Fama and French model. Bollerslev-Wooldridge robust t-statistics are in parentheses. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels for a two-sided test.

	Winner		Loser		Momentum	
	MM	FFM	MM	FFM	MM	FFM
α	0.0078	0.0161	0.0501	0.0132	-0.0016	0.0004
	(1.04)	(3.15) [a]	(3.29) [a]	(1.82) [c]	(-0.21)	(0.10)
β	0.7101	0.9358	0.7140	0.9882	0.0214	-0.0650
	(21.87) [a]	(37.72) [a]	(19.00) [a]	(24.94) [a]	(0.53)	(-1.67)
s		0.8512		1.0336		-0.2130
		(24.19) [a]		(19.59) [a]		(-3.46) [a]
h		0.0180		0.5426		-0.4957
		(0.44)		(7.46) [a]		(-5.98) [a]
δ	-0.1696	-0.7808	-1.3611	-0.8931	0.4340	0.4368
	(-0.65)	(-2.76) [a]	(-3.60) [a]	(-3.74) [a]	(2.64) [a]	(2.30) [b]
ω	0.0002	0.0001	0.0002	0.0001	0.0001	0.0001
	(2.45) [b]	(2.73) [a]	(1.93) [c]	(1.65)	(1.48)	(1.51)
$\gamma+\eta/2$	0.2467	0.3336	0.1413	0.1450	0.2426	0.2243
	(2.00) [b]	(2.66) [a]	(-0.83)	(2.08) [b]	(1.83) [c]	(1.98) [b]
η	-0.1852	0.0949	0.3028	0.2203	-0.3334	-0.2750
	(-1.38)	(0.52)	(3.28) [a]	(2.53) [b]	(-2.66) [a]	(-2.01) [b]
θ	0.5785	0.5017	0.7911	0.8072	0.7357	0.7489
	(5.36) [a]	(4.62) [a]	(13.93) [a]	(14.16) [a]	(10.25) [a]	(10.56) [a]
$\gamma+\eta/2+\theta$	0.8339	0.7885	0.9172	0.9623	0.9813	0.9727

average η coefficient in Table 3.6 equals -0.1852 for the conditional market model and 0.0949 for the conditional Fama and French model, with 14 out of 18 coefficients that are insignificant at the 5% level in Table 3.5. It follows that the announcement of bad news does not have any noticeable impact on the volatility of the winners. It may be the case that stocks whose recent performance has already been poor are hit much harder by further bad news than stocks recently performing well, which are able to absorb bad news more easily.

The evidence of Table 3.5 thus far indicates that, with relatively few exceptions, the losers have higher η and θ, and lower γ, than the winners. Tables 3.5 and 3.6 also report the persistence in volatility of the winners and losers, measured as $\gamma+\eta/2+\theta$. The volatility of the losers appears to be more persistent than that of the winners. Indeed, the average $\gamma+\eta/2+\theta$ of the losers (winners) in Table 3.6 equals 0.9172 (0.8339) for the conditional market model and 0.9623 (0.7885) for the conditional Fama and French model. For the conditional market model, this converts into volatility half-lives of 3 months and 18 days for the winners and 8 months for the losers. The volatility half-lives estimated from the conditional Fama and French model equal 2 months and 20 days for the winners and 18 months for the losers. Clearly and with only one exception out of 18 regressions,[16] the volatility persistence of the losers exceeds that of the winners.

The impact of time-varying firm specific risk on momentum profits

Table 3.5 also reports, through δ, the impact of conditional volatility on the returns of the winners, losers and momentum portfolios. An increase in conditional volatility

[16] The exception is the 12-12 winner for the conditional market model (Table 3.4).

decreases the return of both the winners and the losers, but increases the momentum returns. The δ coefficients of the momentum portfolios from the conditional market model range from 0.2718 (12-6 strategy) to 0.7616 (6-3 strategy) (Table 3.5) with an average at 0.4340 (Table 3.6). 6 (9) coefficients out of 9 are significant at the 5% (10%) level. Similar results are reported for the conditional Fama and French model, for which δ equals 0.4368 on average (Table 3.6), with 6 (8) coefficients out of 9 that are significant and positive at the 5% (10%) level. This suggests that there is a positive relationship between time-varying risk and momentum return: A 1% increase in conditional volatility leads, on average, to a 0.43% increase in monthly momentum returns.

The factor loadings on R_{Mt}, SMB_t and HML_t for the conditional volatility model in Table 3.5 indicate that the winners and the losers have value characteristics (h>0) and are tilted towards small-capitalization stocks (s>0) and the losers have higher market risk than the winners ($\beta_L > \beta_W$). The latter two characteristics appear to corroborate the evidence from the unconditional Fama and French model (Table 3.3). As the loadings of the losers on R_{Mt}, SMB_t and HML_t are typically higher than those of the winners, the momentum portfolios have coefficients on the three Fama and French factors that are predominantly negative.

The main contribution of this chapter is to test whether momentum profits are a compensation for time-varying idiosyncratic risk as described by the GJR-GARCH(1,1)-M model. If this is indeed the case, then the α coefficients of momentum strategies should be statistically indistinguishable from zero when these terms are incorporated into the risk attribution model. This conjecture is supported uniformly at the 5% level for both the conditional market and Fama and French models. The GJR-GARCH(1,1)-M market model is able to explain the momentum returns, since the alpha estimates are reduced both in magnitude and in statistical significance. The alphas indeed range from -0.0103 (12-3 strategy in Table 3.5) to 0.0093 (12-6 strategy in Table 3.5), with a mean at -0.0016 (Table 3.6). The GJR-GARCH(1,1)-M Fama and French model does a good job of explaining momentum profits too, with an average alpha of 0.0004 (Table 3.6) and a range of -0.0085 (12-3 strategy in Table 3.5) to 0.0093 (6-6 strategy in Table 3.5). Clearly, the results of Tables 3.3 and 3.5 suggest that adding a GJR-GARCH(1,1)-M structure to the models traditionally used to measure performance is crucial in explaining the abnormal return of momentum strategies. Interestingly, the considerable reduction in momentum returns after allowing for time-varying risk seems due to an increase in the abnormal performance of the loser portfolios. This suggests that the underperformance of the losers identified in Table 3.3 can be partly explained by their sluggish and asymmetric reaction to bad news.

Analysis of results

A negative relationship between stock return and conditional volatility has long been recognized by financial literature (see, for example, Black, 1976; Christie, 1982; French, Schwert and Stambaugh, 1987; Nelson, 1991; Glosten, Jagannathan and Runkle, 1993; Campbell, 1993, 1996; Bekaert and Wu, 2000, and Ang, Hodrick, Xing and Zhang, 2006). Campbell and Hentschel (1992) explain this relationship as evidence of a volatility feedback effect, whereby large pieces of good news and bad news increase the future volatility of stock; the increased volatility raises the required rate of return and causes an immediate drop in stock price. Our results of negative δ coefficients for the winners and losers in Table 3.5 are consistent with the explanation of the volatility feedback hypothesis that recent and distant news increase volatility of the winners and losers; the increased volatility implies a reduction in future investment opportunities. This leads to an increase on the required rate of return for winner and loser stocks and causes to an immediate drop in price; however, the price drop will be followed by a price rise for the winners and the losers in the future.

Proponents of the efficient markets hypothesis could argue that our results are an indication of momentum profits being merely a compensation for idiosyncratic risks common to the winners and losers but stronger for the former than the latter. This line of thought would therefore conclude that our findings are consistent with rational pricing in efficient markets. Thus, future research could seek to determine why idiosyncratic risk is important.

However, our results are also consistent with a behavioural explanation along the lines of Hong, Lim and Stein (2000), where information on loser stocks takes longer to be fully reflected in prices. The strong impact of old news identified for the losers and the persistence in their volatility are in support of the statement of Hong, Lim and Stein (2000) that "bad news travels slowly". When a firm with no or low analyst coverage receives bad news, its managers are likely to withhold that news as disclosing it would put downward pressure on price. Since losers are more likely than winners to sit on bad news, they are also more likely to withhold information. For the losers, this converts into higher volatility persistence (or higher volatility half-lives) and higher sensitivity of volatility to distant news. The results in Table 3.5 also give credence to the conjecture that, for winners, good news travels fast. Managers of no or low coverage firms have strong incentives to disclose good news the minute it arrives as this stimulates the share price. Since winners are, by definition, more likely than losers to receive good news, they are more eager to disclose information. This converts in our setting into a higher sensitivity of winners' volatility to recent news and less volatility persistence (or lower volatility half-lives).

We identify another interesting pattern in the volatility of the winner and losers. Relative to the volatility of the winners, the volatility of the losers clearly shows an asymmetric response to good and bad news: bad news substantially increases the volatility of the losers, while it does not impact on that of the winners. This is in line with the prediction of the behavioural argument put forward above. Since, relative to winners, losers have a higher probability of disclosing bad news, negative return shocks increase their volatility more than they increase that of the winners. The asymmetric response of losers to negative returns shocks could be explained as follows. Relative to winners, the probability that losers disclose bad news is far greater. Thus the announcement of a bad piece of news does not alter the volatility of winners (as bad news is expected to be transitory only) while it pushes up that of losers. When losers do disclose bad news, investors interpret this as a sign that their beliefs are correct, leading them to sell the losers. As a result, their volatility increases and becomes more persistent.

A failure to explicitly model the asymmetric response of the losers and winners to bad news might therefore lead us to under-estimate the volatility of the losers, and consequently their performance, following a price drop or to over-estimate the volatility of the winners, and consequently their performance, following a price rise. This motivates the hypothesis that the momentum profits might, at least in part, be a compensation for an asymmetric response of winners and losers to negative return shocks.

Robustness of the results to the specification of the GARCH(1,1) model

In this section, we test whether the momentum profits can be explained by a simplified version of the conditional models. Table 3.7 reports the parameter estimates of systems (5) and (6) for the winner, loser and momentum portfolios. Table 3.8 reports the average parameter estimates across 9 strategies. Table 3.7 therefore assumes that the return and conditional volatility of the momentum portfolios are better described by a GARCH(1,1)-M model.

The omission of the leverage effect in Table 3.7 does not alter the main conclusions of Table 3.5 with regards to the pattern of volatility for the winners and the losers. For example, Tables 3.6 and 3.8 document that the volatility of the winners (*W*) is more sensitive to recent news than the volatility of the losers (*L*); namely, $\gamma_W > \gamma_L$. Similarly, the impact of old news on volatility in Tables 3.6 and 3.8 is stronger for the losers; namely, $\theta_L > \theta_W$. Finally, volatility in both tables is found to be more persistent for the losers; namely, $\gamma_L + \eta_L/2 + \theta_L >$ $\gamma_W + \eta_W/2 + \theta_W$ in Table 3.6 and $\gamma_L + \theta_L >$ $\gamma_W + \theta_W$ in Table 3.8[17]. As a result, the average volatility half-lives are much smaller for the winners than for the losers. Across GARCH specifications, ranking periods, and holding periods, the volatility half-life of the winners is 3 months and 5 days on average, while that of the losers is 24 months and 13 days.

[17] Again, there are a few exceptions ($\gamma_L > \gamma_W$) for the 3-3 and 3-12 winners of the conditional Fama and French model in Table 3.6, but these are extremely rare.

The omission of the leverage effect however has a direct impact on the significance of the time-varying risk parameter δ in Table 3.7. Of the 18 δ coefficients estimated for the momentum strategies in Table 3.5, 12 are significant at the 5% level. When, as in Table 3.7, the impact of news on volatility is assumed to be symmetric, the number of significant δ coefficients drops to 3. As a result, the market and Fama and French models with GARCH(1,1)-M terms are less able to explain the momentum profits. Though largely insignificant in Table 3.7, the average abnormal returns of the momentum strategies in Table 3.8 equal 0.0125 a month for the GARCH(1,1)-M market model and 0.0079 for the GARCH(1,1)-M Fama and French model. These average α coefficients are in excess of the -0.0016 and 0.0004 average abnormal return for the GJR-GARCH(1,1)-M market model and the GJR-GARCH(1,1)-M Fama and French model, respectively.

To summarize, the evidence in Tables 3.5 and 3.7 suggests that it is both the asymmetric response of the losers to good and bad news and the conditional risk premium that explain the profitability of the momentum strategies. Neither the leverage effect, nor the conditional risk premium in isolation can explain the abnormal performance of the momentum strategies. It is the interaction between two that drives the momentum returns.

To judge the relative merits of models (1) to (6), the Akaike information criterion (AIC) is calculated for the winner, loser and momentum portfolios. AIC trades off better model fit for greater numbers of parameters, and thus a preferred model is one with the lowest value of the criterion. The results are reported in Table 3.9 for different specifications of the market and Fama and French models. These specifications include the static models (1) and (2), the GJR-GARCH(1,1)-M models (3) and (4), and the GARCH(1,1)-M models (5) and (6).

For a given specification of the risk-return relationship, the data always favour the Fama and French model over the market model. This indicates that the size and book-to-market value risk factors add explanatory power to the models over and above that provided by the market return. More pertinent to our study, the data evidently prefer the GJR-GARCH(1,1)-M models to the static approaches. The GJR-GARCH(1,1)-M market and Fama and French models have the lowest values of AIC in the vast majority of the cases, and never rank last in terms of AIC values. These results for the GJR-GARCH (1,1)-M models compare favorably to the AIC of the GARCH(1,1)-M. Irrespective of the ranking and holding periods, the static versions of the market and Fama and French models stand out as having the highest values of the AIC. This suggests that of the three specifications of the market and Fama and French models, the static versions provide the worst account of the returns of the winner, loser and momentum portfolios, while the time-varying conditional volatility models allowing for asymmetries provide the best.

Table 3.7. Conditional market and Fama and French models with a GARCH (1, 1)-M term

The table reports coefficient estimates for systems (5) and (6) for the winner, loser and momentum portfolios. Winner (Loser) is an equally-weighted non-overlapping portfolio containing the 10% of stocks that performed the best (worst) over a given ranking period. Momentum is a portfolio that buys the winner portfolio and short sells the loser portfolio. α measures the portfolio's abnormal performance, β measures the market risk, s and h are the portfolio loadings on the size and book-to-market value factors as measured by Fama and French (1993). $\delta\sigma_t$ is the time-varying risk exposure. The conditional variance of the portfolio returns follows a GARCH(1,1) structure as $\sigma_t^2 = \omega + \gamma\varepsilon_{t-1}^2 + \theta\sigma_{t-1}^2$, where ω, γ and θ are parameters. MM refers to the market model and FFM refers to the Fama and French model. Bollerslev-Wooldridge robust t-statistics are in parentheses. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels for a two-sided test.

	Holding period of 3 months						Holding period of 6 months						Holding period of 12 months					
	Winner		Loser		Momentum		Winner		Loser		Momentum		Winner		Loser		Momentum	
	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM
Panel A: Ranking period of 3 months																		
α	0.0172	0.0163	-0.0150	0.0031	0.0109	0.0092	0.0130	0.0078	-0.0071	0.0032	0.0067	0.0067	0.0035	0.0153	-0.0071	0.0012	0.0077	0.0064
	(1.75)[c]	(2.53)[b]	(-2.38)[b]	(0.60)	(1.57)	(1.25)	(2.22)[b]	(2.05)[b]	(-1.05)	(0.79)	(1.09)	(1.24)	(0.58)	(2.12)[b]	(-1.09)	(0.24)	(1.54)	(1.14)
β	0.7171	0.9410	0.7700	1.0342	-0.0558	-0.1376	0.6950	0.8734	0.7387	1.0441	-0.0749	-0.1802	0.7355	0.9907	0.6657	0.9779	0.0668	0.0166
	(16.67)[a]	(34.45)[a]	(15.46)[a]	(18.26)[a]	(-1.41)	(-3.23)[a]	(18.43)[a]	(28.30)[a]	(15.22)[a]	(27.21)[a]	(-1.93)[c]	(-4.25)[a]	(24.39)[a]	(50.51)[a]	(13.54)[a]	(33.22)[a]	(2.07)[b]	(0.51)
s	—	0.8956	—	1.0596	—	-0.2162	—	0.8078	—	1.0992	—	-0.2886		0.8964	—	1.0494	—	-0.1385
		(21.94)[a]		(17.66)[a]		(-3.27)[a]		(21.28)[a]		(24.30)[a]		(-4.85)[a]		(27.37)[a]		(22.95)[a]		(-2.51)[b]
h	—	0.0685	—	0.3909	—	-0.3291	—	0.1073	—	0.5567	—	-0.5041		0.1340	—	0.4895	—	-0.3182
		(1.10)		(4.60)[a]		(-3.86)[a]		(2.16)[b]		(7.56)[a]		(-6.07)[a]		(2.90)[a]		(9.58)[a]		(-4.59)[a]
δ	-0.5803	-0.9597	0.1459	-0.3789	-0.0829	-0.0042	-0.3731	-0.4330	-0.0298	-0.4875	0.1000	0.1825	-0.1001	-0.7551	-0.0524	-0.4790	0.0989	0.1898
	(-1.94)[c]	(-2.78)[a]	(1.01)	(-2.28)[b]	(-0.43)	(-0.02)	(-2.06)[b]	(-2.04)[b]	(-0.20)	(-3.31)[a]	(0.58)	(1.10)	(-0.52)	(-2.12)[b]	(-0.34)	(-2.32)[b]	(0.60)	(1.02)
ω	0.0003	0.0001	0.0001	0.0001	0.0002	0.0001	0.0003	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0000	0.0001	0.0001
	(2.85)[a]	(2.56)[b]	(1.16)	(1.39)	(1.87)[c]	(1.66)	(3.39)[a]	(3.78)[a]	(0.98)	(1.42)	(2.10)[b]	(1.89)[c]	(2.14)[b]	(2.76)[a]	(1.49)	(1.47)	(1.60)	(1.48)
γ	0.2416	0.1568	0.1818	0.2060	0.2466	0.2103	0.3767	0.3992	0.1676	0.2590	0.2758	0.2870	0.2742	0.2050	0.2603	0.2237	0.2395	0.1949
	(2.85)[a]	(2.96)[a]	(3.27)[a]	(3.22)[a]	(2.63)[a]	(2.59)[a]	(3.53)[a]	(2.45)[b]	(2.84)[a]	(3.66)[a]	(3.20)[a]	(3.16)[a]	(2.88)[a]	(2.36)[b]	(2.00)[b]	(3.85)[a]	(2.94)[a]	(3.09)[a]
θ	0.4927	0.7286	0.8114	0.7609	0.7012	0.7349	0.4405	0.3723	0.8274	0.7265	0.7079	0.7033	0.6642	0.5263	0.7110	0.7642	0.7327	0.7772
	(3.83)[a]	(11.22)[a]	(13.71)[a]	(9.48)[a]	(7.05)[a]	(7.85)[a]	(4.77)[a]	(3.36)[a]	(12.73)[a]	(10.47)[a]	(9.00)[a]	(8.05)[a]	(8.76)[a]	(5.09)[a]	(5.70)[a]	(13.63)[a]	(8.37)[a]	(10.42)[a]
$\gamma+\theta$	0.7342	0.8854	0.9932	0.9669	0.9478	0.9452	0.8172	0.7715	0.9950	0.9855	0.9837	0.9903	0.9384	0.7313	0.9713	0.9879	0.9722	0.9721

	Holding period of 3 months						Holding period of 6 months						Holding period of 12 months					
	Winner		Loser		Momentum		Winner		Loser		Momentum		Winner		Loser		Momentum	
	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM
Panel B: Ranking period of 6 months																		
α	0.0283	0.0150	-0.0150	0.0021	0.0213	0.0165	0.0190	0.0108	-0.0114	0.0057	0.0186	0.0181	0.0091	0.0138	-0.0128	0.0045	0.0081	-0.0003
	(2.18) [b]	(2.91) [a]	(-2.37) [b]	(0.41)	(3.61) [a]	(2.65) [a]	(2.52) [b]	(3.12) [a]	(-1.67)	(1.15)	(3.14) [a]	(3.13) [a]	(1.71) [c]	(3.31) [a]	(-1.81) [c]	(0.89)	(1.40)	(-0.05)
β	0.7224	0.8992	0.7192	1.0109	-0.0117	-0.1313	0.6980	0.8930	0.7153	0.9828	-0.0419	-0.1289	0.7323	0.9255	0.7129	1.0051	0.0254	-0.0387
	(18.86) [a]	(47.75) [a]	(14.72) [a]	(23.67) [a]	(-0.30)	(-3.31) [a]	(16.12) [a]	(34.37) [a]	(14.33) [a]	(24.88) [a]	(-1.10)	(-3.45) [a]	(18.46) [a]	(31.52) [a]	(16.18) [a]	(21.22) [a]	(0.77)	(-1.00)
s	—	0.7512	—	1.0820	—	-0.3124	—	0.8611	—	1.0449	—	-0.2304	—	0.9008	—	1.0502	—	-0.1232
		(24.65) [a]		(18.29) [a]		(-4.68) [a]		(27.49) [a]		(20.01) [a]		(-4.03) [a]		(23.45) [a]		(18.88) [a]		(-2.13) [b]
h	—	0.0432	—	0.5991	—	-0.6037	—	-0.0709	—	0.6771	—	-0.6706	—	0.0039	—	0.5533	—	-0.5045
		(1.06)		(6.33) [a]		(-7.10) [a]		(-1.07)		(8.10) [a]		(-8.58) [a]		(0.06)		(6.14) [a]		(-7.15) [a]
δ	-0.8193	-0.7123	0.1034	-0.4411	-0.1711	-0.0009	-0.4831	-0.4164	0.0056	-0.6419	-0.0413	0.0528	-0.2518	-0.7034	0.0394	-0.5709	0.1384	0.4128
	(-2.04) [b]	(-2.44) [b]	(0.76)	(-2.64) [a]	(-1.10)	(-0.01)	(-2.08) [b]	(-2.01) [b]	(0.04)	(-3.82) [a]	(-0.25)	(0.31)	(-1.49)	(-2.91) [a]	(0.25)	(-3.32) [a]	(0.84)	(2.39) [b]
ω	0.0004	0.0001	0.0001	0.0000	0.0002	0.0002	0.0004	0.0001	0.0001	0.0000	0.0002	0.0001	0.0002	0.0001	0.0001	0.0000	0.0001	0.0001
	(2.72) [a]	(3.16) [a]	(1.41)	(1.39)	(1.87) [c]	(1.74) [c]	(2.62) [a]	(2.98) [a]	(1.01)	(1.20)	(1.99) [b]	(1.93) [c]	(2.37) [b]	(1.82) [c]	(1.27)	(1.64)	(1.69) [c]	(1.45)
γ	0.2899	0.3016	0.2145	0.1829	0.3538	0.2935	0.3046	0.4324	0.1681	0.1718	0.3023	0.2729	0.3081	0.3285	0.1907	0.1914	0.2142	0.1774
	(2.07) [b]	(2.38) [b]	(3.52) [a]	(3.61) [a]	(2.74) [a]	(2.92) [a]	(2.72) [a]	(3.40) [a]	(3.27) [a]	(3.26) [a]	(2.68) [a]	(2.89) [a]	(3.14) [a]	(2.50) [b]	(2.39) [b]	(3.15) [a]	(2.59) [a]	(2.86) [a]
θ	0.3836	0.4132	0.7716	0.7975	0.6171	0.6523	0.3984	0.2998	0.8216	0.8234	0.6607	0.6804	0.5673	0.4610	0.7868	0.7920	0.7440	0.7942
	(2.32) [b]	(3.20) [a]	(12.04) [a]	(14.11) [a]	(5.13) [a]	(6.42) [a]	(2.91) [a]	(2.24) [b]	(12.87) [a]	(16.19) [a]	(6.32) [a]	(7.48) [a]	(5.07) [a]	(2.50) [b]	(8.92) [a]	(13.79) [a]	(8.35) [a]	(11.28) [a]
$\gamma+\theta$	0.6735	0.7148	0.9861	0.9803	0.9709	0.9458	0.7030	0.7322	0.9897	0.9952	0.9630	0.9533	0.8754	0.7895	0.9776	0.9834	0.9582	0.9716
Panel C: Ranking period of 12 months																		
α	0.0188	0.0240	-0.0033	0.0097	0.0043	-0.0038	0.0194	0.0174	-0.0204	-0.0004	0.0258	0.0190	0.0081	0.0142	-0.0175	0.0022	0.0090	-0.0005
	(2.48) [b]	(3.27) [a]	(-0.55)	(1.21)	(1.09)	(-0.55)	(2.47) [b]	(4.56) [a]	(-2.58) [a]	(-0.09)	(4.01) [a]	(3.31) [a]	(1.27)	(3.62) [a]	(-1.97) [b]	(0.38)	(1.33)	(-0.07)
β	0.7668	0.9608	0.7292	0.9202	0.0817	0.0590	0.7456	0.9422	0.7036	0.9677	0.0068	-0.0337	0.7682	0.9475	0.7211	1.0180	0.0714	-0.0255
	(18.82) [a]	(30.94) [a]	(13.73) [a]	(28.97) [a]	(1.66)	(1.36)	(15.96) [a]	(33.91) [a]	(13.72) [a]	(21.57) [a]	(0.16)	(-0.89)	(17.96) [a]	(27.76) [a]	(14.16) [a]	(21.96) [a]	(2.01) [b]	(-0.71)
s	—	0.7943	—	0.8104	—	-0.0637	—	0.8215	—	1.0589	—	-0.1675	—	0.8626	—	1.0649	—	-0.1756
		(18.70) [a]		(15.46) [a]		(-0.96)		(23.06) [a]		(16.87) [a]		(-3.09) [a]		(25.63) [a]		(17.37) [a]		(-3.27) [a]
h	—	-0.0819	—	0.6079	—	-0.7050	—	-0.0239	—	0.7065	—	-0.6651	—	-0.0270	—	0.6457	—	-0.6850
		(-0.95)		(8.50) [a]		(-8.13) [a]		(-0.43)		(9.05) [a]		(-9.29) [a]		(-0.38)		(7.47) [a]		(-9.12) [a]
δ	-0.4758	-1.0101	-0.0826	-0.5962	0.1349	0.4670	-0.4290	-0.6628	0.1762	-0.4581	-0.1593	0.0486	-0.2008	-0.6705	0.1279	-0.5228	0.1417	0.4794
	(-1.94) [c]	(-2.99) [a]	(-0.56)	(-2.26) [b]	(1.34)	(2.52) [b]	(-1.78) [c]	(-3.21) [a]	(1.01)	(-2.68) [a]	(-0.92)	(0.31)	(-0.99)	(-3.02) [a]	(0.64)	(-2.71) [a]	(0.75)	(2.18) [b]
ω	0.0002	0.0001	0.0001	0.0000	0.0001	0.0000	0.0003	0.0001	0.0001	0.0000	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	(2.24) [b]	(2.47) [b]	(1.53)	(1.14)	(2.32) [b]	(1.13)	(1.76) [c]	(2.54) [b]	(1.23)	(0.97)	(1.75) [c]	(1.89) [c]	(1.42)	(1.97) [b]	(1.17)	(2.25) [b]	(1.58)	(1.79) [c]
γ	0.2316	0.2274	0.1965	0.1757	0.2766	0.1391	0.2645	0.3274	0.1758	0.1521	0.2526	0.3033	0.1491	0.2871	0.1411	0.2051	0.1836	0.2010
	(2.66) [a]	(2.08) [b]	(2.81) [a]	(2.76) [a]	(2.76) [a]	(2.41) [b]	(2.43) [b]	(2.26) [b]	(2.75) [a]	(2.89) [a]	(3.04) [a]	(4.18) [a]	(1.90) [c]	(2.01) [b]	(3.04) [a]	(2.81) [a]	(2.51) [b]	(2.50) [b]
θ	0.5783	0.5558	0.7871	0.8164	0.7060	0.8581	0.4998	0.5079	0.8034	0.8468	0.7275	0.6882	0.7959	0.5742	0.8280	0.7152	0.7779	0.7192
	(4.34) [a]	(3.88) [a]	(11.24) [a]	(12.78) [a]	(13.92) [a]	(14.77) [a]	(2.52) [b]	(3.80) [a]	(10.87) [a]	(14.69) [a]	(9.35) [a]	(9.51) [a]	(8.00) [a]	(3.93) [a]	(11.55) [a]	(8.64) [a]	(9.79) [a]	(7.43) [a]
$\gamma+\theta$	0.8099	0.7832	0.9836	0.9921	0.9826	0.9972	0.7643	0.8352	0.9792	0.9989	0.9801	0.9916	0.9450	0.8613	0.9691	0.9203	0.9615	0.9202

Table 3.8. Average coefficient estimates of conditional market and Fama and French models with a GARCH (1, 1)-M term across ranking and holding periods

The table reports average coefficient estimates for systems (5) and (6) across ranking and holding periods for the winner, loser and momentum portfolios. Winner (Loser) is an equally-weighted non-overlapping portfolio containing the 10% of stocks that performed the best (worst) over a given ranking period. Momentum is a portfolio that buys the winner portfolio and short sells the loser portfolio. α measures the portfolio's abnormal performance, β measures the market risk, s and h are the portfolio loadings on the size and book-to-market value factors as measured by Fama and French (1993), δ is the time-varying risk exposure. The conditional variance of the portfolio returns follows a GARCH(1,1) structure as $\sigma_t^2 = \omega + \gamma\varepsilon_{t-1}^2 + \theta\sigma_{t-1}^2$, where ω, γ and θ are parameters. MM refers to the market model and FFM refers to the Fama and French model. Bollerslev-Wooldridge robust t-statistics are in parentheses. Significance is denoted by superscripts at the 1% (^{a}), 5% (^{b}) and 10% (^{c}) levels for a two-sided test.

	Winner		Loser		Momentum	
	MM	FFM	MM	FFM	MM	FFM
α	0.0152	0.0150	-0.0122	0.0035	0.0125	0.0079
	(1.91) ^{c}	(3.05) ^{a}	(-1.72) ^{c}	(0.62)	(2.09) ^{b}	(1.34)
β	0.7312	0.9304	0.7195	0.9956	0.0075	-0.0667
	(18.41) ^{a}	(35.50) ^{a}	(14.56) ^{a}	(24.55) ^{a}	(0.22)	(-1.66)
s		0.8435		1.0355		-0.1907
		(23.73) ^{a}		(19.09) ^{a}		(-3.20) ^{a}
h		0.0170		0.5807		-0.5539
		(0.49)		(7.48) ^{a}		(-7.10) ^{a}
δ	-0.4126	-0.7026	0.0482	-0.5085	0.0177	0.2031
	(-1.65)	(-2.61) ^{a}	(0.29)	(-2.81) ^{a}	(0.16)	(1.09)
ω	0.0002	0.0001	0.0001	0.0001	0.0001	0.0001
	(2.39) ^{b}	(2.67) ^{a}	(1.25)	(1.43)	(1.86) ^{c}	(1.66)
γ	0.2711	0.2962	0.1885	0.1964	0.2605	0.2310
	(2.69) ^{a}	(2.49) ^{b}	(2.87) ^{a}	(3.25) ^{a}	(2.79) ^{a}	(2.95) ^{a}
θ	0.5356	0.4932	0.7943	0.7825	0.7083	0.7342
	(4.72) ^{a}	(4.36) ^{a}	(11.07) ^{a}	(12.64) ^{a}	(8.59) ^{a}	(9.25) ^{a}
$\gamma+\theta$	0.8068	0.7894	0.9827	0.9789	0.9689	0.9653

Table 3.9. Akaike's information criterion

The table reports Akaike's information criterion for three specifications of the market model (MM) and the Fama and French model (FFM). These specifications are the static model, the GJR-GARCH(1,1)-M model and the GARCH(1,1)-M model. Winner (Loser) is an equally-weighted non-overlapping portfolio containing the 10% of stocks that performed the best (worst) over a given ranking period. Momentum is a portfolio that buys the winner portfolio and short sells the loser portfolio. The highlighted entries denote the minimum values for each ranking and holding period

	Holding period of 3 months						Holding period of 6 months						Holding period of 12 months					
	Winner		Loser		Momentum		Winner		Loser		Momentum		Winner		Loser		Momentum	
	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM
Panel A: Ranking period of 3 months																		
Static	-3.5705	-4.7005	-3.0319	-3.6139	-3.2293	-3.2527	-3.4921	-4.5723	-3.0299	-3.6719	-3.1306	-3.1827	-3.3852	-4.4449	-3.1774	-3.9119	-3.2506	-3.3900
GJR-GARCH(1,1)-M	-3.8980	-4.9116	-3.2531	-3.9252	-3.6228	-3.6636	-4.0527	-5.0383	-3.3035	-4.1226	-3.5992	-3.7186	-3.8670	-4.8225	-3.4542	-4.3080	-3.8732	-3.8994
GARCH(1,1)-M	-3.8930	-4.9180	-3.2528	-3.9117	-3.5990	-3.6371	-3.9968	-5.0433	-3.2382	-4.0912	-3.5884	-3.7129	-3.8314	-4.8120	-3.3521	-4.2663	-3.8580	-3.8925
Panel B: Ranking period of 6 months																		
Static	-3.5999	-4.6875	-2.9686	-3.5447	-3.0217	-3.1060	-3.5918	-4.7269	-3.0307	-3.6506	-3.1062	-3.1966	-3.5481	-4.6835	-3.1310	-3.7894	-3.1561	-3.2989
GJR-GARCH(1,1)-M	-4.0511	-5.1124	-3.2896	-3.9190	-3.3642	-3.6043	-4.0917	-5.1440	-3.3278	-4.0353	-3.5974	-3.7318	-3.9930	-5.0968	-3.3462	-4.0672	-3.6856	-3.7464
GARCH(1,1)-M	-4.0545	-5.1138	-3.1718	-3.8702	-3.4429	-3.5613	-4.0238	-5.1474	-3.2341	-4.0151	-3.5494	-3.6994	-3.9647	-5.0967	-3.2905	-4.0503	-3.6769	-3.7447
Panel C: Ranking period of 12 months																		
Static	-3.6854	-4.7215	-3.1856	-3.6968	-3.1413	-3.2469	-3.6710	-4.7510	-3.0987	-3.7613	-3.1607	-3.3108	-3.6950	-4.8780	-3.1833	-3.8806	-3.3297	-3.5177
GJR-GARCH(1,1)-M	-4.1297	-4.9484	-3.4974	-4.0284	-3.5332	-3.5948	-3.9877	-5.1261	-3.3148	-4.0819	-3.5212	-3.6705	-4.0313	-5.2009	-3.3404	-4.0422	-3.6828	-3.7880
GARCH(1,1)-M	-4.0490	-4.9548	-3.3972	-3.9636	-3.4861	-3.5878	-3.9936	-5.1250	-3.2375	-3.9895	-3.5142	-3.6411	-3.9855	-5.1837	-3.2587	-4.0371	-3.6703	-3.7954

Robustness of the results to the market examined

In order to determine whether the ability of the asymmetric conditional volatility model to explain the results of the momentum portfolios results from some specific feature of the UK market, or whether it is likely to be more general, we repeat the entire analysis above on winner, loser and momentum portfolios formed from US stocks. The US data cover the period January 1978 to December 2001, and are obtained from Datastream. The mean returns of the winner, loser, and momentum portfolios, formed in an identical way to that described above for the UK market, are presented in Table 3.10. There is ample evidence of momentum effects, with the winner portfolio average returns statistically significantly exceeding those of the losers for all nine portfolio formation and holding periods examined. While the sizes of the momentum effects are slightly smaller for the US, they are of the same order of magnitude as they are for the UK. For example, for the 12-12 strategy, the average monthly return for the UK is 1.43%, and for the US it is 1.12%. For the latter market, profitability is highest at 1.71% per month for the 12-3 strategy, whereas it is maximized at 1.93% for the 6-6 strategy in the UK.

Table 3.11 reports the parameter estimates for the statistic market and Fama-French models using the US data. It is evident that the three - factor model is no more able to explain the profitability of relative strength portfolios for this market than it is for the UK. For all nine (eight of the nine) combinations of portfolio formation and holding periods examined, the momentum profits are still positive and statistically significant at the 5% (1%) level.

Table 3.10. Mean return and *p*-values for momentum strategies for various ranking and holding periods for US Data.

Winner (Loser) is an equally-weighted non-overlapping portfolio containing the 10% of stocks that performed the best (worst) over a given ranking period. Momentum is a portfolio that buys the winner portfolio and sells the loser portfolio short. Returns are measured as proportions rather than percentages. Reward-to-risk ratio is the ratio of the monthly mean to the monthly standard deviation. The p-values in parentheses are for the significance of the mean. They are based on heteroskedasticity and autocorrelation robust (Newey-West) standard errors. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels for a two-sided test.

	Holding period of 3 months			Holding period of 6 months			Holding period of 12 months		
	Winner	Loser	Momentum	Winner	Loser	Momentum	Winner	Loser	Momentum
Panel A: Ranking period of 3 months									
Mean	0.0117	0.0056	0.0061	0.0123	0.0034	0.0089	0.0123	0.0036	0.0087
p-value	(0.00) [a]	(0.20)	(0.05) [c]	(0.00) [a]	(0.42)	(0.00) [a]	(0.00) [a]	(0.32)	(0.00) [a]
Panel B: Ranking period of 6 months									
Mean	0.0154	0.0008	0.0147	0.0145	0.0007	0.0139	0.0132	0.0012	0.0120
p-value	(0.00) [a]	(0.85)	(0.00) [a]	(0.00) [a]	(0.87)	(0.00) [a]	(0.00) [a]	(0.76)	(0.00) [a]
Panel C: Ranking period of 12 months									
Mean	0.0166	-0.0006	0.0171	0.0154	-0.0010	0.0163	0.0122	0.0010	0.0112
p-value	(0.00) [a]	(0.89)	(0.00) [a]	(0.00) [a]	(0.81)	(0.00) [a]	(0.00) [a]	(0.80)	(0.00) [a]

Table 3.11. Static market and Fama and French models for US Data

The table reports coefficient estimates for equations (1) and (2) for the winner, loser and momentum portfolios. Winner (Loser) is an equally-weighted non-overlapping portfolio containing the 10% of stocks that performed the best (worst) over a given ranking period. Momentum is a portfolio that buys the winner portfolio and short sells the loser portfolio. α measures the portfolio abnormal performance, β measures the market risk of the portfolio, s and h are the portfolio loadings on the size and book-to-market value factors as measured by Fama and French (1993). MM refers to the market model and FFM refers to the Fama and French model. White's heteroskedasticity robust t-statistics are in parentheses. Significance is denoted by superscripts at the 1% (^{a}), 5% (^{b}) and 10% (^{c}) levels for a two-sided test.

	Holding period of 3 months						Holding period of 6 months						Holding period of 12 months					
	Winner		Loser		Momentum		Winner		Loser		Momentum		Winner		Loser		Momentum	
	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM
Panel A: Ranking period of 3 months																		
α	-0.0002	-0.0021	-0.0070	-0.0082	0.0067	0.0062	0.0003	-0.0015	-0.0091	-0.0106	0.0094	0.0091	0.0000	-0.0018	-0.0084	-0.0096	0.0084	0.0078
	(-0.11)	(-1.36)	(-2.45) ^{b}	(-3.05) ^{a}	(2.21) ^{b}	(1.90) ^{c}	(0.14)	(-1.05)	(-3.44) ^{a}	(-4.44) ^{a}	(3.81) ^{a}	(3.38) ^{a}	(0.00)	(-1.17)	(-3.82) ^{a}	(-4.93) ^{a}	(3.83) ^{a}	(3.63) ^{a}
β	1.2058	1.1486	1.3507	1.2593	-0.1448	-0.1107	1.2283	1.1585	1.3129	1.2391	-0.0846	-0.0806	1.3144	1.2370	1.1910	1.1278	0.1234	0.1093
	(20.19) ^{a}	(13.57) ^{a}	(19.12) ^{a}	(16.57) ^{a}	(-1.75) ^{c}	(-1.20)	(22.22) ^{a}	(16.93) ^{a}	(20.26) ^{a}	(16.34) ^{a}	(-1.22)	(-1.19)	(21.82) ^{a}	(15.94) ^{a}	(22.33) ^{a}	(15.50) ^{a}	(1.74) ^{c}	(1.42)
s		0.8141		0.8650		-0.0508		0.8710		0.8303		0.0407		0.9282		0.7031		0.2250
		(3.80) ^{a}		(5.78) ^{a}		(-0.30)		(5.11) ^{a}		(4.99) ^{a}		(0.38)		(4.74) ^{a}		(5.25) ^{a}		(2.02) ^{b}
h		0.2004		0.1207		0.0797		0.1883		0.1577		0.0306		0.1919		0.1314		0.0604
		(1.63)		(0.85)		(0.44)		(1.94) ^{c}		(1.21)		(0.25)		(1.57)		(1.26)		(0.51)
Panel B: Ranking period of 6 months																		
α	0.0031	0.0016	-0.0115	-0.0127	0.0146	0.0143	0.0020	0.0011	-0.0114	-0.0129	0.0134	0.0141	0.0006	-0.0010	-0.0108	-0.0115	0.0115	0.0105
	(1.37)	(1.11)	(-3.99) ^{a}	(-4.54) ^{a}	(4.51) ^{a}	(4.13) ^{a}	(0.93)	(0.81)	(-4.05) ^{a}	(-4.72) ^{a}	(4.52) ^{a}	(4.29) ^{a}	(0.29)	(-0.71)	(-4.39) ^{a}	(-5.10) ^{a}	(4.78) ^{a}	(4.16) ^{a}
β	1.2834	1.2107	1.3081	1.2218	-0.0247	-0.0111	1.3048	1.2125	1.2572	1.1855	0.0476	0.0270	1.3586	1.2856	1.1958	1.1020	0.1628	0.1836
	(22.39) ^{a}	(14.26) ^{a}	(19.05) ^{a}	(15.67) ^{a}	(-0.28)	(-0.12)	(22.93) ^{a}	(14.33) ^{a}	(19.07) ^{a}	(14.60) ^{a}	(0.58)	(0.28)	(24.44) ^{a}	(18.08) ^{a}	(19.55) ^{a}	(13.80) ^{a}	(2.26) ^{b}	(2.27) ^{b}
s		0.7969		0.8084		-0.0115		0.7656		0.8314		-0.0659		0.8587		0.7298		0.1289
		(3.72) ^{a}		(4.99) ^{a}		(-0.07)		(3.56) ^{a}		(5.25) ^{a}		(-0.40)		(4.96) ^{a}		(4.69) ^{a}		(1.31)
h		0.1457		0.1102		0.0355		0.0723		0.1648		-0.0925		0.1732		0.0515		0.1217
		(1.19)		(0.72)		(0.18)		(0.58)		(1.16)		(-0.54)		(1.67)		(0.43)		(1.05)
Panel C: Ranking period of 12 months																		
α	0.0038	0.0036	-0.0125	-0.0138	0.0163	0.0174	0.0027	0.0026	-0.0131	-0.0147	0.0157	0.0172	-0.0006	-0.0011	-0.0108	-0.0127	0.0102	0.0116
	(1.73) ^{c}	(2.38) ^{b}	(-4.62) ^{a}	(-4.94) ^{a}	(5.15) ^{a}	(4.89) ^{a}	(1.24)	(1.78) ^{c}	(-4.94) ^{a}	(-5.63) ^{a}	(5.27) ^{a}	(5.29) ^{a}	(-0.31)	(-0.87)	(-4.25) ^{a}	(-5.23) ^{a}	(3.71) ^{a}	(4.00) ^{a}
β	1.3729	1.2558	1.2014	1.1341	0.1716	0.1217	1.3604	1.2400	1.2268	1.1632	0.1336	0.0768	1.3866	1.2821	1.1740	1.1245	0.2126	0.1575
	(24.99) ^{a}	(15.65) ^{a}	(17.33) ^{a}	(13.70) ^{a}	(1.85) ^{c}	(1.15)	(25.64) ^{a}	(15.53) ^{a}	(19.03) ^{a}	(15.31) ^{a}	(1.64)	(0.80)	(28.86) ^{a}	(16.65) ^{a}	(18.45) ^{a}	(16.36) ^{a}	(2.92) ^{a}	(1.87) ^{c}
s		0.7214		0.7224		-0.0010		0.7102		0.7870		-0.0768		0.7276		0.7879		-0.0603
		(3.65) ^{a}		(5.07) ^{a}		(-0.01)		(3.60) ^{a}		(5.63) ^{a}		(-0.49)		(3.71) ^{a}		(5.94) ^{a}		(-0.40)
h		-0.0229		0.1280		-0.1509		-0.0377		0.1689		-0.2066		0.0179		0.2117		-0.1938
		(-0.20)		(0.94)		(-0.85)		(-0.32)		(1.31)		(-1.23)		(0.16)		(1.68)		(-1.18)

Finally, Table 3.12 shows the parameters for the conditional market and Fama and French models with a GJR-GARCH (1, 1)-M term estimated using US Data. While the importance of time-varying idiosyncratic risk appears more uniformly high whatever combination of portfolio formation and holding period are used in the UK context than for the US, in the latter case, the momentum profits are again largely explained by the incorporation of the idiosyncratic risk terms into the equations. This leads both the sizes of the estimated alphas and their levels of statistical significance to reduce. For instance, when the time-varying idiosyncratic risk terms are included in the model, the alpha for the 6-6 momentum strategy of 0.0134 when the market model is used is reduced by 40% to 0.085 and it is reduced by 25% to 0.012 when the Fama-French model is used. For the augmented market model and the Fama-French model presented, 5 out of 9 strategies are significantly profitable at the 5% level. Our other major findings concerning the speed of adjustment of volatility and the asymmetric response of volatility to good and bad news for the winners relative to the losers still holds.

3.4. Conclusions

This chapter considers whether the widely documented momentum profits are a compensation for time-varying idiosyncratic risk as described by the family of autoregressive conditionally heteroskedastic models. The motivation for estimating a GJR-GARCH(1,1)-M model stems from the fact that since losers have a higher probability than winners to disclose bad news, one cannot assume a symmetric response of volatility to good and bad news. Neither can we presuppose that the speed of adjustment of volatility to news is the same for the winners and the losers. Our results suggest that the volatility of the winners indeed differs from that of the losers. For example, the volatility of the winners is found to be more sensitive to recent news and less persistent than that of the losers. The converse, that the volatility of the losers is found to be more sensitive to distant news and more persistent than that of the winners, also holds.

Most importantly, we also document that the GJR-GARCH(1,1)-M models explain much of the profitability of the momentum strategies, and certainly have more descriptive power than the commonly used size and value risk factors. Interestingly, neither the GJR-GARCH(1,1) nor the GARCH(1,1)-M specifications alone could account for the abnormal return of the relative-strength portfolios. It is therefore a combination of the asymmetric response of the losers to good and bad news, the sluggish response of losers to bad news and the conditional risk premium embedded in the GARCH(1,1)-M model, that explain the profitability of the relative-strength portfolios.

Table 3.12. Conditional market and Fama and French models with a GJR-GARCH (1, 1)-M term for US Data

The table reports coefficient estimates for systems (3) and (4) for the winner, loser and momentum portfolios. Winner (Loser) is an equally-weighted non-overlapping portfolio containing the 10% of stocks that performed the best (worst) over a given ranking period. Momentum is a portfolio that buys the winner portfolio and short sells the loser portfolio. α measures the portfolio abnormal performance, β measures the market risk of the portfolio, s and h are the portfolio loadings on the size and book-to-market value factors as measured by Fama and French (1993). $\delta\sigma_t$ is the time-varying risk exposure. The conditional variance of the portfolio returns follows a GJR-GARCH(1,1) structure as $\sigma_t^2 = \omega + \gamma\varepsilon_{t-1}^2 + \eta I_{t-1}\varepsilon_{t-1}^2 + \theta\sigma_{t-1}^2$, where ω, γ, η and θ are estimated parameters and I_{t-1} takes a value of 1, when ε_{t-1} is negative and a value of 0, otherwise. MM refers to the market model and FFM refers to the Fama and French model. Bollerslev-Wooldridge robust t-statistics are in parentheses. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels for a two-sided test.

	Holding period of 3 months						Holding period of 6 months						Holding period of 12 months					
	Winner		Loser		Momentum		Winner		Loser		Momentum		Winner		Loser		Momentum	
	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM
Panel A: Ranking period of 3 months																		
α	-0.0248	-0.0087	-0.0115	-0.0133	0.0245	0.0253	-0.0391	0.0171	-0.0207	-0.0133	0.0143	0.0159	0.0005	-0.0073	-0.0064	-0.0189	0.0093	0.0124
	(-2.51) [b]	(-1.74) [c]	(-1.09)	(-2.97) [a]	(3.40) [a]	(3.42) [a]	(-2.67) [a]	(1.46)	(-2.72) [a]	(-3.62) [a]	(2.84) [a]	(3.08) [a]	(0.04)	(-1.05)	(-0.91)	(-4.94) [a]	(1.51)	(1.95) [c]
β	1.1271	1.0513	1.1243	1.0959	0.0346	0.0095	1.1675	1.0877	1.1518	1.0468	0.0559	0.0261	1.2776	1.1693	1.1252	1.0158	0.1040	0.0934
	(32.96) [a]	(42.37) [a]	(13.79) [a]	(21.68) [a]	(0.75)	(0.18)	(31.72) [a]	(37.89) [a]	(29.14) [a]	(31.71) [a]	(1.45)	(0.60)	(31.22) [a]	(34.54) [a]	(28.55) [a]	(31.95) [a]	(3.20) [a]	(2.55) [b]
s		1.0197		1.0474		0.0156		1.0988		1.0313		0.0837		1.0943		0.9380		0.1798
		(28.28) [a]		(12.06) [a]		(0.22)		(29.23) [a]		(20.20) [a]		(1.43)		(24.68) [a]		(19.43) [a]		(3.44) [a]
h		-0.0209		0.0848		-0.1052		0.0614		0.0831		-0.1046		0.1646		0.0095		-0.0267
		(-0.52)		(1.32)		(-1.21)		(1.47)		(1.41)		(-1.47)		(3.53) [a]		(0.18)		(-0.41)
δ	0.6379	0.2654	0.1217	0.1003	-0.3409	-0.3463	1.0231	-0.7667	0.2944	0.0880	-0.1184	-0.1404	-0.0399	0.2105	-0.0440	0.3082	-0.0319	-0.1223
	(2.32) [b]	(1.30)	(0.52)	(0.72)	(-1.96) [b]	(-1.93) [c]	(2.63) [a]	(-1.58)	(1.60)	(0.70)	(-0.82)	(-0.95)	(-0.12)	(0.72)	(-0.22)	(2.14) [b]	(-0.17)	(-0.64)
ω	0.0004	0.0002	0.0003	0.0001	0.0003	0.0003	0.0004	0.0003	0.0001	0.0001	0.0002	0.0002	0.0003	0.0004	0.0000	0.0001	0.0001	0.0001
	(2.43) [b]	(2.87) [a]	(2.07) [b]	(1.90) [c]	(2.72) [a]	(2.71) [a]	(2.24) [b]	(1.80) [c]	(3.21) [a]	(2.30) [b]	(2.01) [b]	(2.04) [b]	(1.78) [c]	(7.15) [a]	(1.60)	(2.37) [b]	(1.73) [c]	(1.70) [c]
γ	0.4716	0.4717	-0.0057	-0.0157	0.4838	0.4857	0.2845	0.0550	-0.0036	0.0442	0.5406	0.5203	0.1017	0.0295	0.0250	0.0606	0.2762	0.2412
	(2.65) [a]	(3.43) [a]	(-0.19)	(-0.39)	(3.37) [a]	(3.27) [a]	(2.06) [b]	(0.69)	(-0.18)	(0.91)	(3.03) [a]	(2.92) [a]	(1.69)	(0.37)	(0.85)	(1.23)	(2.05) [b]	(2.02) [b]
η	-0.3916	-0.3296	0.4769	0.6649	-0.5105	-0.5105	-0.2585	0.1486	0.2371	0.5284	-0.4020	-0.3968	0.0472	-0.0419	0.1188	0.3862	-0.1068	-0.1011
	(-2.31) [b]	(-2.07) [b]	(3.04) [a]	(3.68) [a]	(-3.46) [a]	(-3.37) [a]	(-1.94) [c]	(0.97)	(4.19) [a]	(3.19) [a]	(-2.33) [b]	(-2.33) [b]	(0.58)	(-0.29)	(2.15) [b]	(2.70) [a]	(-0.85)	(-0.90)
θ	0.4973	0.4913	0.6899	0.6744	0.7281	0.7202	0.5557	0.4380	0.8421	0.6822	0.6211	0.6320	0.6957	0.4779	0.9009	0.7274	0.6944	0.7330
	(3.67) [a]	(5.57) [a]	(6.36) [a]	(12.44) [a]	(11.61) [a]	(10.98) [a]	(3.69) [a]	(1.52)	(30.39) [a]	(9.28) [a]	(6.08) [a]	(6.20) [a]	(5.38) [a]	(6.74) [a]	(23.87) [a]	(11.57) [a]	(6.25) [a]	(7.31) [a]
$\gamma+\eta/2+\theta$	0.7731	0.7982	0.9226	0.9911	0.9566	0.9506	0.7109	0.5674	0.9570	0.9905	0.9607	0.9540	0.8210	0.4864	0.9853	0.9811	0.9172	0.9236

	Holding period of 3 months						Holding period of 6 months						Holding period of 12 months					
	Winner		Loser		Momentum		Winner		Loser		Momentum		Winner		Loser		Momentum	
	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM	MM	FFM
Panel B: Ranking period of 6 months																		
α	-0.0174	-0.0028	-0.0039	-0.0197	0.0192	0.0203	-0.0117	0.0014	0.0014	-0.0142	0.0085	0.0112	-0.2392	-0.0160	0.0015	-0.0174	0.0008	0.0032
	(-1.91) [c]	(-0.51)	(-0.52)	(-3.18) [a]	(2.82) [a]	(2.89) [a]	(-1.22)	(0.17)	(0.17)	(-3.11) [a]	(0.89)	(1.11)	(-1.45)	(-1.91) [c]	(0.25)	(-3.23) [a]	(0.08)	(0.30)
β	1.2400	1.1250	1.1771	1.0552	0.1688	0.1453	1.2786	1.1372	1.0883	1.0537	0.1658	0.0677	1.3557	1.1951	1.0790	0.9493	0.2068	0.2343
	(34.06) [a]	(40.46) [a]	(26.58) [a]	(15.66) [a]	(3.92) [a]	(2.80) [a]	(36.76) [a]	(42.06) [a]	(21.92) [a]	(29.77) [a]	(3.73) [a]	(1.43)	(33.14) [a]	(38.90) [a]	(24.69) [a]	(28.10) [a]	(4.95) [a]	(4.73) [a]
s		1.0736		0.9813		0.0004		1.0342		0.9924		-0.0038		1.0232		0.8273		0.1708
		(29.40) [a]		(11.67) [a]		(0.01)		(28.03) [a]		(17.17) [a]		(-0.05)		(25.07) [a]		(15.63) [a]		(2.44) [b]
h		-0.0697		0.2133		-0.0866		-0.1439		0.2158		-0.3584		-0.0299		-0.1060		0.1019
		(-1.50)		(2.55) [b]		(-0.99)		(-3.60) [a]		(3.36) [a]		(-4.68) [a]		(-0.60)		(-1.81) [c]		(1.22)
δ	0.5419	0.1743	-0.1789	0.1440	-0.0802	-0.0923	0.3632	-0.0308	-0.2375	-0.0126	0.1617	0.1438	6.0567	0.5939	-0.2955	0.1752	0.2716	0.1911
	(2.09) [b]	(0.65)	(-1.00)	(0.79)	(-0.49)	(-0.55)	(1.32)	(-0.08)	(-1.19)	(-0.08)	(0.72)	(0.61)	(1.44)	(1.62)	(-1.90) [c]	(1.02)	(0.96)	(0.70)
ω	0.0003	0.0001	0.0002	0.0004	0.0006	0.0006	0.0002	0.0003	0.0001	0.0001	0.0005	0.0005	0.0009	0.0003	0.0000	0.0001	0.0003	0.0002
	(2.35) [b]	(2.60) [a]	(2.03) [b]	(3.47) [a]	(3.89) [a]	(3.67) [a]	(2.16) [b]	(1.59)	(1.81) [c]	(2.59) [a]	(2.09) [b]	(1.97) [b]	(2.37) [b]	(4.22) [a]	(1.20)	(2.36) [b]	(1.94) [c]	(1.83) [c]
γ	0.3611	0.1885	-0.0043	0.1285	0.8697	0.8612	0.2314	0.0120	-0.0230	0.0266	0.5761	0.5012	0.0159	0.3516	-0.0119	0.0261	0.3063	0.2866
	(2.85) [a]	(3.40) [a]	(-0.26)	(1.55)	(3.65) [a]	(3.46) [a]	(2.78) [a]	(0.34)	(-0.91)	(0.92)	(2.44) [b]	(2.31) [b]	(1.23)	(5.39) [a]	(-0.84)	(0.68)	(2.55) [b]	(2.57) [b]
η	-0.3564	-0.1121	0.4418	0.6588	-0.7945	-0.7886	-0.2195	0.2999	0.4435	0.7130	-0.5347	-0.4499	-0.0236	-0.0613	0.2101	0.4028	-0.2895	-0.2736
	(-2.76) [a]	(-1.65)	(2.93) [a]	(3.26) [a]	(-3.26) [a]	(-3.08) [a]	(-2.65) [a]	(1.88) [c]	(3.63) [a]	(3.79) [a]	(-2.21) [b]	(-2.00) [b]	(-1.17)	(-0.44)	(2.93) [a]	(3.02) [a]	(-2.29) [b]	(-2.36) [b]
θ	0.6556	0.7499	0.7618	0.4320	0.4141	0.4164	0.7684	0.3713	0.7966	0.6056	0.5783	0.5684	0.3807	0.2814	0.8716	0.7358	0.7149	0.7590
	(6.24) [a]	(13.14) [a]	(11.89) [a]	(5.77) [a]	(4.16) [a]	(4.05) [a]	(9.68) [a]	(1.13)	(11.77) [a]	(7.27) [a]	(4.07) [a]	(3.52) [a]	(1.55)	(2.80) [a]	(22.67) [a]	(10.24) [a]	(6.95) [a]	(8.23) [a]
$\gamma+\eta/2+\theta$	0.8385	0.8823	0.9784	0.8899	0.8865	0.8832	0.8901	0.5333	0.9954	0.9887	0.8871	0.8447	0.3847	0.6024	0.9648	0.9633	0.8765	0.9087
Panel C: Ranking period of 12 months																		
α	0.0030	0.0026	-0.0067	-0.0215	0.0258	0.0286	0.0032	0.0021	-0.0033	-0.0165	0.0179	0.0204	0.0040	-0.0011	-0.0018	-0.0134	0.0081	0.0073
	(0.29)	(0.81)	(-1.21)	(-4.72) [a]	(2.79) [a]	(3.16) [a]	(0.29)	(0.43)	(-0.55)	(-3.55) [a]	(2.08) [b]	(2.25) [b]	(0.31)	(-0.29)	(-0.27)	(-3.09) [a]	(0.83)	(0.75)
β	1.3219	1.2280	1.0630	0.8895	0.3319	0.2280	1.3202	1.1897	1.1213	0.9930	0.2680	0.1579	1.3647	1.2234	1.1108	0.9746	0.2612	0.1955
	(34.24) [a]	(36.83) [a]	(23.09) [a]	(16.85) [a]	(6.35) [a]	(3.98) [a]	(33.08) [a]	(40.93) [a]	(28.55) [a]	(25.29) [a]	(5.97) [a]	(2.96) [a]	(33.20) [a]	(39.34) [a]	(28.86) [a]	(29.91) [a]	(6.33) [a]	(4.12) [a]
s		0.9638		0.7626		0.1328		0.9585		0.8347		0.0667		1.0089		0.7669		0.1821
		(14.94) [a]		(11.46) [a]		(1.73) [c]		(25.01) [a]		(16.10) [a]		(0.85)		(19.30) [a]		(16.85) [a]		(2.56) [b]
h		-0.0862		0.0186		-0.3464		-0.1481		0.1778		-0.4090		-0.0879		0.0274		-0.2614
		(-1.81) [c]		(0.34)		(-4.37) [a]		(-3.13) [a]		(2.89) [a]		(-4.94) [a]		(-1.88) [c]		(0.47)		(-3.23) [a]
δ	0.0163	0.0279	-0.1290	0.2298	-0.1674	-0.1858	-0.0230	-0.0412	-0.2334	0.0194	-0.0212	-0.0278	-0.1309	-0.0068	-0.2326	0.0088	0.0927	0.1235
	(0.06)	(0.21)	(-0.93)	(1.73) [c]	(-0.85)	(-0.95)	(-0.07)	(-0.19)	(-1.52)	(0.13)	(-0.11)	(-0.14)	(-0.35)	(-0.04)	(-1.34)	(0.06)	(0.41)	(0.54)
ω	0.0002	0.0001	0.0001	0.0001	0.0005	0.0005	0.0002	0.0001	0.0001	0.0001	0.0002	0.0003	0.0002	0.0001	0.0000	0.0001	0.0001	0.0001
	(1.72) [c]	(2.62) [a]	(1.76) [c]	(2.28) [b]	(2.33) [b]	(2.50) [b]	(1.58)	(3.16) [a]	(1.60)	(2.25) [b]	(1.81) [c]	(1.92) [c]	(1.53)	(4.04) [a]	(1.67)	(1.56)	(1.41)	(1.34)
γ	0.1941	0.6725	0.0019	0.0140	0.5729	0.6220	0.1834	0.4409	0.0079	0.0238	0.3752	0.4545	0.1460	0.6199	0.0106	0.0516	0.2348	0.1657
	(2.47) [b]	(1.48)	(0.07)	(0.43)	(2.71) [a]	(2.89) [a]	(2.47) [b]	(6.34) [a]	(0.32)	(0.65)	(2.62) [a]	(2.45) [b]	(2.18) [b]	(1.00)	(0.67)	(1.43)	(2.10) [b]	(2.07) [b]
η	-0.2081	-0.5849	0.3501	0.4977	-0.5216	-0.5511	-0.1670	-0.2973	0.2808	0.6291	-0.3580	-0.4207	-0.0788	-0.1905	0.1391	0.4295	-0.2212	-0.1517
	(-2.56) [b]	(-1.33)	(3.07) [a]	(3.24) [a]	(-2.48) [b]	(-2.56) [b]	(-2.25) [b]	(-2.41) [b]	(2.59) [a]	(3.42) [a]	(-2.52) [b]	(-2.28) [b]	(-0.97)	(-0.36)	(2.83) [a]	(3.56) [a]	(-2.01) [b]	(-1.92) [c]
θ	0.7963	0.6000	0.8042	0.7242	0.6004	0.5592	0.7861	0.6202	0.8484	0.6555	0.7677	0.6812	0.7352	0.3625	0.9095	0.7200	0.8353	0.8717
	(8.57) [a]	(5.56) [a]	(29.48) [a]	(10.40) [a]	(5.43) [a]	(5.01) [a]	(7.91) [a]	(8.71) [a]	(15.79) [a]	(10.32) [a]	(10.43) [a]	(6.56) [a]	(5.32) [a]	(2.40) [b]	(29.04) [a]	(9.22) [a]	(11.20) [a]	(14.78) [a]
$\gamma+\eta/2+\theta$	0.8864	0.9800	0.9811	0.9870	0.9125	0.9056	0.8860	0.9125	0.9967	0.9938	0.9638	0.9254	0.8417	0.8871	0.9897	0.9864	0.9595	0.9616

Chapter 4. The Value Premium and Time-Varying Idiosyncratic Risk

4.1. Introduction

The value premium, or the difference in returns between a portfolio of value stocks and a portfolio of growth stocks, has been identified in academic studies and exploited by financial market practitioners for over a decade. Basu (1977), Fama and French (1992, 1993, 1995 and 1996) and Lakonishok, Shleifer and Vishny (1994) report US evidence that value stocks with high figures for the ratios of B/M, C/P or E/P outperform growth stocks with low figures for these ratios. Similar evidence has also been found in the UK and other international stock markets by Dimson, Nagel and Quigley (2003) and Fama and French (1998). While the existence of this value premium goes largely undisputed, interpreting the premium and identifying its causes has been more controversial.

Haugen (1995), Lakonishok, Shleifer and Vishny (1994) and La Porta, Lakonishok, Shleifer and Vishny (1997) focus on behavioral explanations, attributing it to the judgment biases of investors. The argument goes that investors base their expectations of future performance on past performance and, as a result, they underprice value stocks and overprice growth stocks. Eventually, overly enthusiastic growth investors are disappointed by the poor earnings announcements of growth stocks while overly pessimistic value investors are pleasantly surprised by the performance of value companies. The market then corrects previous mis-pricings such that value stocks become winners and growth stocks become losers. However, Levis and Liodakis (2001) report that the market does not extrapolate from either past earnings growth or past price performance. Their evidence suggests that positive and negative surprises have an asymmetric effect on the returns of value and growth stocks. Positive shocks have a strong positive impact on the returns of value stocks, while negative shocks have a strong negative impact on the returns of growth stocks.

By contrast, Fama and French (1993, 1995 and 1996) and Chen and Zhang (1998) document that the value premium is a compensation for risk. They argue that high B/M, C/P and E/P companies (value stocks) suffer from a relatively high likelihood of financial distress with continuously low earnings and high earnings risk. On the other hand, low B/M, C/P and E/P companies (growth stocks) experience strong growth with continuously high earnings and low earnings risk. Therefore, they propose that the superior returns from value investing are merely compensation for holding risky stocks. The two studies by Fama and French (2006) and Ang and Chen (2007) examine the value premium using the CAPM of Sharpe (1964) and Lintner (1965). They find that the CAPM is able to capture the value premium of 1926-1963, but fails to explain it for the post-1963 period.

Jagannathan and Wang (1996), Lettau and Ludvigson (2001), Ang and Chen (2007) and Adrian and Franzoni (2005) argue that a significant weakness of the static CAPM is its assumption that the beta of the asset is constant through time. They develop a conditional CAPM by allowing betas and expected returns to vary over time and find that the conditional CAPM performs substantially better than the static CAPM in explaining the cross-sectional variation in expected returns on size and B/M portfolios. However, Lewellen and Nagel (2006) argue that while betas do fluctuate substantially over time, these variations are not large enough to explain the value premium and the momentum effect, a result echoed by Petkova and Zhang

(2005). Fama and French (2006) confirm that even allowing betas to vary annually, the conditional CAPM still fails to describe the post-1963 value premium.

There is increasing evidence that idiosyncratic risk may matter. The question as to whether average stock variance is priced is still open with convincing evidence on both sides of the debate. On one hand, Campbell, Lettau, Malkiel and Xu (2001), Goyal and Santa-Clara (2003), Ghysels, Santa-Clara and Valkanov (2005), Fu (2005), Diavatopoulos, Doran and Peterson (2006) and Jiang and Lee (2006) show that there is a positive relationship between idiosyncratic risk and stock market return. On the other hand, Bali, Cakici, Yan and Zhang (2005) and Bali and Cakici (2007) put forward the claim that the relation could be spurious since it is driven by illiquid small capitalization stocks traded on the NASDAQ and depends on the measure of idiosyncratic volatility used, on the sample analyzed and on the data frequency.

The goal of this chapter is to analyze the post-1963 value premium defined using the ratios of B/M, C/P and E/P. Instead of using the capital asset pricing model, it examines time-varying risk as measured by a model for the conditional variance of the value and growth portfolios and tests whether value stocks are riskier than growth stocks in the sense of time-varying risk through a conditional measure of portfolio-specific risk. We follow the methodology used in Chapter 3 and model the time-dependent structure of conditional volatility and its impact on the returns of value and growth portfolios through a GARCH process (see Engle, 1982 and Bollerslev, 1986).

The rationale for choosing this model is that, as well as having constant betas, the static CAPM also assumes that the variances of the error terms are constant.

However, numerous researchers have found that for financial time series, the variances of the error terms change over time in a partially predictable fashion (see, for example, French, Schwert and Stambaugh, 1987 and Schwert and Seguin, 1990) and exhibit volatility clustering, where large (small) volatility changes tend to be followed by large (small) volatility changes. In the financial literature, the error term in asset pricing models is often interpreted as representing information arriving in the market. The static CAPM ignores the impact of conditional information on the expected stock return caused by heteroskedasticity. By contrast, the GARCH model is designed to capture the impact of new information on the conditional variance through the most recent squared error. The essence of the motivation for using the GARCH model is that the release of new information (captured by the error term) may cause the risk (conditional variance) of value and growth stocks to change over time in a way that is priced and can be captured by the model.

Another rationale for explaining the value premium through this model is that the premium may not solely rely on systematic risk. The traditional CAPM implies that idiosyncratic risk can be diversified away when investors hold a market portfolio. However, Levy (1978), Merton (1987) and Malkiel and Xu (2001) extend the CAPM and find that idiosyncratic risk can also be priced if investors do not hold the market portfolio. Chen and Zhang (1998) report that the value portfolio largely consists of stocks that have high likelihoods of financial distress with high earnings uncertainty. Lakonishok, Shleifer and Vishny (1994) show that the growth portfolio largely consists of stocks that have long records of high growth rates of sales, earnings and cash flow. Therefore, the value and growth portfolios may be not perfectly diversified in terms of market portfolio although they consist of large numbers of stocks. Chapter 3 provides evidence that time-varying idiosyncratic risk can fully explain momentum profits. Thus, it may also can capture the value premium.

This chapter uses a similar methodology as in Chapter 3 and models idiosyncratic risk of the value and growth portfolios through a GARCH framework. Extending from Bollerslev, Engle and Wooldridge (1988), we specify different versions of the GARCH-based conditional variances with the CAPM and market capitalization. In particular, we examine whether the value premium is a compensation for exposure to 1) the time-varying risk of the market; 2) the time-varying risk of a size factor; 3) idiosyncratic risks that affect value and growth portfolios in opposite ways that are captured by the GARCH specification; and 4) a combination of all three. The advantage of this approach is that it allows estimation of the CAPM and GARCH-in-mean model simultaneously.

The contributions of this chapter to the literature can be further specified as follows. We use a conditional variance term in the equation for returns which does not assume that the level of risk is time-invariant. Our results are in support of the idea that value stocks do not have higher *market* risk than growth stocks. While the CAPM beta has strong explanatory power for the value and growth portfolio returns when examined separately, it cannot explain the post-1963 value premium. We find that this premium is a compensation for exposure to unsystematic risk which can be fully explained by the conditional variance model. The results are robust to different definitions of value and growth stocks (B/M, C/P and E/P) and to variations in the country under review (the US and UK). Our model is able to explain the value premium without resorting to *ad hoc* rationalizations based on behavioural considerations, transactions costs or illiquidity. Our risk measure is based on the total risk of the value and growth portfolios, hence allowing the idiosyncratic component of risk to vary over time.

The remainder of chapter is organized as follows. Section 4.2 develops a model for the time-varying idiosyncratic risk within a GARCH-M framework and discusses the econometric specifications. Section 4.3 describes the data. Sections 4.4 and 4.5 report the empirical results for US and UK data respectively. Section 4.6 provides an analysis of the findings and finally, Section 4.7 offers some concluding remarks.

4.2. Econometric Framework

4.2.1. The Static CAPM

Letting r_{it} and r_{mt} denote excess returns on asset i and on the market portfolio of all assets in period t, the static CAPM of Sharpe (1964) and Lintner (1965), which is further developed by Black (1972), can be written as follows

$$E\left(r_{it}\right) = \beta_i E\left(r_{mt}\right) \qquad i = 1, \ldots, n \tag{1}$$

where $$\beta_i = Cov\left(r_{it}, r_{mt}\right) / Var\left(r_{mt}\right) \tag{2}$$

and $E(.)$, $Cov(.)$ and $Var(.)$ denote the expectation, covariance and variance, respectively. This single-period CAPM assumes that the ratio of the expected market excess return to the expected asset excess return remains constant over time; that is, all investors have the same expectations about asset returns for any given time period. However, in practice investors may update their expectations each period according to new information and this leads to conditional expectations, which are stochastic rather than constant.

4.2.2. Model Specifications

We start by considering the static CAPM in *ex post* form given by

Model 1:

$$r_{Pt} = \alpha + \beta\left(R_{mt} - R_{ft}\right) + \varepsilon_{Pt} \tag{3}$$

where r_{Pt} is either the excess returns on the value and growth portfolios or the return on the high-minus-low (HML) portfolio, R_{mt} is the value-weighted return on the market portfolio of all assets, R_{ft} is the three-month Treasury bill rate and $\varepsilon_{Pt} \sim N\left(0, \sigma^2\right)$. If the static CAPM is sufficient, the alpha coefficient should be equal to zero in statistical terms.

The CAPM model with a standard GARCH (1, 1) process (see Bollerslev, 1986) for the conditional variance of portfolio returns is given by

Model 2:

$$\begin{aligned} r_{Pt} &= \alpha + \beta\left(R_{Mt} - R_{ft}\right) + \varepsilon_{Pt} \\ \sigma^2_{Pt} &= \omega + \gamma\varepsilon^2_{Pt-1} + \theta\sigma^2_{Pt-1} \end{aligned} \tag{4}$$

where $\varepsilon_{Pt} \sim N\left(0, \sigma^2_{Pt}\right)$, σ^2_{Pt} is the conditional variance of portfolio returns, γ, θ, and ω are parameters to be estimated. To ensure that σ^2_{Pt} is non-negative, non-degenerate and that the GARCH (1, 1) process is covariance stationarity, the conditions $\omega > 0, 0 < \gamma < 1, 0 \leq \theta < 1$ and $\gamma + \theta < 1$ are imposed. The CAPM with a GARCH specification for the conditional variance allows expected excess returns, the conditional variances and the covariances of asset returns to vary over time. It follows that the conditional variance depends not only on past shocks but also on past realizations of the conditional variance itself.

According to Nelson (1991), Glosten, Jaganathan and Runkle (1993) and Rabemananjara and Zakoian (1993), good news (as measured by positive shocks) and bad news (as measured by negative shocks) may have an asymmetric impact on the conditional variance of stock returns. In particular, it has been shown that volatility is higher for negative returns than positive returns of the same magnitude. This has been argued to arise either from "leverage" (the impact of falling versus rising stock prices on a firm's debt-to-equity ratio) or "volatility feedback" effects. In Model 3, we explicitly capture this potential asymmetric effect and test whether value and growth stocks respond in the same way to good and bad news. Therefore, we obtain:

Model 3:

$$\begin{aligned} r_{Pt} &= \alpha + \beta(R_{Mt} - R_{ft}) + \varepsilon_{Pt} \\ \sigma^2_{Pt} &= \omega + \gamma\varepsilon^2_{Pt-1} + \eta I_{t-1}\varepsilon^2_{Pt-1} + \theta\sigma^2_{Pt-1} \end{aligned} \tag{5}$$

where η measures any asymmetric response of volatility to good and bad news, $\varepsilon_{Pt} \sim N(0, \sigma^2_{Pt})$, $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$ (bad news) and $I_{t-1} = 0$ otherwise. Now the conditions for non-negative and non-degenerate σ^2_{Pt} and covariance stationarity are $\omega > 0$, $0 < \gamma < 1$, $0 \leq \theta < 1$, $\gamma + \eta / 2 \geq 0$ and $\gamma + \eta / 2 + \theta < 1$.

In Models 4 and 5, we follow Bollerslev, Engle and Wooldridge (1988) and add to Models 2 and 3 a conditional standard deviation term in the mean equation that models the time-varying risk premium of value and growth portfolios. The resulting model, which we term the GJR-GARCH-M (Standard Deviation) (hereafter GARCH-M (SD)) formulation, is

Model 4:

$$\begin{aligned} r_{Pt} &= \alpha + \beta(R_{Mt} - R_{ft}) + \delta\sigma_{Pt} + \varepsilon_{Pt} \\ \sigma^2_{Pt} &= \omega + \gamma\varepsilon^2_{Pt-1} + \theta\sigma^2_{Pt-1} \end{aligned} \qquad (6)$$

Model 5:

$$\begin{aligned} r_{Pt} &= \alpha + \beta(R_{Mt} - R_{ft}) + \delta\sigma_{Pt} + \varepsilon_{Pt} \\ \sigma^2_{Pt} &= \omega + \gamma\varepsilon^2_{Pt-1} + \eta I_{t-1}\varepsilon^2_{Pt-1} + \theta\sigma^2_{Pt-1} \end{aligned} \qquad (7)$$

where δ measures the risk premium, σ_{Pt} captures the time-varying risk, and $\varepsilon_{Pt} \sim N(0, \sigma^2_{Pt})$. These models imply that increased risk as measured by the conditional standard deviation leads to a rise ($\delta > 0$) or fall ($\delta < 0$) in the level of compensation for holding the asset.

Following Nelson (1991) and Hentschel (1995), for comparison and completeness we adopt another commonly used functional form for capturing the time-varying risk in Models 6 and 7, which instead of the conditional standard deviation, uses the conditional variance in the mean equation. We term it as the GJR-GARCH-M (Variance) (hereafter GARCH-M (V)). Therefore, we obtain

Model 6

$$r_{Pt} = \alpha + \beta\left(R_{Mt} - R_{ft}\right) + \nu\sigma_{Pt}^2 + \varepsilon_{Pt}$$
$$\sigma_{Pt}^2 = \omega + \gamma\varepsilon_{Pt-1}^2 + \theta\sigma_{Pt-1}^2 \qquad (8)$$

Model 7:

$$r_{Pt} = \alpha + \beta\left(R_{Mt} - R_{ft}\right) + \nu\sigma_{Pt}^2 + \varepsilon_{Pt}$$
$$\sigma_{Pt}^2 = \omega + \gamma\varepsilon_{Pt-1}^2 + \eta I_{t-1}\varepsilon_{Pt-1}^2 + \theta\sigma_{Pt-1}^2 \qquad (9)$$

where $\nu\sigma_{Pt}^2$ measures the time-varying risk premium and $\varepsilon_{Pt} \sim N\left(0, \sigma_{Pt}^2\right)$. The models specified in equations (6) to (9) imply that there are serial correlations in asset returns which arise through the introduction of the conditional variance, which is itself autocorrelated, in the mean equation. In addition, the conditional expected portfolio return is a linear function of the conditional variance.

Using Models 2 to 7, the main hypothesis involves whether the value premium can be explained by the conditional GARCH-CAPM model, which would imply $\alpha = 0$ for HML (high minus low) portfolio. Therefore, two-sided test is more appropriate than one-sided test on parameters of Models 2 to 7. We also analyze the impact of more recent information (as measured by γ) and older information (as measured by θ) on the volatility of the value and growth portfolio returns. For Models 6, 7, 8 and 9, we examine the null hypothesis that the value premium is a compensation for time-varying risk, which implies that either $\delta > 0$ or $\nu > 0$. For Models 5, 7 and

9, we further test for the existence of any asymmetric impact of good and bad news on the volatility of the value and growth portfolios returns under the null hypothesis that $\eta = 0$.

4.3. Data Description

Our US data comprise portfolios that include all NYSE, AMEX, and NASDAQ stocks.[18] At the end of June each year during the sample period, all stocks are ranked into 10-decile portfolios based on the ratios of B/M, C/P and E/P and then the value-weighted returns of portfolios for the following 12 months are calculated. A value portfolio contains the top 10% of stocks ranked by each ratio and a growth portfolio contains stocks in the bottom 10%. The full sample period for B/M portfolios runs from July 1926 to June 2006 for consistency with the studies of Fama and French (2006) and Ang and Chen (2007). For the C/P- and E/P -sorted portfolios, the sample covers the period July 1963 to June 2006.

In order to provide comparative evidence for a different market, we obtain the UK return series of the value and growth portfolios sorted on B/M, C/P and E/P, also from Kenneth R. French's website. However, the ranking method for the UK value and growth portfolios is slightly different to that of the US portfolios. At the end of December each year, all stocks listed on the UK stock market are ranked into 3 groups based on the ratios of B/M, C/P and E/P. The value portfolio is constructed to contain stocks in the top 30% after ranking according to each ratio and the growth portfolio contains stocks in the bottom 30%. The sample period runs from January

[18] The return series of portfolios are downloaded from Kenneth R. French's website: Data are obtained from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

1975 to December 2002. We find that the high B/M portfolio does not significantly outperform the low B/M portfolio for the UK data over the 1975 to 2001 period. Fama and French (1998) report a similar result for the period 1975 to 1995. By contrast, Dimson, Nagel and Quigley (2003) show a strong value premium (when value is measured by B/M) in the UK stock market over the period 1955 to 2001. These possibly are due to the different sample period and ranking method as Dimson, Nagel and Quigley (2003) include stocks in the top (bottom) 40% by B/M ranking to form value (growth) portfolio. In order to investigate this value premium, in all subsequent tests using UK data in this study, we use the same return series of value and growth portfolios sorted on B/M as employed in the study of Dimson, Nagel and Quigley (2003).[19] The sample covers the period January 1963 to December 2001.

4.4. The US Value Premium Sorted on B/M, C/P and E/P

The core objective of this chapter is to examine whether time-varying risk can explain the post-1963 value premia. However, before moving on to this, we first analyze the mean returns on the US B/M, C/P and E/P portfolios and then examine their performance within the static CAPM. Next, we allow for time-varying risk of the value, growth and HML portfolios through different GARCH model specifications. Finally, we add a size factor to the conditional variance model.

4.4.1. The Mean Return on Value and Growth Portfolios

Table 4.1 presents summary statistics for the monthly returns on the US B/M, C/P and E/P portfolios. *High* represents a value portfolio containing stocks in the top

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[19] Data are obtained from Stefan Nagel's web site: http://faculty-gsb.stanford.edu/nagel/index.htm.

10% of each ratio, while *Low* represents a growth portfolio containing stocks in the bottom 10% of each ratio. HML is a portfolio with the average returns on the value portfolio minus the average returns on the growth portfolio. The value premium is then defined as the average return on the HML portfolio. To be more comparable with the studies of Fama and French (2006) and Ang and Chen (2007), we explore the monthly return on B/M-sorted portfolios for the full sample period from July 1926 to June 2006 (hereafter 26-06), and two sub-sample periods from July 1926 to June 1963 (hereafter 26-63) and from July 1963 to June 2006 (hereafter 63-06). For the C/P and E/P portfolios, the sample period covers July 1963 to June 2006. The t-statistics reported in Table 4.1 are for the significance of the mean based on heteroskedasticity- and autocorrelation-robust (Newey and West, 1987) standard errors.

Consistent with the evidence in Fama and French (1992, 1993 and 2006), Davis, Fama and French (2000) and Ang and Chen (2007), we find that the growth portfolio has low mean returns from 0.81% to 0.93% per month on the B/M-sorted portfolios for the full period and the sub-samples. By contrast, the value portfolio has high mean returns from 1.39% to 1.43% per month. As a result, there is a reliable value premium in returns. The value premium is 0.54% per month on average over the period 26-06 and is significant at the 5% level (t = 2.49). For the two sub-samples, the value premium is 0.5% (t = 1.23) and 0.57% (t = 2.88) per month over the 26-63 and 63-06 periods, respectively.

Table 4.1. Summary statistics for monthly returns on US value, growth and HML portfolios

This table reports the monthly mean returns (%), standard deviations (Std Dev, %) and *t*-statistics for the significance of the mean for the value-weighted portfolios. At the end of June each year during the sample period, all stocks listed on NYSE, AMEX and NASDAQ are ranked into 10-decile portfolios based on the ratios of B/M, C/P and E/P. B/M is the ratio of the book value of equity to market value of equity; C/P is the ratio of cash flow to market value of equity; E/P is the ratio of earnings to market value of equity. High represents a value portfolio containing stocks in the top 10% by each ratio. Low represents a growth portfolio containing stocks in the bottom 10%. HML (high minus low) is a portfolio with the average returns on the value portfolio minus those on the growth portfolio. The full sample period for B/M portfolios runs from July 1926 to June 2006, and two sub-sample periods run from July 1926 to June 1963 and from July 1963 to June 2006. The sample period for C/P and E/P portfolios runs from July 1963 to June 2006. The *t*-statistics in parentheses are based on Newey-West standard errors. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels for a two-sided test.

	B/M Portfolio			C/P Portfolio			E/P Portfolio		
	High	Low	HML	High	Low	HML	High	Low	HML
7/1926-6/2006				*7/1963-6/2006*			*7/1963-6/2006*		
Mean (%)	1.40	0.87	0.54	1.33	0.84	0.49	1.42	0.82	0.60
t-statistic	(4.63) [a]	(4.65) [a]	(2.49) [b]	(6.03) [a]	(3.42) [a]	(2.58) [a]	(6.12) [a]	(3.24) [a]	(2.96) [a]
Std Dev (%)	9.40	5.77	6.69	5.01	5.58	4.30	5.27	5.74	4.60
7/1926-6/1963									
Mean (%)	1.43	0.93	0.50						
t-statistic	(2.39) [b]	(3.05) [a]	(1.23)						
Std Dev (%)	12.57	6.39	8.55						
7/1963-6/2006									
Mean (%)	1.39	0.81	0.57						
t-statistic	(5.90) [a]	(3.58) [a]	(2.88) [a]						
Std Dev (%)	5.34	5.18	4.52						

The estimates of monthly standard deviation suggest that the average level of total risk has changed over time. The average standard deviation of the B/M value portfolio is 12.57% per month over the period 26-63 and only 5.34% per month over the period 63-06. Similarly, for the B/M growth portfolio, it is 6.39% per month for 26-63 and 5.18% per month for 63-06. In addition, the results also show that the value portfolio has more total risk than the growth portfolio over the early period 26-63; but over the period 63-06, the average standard deviations of the value and growth portfolios are almost the same. Consequently, the value premium of 26-63 has more total risk attached than that of 63-06. The average standard deviation of the HML portfolio is 8.55% per month for 26-63 and 4.52% per month for 63-06.

For the C/P and E/P portfolios, the magnitudes of the monthly mean returns and standard deviations are similar to those of the B/M portfolios over the same sample period. For example, the mean returns are 0.84% and 0.82% per month for the C/P and E/P growth portfolios respectively, versus 0.81% per month for the B/M growth portfolio. The average standard deviations are 5.01% and 5.27% per month for the C/P and E/P value portfolios respectively; the figure is almost the same at 5.34% for the B/M value portfolio. The value premia in returns are 0.49% and 0.6% per month for the C/P and E/P HML portfolios respectively; both of these are statistically significant at the 1% level.

4.4.2. The Static CAPM

Table 4.2 reports OLS estimates of the static CAPM for the B/M, C/P and E/P portfolios. The results confirm the findings of Fama and French (1992, 1993 and 2006) and Ang and Chen (2007) that the (B/M) value premium of 26-06 and 26-63 can be explained by the static CAPM as the α coefficient is 0.25% per month (t = 1.36) for 26-06 and -0.13% per month (t = -0.43) for 26-63. In particular, the t-statistic shows that both the α coefficients are statistically insignificant. On the other hand, the static CAPM is rejected for the B/M, C/P and E/P value premia of 63-06 since the α coefficients are 0.62%, 0.59% and 0.69% per month respectively, and all of them are significant at the 1% level. The goodness of fit statistics confirms this finding. The R-squared values are much higher in periods when the static CAPM captures the value premium (13% to 31% for the periods 26-06 and 26-63, versus 1% to 5% only for the period 63-06 and for the B/M, C/P and E/P-sorted value premia).

The market risk as measured by beta also changes over time. The CAPM beta of the B/M value portfolio decreases from 1.7 for 26-63 to 0.98 for 63-06. Conversely, the estimated beta of the B/M growth portfolio increases from 0.96 for 26-63 to 1.09 for 63-06. Over the period 26-63, the value portfolio has higher market risk than the growth portfolio. However, over the 63-06 period, the value portfolio has less market risk than the growth portfolio. As a result, the market beta of the B/M HML portfolio is positive and significant for 26-63, (β = 0.74, t = 5.95), while it is negative and insignificant for 63-06 (β = -0.11, t = -1.69). Similarly, the market betas of the C/P and E/P HML portfolios are also negative and significant at the 1% level. These results suggest that beta cannot explain the positive value premium of 63-06.

Table 4.2. Estimates of the static CAPM for US value, growth and HML portfolios

The table reports coefficient estimates of the static CAPM, given by

$$r_{Pt} = \alpha + \beta(R_{mt} - R_{ft}) + \varepsilon_{Pt}$$

where r_{Pt} is either the excess returns on the value and growth portfolios or the return on the high-minus-low portfolio, R_{mt} is the value-weighted return on the market portfolio of all assets, R_{ft} is the three-month Treasury bill rate. α (%) measures the abnormal performance of the portfolio; β measures the market risk of the portfolio. R^2 is used to compare the goodness-to-fit of the model. At the end of June each year during the sample period, all stocks listed on NYSE, AMEX and NASDAQ are ranked into 10-decile portfolios based on the ratios of B/M, C/P and E/P. High represents a value portfolio containing stocks in the top 10% by each ratio. Low represents a growth portfolio containing stocks in the bottom 10%. HML (high minus low) is a portfolio with the average returns on the value portfolio minus those on the growth portfolio. The full sample period for B/M portfolios runs from July 1926 to June 2006, and two sub-sample periods run from July 1926 to June 1963 and from July 1963 to June 2006. The sample period for C/P and E/P portfolios runs from July 1963 to June 2006. White's heteroskedasticity robust *t*-statistics are in parentheses. Significance is denoted by superscripts at the 1% (a), 5% (b) and 10% (c) levels for a two-sided test..

	B/M Portfolio			C/P Portfolio			E/P Portfolio		
	High	Low	HML	High	Low	HML	High	Low	HML
7/1926-6/2006				*7/1963-6/2006*			*7/1963-6/2006*		
α (%)	0.17	-0.09	0.25	0.41	-0.18	0.59	0.48	-0.21	0.69
	(1.11)	(-1.45)	(1.36)	(3.48) a	(-1.97) b	(3.22) a	(3.73) a	(-2.04) b	(3.45) a
β_m	1.45	1.00	0.44	0.96	1.18	-0.22	1.00	1.20	-0.19
	(17.06) a	(58.62) a	(4.51) a	(22.34) a	(46.60) a	(-3.45) a	(22.51) a	(39.84) a	(-2.84) a
R^2	0.70	0.90	0.13	0.71	0.86	0.05	0.70	0.84	0.03
7/1926-6/1963									
α (%)	-0.14	0.00	-0.13						
	(-0.51)	(-0.04)	(-0.43)						
β_m	1.70	0.96	0.74						
	(15.63) a	(47.28) a	(5.95) a						
R^2	0.76	0.94	0.31						
7/1963-6/2006									
α (%)	0.46	-0.16	0.62						
	(3.31) a	(-1.87) c	(3.15) a						
β_m	0.98	1.09	-0.11						
	(21.10) a	(44.64) a	(-1.69) c						
R^2	0.65	0.86	0.01						

If the static CAPM is an adequate characterization of the temporal variation in returns, the variances of the error terms should be constant. This motivates us to perform a series of Lagrange Multiplier (LM) tests to assess the validity of the static CAPM under the null hypothesis that there is no ARCH (Engle 1982), in the errors. Following previous studies in the time-series literature, we test for ARCH-effects of order up to 5. The test statistic is asymptotically distributed as a χ^2 with 5 degrees of freedom under the null hypothesis of no ARCH.

Table 4.3 reports the ARCH LM test statistics and *p*-values. Interestingly, the B/M, C/P and E/P value, growth and HML portfolios over the 63-06 period show substantial evidence of ARCH effects as all the LM statistics are significant at the 5% level. Conversely, the LM statistics of the B/M portfolios over the earlier 26-63 period are statistically insignificant. Therefore, it is perhaps no surprise that the static CAPM cannot explain the post-1963 value premium but can capture the value premium of 26-63. It is evident that there are problems of heteroskedasticity (and autocorrelation) contained in the post-1963 HML portfolio returns, which are not captured by the static CAPM. On the other hand, there is no heteroskedasticity or autocorrelation in the pre-1963 HML portfolio returns, and the static CAPM works well in explaining the value premium over this period.

Table 4.3. LM tests for ARCH in the residuals of the static CAPM

The table reports autoregressive conditional heteroskedasticity (ARCH) Lagrange Multiplier (LM) test statistics, which are asymptotically distributed as $\chi^2(5)$-variants under the null hypothesis that there is no ARCH up to order 5 in the residuals of the static CAPM. At the end of June each year during the sample period, all stocks listed on NYSE, AMEX and NASDAQ are ranked into 10-decile portfolios based on the ratios of B/M, C/P and E/P. High represents a value portfolio containing stocks in the top 10% by each ratio. Low represents a growth portfolio containing stocks in the bottom 10%. HML (high minus low) is a portfolio with the average returns on the value portfolio minus those on the growth portfolio. The full sample period for B/M portfolios runs from July 1926 to June 2006, and two sub-sample periods run from July 1926 to June 1963 and from July 1963 to June 2006. The sample period for the C/P and E/P portfolios runs from July 1963 to June 2006. *p*-values are presented in parentheses. Significance is denoted by superscripts at the 1% (^{a}), 5% (^{b}) and 10% (^{c}) levels for a two-sided test.

	B/M Portfolio			C/P Portfolio			E/P Portfolio		
	High	Low	HML	High	Low	HML	High	Low	HML
7/1926-6/2006				*7/1963-6/2006*			*7/1963-6/2006*		
LM test statistic	23.01	26.43	23.84	27.82	12.70	26.07	82.72	25.91	70.15
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)
7/1926-6/1963									
LM test statistic	4.51	8.45	3.58						
p-value	(0.21)	(0.13)	(0.31)						
7/1963-6/2006									
LM test statistic	27.24	10.94	19.26						
p-value	(0.00)	(0.05)	(0.00)						

4.4.3. The CAPM within a GARCH Framework

In order to allow for heteroskedasticity (and autocorrelation) in the errors of the CAPM models for the post-1963 value, growth and HML portfolios, we assume that the conditional variances of portfolio returns follow a GARCH (1, 1) process. Table 4.4 report the results of normality test for the errors of the value, growth and HML portfilios in Models 2 to 7. The decision to allocate a stock to either the value or

Table 4.4. Jarque-Bera test for normality of the conditional market model

The table reports Jarque-Bera (JB) test statistics and *p*-values for normality of Models 2 to 7 for the value, growth and HML portfolios over the 63-06 period. At the end of June each year during the sample period, all stocks listed on NYSE, AMEX and NASDAQ are ranked into 10-decile portfolios based on the ratios of B/M, C/P and E/P. High represents a value portfolio containing stocks in the top 10% by each ratio. Low represents a growth portfolio containing stocks in the bottom 10%. HML (high minus low) is a portfolio with the average returns on the value portfolio minus those on the growth portfolio. The sample period for the B/M, C/P and E/P portfolios runs from July 1963 to June 2006. *p*-values are presented in parentheses.

	High						Low						HML					
	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Panel A: B/M Portfolios																		
JB test statistic	53.55	47.35	47.76	42.15	49.45	43.68	8.82	9.99	9.64	10.17	9.22	10.18	3.08	3.18	2.78	2.69	2.63	2.47
p-vaue	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.21)	(0.20)	(0.25)	(0.26)	(0.27)	(0.29)
Panel B: C/P Portfolios																		
JB test statistic	129.68	103.19	141.38	111.37	136.96	107.87	9.62	9.29	10.01	9.54	9.82	9.48	11.88	15.60	12.89	15.22	12.36	15.22
p-vaue	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Panel C: E/P Portfolios																		
JB test statistic	15.01	16.92	14.35	15.85	13.19	14.91	3.22	2.99	3.36	3.17	3.37	3.19	1.01	1.20	0.83	1.01	0.65	0.88
p-vaue	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.20)	(0.22)	(0.19)	(0.20)	(0.19)	(0.20)	(0.60)	(0.55)	(0.66)	(0.60)	(0.72)	(0.64)

growth portfolio is based on B/M in Panel A, on C/P in Panel B and on E/P in Panel C. The results show that except for HML portfolio sorted on B/M and E/P and growth portfolio sorted on E/P, the errors of others portfolios are non-normal distributed.

Table 4.5 presents the estimates of Models 2 to 7 for the value, growth and HML portfolios over the 63-06 period. The estimation methods for GARCH family models reported in this table and the rest of this chapter are the same to chapter 3, which compute Bollerslev-Wooldridge robust standard errors. These approaches use maximum likelihood estimators together with non-normality robust standard errors, which take into account of the biased standard error due to the non-normality of errors. AIC values are also reported in Table 4.5. AIC is a function of the maximized value of the log-likelihood function and is used to compare the relative merits of models. The rationale for reporting AIC instead of R^2 is that the former is designed for any model while the latter is only applicable for linear regression models and will not reflect any goodness of fit in the conditional variance equation. A model with the lowest value of AIC is preferred.

Portfolios sorted on B/M

Table 4.5, Panel A, Model 2 reports the estimates of the conditional CAPM with a standard GARCH (1, 1) specification (Model 2). The market beta of the value portfolio is 0.96 (t = 28.04) and of the growth portfolio is 1.09 (t = 48.91). Clearly, the value portfolio has less market risk than the growth portfolio and beta has strong explanatory power for the separate value and growth portfolio returns. However, the beta of the HML portfolio is negative (β = -0.07, t = -1.5), implying that the CAPM cannot explain the positive B/M value premium. The γ coefficient measures the impact of recent information on volatility and is equal to 0.13 for the value portfolio and 0.04 for the growth portfolio, indicating that recent information has a stronger impact on the volatility of the value portfolio than on that of the growth portfolio. The θ coefficient captures the impact of historical information on volatility and is equal to 0.85 for the value portfolio and 0.94 for the growth portfolio, suggesting that older information has less influence on the volatility of the value portfolio than on that of the growth portfolio. The positive and significant coefficients γ and θ also suggest that both historical and more recent information have strong impact on the volatility of the value, growth and HML portfolios.

Model 3 allows good news and bad news to have an asymmetric impact on the volatility of portfolio returns by adding a leverage effect term, $\eta I_{t-1}\varepsilon_{t-1}^2$, to the variance equation of Model 2. The estimated value of this parameter for the value portfolio is 0.07, which is insignificantly different from zero (t = 1.01). Thus, no matter whether the announcement represents good news or bad news, the impact on the volatility of the value portfolio is symmetric. On the other hand, η for the growth portfolio is -0.05[20], which is statistically significant at the 5% level. Therefore, after an announcement of good news, the volatility of the growth portfolio increases more than after the announcement of bad news.

In models 4 and 5, we add a time-varying risk term, $\delta\sigma_t$, to the mean equations of Models 2 and 3. The results show that the excess return on the value portfolio is

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[20] In GJR-GARCH model, both γ and η measure the impact of new information and η only represents half of new information, so the non-negative condition should be $\gamma + \eta / 2 \geq 0$, therefore, the negative γ, η and $\gamma + \eta < 0$ in here are allowed.

positively related to its time-varying premium as the δ coefficient of Model 4 is 0.35 (t = 2.16) and of Model 5 is 0.33 (t = 2.07). Conversely, the excess return on the growth portfolio is negatively related to its premium as the δ coefficient of Model 4 is -0.32 (t = -2.04) and of Model 5 is -0.23 (t = -1.69). While a negative premium on time-varying total risk for the growth portfolios might at first blush appear counter-intuitive, this result is entirely consistent with that of Hirt and Pandher (2005), who show that idiosyncratic risk is negatively priced in S&P 500 stocks. This can be attributed to the key characteristic of S&P 500 companies that they have low book-to-market ratios, high price-to-earnings ratios and low cashflow-to-price ratios - i.e., that they are growth stocks.

Therefore, once we explicitly model the time-varying total risk of the value and growth portfolios, the value portfolio appears to command a higher risk premium than the growth portfolio ($\delta_{value} > \delta_{growth}$). As a result, the expected return on the HML portfolio is positively and significantly related to its time-varying risk and the δ coefficient of Model 4 is 0.50 (t = 2.46) and of Model 5 is 0.46 (t = 2.36). These suggest that the value premium could in part be the result of increased levels of risk, as modeled by the conditional standard deviation of the HML portfolio returns. More importantly, the α coefficient of Model 4 supports the hypothesis that indeed conditional risk is the reason behind the better performance of value stocks in Table 4.1. Once the portfolio-specific time-varying risk of the value and growth stocks is explicitly modeled, the alpha of the value portfolio drops from 0.46% a month in Table 4.2 to -0.49% in Table 4.5 (Model 4). Similarly, the risk-adjusted return of the growth stocks in Table 4.5 (0.45%) is much better than the raw returns suggested (-0.16% in Table 4.2). Interestingly, the alpha of the value portfolio is statistically insignificant in Table 4.5, while it is positive at the 1% level in Table 4.2. Similarly,

Table 4.5. Estimates of the conditional model with GARCH-M specifications for the US value premium

The table reports coefficient estimates for Models 2 through 7 for value, growth and HML portfolios. The models are defined by:

$$r_{Pt} = \alpha + \beta_m (R_{Mt} - R_{ft}) + \delta\sigma_{Pt} + v\sigma^2_{Pt} + \varepsilon_{Pt}$$
$$\sigma^2_{Pt} = \omega + \gamma\varepsilon^2_{Pt-1} + \eta I_{t-1}\varepsilon^2_{Pt-1} + \theta\sigma^2_{Pt-1}$$

where $\varepsilon_{Pt} \sim (0, \sigma^2_{Pt})$, r_{Pt} is either the excess returns on value, growth portfolios or the return on the HML portfolio, R_{mt} is the value-weighted return on the market portfolio of all assets, R_{ft} is the three-month Treasury bill rate. α (%) measures the abnormal performance of the portfolio; β_m measures the market risk of the portfolio; $\delta\sigma_{Pt}$ and $v\sigma^2_{Pt}$ (with either $\delta = 0$ or $v = 0$) are the two competing estimates of the time-varying risk exposures; ω, γ, η and θ are estimated parameters and $\omega > 0$, $0 \le \gamma < 1$, $0 \le \theta < 1$, $\gamma + \eta/2 + \theta < 1$, I_{t-1} takes a value of 1, when ε_{t-1} is negative and a value of 0, otherwise. At end of June each year during the sample period, all stocks listed on NYSE, AMEX and NASDAQ are ranked into 10-decile portfolios based on the ratios of B/M, C/P and E/P. B/M is the ratio of book value of equity to market value of equity; C/P is the ratio of cash flow to market value of equity; E/P is the ratio of earnings to market value of equity. High represents a value portfolio containing stocks in the top 10% by each ratio. Low represents a growth portfolio containing stocks in the bottom 10%. HML (high minus low) is a portfolio with the average returns on the value portfolio minus those on the growth portfolio. The sample period runs from July 1963 to June 2006. Akaike's information criterion (AIC) is based on the maximized value of the log-likelihood function and is used to select the preferred model, which will have the lowest value. Bollerslev-Wooldridge robust *t*-statistics are in parentheses. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels for a two-sided test.

	High						Low						HML					
Panel A: B/M Portfolios	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
a (%)	0.46	0.41	-0.49	-0.48	0.08	0.07	-0.12	-0.11	0.45	0.30	0.27	0.18	0.52	0.46	-1.51	-1.39	-0.45	-0.44
	(3.51) [a]	(3.34) [a]	(-1.12)	(-1.11)	(0.37)	(0.31)	(-1.45)	(-1.37)	(1.58)	(1.20)	(1.43)	(1.08)	(2.97) [a]	(2.60) [a]	(-1.81) [c]	(-1.76) [c]	(-1.07)	(-1.12)
β_m	0.96	0.96	0.96	0.96	0.96	0.96	1.09	1.10	1.09	1.09	1.09	1.09	-0.07	-0.08	-0.07	-0.08	-0.07	-0.08
	(28.04) [a]	(28.26) [a]	(28.20) [a]	(28.40) [a]	(27.88) [a]	(28.14) [a]	(48.91) [a]	(46.54) [a]	(49.36) [a]	(47.11) [a]	(49.42) [a]	(47.41) [a]	(-1.50)	(-1.64)	(-1.45)	(-1.60)	(-1.44)	(-1.59)
δ			0.35	0.33					-0.32	-0.23					0.50	0.46		
			(2.16) [b]	(2.07) [b]					(-2.04) [b]	(-1.69) [c]					(2.46) [b]	(2.36) [b]		
ν					4.68	4.29					-11.30	-8.64					5.63	5.28
					(1.88) [c]	(1.79) [c]					(-2.21) [b]	(-1.83) [c]					(2.48) [b]	(2.46) [b]
w (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01
	(1.48)	(1.33)	(1.55)	(1.54)	(1.55)	(1.54)	(1.95) [c]	(1.68)	(1.81) [c]	(1.73) [c]	(2.57) [b]	(2.31) [b]	(1.66)	(1.36)	(1.70) [c]	(1.70) [c]	(1.71) [c]	(1.72) [c]
γ	0.13	0.10	0.13	0.10	0.13	0.10	0.04	0.04	0.04	0.04	0.04	0.04	0.10	0.06	0.09	0.06	0.10	0.06
	(3.53) [a]	(2.43) [b]	(3.77) [a]	(2.61) [a]	(3.65) [a]	(2.60) [a]	(2.45) [b]	(2.42) [b]	(2.73) [a]	(2.58) [b]	(2.72) [a]	(2.64) [a]	(3.43) [a]	(2.18) [b]	(3.57) [a]	(2.29) [b]	(3.57) [a]	(2.37) [b]
η		0.07		0.06		0.06		-0.05		-0.04		-0.04		0.07		0.05		0.05
		(1.01)		(0.95)		(0.96)		(-1.98) [b]		(-1.84) [c]		(-1.78) [c]		(1.58)		(1.31)		(1.34)
θ	0.85	0.85	0.85	0.85	0.85	0.85	0.94	0.96	0.94	0.96	0.94	0.96	0.87	0.88	0.88	0.89	0.88	0.89
	(18.84) [a]	(19.39) [a]	(21.93) [a]	(22.49) [a]	(20.81) [a]	(21.27) [a]	(44.35) [a]	(59.51) [a]	(43.52) [a]	(59.18) [a]	(51.25) [a]	(66.59) [a]	(22.33) [a]	(26.70) [a]	(25.93) [a]	(30.41) [a]	(26.27) [a]	(31.22) [a]
$\gamma+\eta/2+\theta$	0.977	0.982	0.981	0.981	0.979	0.980	0.974	0.983	0.977	0.982	0.978	0.981	0.971	0.981	0.972	0.975	0.973	0.976
AIC	-4.177	-4.178	-4.181	-4.181	-4.179	-4.180	-5.040	-5.046	-5.043	-5.045	-5.045	-5.046	-3.433	-3.435	-3.440	-3.440	-3.441	-3.441

Panel B: C/P Portfolios																		
	High						Low						HML					
	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
a (%)	0.28	0.30	-0.27	-0.27	-0.02	0.00	-0.14	-0.13	0.50	0.40	0.23	0.19	0.46	0.43	-0.66	-0.61	-0.18	-0.19
	(2.30) [b]	(2.78) [a]	(-0.61)	(-0.63)	(-0.07)	(0.01)	(-1.80) [c]	(-1.57)	(1.63)	(1.34)	(1.36)	(1.14)	(2.78) [a]	(2.67) [a]	(-0.98)	(-0.91)	(-0.50)	(-0.53)
β_m	0.97	0.98	0.98	0.98	0.98	0.98	1.17	1.17	1.17	1.17	1.17	1.17	-0.19	-0.19	-0.18	-0.18	-0.18	-0.18
	(32.13) [a]	(32.97) [a]	(31.71) [a]	(32.62) [a]	(31.90) [a]	(32.77) [a]	(55.20) [a]	(55.68) [a]	(54.44) [a]	(54.83) [a]	(54.32) [a]	(54.72) [a]	(-4.01) [a]	(-3.93) [a]	(-3.74) [a]	(-3.73) [a]	(-3.75) [a]	(-3.73)
δ			0.24	0.25					-0.34	-0.29					0.31	0.29		
			(1.24)	(1.35)					(-2.06) [b]	(-1.77) [c]					(1.68)	(1.61)		
ν					5.17	5.27					-10.13	-8.82					4.52	4.40
					(1.46)	(1.55)					(-2.21) [b]	(-1.97) [b]					(1.95) [c]	(1.93)
w (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(2.27) [b]	(2.28) [b]	(2.31) [b]	(2.24) [b]	(2.29) [b]	(2.20) [b]	(2.39) [b]	(2.11) [b]	(2.26) [b]	(2.25) [b]	(2.71) [a]	(2.64) [a]	(2.33) [b]	(2.14) [b]	(2.30) [b]	(2.34) [b]	(2.29) [b]	(2.35)
γ	0.08	0.11	0.08	0.11	0.08	0.11	0.07	0.08	0.07	0.08	0.07	0.08	0.08	0.05	0.08	0.06	0.08	0.06
	(2.99) [a]	(2.46) [b]	(3.16) [a]	(2.64) [a]	(3.17) [a]	(2.63) [a]	(3.05) [a]	(2.94) [a]	(3.12) [a]	(2.89) [a]	(3.16) [a]	(2.93) [a]	(2.91) [a]	(1.57)	(3.05) [a]	(1.74) [c]	(3.08) [a]	(1.73)
η		-0.04		-0.04		-0.04		-0.04		-0.03		-0.03		0.04		0.03		0.03
		(-0.50)		(-0.62)		(-0.61)		(-1.21)		(-0.95)		(-0.93)		(0.86)		(0.71)		(0.71)
θ	0.89	0.88	0.89	0.89	0.89	0.89	0.90	0.92	0.91	0.91	0.91	0.92	0.90	0.91	0.89	0.90	0.90	0.90
	(26.81) [a]	(27.62) [a]	(28.35) [a]	(28.40) [a]	(29.01) [a]	(28.86) [a]	(32.89) [a]	(34.57) [a]	(33.74) [a]	(35.35) [a]	(36.51) [a]	(38.10) [a]	(30.45) [a]	(32.45) [a]	(31.17) [a]	(33.44) [a]	(32.52) [a]	(34.90)
$\gamma+\eta/2+\theta$	0.974	0.973	0.974	0.976	0.975	0.977	0.971	0.979	0.973	0.976	0.974	0.976	0.978	0.981	0.977	0.977	0.978	0.978
AIC	-4.484	-4.482	-4.484	-4.483	-4.485	-4.484	-4.975	-4.976	-4.978	-4.977	-4.980	-4.978	-3.593	-3.592	-3.595	-3.593	-3.598	-3.595

Panel C: E/P Portfolios

	High						Low						HML					
	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
a (%)	0.37	0.33	-0.88	-0.86	-0.18	-0.22	-0.10	-0.09	0.66	0.66	0.28	0.28	0.39	0.35	-1.54	-1.47	-0.43	-0.43
	(3.22) a	(2.94) a	(-1.58)	(-1.51)	(-0.71)	(-0.84)	(-1.12)	(-1.00)	(1.96) c	(1.99) b	(1.56)	(1.60)	(2.38) b	(2.08) b	(-2.28) b	(-2.23) b	(-1.30)	(-1.34)
β_m	1.04	1.03	1.04	1.03	1.04	1.03	1.15	1.16	1.15	1.15	1.15	1.15	-0.08	-0.10	-0.08	-0.09	-0.08	-0.09
	(33.41) a	(31.91) a	(33.42) a	(32.39) a	(33.37) a	(32.22) a	(47.40) a	(47.26) a	(47.78) a	(47.73) a	(48.00) a	(48.02) a	(-1.72) c	(-1.89) c	(-1.58)	(-1.73) c	(-1.61)	(-1.78)
δ			0.51	0.49					-0.38	-0.37					0.51	0.49		
			(2.28) b	(2.19) b					(-2.23) b	(-2.24) b					(2.91) a	(2.84) a		
ν					8.83	9.02					-8.71	-8.58					5.44	5.26
					(2.32) b	(2.36) b					(-2.22) b	(-2.22) b					(2.78) a	(2.81)
w (%)	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01
	(2.38) b	(1.97) b	(2.40) b	(2.31) b	(2.45) b	(2.36) b	(2.16) b	(2.00) b	(2.01) b	(2.04) b	(2.05) b	(2.08) b	(2.55) b	(2.27) b	(2.51) b	(2.59) a	(2.58) b	(2.63)
γ	0.11	0.06	0.11	0.06	0.11	0.06	0.09	0.10	0.08	0.09	0.08	0.09	0.10	0.07	0.10	0.08	0.10	0.07
	(2.43) b	(1.65)	(2.61) a	(1.80) c	(2.55) b	(1.71) c	(3.63) a	(3.07) a	(3.57) a	(3.10) a	(3.61) a	(3.11) a	(2.91) a	(1.93) c	(3.23) a	(2.30) b	(3.19) a	(2.24)
η		0.09		0.08		0.08		-0.03		-0.02		-0.02		0.07		0.05		0.05
		(1.38)		(1.56)		(1.68)		(-0.67)		(-0.53)		(-0.48)		(1.47)		(1.19)		(1.30)
θ	0.83	0.84	0.83	0.83	0.83	0.83	0.89	0.89	0.90	0.90	0.90	0.90	0.87	0.88	0.86	0.87	0.87	0.87
	(15.43) a	(16.18) a	(16.28) a	(16.99) a	(16.06) a	(16.99) a	(31.89) a	(32.21) a	(33.19) a	(33.55) a	(34.33) a	(34.69) a	(26.26) a	(27.42) a	(27.09) a	(27.92) a	(28.13) a	(29.25)
$\gamma+\eta/2+\theta$	0.935	0.947	0.937	0.937	0.936	0.935	0.976	0.979	0.977	0.977	0.978	0.978	0.971	0.980	0.969	0.969	0.971	0.970
AIC	-4.421	-4.423	-4.429	-4.430	-4.430	-4.432	-4.769	-4.766	-4.775	-4.771	-4.775	-4.771	-3.514	-3.515	-3.527	-3.526	-3.528	-3.527

the alpha of the growth portfolio in Table 4.5 is ditinguishable from 0. Results that are qualitatively similar are obtained from alternative specifications of the model.Altogether, the evidence in Table 4.5 suggests that the conditional CAPM with a (GJR-) GARCH-M (SD) specification is able to capture the expected returns on the value and growth portfolios.

Models 6 and 7 use the conditional variance to replace the conditional standard deviation as a time-varying measure of risk in the mean equations of Models 4 and 5. Most of the estimates from these two models are similar to those of Models 4 and 5. The time-varying risk premium coefficient, v, of the HML portfolio is 5.63 (t = 2.48) for Model 6 and 5.28 (t = 2.46) for Model 7. Both of them are statistically significant at the 5% level. The null hypothesis of $\alpha = 0$ is also supported by Models 6 and 7 not only for the value and growth portfolios, but also for the HML portfolio. The α coefficient of the HML portfolio is -0.45% (t = -1.07) per month for Model 6 and -0.44% (t = -1.12) per month for Model 7. The AIC results also support this finding that Models 6 and 7 are the preferred models for capturing the value premium since they have the lowest AIC figures.

Portfolios sorted on C/P

Panel B presents similar results as in Panel A, but this time we sort stocks into value or growth portfolios based on their C/P ratios. Like the B/M portfolios, the value portfolio has less market risk than the growth portfolio since the average CAPM beta is 0.98 for the C/P value portfolio and 1.17 for the C/P growth portfolio. Additionally, the betas of the value and growth portfolios are positive and significant at the 1% level. These estimates suggest that beta is again an important variable in explaining temporal variations in the returns on the C/P value and growth portfolios. By contrast, the beta of the HML portfolio is negative and significant at the 1% level. Thus, the CAPM fails to explain the positive C/P value premium. The risk premium coefficients, δ and ν, are positive for the value portfolio and negative for the growth portfolio as for the B/M sort. This suggests that the value portfolio is more risky than the growth portfolio in the sense of time-varying total portfolio risk. Therefore, the superior return on the value portfolio may be a compensation for the additional risk of holding the value portfolio. The risk premium coefficient ν for the HML portfolio is 4.52 (t = 1.95) for Model 6 and 4.4 (t = 1.93) for Model 7. These results confirm that time-varying risk plays a central role in explaining the C/P value premium.

Moreover, the CAPM with the (GJR-) GARCH (1, 1)-M (SD) and (GJR-) GARCH (1, 1)-M (V) specifications are able to explain expected returns on the value and growth portfolios since all of the α coefficients of Models 4 to 7 are statistically insignificant for the value and growth portfolios. The alpha of the HML portfolio is -0.18% (t = -0.5) per month for Model 6 and -0.19% (t = -0.53) per month for Model 7. The AIC results suggest that Model 6 should be chosen for the HML portfolio since it has the lowest AIC of -3.598. Overall, the results of the C/P portfolios are consistent with our findings for the B/M portfolios that once time-varying total portfolio risk is taken into account, the value premium measured using C/P does not exist.

Portfolios sorted on E/P

In Panel C, the results are similar to those of the B/M and C/P portfolios. The value portfolio again has less market risk than the growth portfolio and the CAPM beta fails to explain the positive value premium on E/P due to the negative market beta. The risk premium coefficients, δ and v, of Models 4 to 7 are positive and significant for the value portfolio and negative and significant for the growth portfolio at the 5% level, indicating that the value portfolio is more risky than the growth portfolio in terms of time-varying total portfolio risk. Time-varying risk also plays an important role in explaining the E/P value premium as both of the risk premium coefficients of Model 6 (v = 5.44, t = 2.78), and Model 7 (v = 5.26, t = 2.81), are statistically significant at the 1% level. Most importantly, the difference in time-varying total risk once more explains most of the difference in average returns that is observed in Table 4.2. For Model 6, the alpha is -0.18% per month for the value portfolio, 0.28% per month for the growth portfolio and -0.43% per month for the HML portfolio. For Model 7, it is -0.22% per month for the value portfolio, 0.28% per month for the growth portfolio and -0.43% per month for the HML portfolio. In particular, none of these alphas are statistically significant at the 5% level. Clearly, the conditional CAPM with a (GJR-) GARCH (1, 1)-M (V) specification not only captures the E/P value premium, but can also explain the returns on the value and growth portfolios. These results provide additional evidence that after taking account of time-varying risk, the value premium does not exit. The AIC values for the E/P sorted HML portfolios also suggest that Model 6 best captures the value premium.[21]

Another interesting finding from Table 4.5 is that value portfolios uniformly have positive time-varying risk premium coefficients, where $\delta > 0$ and $v > 0$; conversely, growth portfolios have uniformly negative time-varying risk premium coefficients,

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[21] In addition, we carry out a series of ARCH LM test for the residuals of Models 2 to 7 for the value, growth and HML portfolios and find that the test statistics are statistically insignificant, suggesting that there is no evidence of ARCH effects in the errors after using GARCH (1, 1) specifications.

where $\delta < 0$ and $v < 0$. These results suggest that the value portfolios have higher total risk than the growth portfolios. The possible explanation follows the view of fundamental analysis. Penman (2007) uses a residual earnings model to value equity and measure the B/M ratio. He finds that when a company generates return on shareholder's equity (ROCEs) lower than its required returns, the company produces negative residual earnings. This leads to a lower valuation than its book value and a high B/M ratio. This type of companies are value stocks. Low ROCEs are affected by firms' unfavourable financial leverage and operating liability leverage. Therefore, value stocks are financial distress companies and have high operating and financial risk, that is, high total risk. On the other hand, when a company produces ROCEs higher than its required returns, the company has positive residual earnings. This causes a higher valuation than its book value and a low B/M ratio. This type of companies consists of growth stocks. High ROCEs are affected by firms' favourable financial leverage and operating liability leverage. As a result, growth stocks have high earning growth and low operating and financial risk with low total risk. Our results appear to support the findings of Chen and Zhang (1998).

4.4.4. The CAPM and Conditional Variance Model Including a Size Factor

Loughran (1997), Daniel and Titman (1997), Davis, Fama and French (2000) and Fama and French (2006) report that the post-1963 value premium is greater for small capitalization stocks than for large capitalization stocks. Their results raise a question as to whether the size effect can explain the post-1963 value premium. We examine this hypothesis by adding a Fama and French (1993)-style size factor into Models 2 to 7 described above. This leads to:

$$r_{Pt} = \alpha + \beta_m(R_{Mt} - R_{ft}) + \beta_{SMB}SMB_t + \delta\sigma_{Pt} + v\sigma^2_{Pt} + \varepsilon_{Pt} \qquad (10)$$
$$\sigma^2_{Pt} = \omega + \gamma\varepsilon^2_{Pt-1} + \eta I_{t-1}\varepsilon^2_{Pt-1} + \theta\sigma^2_{Pt-1}$$

where $\varepsilon_{Pt} \sim N(0,\sigma^2_{Pt})$, SMB_t is the Fama and French size factor, which is the difference between the average returns on the small market capitalization portfolio and the average returns on the big market capitalization portfolio, and β_{SMB} measures portfolio loadings on the size factor. All other notation is as described above and either $\delta = 0$ or $v = 0$.

Table 4.6 presents estimates of this model for the value, growth and HML portfolios. Panel A reports the results for the B/M portfolios. The value portfolio sorted on B/M loads heavily on small capitalization stocks, while conversely, the B/M growth portfolio loads heavily on big capitalization stocks. For the B/M HML portfolio, we find that the ability of the model to explain the expected return is improved once the size factor is added. For example, the alpha of Model 7 drops from -0.44% (t = -1.12) per month in Table 4.5 to -0.22% (t = -0.57) per month in Table 4.6. Additionally, the β_{SMB} estimates from all models are positive and significant at the 1% level. These results suggest that the size effect indeed can explain part of the value premium and the AIC values also support this finding. For instance, the AIC of Model 7 decreases from -3.441 in Table 4.5 to -3.473 in Table 4.6. On the other hand, even adding a size factor, Models 2 and 3 are still rejected for the value premium as the alphas (α_{model2}= 0.51%, t_{model2}= 2.96; α_{model3}= 0.45%, t_{model3}= 2.58) are still significant at the 1% level. This result indicates that the size effect cannot fully explain the post-1963 B/M value premium, a result consistent with the study of Lakonishok, Shleifer and Vishny (1994).

Table 4.6. Estimates of the conditional model with GARCH-M specifications including size factor for the US value premium

The table reports coefficient estimates for models with an added Fama and French (1993) Size factor in Models 2 through 7 for value, growth and HML portfolios. The models are defined by:

$$r_{Pt} = \alpha + \beta_m (R_{Mt} - R_{ft}) + \beta_{SMB} SMB_t + \delta\sigma_{Pt} + \nu\sigma^2_{Pt} + \varepsilon_{Pt}$$
$$\sigma^2_{Pt} = \omega + \gamma\varepsilon^2_{Pt-1} + \eta I_{t-1}\varepsilon^2_{Pt-1} + \theta\sigma^2_{Pt-1}$$

where $\varepsilon_{Pt} \sim (0, \sigma^2_{Pt})$, r_{Pt} is either the excess returns on value, growth portfolios or the return on the HML portfolio, $R_{m,t}$ is the value-weighted return on the market portfolio of all assets, R_{ft} is the three-month Treasury bill rate, SMB_t is the Fama and French size factor, which is the difference between the average returns on a small market capitalization portfolio and the average returns on a big market capitalization portfolio. α (%) measures the abnormal performance of the portfolio; β_m measures the market risk of the portfolio; β_{SMB} measures the portfolio loadings on the size factor. $\delta\sigma_{Pt}$ and $\nu\sigma^2_{Pt}$ are the time-varying risk exposures; ω, γ, η and θ are estimated parameters and $\omega > 0$, $0 < \gamma < 1$, $0 \le \theta < 1$, $\gamma + \eta/2 + \theta < 1$. I_{t-1} takes a value of 1, when ε_{t-1} is negative and a value of 0, otherwise. At end of June each year during the sample period, all stocks listed on NYSE, AMEX and NASDAQ are ranked into 10-decile portfolios based on the ratios of B/M, C/P and E/P. B/M is the ratio of the book value of equity to market value of equity; C/P is the ratio of cash flow to market value of equity; E/P is the ratio of earnings to market value of equity. High represents a value portfolio containing stocks in the top 10% by each ratio. Low represents a growth portfolio containing stocks in the bottom 10%. HML (high minus low) is a portfolio with the average returns on the value portfolio minus those on the growth portfolio. The sample period runs from July 1963 to June 2006. Akaike's information criterion (AIC) is based on the maximized value of the log-likelihood functions and is used to select the preferred model, which will be the one with the lowest value. Bollerslev-Wooldridge robust *t*-statistics are in parentheses. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels for a two-sided test.

Panel A: B/M Portfolios

	High						Low						HML					
	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
a (%)	0.43	0.38	-0.21	-0.17	0.18	0.18	-0.12	-0.11	0.37	0.26	0.23	0.16	0.51	0.45	-1.13	-0.94	-0.29	-0.22
	(3.57) [a]	(3.27) [a]	(-0.42)	(-0.35)	(0.78)	(0.82)	(-1.48)	(-1.40)	(1.33)	(1.01)	(1.22)	(0.97)	(2.96) [a]	(2.58) [b]	(-1.32)	(-1.17)	(-0.68)	(-0.57)
β_m	0.94	0.93	0.94	0.93	0.94	0.93	1.10	1.11	1.10	1.10	1.10	1.10	-0.12	-0.13	-0.11	-0.12	-0.11	-0.12
	(25.41) [a]	(25.38) [a]	(25.04) [a]	(25.06) [a]	(24.97) [a]	(24.99) [a]	(49.37) [a]	(47.90) [a]	(49.21) [a]	(48.00) [a]	(49.22) [a]	(48.25) [a]	(-2.29) [b]	(-2.45) [b]	(-2.15) [b]	(-2.31) [b]	(-2.14) [b]	(-2.28) [b]
β_{SMB}	0.26	0.26	0.25	0.26	0.26	0.26	-0.06	-0.05	-0.06	-0.05	-0.06	-0.05	0.30	0.30	0.29	0.29	0.29	0.29
	(5.25) [a]	(5.42) [a]	(5.06) [a]	(5.22) [a]	(5.08) [a]	(5.23) [a]	(-2.11) [b]	(-1.79) [c]	(-1.88) [c]	(-1.66)	(-1.86) [c]	(-1.68)	(4.36) [a]	(4.44) [a]	(4.03) [a]	(4.13) [a]	(4.04) [a]	(4.11) [a]
δ			0.24	0.21					-0.28	-0.21					0.41	0.35		
			(1.29)	(1.15)					(-1.78) [c]	(-1.45)					(1.93) [c]	(1.75) [c]		
ν					3.25	2.75					-10.15	-8.06					4.76	4.11
					(1.17)	(1.03)					(-1.98) [b]	(-1.69)					(2.01) [b]	(1.87) [c]
w (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01
	(1.43)	(1.30)	(1.44)	(1.38)	(1.44)	(1.37)	(1.89) [c]	(1.68)	(1.77) [c]	(1.70) [c]	(2.51) [b]	(2.59) [a]	(1.66)	(1.41)	(1.66)	(1.64)	(1.68)	(1.65)
γ	0.12	0.09	0.12	0.09	0.12	0.09	0.04	0.04	0.04	0.04	0.04	0.04	0.10	0.06	0.09	0.06	0.09	0.06
	(3.37) [a]	(2.29) [b]	(3.41) [a]	(2.32) [b]	(3.37) [a]	(2.32) [b]	(2.54) [b]	(2.35) [b]	(2.73) [a]	(2.49) [b]	(2.75) [a]	(2.52) [b]	(3.55) [a]	(2.14) [b]	(3.54) [a]	(2.19) [b]	(3.57) [a]	(2.26) [b]
η		0.07		0.06		0.06		-0.04		-0.04		-0.04		0.07		0.06		0.05
		(1.09)		(1.03)		(1.04)		(-1.82) [c]		(-1.69)		(-1.64)		(1.75) [c]		(1.51)		(1.47)
θ	0.84	0.84	0.85	0.85	0.85	0.84	0.93	0.96	0.93	0.96	0.94	0.96	0.87	0.89	0.88	0.89	0.88	0.89
	(15.96) [a]	(15.63) [a]	(17.22) [a]	(16.55) [a]	(16.71) [a]	(16.04) [a]	(41.56) [a]	(57.40) [a]	(41.22) [a]	(56.68) [a]	(49.84) [a]	(66.59) [a]	(22.95) [a]	(26.81) [a]	(25.77) [a]	(29.22) [a]	(26.10) [a]	(29.25) [a]
$\gamma+\eta/2+\theta$	0.965	0.970	0.968	0.969	0.967	0.968	0.973	0.981	0.976	0.980	0.976	0.980	0.969	0.979	0.970	0.974	0.971	0.974
AIC	-4.235	-4.236	-4.235	-4.235	-4.234	-4.234	-5.045	-5.049	-5.046	-5.048	-5.048	-5.048	-3.469	-3.472	-3.472	-3.473	-3.473	-3.473

Panel B: C/P Portfolios

	High						Low						HML					
	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
a (%)	0.31	0.31	-0.16	-0.16	0.04	0.04	-0.14	-0.12	0.55	0.45	0.24	0.20	0.47	0.44	-0.63	-0.57	-0.17	-0.18
	(2.52) [b]	(2.88) [a]	(-0.32)	(-0.33)	(0.16)	(0.18)	(-1.82) [c]	(-1.52)	(1.97) [b]	(1.65)	(1.58)	(1.26)	(2.81) [a]	(2.69) [a]	(-0.91)	(-0.82)	(-0.47)	(-0.50)
β_m	0.95	0.95	0.95	0.95	0.95	0.95	1.16	1.16	1.15	1.16	1.15	1.16	-0.20	-0.20	-0.19	-0.20	-0.19	-0.19
	(29.77) [a]	(29.16) [a]	(29.42) [a]	(29.33) [a]	(29.64) [a]	(29.64) [a]	(53.90) [a]	(54.81) [a]	(52.71) [a]	(53.41) [a]	(52.67) [a]	(53.14) [a]	(-4.03) [a]	(-3.89) [a]	(-3.73) [a]	(-3.69) [a]	(-3.73) [a]	(-3.68) [a]
β_{SMB}	0.16	0.16	0.16	0.16	0.16	0.15	0.07	0.07	0.08	0.08	0.08	0.08	0.07	0.08	0.06	0.07	0.06	0.07
	(3.84) [a]	(3.57) [a]	(3.71) [a]	(3.43) [a]	(3.71) [a]	(3.43) [a]	(2.32) [b]	(2.52) [b]	(2.58) [a]	(2.67) [a]	(2.52) [b]	(2.62) [a]	(1.11)	(1.26)	(0.94)	(1.10)	(0.94)	(1.09)
δ			0.20	0.20					-0.38	-0.32					0.30	0.27		
			(0.97)	(1.00)					(-2.43) [b]	(-2.10) [b]					(1.59)	(1.49)		
ν					4.64	4.66					-10.62	-9.12					4.50	4.35
					(1.22)	(1.24)					(-2.50) [b]	(-2.18) [b]					(1.87) [c]	(1.84) [c]
w (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(2.35) [b]	(2.32) [b]	(2.34) [b]	(2.34) [b]	(2.35) [b]	(2.34) [b]	(2.29) [b]	(1.95) [c]	(2.16) [b]	(2.16) [b]	(2.60) [a]	(2.30) [b]	(2.32) [b]	(2.15) [b]	(2.30) [b]	(2.36) [b]	(2.29) [b]	(2.37) [b]
γ	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.10	0.08	0.09	0.07	0.09	0.08	0.05	0.08	0.05	0.08	0.05
	(2.60) [a]	(1.79) [c]	(2.69) [a]	(1.96) [b]	(2.72) [a]	(1.98) [b]	(3.24) [a]	(3.14) [a]	(3.36) [a]	(3.13) [a]	(3.39) [a]	(3.18) [a]	(2.86) [a]	(1.36)	(2.98) [a]	(1.52)	(3.01) [a]	(1.51)
η		0.00		-0.01		-0.01		-0.05		-0.04		-0.04		0.05		0.04		0.04
		(-0.02)		(-0.08)		(-0.09)		(-1.38)		(-1.05)		(-1.06)		(0.95)		(0.82)		(0.82)
θ	0.89	0.89	0.89	0.89	0.89	0.89	0.90	0.91	0.90	0.91	0.90	0.91	0.90	0.91	0.89	0.90	0.90	0.91
	(24.12) [a]	(26.79) [a]	(24.78) [a]	(26.46) [a]	(25.55) [a]	(26.93) [a]	(32.86) [a]	(33.62) [a]	(33.91) [a]	(34.94) [a]	(36.72) [a]	(36.65) [a]	(30.38) [a]	(32.60) [a]	(30.98) [a]	(33.54) [a]	(32.37) [a]	(34.99) [a]
$\gamma+\eta/2+\theta$	0.967	0.968	0.968	0.969	0.969	0.970	0.975	0.984	0.978	0.980	0.978	0.980	0.976	0.980	0.975	0.976	0.977	0.976
AIC	-4.507	-4.503	-4.505	-4.501	-4.507	-4.503	-4.981	-4.983	-4.987	-4.986	-4.987	-4.986	-3.591	-3.591	-3.593	-3.591	-3.595	-3.594

	High						Low						HML					
	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
a (%)	0.35	0.29	-0.61	-0.58	-0.06	-0.14	-0.09	-0.08	0.75	0.75	0.31	0.31	0.38	0.34	-1.49	-1.43	-0.41	-0.41
	(3.22) [a]	(2.74) [a]	(-1.15)	(-1.08)	(-0.24)	(-0.61)	(-1.11)	(-0.90)	(2.44) [b]	(2.50) [b]	(1.92) [c]	(1.98) [b]	(2.29) [b]	(2.01) [b]	(-2.16) [b]	(-2.10) [b]	(-1.22)	(-1.25)
β_m	1.00	0.98	1.00	0.98	1.00	0.98	1.13	1.13	1.12	1.13	1.12	1.13	-0.10	-0.12	-0.09	-0.10	-0.10	-0.11
	(32.74) [a]	(27.28) [a]	(32.33) [a]	(27.42) [a]	(32.23) [a]	(26.22) [a]	(43.82) [a]	(43.72) [a]	(43.19) [a]	(43.19) [a]	(43.37) [a]	(43.46) [a]	(-1.96) [c]	(-2.11) [b]	(-1.77) [c]	(-1.90) [c]	(-1.80) [c]	(-1.93) [c]
β_{SMB}	0.26	0.27	0.25	0.26	0.25	0.26	0.12	0.12	0.13	0.13	0.13	0.13	0.12	0.12	0.11	0.11	0.11	0.11
	(6.27) [a]	(6.21) [a]	(6.01) [a]	(6.00) [a]	(6.03) [a]	(5.86) [a]	(3.70) [a]	(3.81) [a]	(3.86) [a]	(3.93) [a]	(3.83) [a]	(3.89) [a]	(1.89) [c]	(1.92) [c]	(1.65)	(1.68)	(1.68)	(1.67)
δ			0.41	0.38					-0.43	-0.42					0.50	0.48		
			(1.87) [c]	(1.70) [c]					(-2.72) [a]	(-2.73) [a]					(2.77) [a]	(2.70) [a]		
ν					6.99	7.65					-9.62	-9.37					5.28	5.10
					(1.91) [c]	(2.18) [b]					(-2.67) [a]	(-2.67) [a]					(2.66) [a]	(2.65) [a]
w (%)	0.01	0.00	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01
	(2.58) [b]	(2.27) [b]	(2.51) [b]	(2.63) [a]	(2.55) [b]	(2.98) [a]	(1.96) [c]	(1.67)	(1.88) [c]	(1.91) [c]	(1.91) [c]	(1.92) [c]	(2.56) [b]	(2.29) [b]	(2.55) [b]	(2.65) [a]	(2.60) [a]	(2.68) [a]
γ	0.13	0.02	0.13	0.02	0.13	0.00	0.10	0.12	0.09	0.11	0.09	0.10	0.10	0.06	0.10	0.07	0.10	0.07
	(2.53) [b]	(0.75)	(2.64) [a]	(0.65)	(2.61) [a]	(0.19)	(4.23) [a]	(3.44) [a]	(4.12) [a]	(3.53) [a]	(4.17) [a]	(3.57) [a]	(2.94) [a]	(1.84) [c]	(3.21) [a]	(2.21) [b]	(3.18) [a]	(2.16) [b]
η		0.16		0.15		0.17		-0.04		-0.03		-0.03		0.07		0.05		0.05
		(2.32) [b]		(2.46) [b]		(2.70) [a]		(-0.97)		(-0.80)		(-0.74)		(1.45)		(1.17)		(1.24)
θ	0.80	0.85	0.80	0.84	0.80	0.83	0.88	0.89	0.89	0.89	0.89	0.90	0.87	0.88	0.86	0.87	0.87	0.87
	(14.50) [a]	(18.82) [a]	(14.50) [a]	(18.14) [a]	(14.75) [a]	(19.37) [a]	(34.34) [a]	(34.81) [a]	(36.14) [a]	(36.44) [a]	(37.61) [a]	(37.94) [a]	(27.05) [a]	(27.69) [a]	(27.44) [a]	(28.11) [a]	(28.57) [a]	(29.36) [a]
$\gamma+\eta/2+\theta$	0.928	0.949	0.926	0.928	0.927	0.918	0.982	0.987	0.983	0.983	0.983	0.984	0.971	0.978	0.969	0.968	0.970	0.969
AIC	-4.482	-4.497	-4.486	-4.500	-4.488	-4.504	-4.788	-4.786	-4.799	-4.796	-4.798	-4.796	-3.516	-3.516	-3.529	-3.527	-3.529	-3.528

Table title: Panel C: E/P Portfolios

Panels B and C of Table 4.6 show estimates for the C/P- and E/P-sorted portfolios. The value and growth portfolios for both value measures load heavily on small capitalization stocks. For the HML portfolio, the β_{SMB} coefficients are statistically insignificant at the 5% level. In addition, the alphas are almost the same between the models with and without the size factor. Therefore, we conclude that there is no size effect in the value premium when it is defined using C/P and E/P. The AIC results also confirm our conclusion since the AIC of Model 6 is -3.598 in Table 4.5 and -3.595 in Table 4.6 for the C/P HML portfolio; and it is -3.528 in Table 4.5 and -3.529 in Table 4.6 for the E/P HML portfolio.

4.5. UK Evidence

Using US data, we show above that the 1963-2006 value premium can be fully explained by the conditional model incorporating a GARCH-in-mean specification. However, in order to ensure that these results are not an artifact unique to this market, in this section we conduct a comparison in which we reapply the models to the UK market.

Table 4.7 reports summary statistics for monthly returns on the UK value, growth and HML portfolios. Consistent with the US evidence, we find that the value premia in returns are 0.5%, 0.42% and 0.36% per month for the B/M, C/P and E/P HML portfolios respectively. The value premium based on B/M is statistically significant at the 5% level. The average unconditional standard deviation of the value portfolio is similar to that of the growth portfolio. For instance, the average standard deviation equals 5.22% per month for the B/M value portfolio and 5.26% per month for the

Table 4.7. Summary statistics for monthly returns on UK value, growth and HML portfolios

This table reports the monthly mean returns (%), standard deviations (Std Dev, %) and *t*-statistics for the significance of the mean for the UK value-weighted portfolios. B/M is the ratio of the book value of equity to market value of equity; C/P is the ratio of cash flow to market value of equity; E/P is the ratio of earnings to market value of equity. At the end of December each year, all stocks listed on the UK stock market are ranked into 3 groups based on the ratios of B/M, C/P and E/P. For the B/M (C/P and E/P) portfolios, High represents a value portfolio containing stocks in the top 40% (30%) of a ratio. Low represents a growth portfolio containing stocks in the bottom 40% (30%) of a ratio. HML (high minus low) is a portfolio with the average returns on the value portfolio minus the average returns on the growth portfolio. The sample period for B/M portfolios runs from January 1963 to December 2001 and for C/P and E/P portfolios it runs from January 1975 to December 2002. The *t*-statistics in parentheses are based on Newey-West standard errors. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels for a two-sided test.

	B/M Portfolio			C/P Portfolio			E/P Portfolio		
	High	Low	HML	High	Low	HML	High	Low	HML
Mean (%)	1.65	1.15	0.50	1.83	1.41	0.42	1.79	1.43	0.36
t-statistic	(6.86) [a]	(4.74) [a]	(4.92) [a]	(5.10) [a]	(4.17) [a]	(1.89) [c]	(5.12) [a]	(4.21) [a]	(1.90) [c]
Std Dev (%)	5.22	5.26	2.21	6.58	6.14	4.10	6.42	6.16	3.55

B/M growth portfolio. Thus the UK results again confirm that the value premium is not a compensation for total unconditional risk.

OLS estimates of the static CAPM for the UK B/M, C/P and E/P portfolios are presented in Table 4.8. The alpha estimates for the B/M, C/P and E/P HML portfolios are 0.52%, 0.77% and 0.60% per month respectively; all of these are significant at the 5% level. These results provide comparative evidence that the static CAPM is also rejected for the UK value premium. The CAPM betas of the HML portfolios are also statistically insignificant.

Table 4.8. Estimates of the static CAPM for UK value, growth and HML portfolios

The table reports coefficient estimates of the static CAPM, given by

$$r_{Pt} = \alpha + \beta_m (R_{mt} - R_{ft}) + \varepsilon_{Pt}$$

where r_{Pt} is either the excess returns on value and growth portfolios or the return on the high-minus-low portfolio, R_{mt} is the value-weighted return on the market portfolio of all assets, R_{ft} is the three-month Treasury bill rate. α (%) measures the abnormal performance of the portfolio; β_m measures the market risk of the portfolio, R^2 is used to assess the goodness-to-fit of the model. At end of December each year, all stocks listed in the UK stock market are ranked into 3 groups based on the ratios of B/M, C/P and E/P. B/M is the ratio of the book value of equity to market value of equity; C/P is the ratio of cash flow to market value of equity; E/P is the ratio of earnings to market value of equity. For the B/M (C/P and E/P) portfolios, High represents a value portfolio containing stocks in the top 40% (30%) of a ratio. Low represents a growth portfolio containing stocks in the bottom 40% (30%) of a ratio. HML (high minus low) is a portfolio with the average returns on the value portfolio minus the average returns on the growth portfolio. The sample period for B/M portfolios runs from January 1963 to December 2001 and for C/P and E/P portfolios it runs from January 1975 to December 2002. White's heteroskedasticity robust *t*-statistics are in parentheses. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels for a two-sided test.

	B/M Portfolio			C/P Portfolio			E/P Portfolio		
	High	Low	HML	High	Low	HML	High	Low	HML
α (%)	0.45	-0.07	0.52	0.44	-0.34	0.77	0.41	-0.19	0.60
	(4.57) [a]	(-0.90)	(5.09) [a]	(1.97) [b]	(-2.28) [b]	(2.39) [b]	(2.05) [b]	(-1.55)	(2.09) [b]
β_m	0.87	0.91	-0.03	1.02	0.97	0.05	1.02	0.99	0.03
	(47.60) [a]	(45.45) [a]	(-1.71) [c]	(55.26) [a]	(66.96) [a]	(1.64)	(54.05) [a]	(77.95) [a]	(1.15)
R^2	0.84	0.89	0.01	0.86	0.92	0.01	0.89	0.95	0.00

Table 4.9. LM tests for ARCH in the residuals of the static CAPM

The table reports the autoregressive conditional heteroskedasticity (ARCH) Lagrange Multiplier (LM) test statistics, which are asymptotically distributed as χ_5^2-variates under the null hypothesis that there is no ARCH of order up to 5 in the residuals of the static CAPM. At end of December each year, all stocks listed on the UK stock market are ranked into 3 groups based on the ratios of B/M, C/P and E/P. B/M is the ratio of the book value of equity to market value of equity; C/P is the ratio of cash flow to market value of equity; E/P is the ratio of earnings to market value of equity. For the B/M (C/P and E/P) portfolios, High represents a value portfolio containing stocks in the top 40% (30%) of a ratio. Low represents a growth portfolio containing stocks in the bottom 40% (30%) of a ratio. HML (high minus low) is a portfolio with the average returns on the value portfolio minus the average returns on the growth portfolio. The sample period for B/M portfolios runs from January 1963 to December 2001 and for C/P and E/P portfolios it runs from January 1975 to December 2002. *p*-values are presented in parentheses.

	B/M Portfolio			C/P Portfolio			E/P Portfolio		
	High	Low	HML	High	Low	HML	High	Low	HML
LM test statistic	20.76	163.58	71.99	21.30	13.64	11.76	32.28	12.20	14.25
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.04)	(0.00)	(0.03)	(0.01)

In order to examine the statistical validity of the static CAPM for UK data, the ARCH-LM statistics and their associated *p*-values are presented in Table 4.9. The results show that all the UK value, growth and HML portfolios, whether they are sorted on B/M, C/P or E/P, have ARCH effects in their errors since the LM statistics are statistically significant at the 5% level or better in all cases. Therefore, using the static CAPM to explain the returns on the value, growth and HML portfolios could lead to misleading inferences.

Table 4.10 presents the parameter estimates for Models 2 to 7 for the UK value, growth and HML portfolios. Overall, the UK results fully support the conclusions from the US data. The CAPM betas of the value and growth portfolios are almost the same; both of them are positive and significant at the 1% level, confirming that beta plays an important role in explaining the temporal returns on the individual value and growth portfolios. However, it cannot explain the value premium since the betas of the HML portfolios are statistically insignificant at the 5% level. The time-varying risk premium coefficients, δ and v, of Models 4 to 7 are positive for the value portfolio and negative for the growth portfolio, suggesting that the value portfolio is more risky than the growth portfolio. The most interesting result is that the GARCH-M models with either the standard deviation or the variance specifications (Models 4 to 7) are able to capture the temporal variation in returns on the value and growth portfolios. The models are also able to explain the value premium since with only one exceptions (the B/M value portfolio from Model 4), the hypothesis that $\alpha = 0$ is uniformly supported at the 5% level for the value, growth and HML portfolios whatever method is used for defining value. The AIC results show that the CAPM with GJR-GARCH (1, 1) - M (SD) specification is the preferred model for the B/M HML portfolio and the CAPM with (GJR-) GARCH (1, 1)-M (V) specification should be chosen for the C/P and E/P HML portfolios.

4.6. Analysis of Results

Our results are in support of the explanation that the HML premium is a compensation for the time-varying idiosyncratic risk inherent in the value-minus-growth portfolio. Thus, while the CAPM in both its conditional and unconditional forms provided insufficient explanatory power, this may have arisen

Table 4.10. Estimates of the conditional model with GARCH specifications for the UK value premium

The table reports coefficient estimates for Models 2 through 7 for value, growth and HML portfolios. The models are defined by:
where $\varepsilon_{Pt} \sim \left(0, \sigma^2_{Pt}\right)$, r_{Pt} is either the excess returns for value, growth portfolios or the return on the HML portfolio, R_{mt} is the value-weighted return on

$$r_{Pt} = \alpha + \beta_m \left(R_{Mt} - R_{ft}\right) + \delta\sigma_{Pt} + v\sigma^2_{Pt} + \varepsilon_{Pt}$$
$$\sigma^2_{Pt} = \omega + \gamma\varepsilon^2_{Pt-1} + \eta I_{t-1}\varepsilon^2_{Pt-1} + \theta\sigma^2_{Pt-1}$$

the market portfolio of all assets, R_{ft} is the three-month Treasury bill rate. α (%) measures the abnormal performance of the portfolio; β_m measures the market risk of the portfolio; $\delta\sigma_{Pt}$ and $v\sigma^2_{Pt}$ (with either $\delta = 0$ or $v = 0$) are the competing measures of time-varying risk exposures; ω, γ, η and θ are estimated parameters and $\omega > 0$, $0 < \gamma < 1$, $0 \leq \theta < 1$, $\gamma + \eta/2 + \theta < 1$, I_{t-1} takes a value of 1, when ε_{t-1} is negative and a value of 0 otherwise. At end of December each year, all stocks listed on the UK stock market are ranked into 3 groups based on the ratios of B/M, C/P and E/P. B/M is the ratio of the book value of equity to market value of equity; C/P is the ratio of cash flow to market value of equity; E/P is the ratio of earnings to market value of equity. For the B/M (C/P and E/P) portfolios, High represents a value portfolio containing stocks in the top 40% (30%) of a ratio. Low represents a growth portfolio containing stocks in the bottom 40% (30%) of a ratio. HML (high minus low) is a portfolio with the average returns on the value portfolio minus the average returns on the growth portfolio. The sample period for B/M portfolios runs from January 1963 to December 2001 and for C/P and E/P portfolios it runs from January 1975 to December 2002. Akaike's information criterion (AIC) is based on the maximized value of the log-likelihood functions and is used to select the preferred model, which will be the one with the lowest value. Bollerslev-Wooldridge robust t-statistics are in parentheses. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels for a two-sided test.

Panel A: B/M Portfolios

	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
a (%)	0.38	0.35	-1.01	-0.60	-0.22	-0.04	-0.04	-0.03	0.18	0.16	0.06	0.05	0.47	0.45	-0.41	-0.11	0.08	0.24
	(4.87) ^{a}	(4.27) ^{a}	(-2.37) ^{b}	(-1.65)	(-1.09)	(-0.23)	(-0.76)	(-0.49)	(0.76)	(0.67)	(0.52)	(0.50)	(6.12) ^{a}	(5.62) ^{a}	(-1.47)	(-0.34)	(0.56)	(1.93) ^{c}
β_m	0.88	0.89	0.88	0.89	0.88	0.89	0.90	0.89	0.89	0.89	0.89	0.89	-0.02	-0.02	-0.03	-0.03	-0.03	-0.02
	(54.19) ^{a}	(53.44) ^{a}	(54.80) ^{a}	(54.77) ^{a}	(54.28) ^{a}	(54.45) ^{a}	(64.29) ^{a}	(63.30) ^{a}	(64.60) ^{a}	(63.73) ^{a}	(64.57) ^{a}	(63.77) ^{a}	(-1.60)	(-1.56)	(-1.64)	(-1.65)	(-1.61)	(-1.59)
δ			0.71	0.50					-0.16	-0.14					0.51	0.33		
			(3.23) ^{a}	(2.54) ^{b}					(-0.97)	(-0.81)					(3.15) ^{a}	(1.78) ^{c}		
ν					15.27	10.03					-4.76	-4.11					10.13	6.02
					(2.91) ^{a}	(2.27) ^{b}					(-1.04)	(-0.88)					(2.62) ^{a}	(1.77) ^{c}
w (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(1.44)	(1.16)	(1.47)	(1.38)	(1.42)	(1.36)	(1.93) ^{c}	(1.83) ^{c}	(1.87) ^{c}	(1.84) ^{c}	(1.86) ^{c}	(1.83) ^{c}	(1.74) ^{c}	(1.75) ^{c}	(1.81) ^{c}	(1.91) ^{c}	(1.77) ^{c}	(1.88) ^{c}
γ	0.13	0.05	0.11	0.07	0.11	0.06	0.12	0.13	0.11	0.12	0.11	0.12	0.16	0.02	0.15	0.05	0.15	0.03
	(3.12) ^{a}	(1.56)	(3.42) ^{a}	(1.85) ^{c}	(3.34) ^{a}	(1.75) ^{c}	(2.62) ^{a}	(2.18) ^{b}	(2.58) ^{b}	(2.12) ^{b}	(2.57) ^{b}	(2.13) ^{b}	(2.74) ^{a}	(0.75)	(2.89) ^{a}	(1.68)	(2.77) ^{a}	(1.25)
η		0.11		0.08		0.08		-0.03		-0.03		-0.02		0.15		0.12		0.13
		(2.18) ^{b}		(1.70) ^{c}		(1.82) ^{c}		(-0.51)		(-0.43)		(-0.41)		(2.27) ^{b}		(2.06) ^{b}		(2.11) ^{b}
θ	0.82	0.87	0.85	0.86	0.85	0.86	0.85	0.86	0.86	0.87	0.86	0.87	0.80	0.87	0.83	0.86	0.83	0.86
	(11.14) ^{a}	(16.15) ^{a}	(15.95) ^{a}	(15.70) ^{a}	(15.29) ^{a}	(16.10) ^{a}	(16.00) ^{a}	(17.49) ^{a}	(17.28) ^{a}	(18.41) ^{a}	(17.31) ^{a}	(18.33) ^{a}	(12.15) ^{a}	(17.73) ^{a}	(16.44) ^{a}	(18.31) ^{a}	(15.19) ^{a}	(18.60) ^{a}
$\gamma+\eta/2+\theta$	0.947	0.981	0.960	0.968	0.959	0.970	0.969	0.973	0.974	0.975	0.974	0.975	0.969	0.968	0.979	0.966	0.977	0.965
AIC	-4.952	-4.968	-4.968	-4.972	-4.966	-4.972	-5.400	-5.497	-5.497	-5.494	-5.498	-5.495	-5.104	-5.134	-5.121	-5.135	-5.115	-5.133

Panel B: C/P Portfolios

	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
a (%)	0.14	0.10	-0.48	-0.41	-0.13	-0.11	-0.27	-0.25	0.52	0.40	0.13	0.09	0.32	0.30	-1.43	-1.33	-0.43	-0.39
	(0.87)	(0.63)	(-1.43)	(-1.34)	(-0.66)	(-0.60)	(-2.45) [b]	(-2.09) [b]	(0.98)	(0.81)	(0.49)	(0.34)	(1.30)	(1.14)	(-1.63)	(-1.61)	(-0.96)	(-0.90)
β_m	0.99	1.00	0.99	0.99	0.99	0.99	0.98	0.97	0.98	0.98	0.98	0.98	0.01	0.01	0.00	0.00	0.00	0.01
	(58.35) [a]	(60.78) [a]	(54.68) [a]	(57.56) [a]	(54.89) [a]	(57.65) [a]	(88.17) [a]	(82.16) [a]	(79.52) [a]	(75.46) [a]	(81.78) [a]	(77.21) [a]	(0.39)	(0.48)	(-0.00)	(0.10)	(0.07)	(0.19)
δ			0.29	0.25					-0.45	-0.37					0.50	0.46		
			(1.95) [c]	(1.76) [c]					(-1.45)	(-1.27)					(2.13) [b]	(2.08) [b]		
ν					5.23	4.39					-12.88	-11.06					5.73	5.26
					(2.04) [b]	(1.82) [c]					(-1.55)	(-1.40)					(2.03) [b]	(1.98) [b]
w (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
	(1.30)	(1.02)	(1.31)	(1.35)	(1.29)	(1.31)	(1.41)	(1.27)	(1.27)	(1.42)	(1.52)	(1.70) [c]	(1.24)	(1.16)	(1.23)	(1.33)	(1.20)	(1.30)
γ	0.20	0.09	0.16	0.08	0.17	0.08	0.07	0.09	0.07	0.09	0.07	0.09	0.13	0.07	0.11	0.07	0.11	0.07
	(3.60) [a]	(1.83) [c]	(3.75) [a]	(1.64)	(3.72) [a]	(1.76) [c]	(2.20) [b]	(1.91) [c]	(2.39) [b]	(2.19) [b]	(2.39) [b]	(2.22) [b]	(2.34) [b]	(1.40)	(2.40) [b]	(1.39)	(2.37) [b]	(1.44)
η		0.13		0.13		0.13		-0.05		-0.05		-0.05		0.08		0.06		0.06
		(2.26) [b]		(2.13) [b]		(2.07) [b]		(-0.88)		(-0.92)		(-0.94)		(1.11)		(1.13)		(1.09)
θ	0.80	0.85	0.83	0.86	0.82	0.85	0.90	0.92	0.90	0.91	0.90	0.91	0.84	0.88	0.87	0.88	0.87	0.88
	(14.51) [a]	(22.99) [a]	(19.29) [a]	(26.12) [a]	(17.92) [a]	(24.71) [a]	(18.62) [a]	(21.34) [a]	(19.06) [a]	(24.28) [a]	(20.56) [a]	(25.97) [a]	(13.18) [a]	(17.67) [a]	(18.16) [a]	(20.63) [a]	(17.06) [a]	(19.81) [a]
$\gamma+\eta/2+\theta$	0.997	0.999	0.992	0.999	0.993	0.999	0.965	0.978	0.969	0.976	0.970	0.975	0.969	0.984	0.978	0.979	0.977	0.978
AIC	-4.556	-4.561	-4.558	-4.562	-4.559	-4.562	-5.200	-5.202	-5.201	-5.202	-5.203	-5.203	-3.704	-3.703	-3.712	-3.711	-3.713	-3.712

Panel C: E/P Portfolios

	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
a (%)	0.33	0.26	-0.03	-0.15	0.15	0.07	-0.12	-0.11	0.25	0.20	0.06	0.04	0.50	0.41	-0.32	-0.42	0.11	0.06
	(2.07) [b]	(1.67)	(-0.08)	(-0.36)	(0.68)	(0.32)	(-1.01)	(-0.92)	(0.49)	(0.40)	(0.24)	(0.14)	(1.94) [c]	(1.64)	(-0.39)	(-0.53)	(0.25)	(0.13)
β_m	1.01	1.01	1.01	1.01	1.01	1.01	1.00	0.99	1.00	0.99	1.00	0.99	0.02	0.02	0.02	0.02	0.02	0.02
	(68.71) [a]	(71.21) [a]	(70.01) [a]	(72.79) [a]	(70.13) [a]	(72.67) [a]	(80.91) [a]	(82.46) [a]	(79.40) [a]	(81.79) [a]	(79.51) [a]	(81.94) [a]	(0.94)	(0.85)	(0.99)	(0.97)	(1.00)	(0.98)
δ			0.19	0.21					-0.27	-0.23					0.27	0.29		
			(0.93)	(1.08)					(-0.81)	(-0.69)					(1.09)	(1.17)		
ν					4.34	4.90					-9.50	-7.85					4.06	3.99
					(1.06)	(1.19)					(-0.88)	(-0.73)					(1.15)	(1.16)
w (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(1.31)	(0.95)	(1.33)	(1.19)	(1.31)	(1.20)	(1.27)	(1.21)	(1.32)	(1.32)	(1.58)	(1.32)	(1.18)	(1.00)	(1.17)	(1.21)	(1.16)	(1.20)
γ	0.11	0.07	0.11	0.06	0.11	0.06	0.08	0.11	0.08	0.11	0.08	0.11	0.09	0.05	0.09	0.05	0.08	0.05
	(3.26) [a]	(1.42)	(3.31) [a]	(1.36)	(3.31) [a]	(1.37)	(2.37) [b]	(2.43) [b]	(2.49) [b]	(2.51) [b]	(2.38) [b]	(2.50) [b]	(3.00) [a]	(1.38)	(3.02) [a]	(1.34)	(3.03) [a]	(1.39)
η		0.08		0.09		0.09		-0.05		-0.05		-0.04		0.07		0.07		0.06
		(1.39)		(1.46)		(1.45)		(-0.87)		(-0.82)		(-0.81)		(1.19)		(1.27)		(1.23)
θ	0.87	0.88	0.87	0.88	0.88	0.88	0.86	0.87	0.86	0.86	0.86	0.86	0.89	0.90	0.89	0.90	0.89	0.90
	(19.60) [a]	(18.77) [a]	(20.91) [a]	(21.48) [a]	(21.14) [a]	(21.80) [a]	(13.74) [a]	(12.49) [a]	(14.16) [a]	(13.22) [a]	(14.51) [a]	(13.05) [a]	(19.97) [a]	(21.84) [a]	(20.93) [a]	(24.22) [a]	(21.02) [a]	(24.13) [a]
$\gamma+\eta/2+\theta$	0.982	0.990	0.983	0.986	0.983	0.986	0.947	0.948	0.946	0.945	0.946	0.945	0.974	0.985	0.976	0.980	0.976	0.980
AIC	-4.781	-4.783	-4.782	-4.784	-4.783	-4.784	-5.642	-5.639	-5.643	-5.641	-5.644	-5.641	-3.952	-3.952	-3.952	-3.953	-3.952	-3.954

because it embodies the wrong measure of risk, and it is in fact idiosyncratic rather than systematic risk that holds the key. This explanation follows from viewing the firm's equity as a call option on the value of its assets (Merton, 1974). Applying Merton's theory of the firm to our present setting helps us understand the positive relationship that we identified between the idiosyncratic risk of value stocks and their average returns. Since value stocks present characteristics that one naturally would associate with financial distress (Chang and Zhang, 1998), one can argue that value managers, who own a call option on the value of the firm, may select risky projects with excessive idiosyncratic risk in an attempt to resurrect their company. Indeed, if the high risk projects turn out to be a success, the shareholders will enjoy the profits. However, in case of distress, the shareholders can invoke their limited liability and thus will not bear the downside risks. This could legitimate our finding that the premium on value stocks is a compensation for excessive time-varying idiosyncratic risk. Along the same lines, since growth companies face a lower probability of default (Chang and Zhang, 1998), growth shareholders have contingent claims on the firm's assets that are relatively less valuable than their value peers. As a result and in line with our finding, they are less likely to excessively increase the idiosyncratic risk of the firm by undertaking projects with high earning risks and consequently demand a lower premium on their equity claim.

Alternatively, it may be that while the value and growth portfolios comprise sufficiently large numbers of stocks that most academics and market practitioners would consider them well diversified, the compositions are not proportionately stratified from an industrial perspective. It is widely known that value portfolios tend to attach disproportionately large weights to utilities, mining, and basic manufacturing companies whereas growth portfolios imply disproportionately large bets on technology, software, advertising and pharmaceutical companies, for example. To the extent that the compositions of the value and growth portfolios have changed over time, an increasing polarization in the nature of value and growth companies may have occurred in a way that is unrelated to the CAPM beta, leading to a non-trivial level of unsystematic risk in these two portfolios that has not been fully diversified away, and which is thus priced in the market.

4.7. Conclusions

The puzzle that the static CAPM fails to capture the post-1963 value premium, variously defined, has been a concern in the financial literature for over a decade. This chapter examines the value premium by assuming that the conditional variance of portfolio returns follows a GARCH-M process. Our results show that this specification can fully explain the value premium and hence the premium can be viewed as a compensation for time-varying idiosyncratic risk. These findings are supported by different characteristics of value and growth stocks and by the use of data from the US and UK stock markets. Our results confirm that the size effect can explain part of the value premium when it is defined using B/M, but it does not account for the value premium defined by C/P and E/P.

The results show that the value portfolio appears to have a higher time-varying risk premium than the growth portfolio, suggesting that the value portfolio is riskier than the growth portfolio in terms of time-varying risk. However, the value portfolio has less market risk than the growth portfolio after taking account of total time-varying risk. The CAPM beta has strong explanatory power for the value and growth portfolios, but it fails to explain the value premium.

We conjecture that the importance of time-varying total risk in explaining the value premium may arise from its ability to capture the idiosyncratic risk present in the value and growth portfolios. Our results are indeed consistent with the idea that, because value stocks are more distressed than their growth counterparts, value managers are more likely to gamble for survival by undertaking projects with high earnings risks. This could translate as in our setting into higher conditional idiosyncratic risks, and thus into a higher risk premium on value stocks.

Chapter 5. Trading Costs for Momentum Strategies

5.1. Introduction

As discussed in Chapters 2 and 3, an increasing literature reports that momentum strategies which buy stocks with the best past performance and sell stocks with the worst past performance generate significant abnormal returns (see Jegadeesh and Titman, 1993, 2001; Rouwenhorst, 1998 and Chan, Jegadeesh and Lakonishok, 1996). The profitability of momentum strategies has also been shown to be predictable by a number of factors, such as the cross-sectional variation in expected returns, industry, trading volume, the business cycle, liquidity risk and trading costs (see, for example, Conrad and Kaul, 1998; Moskowitz and Grinblatt, 1999; Lee and Swaminathan, 2000; Chordia and Shivakumar, 2002; Sadka, 2006; Lesmond, Schill and Zhou, 2004 and Korajczyk and Sadka, 2004). We also find in Chapter 3 that time-varying idiosyncratic risk play an important role in explaining the momentum returns. Among these factors, trading cost is often regarded as one of the most important predictors.

The majority of early studies on momentum (see, for example, Jegadeesh and Titman, 1993; Rouwenhorst, 1998; Moskowitz and Grinblatt, 1999 and Liu, Strong and Xu, 1999) assume a round-trip cost of up to 2% and conclude that momentum profits are large enough to be exploited after taking trading costs into account. However, recent evidence has made it clear that the profitability of momentum strategies very much depends on the size and the constituents of transaction costs. Grundy and Martin (2001), for example, show that a round-trip cost in excess of 1.5% does wipe out the profitability of momentum strategies. Lesmond, Schill and Zhou (2004) explain that the losers, and to a lesser extent the winners, are heavily tilted towards off-NYSE stocks with small capitalization and low price, suggesting therefore that the long-short portfolios comprise stocks with low liquidity and high trading costs.[22] Looking at a battery of transaction costs,[23] they conclude that the alleged momentum profits are an illusion. Once these costs are taken into account, the so-called profits disappear. However, their finding is recently questioned by Hanna and Ready (2005), who found that both equally-weighted and value-weighted momentum strategies can earn significant excess returns after trading costs. Korajczyk and Sadka (2004) also study the impact of transaction costs on momentum profits. Unlike Lesmond, Schill and Zhou (2004), they conclude that the abnormal performance of equally- and value-weighted momentum portfolios exceed proportional transaction costs (such as effective or quoted spreads). Yet these abnormal returns quickly decline with the price impact of trading. In effect, the profits of equally- and value-weighted momentum strategies do persist but only for relatively small investment mandates (of less than $200 million and $2 billion, respectively).[24] Finally, Ali and Trombley (2006) relate momentum profits to short sales constraints and show that the later are important in explaining why momentum profits are not arbitraged away. Altogether, the evidence suggests that transaction costs are substantially higher than initially thought, calling into question the net profitability of relative-strength strategies.

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[22] Several US studies find that trading costs are associated with the market capitalization of stocks whereby small stocks have higher trading costs than large stocks (see Chan and Lakonishok, 1995, 1997; Bessembinder and Kaufman, 1997; Keim and Madhavan, 1997). For example, Chan and Lakonishok (1997) report that an average round-trip cost is 0.9% for large capitalisation stocks and 3.31% for small capitalisation stocks on the NYSE.

[23] Aside from commissions, Lesmond, Schill and Zhou (2004) measure transaction costs via quoted spreads, direct effective spreads, the effective spread of Roll (1984) and the limited dependent variable estimate of Lesmond, Ogden and Trzcinka (1999) which incorporates not only the spread component of transaction costs but also, to some extent, the commissions, short sale costs and price impact.

[24] The alphas are less likely to be wiped out by price impact costs when stocks in the long-short portfolios are weighted according to their price impact itself. $5 billion needs then to be invested in the liquidity-weighted momentum strategy for the profits to disappear.

We contribute to the literature on the impact of transaction costs on the profitability of long-short strategies in three ways. First, while the studies of Lesmond, Schill and Zhou (2004) and Hanna and Ready (2005) look at the net profits of one momentum strategy in the US, we analyze in this chapter the robustness of their conclusions to 9 combinations of ranking and holding periods in the UK. Like Lesmond, Schill and Zhou (2004) for the US, we show for the UK that the loser portfolios, and to a lower extent the winner portfolios, are heavily tilted towards low capitalization stocks with low price and low trading volume. As a result, the average round-trip quoted spread for the losers are much higher than once thought (3.76%) and greatly exceed those of the winners (2.21%). When commissions, short selling costs and stamp duties are added, the average round-trip transaction cost based on the quoted spread rises to 3.77% for winners and 6.71% for losers. Once actual transaction costs are taken into account, the alleged momentum profits disappear.

Our second contribution relates to a detailed consideration of the reasons behind the relatively high trading costs of losers. A number of US studies report that stock prices respond differently between buyer- and seller-initiated trades (see, for example, Kraus and Stoll, 1972; Holthausen, Leftwich and Mayers, 1987; Chan and Lakonoshok, 1993 and Keim and Madhavan, 1996). We analyze the observed asymmetry in the trading costs of winners and losers by decomposing each round-trip trade into buyer- or seller-initiated trades. This seems important since a long position in a winner stock will necessarily end with the stock being sold when the long position is closed out. Similarly, a short position in a loser stock will necessarily end with that stock being bought back when the short position is closed. The distinction between buyer- and seller-initiated trades proves to be important as it sheds some light on the asymmetric pattern in transaction costs between winners and losers. Losers are more expensive than winners because of selling costs that are on average 2.3 times higher: selling a loser costs about 2.67% on average, while selling a winner costs only 1.18%. A closer analysis of the factors that impact the costs of buyer- and seller-initiated trades for winners and losers reveals that losers with low capitalization and low trading volume are particularly expensive to sell.

Our third contribution relates to a new type of relative-strength strategy. We term this a low-cost momentum strategy, which selects L% (L=10, 20, 50, 80 and 90) of winner and loser stocks with the lowest total trading costs – namely, the stocks that are the cheapest to trade. Based on actual turnover, low-cost relative-strength strategies that select the 10% and 20% of winners and losers with the lowest effective spreads generate positive and significant net average returns of 19.10% and 15.53%, respectively. Even after adjusting for market risk and Fama and French three risk factors, low-cost momentum strategies with L = 10% and L = 20% still can produce positive and significant net abnormal returns at the 5% level. This chapter therefore severely questions the profitability of standard momentum strategies but concludes that there is still room for momentum-based return enhancement, should asset managers decide to adopt low-cost momentum strategies.

The rest of the chapter is organized as follows. Section 5.2 describes the data. Section 5.3 presents the methodology and some preliminary results on the relationship between size and transaction costs. The three following sections present our results with Section 5.4 focusing on an extension of the Lesmond, Schill and Zhou (2004) to the UK, Section 5.5 analyzing the reason behind the asymmetry in trading costs between losers and winners and Section 5.6 focusing on the low-cost momentum strategies that we propose. Finally, Section 5.7 presents some concluding remarks.

5.2. Data

Our sample covers the period 31 December 1985 – 31 December 2005. All data are obtained from Primark Datastream. In order to avoid survivorship bias, we first construct a list of all the UK companies that are part of the LSPD over the sample period. Following Fama and French (1992), we exclude financial companies from our sample. This deletion is implemented for two reasons: first, to avoid double counting of the companies in which the financial institutions invest; and second, to preserve the momentum returns (since most financial institutions trade on large market indices, they belong neither to the winner portfolio nor to the loser portfolio and including them may thus dilute momentum profits). We also exclude from our sample the lowest 5% of shares by market capitalization in any given year and the companies with mid-prices that are less than 5p. This is to address the concern that the momentum profits may be solely driven by these extremely small and illiquid stocks. As noted below, momentum profits persist even after removing these extreme stocks. The treatment of dead stocks follows the method in Chapter 3: delisted stocks are assigned a return of -100% for death types 7, 14, 16, 20 and 21[25] in the LSPD and a return of 0 for other death types such as acquisition, takeovers, mergers, etc.

This process results in a cross-section of 3,520 companies for which we download information on the monthly total return index: the intraday highest (ask) and lowest

[25] These death types represent: liquidation, quotation cancelled for reason unknown, receiver appointed/liquidation, in administration/administrative receivership, and cancelled and assumed valueless.

(bid) prices at the end of each month; the closing price adjusted for capital actions at the end of each month; the monthly market value; and the trading volume – that is, the number of shares that are traded at the end of the month. We also download the same information as above for each of the constituents of the FTSE 100 index and the Alternative Investment Market (AIM[26]) index. The rationale for doing so is to analyze the impact of size on transaction costs in the UK and to compare the characteristics of the winner and loser stocks in terms of size, price and trading volume relative to those of the constituents of a large capitalization index (the FTSE 100 index) and a small capitalization index (the AIM index).

5.3. Methodology and Preliminary Analysis

This section presents the methodology employed to estimate transaction costs. While the purpose of this chapter is to analyze the impact of transaction costs on UK momentum profits, we begin our analysis by looking at the relation between market capitalization and transaction costs in the UK. The idea is to determine the factors that may impact the size of the net momentum profits.

5.3.1. Methodology Used to Estimate Trading Costs

Our analysis of transaction costs includes the bid-ask spread (estimated based on quoted spread and effective spread), commissions, stamp duties and short-selling costs. The estimation procedure is explained below.

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[26] The AIM is a branch of the London Stock Exchange that allows smaller firms to float their shares with more flexibility and with less stringent reporting and other requirements than on the Main Market.

Quoted spread estimate

The quoted bid-ask spread is the simplest measure of trading costs. It is measured as the difference between the quoted ask price and the quoted bid price. Following Chordia, Roll and Subrahmanyam (2000), we measure the proportional quoted spread as

$$Quoted\ Spread = 100 \times \left(\frac{P_{Ait} - P_{Bit}}{P_{Mit}} \right) \quad (1)$$

where P_{Ait} is the ask price, P_{Bit} is the bid price and P_{Mit} is the bid-ask midpoint for asset i on the last trading day of month t. The quoted spread measures the percentage trading cost incurred in a round-trip trade. Due to reporting errors, we filter out and remove stocks with negative quoted spreads and those with quoted spreads greater than 100%. This helps us mitigate the problem of having estimates of trading costs driven by a few winner and loser stocks with extremely high or low spreads.

Effective spread estimate

The effective spread is the difference between the transaction price and the bid-ask midpoint. Lee and Ready (1991) argue that quoted spreads may overstate actual trading costs. The effective bid-ask spread is supposed to provide a more accurate measure of actual trading costs than the quoted spread since it accounts for potential price improvement when market orders are crossed or when specialists "stop" their orders before trades take place. Following Lesmond, Schill and Zhou (2004), the proportional half effective spread is calculated as

$$Half\ effective\ spread = 100 \times \left(\frac{P_{it} - P_{Mit}}{P_{Mit}} \right) \tag{2}$$

where P_{it} is the transaction price for asset i on the last trading day of month t. We follow the algorithm introduced by Lee and Ready (1991) to classify buyer- or seller-initiated trades. The trade is defined as seller-initiated when the transaction price is less than the bid-ask midpoint while it is defined as buyer-initiated when the transaction price is larger than the bid-ask midpoint. The half effective spread measures the percentage trading cost paid in a one-way trade. We compute a round-trip effective spread as the absolute half effective spread for a buyer-initiated trade plus the absolute half effective spread for a seller-initiated trade.

Commissions, stamp duties and short-selling costs

Bid-ask spread is not the only cost associated with trading stocks. Equity investors must pay brokerage commissions as well as certain fees and stamp duties. Commission is measured as a percentage of the total trade value and it generally decreases as the total trade value increases. The following commission charges schedule is obtained from Barclays Stockbrokers[27] for company dealing accounts (see Appendix 1):

Transaction value	Commission
£0-£10,000	1.75% of Trade Value
£10,001-£20,000	1.125% of Trade Value
£20,001-£40,000	0.5% of Trade Value
£40,001-£100,000	0.4% of Trade Value
£100,001+	0.3% of Trade Value
Minimum	£100

[27] http://www.stockbrokers.barclays.co.uk/?category=whatweoffer&usecase=landing48

Aside from commissions, we also consider stamp duty (payable at the rate of 0.5% at the time of dealing on all UK equity purchases) and short-selling costs. Accounting for the impact of short-selling costs on the size of the momentum profits is critical since many studies (among others, Moskowitz and Grinblatt, 1999; Hong, Lim and Stein, 2000 and Ali and Trombley, 2006) suggest that the momentum effect is mainly driven by the losers. We assume a short-selling cost of 1.5% per year, an estimate that is similar to the cost levied by Barclays Stockbrokers. We assume throughout that traders can short-sell loser stocks when they see it fit. While the up-tick rule previously forbade US traders from short selling on a downtick, the Financial Service Authority has never ruled against the practice in the UK. Since short-selling losers is allowed in the UK and is forbidden on a downtick in the US,[28] our UK-based momentum strategy is replicable, while the returns reported in the US over the same period can only be regarded as "paper" profits.

5.3.2. Preliminary analysis: relationship between size and transaction costs

Several US studies (Chan and Lakonishok, 1995, 1997; Bessembinder and Kaufman, 1997 and Keim and Madhavan, 1997) identify market capitalization as one of the most important factors that affect trading costs. Other things being equal, there is a negative relationship between size and transaction costs. As a preliminary step before analyzing the net momentum profits, we study the relationship between size and trading costs in the UK by focusing on the constituents of the FTSE 100 and of the AIM index. Figures 5.1 and 5.2 compare the mean quoted and effective spreads of the constituent stocks of the two indices over time. Consistent with the results of US

[28] The up-tick rule is initially established in 1938 but is abandoned in June 2007 following a gradual reduction in the scope of securities covered. However, the rule applied to all US equities for most of our sample period.

studies, we find that stocks traded on the AIM are more expensive than those traded on the FTSE 100 in terms of both quoted and effective spreads. On average, the mean quoted spread is 3.98% for the constituent stocks of the AIM, ranging from a low of 1.87% to a high of 7.35%; and it is 2.22% on average for the constituent stocks of the FTSE 100, ranging from a low of 0.86% to a high of 6.96%. Similar conclusions are reported for the mean effective spreads. A casual look at Figures 5.1 and 5.2 also suggests that a unique measure of transactions cost will necessarily fail to capture the changing nature of costs over time.

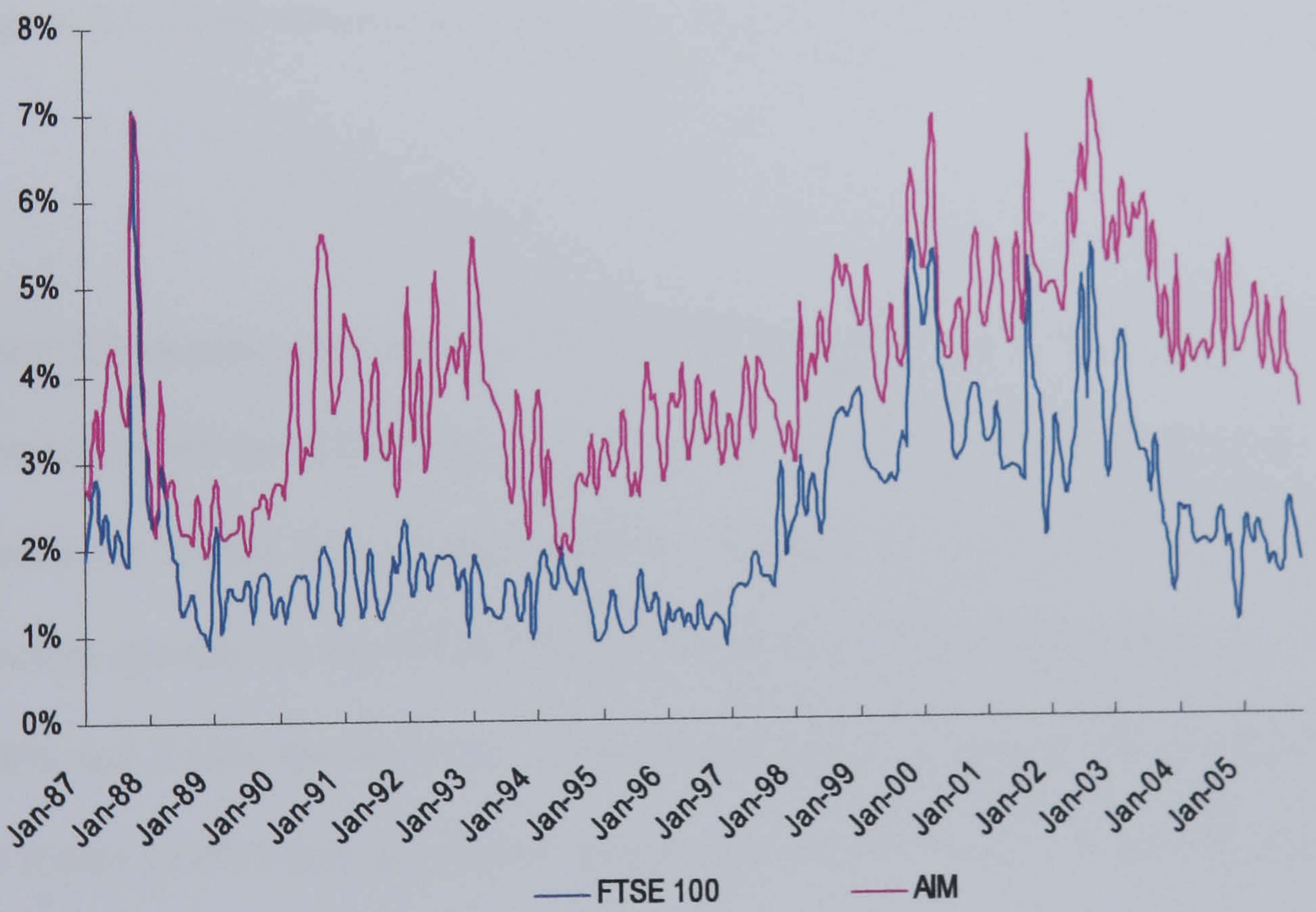

Figure 5.1. Mean quoted spreads for the constituent stocks of the FTSE 100 and the AIM indices over time.

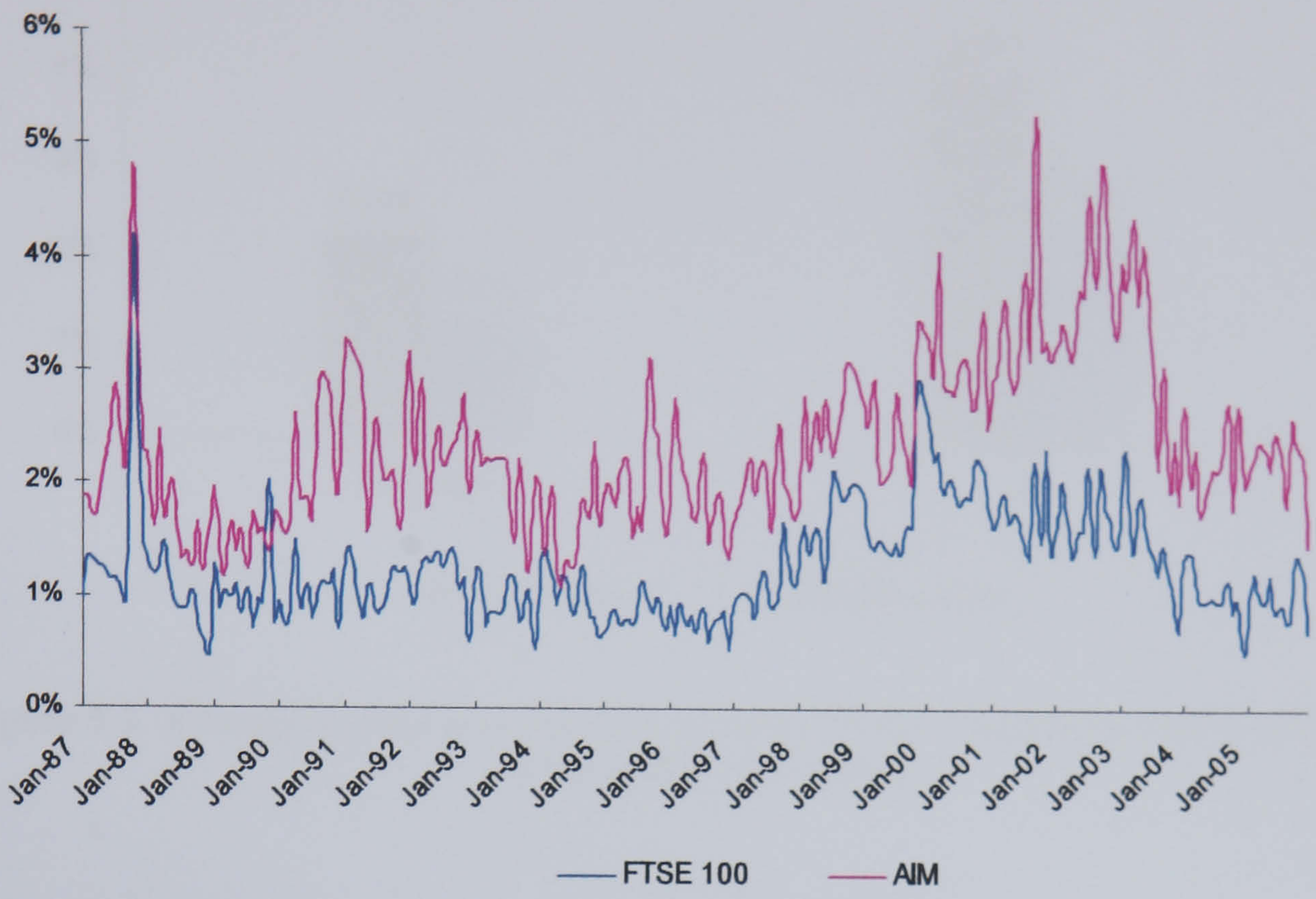

Figure 5.2. Mean effective spreads for the constituent stocks of the FTSE 100 and the AIM indices over time

Figure 5.3 compares the average quoted spreads and average effective spreads of the constituents of the FTSE 100 and the AIM indices. It shows that average quoted spreads are higher than average effective spreads. Indeed, the average quoted and effective spreads for the FTSE 100 are 2.22% and 1.27%, respectively; and they are 3.98% and 2.38% for the AIM. These results appear to support the argument of Lee and Ready (1991) that the quoted spread may overstate the true spread since trades are often executed inside the quoted spread. The overall conclusion from Figures 5.1, 5.2 and 5.3 is that trading costs are not constant over time and are highly negatively correlated to the market capitalization of the stock considered: small cap stocks have higher trading costs than larger stocks.

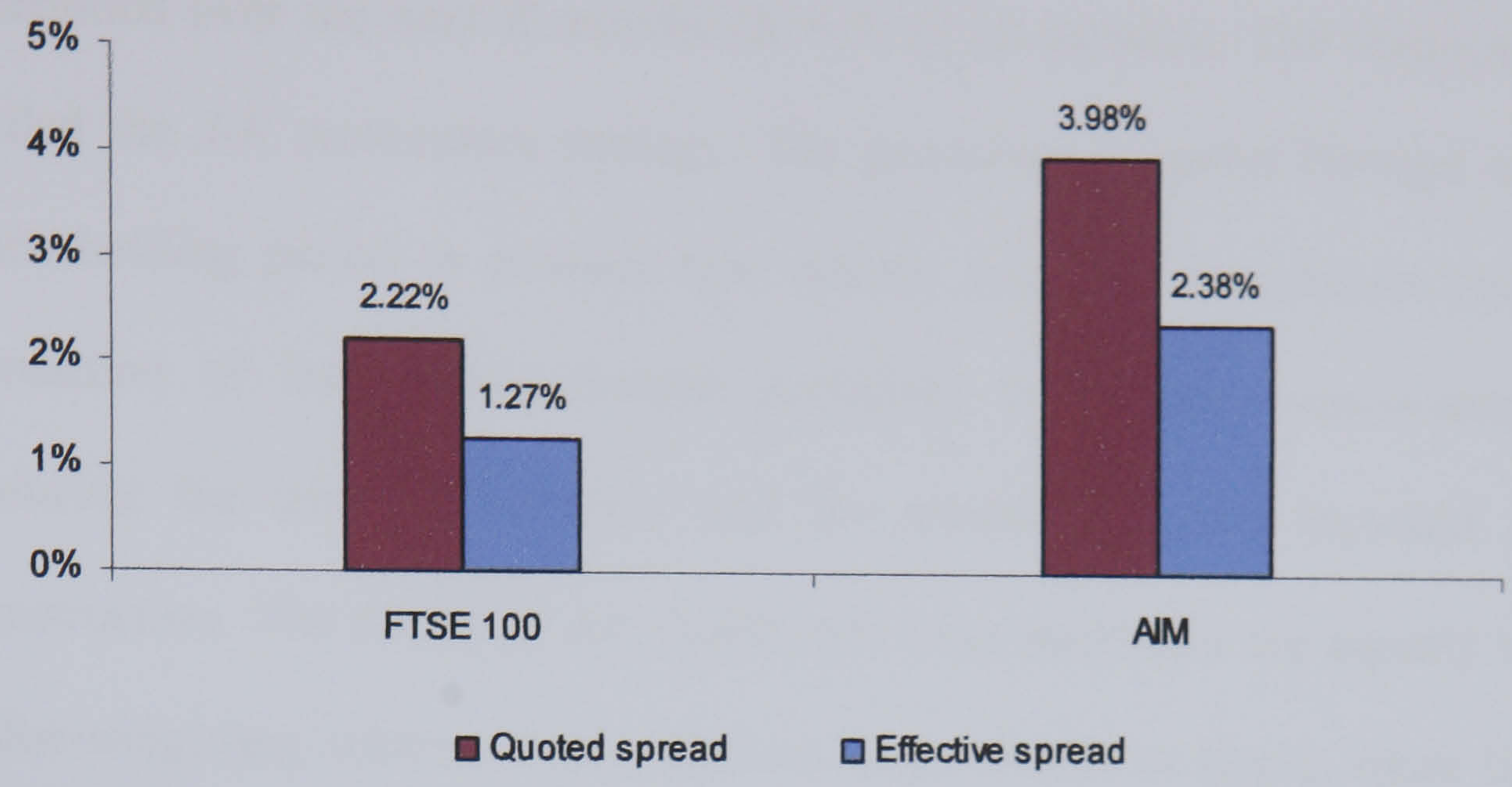

Figure 5.3. Average quoted and effective spreads for the constituent stocks of the FTSE 100 and the AIM indices.

5.4. Net Momentum Returns: Evidence from the UK

This section extends to the UK the analysis of Lesmond, Schill and Zhou (2004) for the US. We analyze the magnitude of trading costs and measure the net profits of 9 relative-strength strategies. We first calculate the average size, price and trading volume of winners and losers and compare them to those of the constituents of the FTSE 100 and AIM indices. Second, we relate the gross momentum profits to the total costs incurred in executing the relative-strength strategies.

5.4.1. Momentum Strategies

Following the method of forming winner, loser and momentum portfolios in Chapter 3, all stocks are ranked and sorted into 10 portfolios based on their past J-month cumulative returns (J = 3, 6, 12 months). The decile portfolio with the highest cumulative return is termed the "winner" portfolio, while the decile portfolio with the lowest cumulative return is called the "loser" portfolio. The return on the momentum portfolio is then measured as the return difference between the winner and loser portfolios over the next K months (K = 3, 6, 12 months). The resulting strategy is called the J-K momentum strategy. The procedure is rolled forward at the end of each holding period to produce new winner, loser and momentum portfolios. The formation of the relative-strength portfolios is therefore non-overlapping, thus reducing the trading frequency and the transaction costs incurred in portfolio construction. The stocks in the winner and loser portfolios are equally weighted. A value-weighting scheme would allocate more wealth to larger, more liquid stocks and thus would have been less costly. On balance, however, we choose an equal-weighting scheme in order to be consistent with the existing literature (Jegadeesh and Titman, 1993, 2001; Hong, Lim and Stein, 2000 and Lesmond, Schill and Zhou, 2004).

Table 5.1 presents monthly mean returns for the winner, loser and momentum portfolios. The rows represent the ranking periods (J = 3, 6 and 12 months) and the columns represent the holding periods (K = 3, 6 and 12 months). Without exception, the winners outperform the losers at the 1% level. Across strategies, the momentum portfolios earn an average return of 1.9% per month. This is larger than that of 1.51% per month reported in Chapter 3. One possible reason for this may be due to different sample sizes and sample periods as the sample in this chapter excludes financial stocks, extreme small market capitalization and low price stocks. Consistent with Moskowitz and Grinblatt (1999), Hong, Lim and Stein (2000) and Lesmond, Schill and Zhou (2004), we find that momentum profits are mainly produced by the short positions. On average, the losers generate a return of -1.58% per month and the winners yield a return of 0.32% per month. The results also strongly reject the criticism that the momentum effect is only produced by extremely small and illiquid stocks: these stocks are excluded from our sample and yet the momentum strategies are still able to generate sizeable positive average returns.

The results reported in Table 5.1 also suggest that the characteristics of the winner and loser stocks in terms of price, size and trading volume substantially differ from those of the average constituents of the FTSE 100 and the AIM indices. Irrespective of the strategy considered, the winner and loser portfolios comprise predominantly stocks that have lower price, lower market capitalization and lower trading volume than the average stock in the FTSE100 index. Table 5.1 therefore suggests that an estimate of transactions cost based on the average costs of trading FTSE100 stocks may underestimate the true trading costs engaged in implemented a momentum strategy in the UK. We will return to this point shortly. Relative to the average stock in the AIM index, the average price, market value and trading volume of the winners and losers exceed those of the AIM stocks. This is consistent with our decision to exclude from the winner and loser portfolios extreme stocks with very small size and very low price.

In line with Lesmond, Schill and Zhou (2004), Table 5.1 also extends to the UK the evidence that the loser portfolios are made of stocks with relatively smaller price, smaller size and lower trading volume than the winner portfolios. In effect, the mean share price is £1.80 for the losers and £2.36 for the winners; the mean market capitalization is £80 million for the losers and £324.7 million for the winners; and the mean trading volume is 17.8 million for the losers and 26.4 million for the winners. This in turn suggests that assuming symmetry of trading costs between losers and winners would be inaccurate.

Table 5.1. Monthly momentum returns and characteristics of winner and loser portfolios

Winner and loser are equally-weighted non-overlapping portfolios containing the 10% of stocks that performed the best and worst over a given ranking period respectively. Momentum is a portfolio that buys winners and sells losers short. Mean return is the monthly average return of the portfolio expressed in %. Price (£) is the average share price of the constituents of the portfolio estimated at the end of the ranking period. MV (£ millions) is the average market capitalization (share price multiplied by number of ordinary shares) at the end of the ranking period. Volume (millions) is the average trading volume (number of shares traded) at the end of the ranking period. *t*-statistics are in parentheses. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels for a two-sided test.

		Holding period of 3 months			Holding period of 6 months			Holding period of 12 months			FTSE 100	AIM
		Winner	Loser	Momentum	Winner	Loser	Momentum	Winner	Loser	Momentum		
Panel A: Ranking period of 3 months												
Mean return		0.22	-1.40	1.62	0.35	-1.50	1.85	0.05	-1.70	1.75		
		(0.75)	(-3.90) [a]	(6.69) [a]	(0.99)	(-3.75) [a]	(6.38) [a]	(0.11)	(-3.57) [a]	(4.96) [a]		
Price	Mean	2.26	2.16		2.37	2.01		2.16	1.51		4.35	1.12
	Median	1.92	1.33		2.12	1.18		2.12	1.22		3.78	0.60
MV	Mean	285.1	110.7		302.7	98.6		284.9	106.3		7189.3	27.5
	Median	205.6	66.2		240.1	76.1		266.3	92.1		3327.9	10.9
Volume	Mean	22.2	17.0		22.5	18.4		26.7	17.8		159.4	3.4
	Median	17.8	12.1		17.9	11.1		23.8	10.9		80.0	0.7
Number of stocks		131	131		137	137		134	134		102	1038
Panel B: Ranking period of 6 months												
Mean return		0.57	-1.61	2.18	0.51	-1.64	2.15	0.04	-1.64	1.68		
		(1.93) [c]	(-4.55) [a]	(8.13) [a]	(1.48)	(-4.08) [a]	(6.93) [a]	(0.10)	(-3.36) [a]	(4.73) [a]		
Price	Mean	2.34	1.94		2.16	1.84		2.03	1.41			
	Median	2.08	1.23		2.08	1.26		1.96	1.15			
MV	Mean	313.7	82.8		329.2	83.3		295.0	65.4			
	Median	243.1	55.1		235.2	53.4		198.7	56.8			
Volume	Mean	24.5	17.0		27.8	18.3		34.7	19.9			
	Median	18.9	10.9		21.7	11.1		23.3	12.0			
Number of stocks		128	128		135	135		132	132			
Panel C: Ranking period of 12 months												
Mean return		0.65	-1.57	2.22	0.48	-1.54	2.02	0.02	-1.63	1.65		
		(2.22) [b]	(-4.63) [a]	(9.31) [a]	(1.47)	(-3.95) [a]	(7.80) [a]	(0.04)	(-3.40) [a]	(5.59) [a]		
Price	Mean	2.69	2.07		2.63	1.86		2.61	1.43			
	Median	2.31	1.01		2.29	1.14		2.30	1.26			
MV	Mean	346.3	63.5		352.0	53.6		413.9	56.0			
	Median	267.0	44.5		279.5	44.5		296.8	43.7			
Volume	Mean	22.9	15.4		26.4	16.9		29.7	19.8			
	Median	16.3	9.9		17.1	11.6		24.4	12.3			
Number of stocks		123	123		127	127		126	126			

5.4.2. The Impact of Trading Costs on Momentum Profits

When implementing a momentum strategy, investors are likely to face significant trading costs. First, the momentum portfolios are heavily weighted toward small stocks with low price and low trading volume (Table 5.1) and these stocks are shown to be relatively more expensive (Figures 5.1 to 5.3). Second, the momentum strategies are highly trading intensive: investors must buy the winners and short sell the losers at the end of the ranking period and close their long-short positions by selling the winners and buying back the losers at the end of the holding period. This requires up to four round-trip trades a year for strategies with 3-month holding period, up to two round-trip trades a year for strategies with 6-month holding period and up to one round-trip trade a year for strategies with 12-month holding period. As a first approximation, the annual execution cost of a 3-month momentum strategy might be four times higher than that of a strategy with a 12-month holding period.

To calculate momentum returns and estimate trading costs for momentum strategies, we first compute the monthly return, quoted, effective spreads and commission for each stock; then we rank the winner and loser stocks based on their past returns; finally, we calculate monthly returns and transaction costs for the winners and losers over the same time.

Table 5.2 reports estimates of annual trading costs for the winner, loser and momentum portfolios based on the assumption of a 100% turnover of the constituents of the long-short portfolios at the end of each holding period. The analysis includes quoted or effective spreads, commission, a 0.5% stamp duty for stock purchases and an annual 1.5% cost on short selling. For example, the total trading cost of the 3-3 winner portfolio based on the quoted spread estimate is 16.11% and can be decomposed as follows: quoted spread of 9.72%, commission of 4.39% and 4 stamp duties of 0.5% each. The total trading for the loser portfolio also includes a yearly short selling cost of 1.5%. Table 5.2 shows that the estimates of the quoted spread, effective spread and commission associated with the losers are systematically higher than those of the winners. Across the 9 strategies, the average quoted spread, effective spread and commission for the losers are 7.84%, 7.73% and 3.68% respectively, which are 73%, 98% and 47% higher than those of the winners (those of the winners are 4.54%, 3.91%, and 2.51%, respectively). When the stamp duties on purchases and the costs of short-selling the losers are added, the total annual trading costs based on quoted spread averaged across the 9 strategies is 15.06% for the losers versus 8.72% for the winners. Based on effective spread, the losers (with an average annual total cost of 14.94%) are 86% more expensive than the winners (which cost 8.02% on average a year).

Those results are consistent with the findings of Lesmond, Schill and Zhou (2004), in which the transaction costs of the winners and losers are much higher than those of the majority of the CRSP stocks. They estimate transaction costs for portfolio P1 (the losers), portfolio P2 (80% of the CRSP sample) and portfolio P3 (the winners). They find that transaction costs for the losers range from 30% to 75% higher than those of P2 and those for the winners range from 18% to 61% higher than those of P2. While the estimates reported in Table 5.2 are yearly, transaction costs are often reported on a round-trip basis. Assuming a 100% turnover of the portfolios, we estimate that the average round-trip quoted spreads are 2.21% for the winners and 3.76% for the losers. Once round-trip commissions, stamp duties and short selling costs are added, round-trip transaction costs equal on average 3.77% for winners and 6.71% for losers.

Lesmond, Schill and Zhou (2004) report a round-trip transaction cost of 4.3% for the winners and 5.1% for the losers. The reason that our round-trip transaction cost of the losers is higher than that of Lesmond, Schill and Zhou (2004) is because that we include 1.5% short selling cost for the losers. Early studies on momentum strategies (Jegadeesh and Titman, 1993; Rouwenhorst, 1998 and Moskowitz and Grinblatt, 1999) assume round-trip transaction costs below 2% for both winners and losers. We find that this estimate vastly underestimates actual trading costs for the UK. As previously reported, symmetric costs on long and short positions will also lead to a severe overstatement of net momentum returns.

The round-trip quoted and effective spreads of Table 5.2 are 2.21% and 1.90% respectively for the winners and 3.76% and 3.72% for the losers. A comparison of these costs to the average quoted and effective spreads of the constituents of the FTSE 100 and AIM indices in Figure 5.3 suggests that the average quoted spread of the winners is comparable to that of the constituents of the FTSE 100 index (2.22%), while the average effective spread of the winners slightly exceeds that of the FTSE 100 (1.26%). While the assumption made in previous studies of an equal spread between the large capitalization index and the winners seem to be valid, this assumption breaks down for the losers. Their quoted and effective spreads resemble much more the ones reported for the AIM index in Figure 5.3 (3.98% and 2.38%, respectively).

Table 5.2. Estimates of trading costs based on full turnover

The table reports estimates of annual trading costs (%) for winner and loser portfolios based on full turnover. Trading costs are measured at the end of the ranking period. The estimates of total trading costs based on quoted spread (%) equal quoted spread plus commission, stamp duty on purchases (0.5% per purchase) and short selling costs for losers (1.5% per year). The estimates of total trading costs based on effective spread (%) equal effective spread plus commission, stamp duty on purchases and short selling costs for losers.

	Holding period of 3 months			Holding period of 6 months			Holding period of 12 months		
	Winner	Loser	Momentum	Winner	Loser	Momentum	Winner	Loser	Momentum
Panel A: Ranking period of 3 months									
Quoted spread	9.72	14.60	24.32	4.84	7.35	12.19	2.80	3.66	6.46
Effective spread	8.52	14.16	22.68	4.14	7.17	11.31	2.55	3.64	6.20
Commission	4.39	6.33	10.72	2.11	3.06	5.17	1.03	1.63	2.66
Total trading costs - Full turnover									
Based on quoted spread	16.11	24.43	40.54	7.94	12.91	20.85	4.33	7.29	11.62
Based on effective spread	14.91	23.99	38.90	7.25	12.73	19.98	4.09	7.27	11.36
Panel B: Ranking period of 6 months									
Quoted spread	8.82	14.93	23.75	4.24	7.71	11.95	2.52	3.87	6.40
Effective spread	7.45	14.69	22.14	3.63	7.71	11.34	2.07	3.87	5.94
Commission	4.32	6.34	10.67	2.09	3.03	5.11	1.03	1.58	2.60
Total trading costs - Full turnover									
Based on quoted spread	15.14	24.78	39.92	7.32	13.24	20.56	4.05	7.45	11.50
Based on effective spread	13.77	24.54	38.31	6.72	13.23	19.95	3.60	7.45	11.05
Panel C: Ranking period of 12 months									
Quoted spread	7.23	14.77	22.00	3.37	7.57	10.93	1.86	3.94	5.80
Effective spread	6.25	14.62	20.88	2.92	7.58	10.50	1.53	3.90	5.43
Commission	4.41	6.48	10.89	2.16	3.12	5.28	1.04	1.58	2.62
Total trading costs - Full turnover									
Based on quoted spread	13.64	24.75	38.38	6.53	13.19	19.72	3.40	7.52	10.92
Based on effective spread	12.66	24.60	37.26	6.09	13.20	19.29	3.07	7.48	10.55

The trading costs reported in Table 5.2 are measured at the end of the ranking period. While the positions are opened at the end of the ranking period, they are closed at the end of the holding period. At that time and depending on how the spreads have evolved, the one-way cost of the closing transaction may differ from the one-way cost of the opening transaction. Assuming, as in Table 5.2, that transaction costs on opening and closing positions are equal, may overestimate (underestimate) actual subsequent costs if spreads have become smaller (larger). Bearing this in mind, Table 5.3 tests the sensitivity of the results of Table 5.2 to the time the positions are opened (the end of the ranking period) and closed (the end of the holding period). The quoted and effective spreads reported for winners and losers in Table 5.3 are of the same magnitude as those reported in Table 5.2. As a result, the estimates of total trading costs are similar in both tables irrespective of the way the spread is measured. Across the 9 strategies, the average total trading cost based on the quoted spread is 23.78% a year in Table 5.2 and 23.28% a year in Table 5.3; the average total trading cost based on effective spread equals 22.96% in Table 5.2 and 22.56% in Table 5.3. Since measuring total trading costs over the holding period does not alter the inference on total transaction costs, the remainder of this chapter measures transaction costs at the end of ranking period.

In reality, momentum traders do not need to close out their entire positions at the end of the holding period as some stocks will stay in the winner and loser portfolios from one holding period to the next. If the momentum strategy recommends retaining the stocks in the following period, trading costs are not actually incurred since there is no need to close the initial position and to re-open a new one. Table 5.4 reports the proportions of winner (respectively, loser) stocks that have remained in the winner (respectively, loser) portfolio in the following holding period. We find that strategies

Table 5.3. Sensitivity of results to the estimation window for trading costs

The table reports estimates of annual trading costs (%) for winner and loser portfolios based on full turnover. The trading costs are measured both at the end of the ranking period (when positions are opened) and at the end of the holding period (when positions are closed). The estimates of total trading costs based on quoted spread (%) equal quoted spread plus commission, stamp duty on purchases (0.5% per purchase) and short selling costs for losers (1.5% per year). The estimates of total trading costs based on effective spread (%) equal effective spread plus commission, stamp duty on purchases and short selling costs for losers.

	Holding period of 3 months			Holding period of 6 months			Holding period of 12 months		
	Winner	Loser	Momentum	Winner	Loser	Momentum	Winner	Loser	Momentum
Panel A: Ranking period of 3 months									
Quoted spread	9.00	13.83	22.83	4.38	7.03	11.41	2.42	3.50	5.92
Effective spread	8.00	13.50	21.50	3.89	6.93	10.81	2.21	3.43	5.65
Commission	4.66	6.28	10.95	2.31	3.13	5.44	1.13	1.59	2.73
Total trading costs - Full turnover									
Based on quoted spread	15.66	23.61	39.27	7.68	12.66	20.35	4.05	7.09	11.14
Based on effective spread	14.66	23.29	37.95	7.19	12.56	19.75	3.85	7.03	10.88
Panel B: Ranking period of 6 months									
Quoted spread	8.28	14.41	22.69	3.99	7.45	11.44	2.20	3.73	5.94
Effective spread	7.12	14.25	21.37	3.47	7.45	10.92	1.86	3.66	5.52
Commission	4.41	6.40	10.81	2.18	3.17	5.35	1.06	1.58	2.64
Total trading costs - Full turnover									
Based on quoted spread	14.68	24.31	38.99	7.18	13.12	20.30	3.76	7.31	11.07
Based on effective spread	13.53	24.15	37.67	6.65	13.12	19.77	3.41	7.24	10.65
Panel C: Ranking period of 12 months									
Quoted spread	7.29	14.26	21.55	3.49	7.32	10.81	1.87	3.68	5.55
Effective spread	6.26	14.10	20.35	3.03	7.28	10.31	1.55	3.63	5.18
Commission	4.30	6.61	10.91	2.14	3.26	5.40	1.02	1.66	2.67
Total trading costs - Full turnover									
Based on quoted spread	13.59	24.37	37.96	6.62	13.08	19.71	3.39	7.34	10.72
Based on effective spread	12.56	24.20	36.76	6.17	13.05	19.21	3.07	7.29	10.36

with long ranking periods and short holding periods have high proportions of stocks remaining in the long-short portfolio in the following holding period. For instance, the 12-3 strategy recommends on average to keep a long (short) position in 53.83% (58.6%) of the winners (losers) in the following period. This implies that on average only 46.17% of the winners and 41.4% of the losers need to change hands at end of holding period. Other things being equal, the 12-3 strategy calls for less rotation in the constituents of the long-short portfolio and is therefore cheaper to implement. At the other end of the spectrum, the longer the holding period is, the more likely it is that the constituents of the long-short portfolios will change hands in the next holding period. For example, the 6-12 strategy recommends that only 11.85% of the winners and 15.57% of the losers be retained at the end of the holding period.

Table 5.4 also reports estimates of annual total trading costs adjusted down for the fraction of position retained. Relative to Table 5.3, total trading costs are considerably reduced when actual turnover is taken into account. The decrease in transaction costs is particularly strong for the strategies with high proportions of winner and loser stocks that are retained in the same portfolio in the following holding period. For example, the total trading costs of the 12-3 strategy based on quoted spread estimates drop from 38.38% for full turnover in Table 5.2 to 19.27% for actual turnover in Table 5.4; the average total trading costs based on effective spread estimates drop from 37.26% to 18.69%.

Table 5.4. Estimates of trading costs based on actual turnover

The table reports estimates of annual trading costs (%) for winner and loser portfolios based on actual turnover. The trading costs are measured at the end of ranking period. "Portfolio position retained" is the mean ratio of winners and losers that remain in the respective portfolios in the following period. The estimates of total trading costs based on quoted spread (%) equal quoted spread plus commission, stamp duty on purchases (0.5% per purchase) and short selling costs for losers (1.5% per year). The estimates of total trading costs based on effective spread (%) equal effective spread plus commission, stamp duty on purchases and short selling costs for losers.

	Holding period of 3 months			Holding period of 6 months			Holding period of 12 months		
	Winner	Loser	Momentum	Winner	Loser	Momentum	Winner	Loser	Momentum
Panel A: Ranking period of 3 months									
Portfolio position retained (%)	12.86	21.40		13.52	19.44		13.52	15.91	
Total trading costs - Actual turnover									
Based on quoted spread	14.30	19.85	34.15	7.14	11.03	18.17	4.04	6.71	10.75
Based on effective spread	13.23	19.50	32.73	6.51	10.88	17.39	3.81	6.69	10.50
Panel B: Ranking period of 6 months									
Portfolio position retained (%)	37.41	44.27		14.36	21.44		11.85	15.57	
Total trading costs - Actual turnover									
Based on quoted spread	10.19	15.18	25.36	6.53	11.11	17.64	3.81	6.87	10.68
Based on effective spread	9.26	15.03	24.30	6.00	11.10	17.10	3.38	6.87	10.25
Panel C: Ranking period of 12 months									
Portfolio position retained (%)	53.83	58.60		35.20	39.58		12.61	17.60	
Total trading costs - Actual turnover									
Based on quoted spread	7.21	12.06	19.27	4.80	9.27	14.08	3.19	6.86	10.05
Based on effective spread	6.70	11.99	18.69	4.48	9.28	13.76	2.88	6.82	9.70

Table 5.5 reports annual momentum returns and net momentum profits after taking account of total trading costs based on full and actual turnovers. All momentum strategies produce significant positive gross returns, with an average return of 23.14% per year across the 9 strategies. The picture is completely different once transaction costs are taken into account. Based on full turnover, none of relative-strength strategies generate positive and significant net profits. The strategies with short holding periods even yield significant negative net average returns at the 5% level. Once we employ the lower and more realistic measure of trading costs based on actual turnover, none of the net momentum returns are significant at the 5% level. In summary, the magnitude of trading costs plays an important role in assessing the profitability of momentum strategies. When trading costs are considered, none of the momentum strategy generates a positive net return.

Robustness of the results to the value-weighted returns and transaction costs

Table 5.6 presents estimates of value-weighted annual gross return, total trading costs and net annual return after total trading costs on momentum strategies based on full turnover. Comparing value-weighted annual returns on momentum portfolios in Table 5.6 to those in Table 5.5, we find that momentum strategies generate smaller value-weighted returns than equally-weighted returns, with only two exceptions (the 3-6 and 3-12 strategies). On average, the value-weighted annual return is 20.05% and the equally-weighted annual return is 23.14%. The estimates of value-weighted annual total trading costs for momentum strategies are uniformly less than the equally-weighted total trading costs based on quoted spreads and full turnover. The average annual total trading cost is 22.38% for value-weighted momentum strategies and 23.78% for equally-weighted momentum strategies. The possible reasons may be

Table 5.5. Estimates of net returns on momentum strategies

The table reports annual mean gross and net returns (%) on momentum strategies based on full and actual turnovers. The estimates of total trading costs based on quoted spread (%) equal quoted spread plus commission, stamp duty on purchases (0.5% per purchase) and short selling costs for losers (1.5% per year). The estimates of total trading costs based on effective spread (%) equal effective spread plus commission, stamp duty on purchases and short selling costs for losers. *t*-statistics are in parentheses. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels for a two-sided test.

	Holding period of 3 months		Holding period of 6 months		Holding period of 12 months	
Turnover	Full	Actual	Full	Actual	Full	Actual
Panel A: Ranking period of 3 months						
Annual momentum return	19.46		22.22		22.05	
	(4.78) [a]		(4.31) [a]		(2.32) [b]	
Net return after total trading cost						
Based on quoted spread	-21.07	-14.69	1.37	4.05	9.31	11.25
	(-5.59) [a]	(-3.87) [a]	(0.28)	(0.84)	(0.92)	(1.17)
Based on effective spread	-19.43	-13.26	2.24	4.83	9.60	11.44
	(-5.15) [a]	(-3.49) [a]	(0.47)	(1.01)	(0.96)	(1.20)
Panel B: Ranking period of 6 months						
Annual momentum return	26.15		25.74		21.10	
	(5.50) [a]		(4.96) [a]		(2.37) [b]	
Net return after total trading cost						
Based on quoted spread	-13.77	0.78	5.18	8.10	8.79	10.40
	(-2.95) [a]	(0.17)	(1.04)	(1.62)	(1.01)	(1.10)
Based on effective spread	-12.16	1.85	5.79	8.64	9.24	10.77
	(-2.71) [a]	(0.41)	(1.19)	(1.76) [c]	(1.08)	(1.17)
Panel C: Ranking period of 12 months						
Annual momentum return	26.65		24.25		20.64	
	(4.90) [a]		(4.11) [a]		(3.10) [a]	
Net return after total trading cost						
Based on quoted spread	-11.74	7.37	4.54	10.17	8.85	10.58
	(-2.15) [b]	(1.36)	(0.79)	(1.76) [c]	(1.23)	(1.55)
Based on effective spread	-10.62	7.96	4.97	10.49	9.26	10.89
	(-2.08) [b]	(1.51)	(0.89)	(1.85) [c]	(1.31)	(1.62)

Table 5.6. Estimates of value-weighted transaction costs and net returns on momentum strategies

The table reports annual value-weighted annual total trading costs (%), mean gross and net returns (%) on momentum strategies based on full turnover. Trading costs are measured at the end of the ranking period. The estimates of total trading costs based on quoted spread (%) equal quoted spread plus commission, stamp duty on purchases (0.5% per purchase) and short selling costs for losers (1.5% per year). *t*-statistics are in parentheses. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels for a two-sided test.

	Holding period of 3 months			Holding period of 6 months			Holding period of 12 months		
	Winner	Loser	Momentum	Winner	Loser	Momentum	Winner	Loser	Momentum
Panel A: Ranking period of 3 months									
Annual value-weighted return									
	4.33	-13.67	17.99	3.92	-19.74	23.65	1.61	-20.99	22.61
	(0.86)	(-1.22)	(1.92) [c]	(0.62)	(-1.53)	(2.07) [b]	(0.20)	(-1.15)	(1.52)
Total trading costs based on quoted spread									
	15.38	22.04	37.42	7.81	11.45	19.26	4.23	6.69	10.92
Net value-weighted return after total trading cost based on full turnover									
			-19.43			4.39			11.69
			(-2.17) [b]			(0.39)			(0.79)
Panel B: Ranking period of 6 months									
Annual value-weighted return									
	9.28	-15.94	25.22	5.56	-18.64	24.20	3.34	-15.52	18.85
	(2.88) [a]	(-1.20)	(2.24) [b]	(0.95)	(-1.51)	(2.39) [b]	(0.59)	(-1.24)	(1.50)
Total trading costs based on quoted spread									
	14.68	22.17	36.85	7.02	12.30	19.32	4.01	6.96	10.97
Net value-weighted return after total trading cost based on full turnover									
			-11.63			4.88			7.89
			(-1.10)			(0.49)			(0.63)
Panel C: Ranking period of 12 months									
Annual value-weighted return									
	8.09	-16.21	24.30	5.96	-16.38	22.34	4.43	-14.83	19.26
	(2.67) [a]	(-1.49)	(2.25) [b]	(0.91)	(-1.51)	(1.60)	(0.93)	(-1.21)	(1.57)
Total trading costs based on quoted spread									
	13.08	23.81	36.89	6.42	12.78	19.20	3.07	7.48	10.55
Net value-weighted return after total trading cost based on full turnover									
			-12.59			3.14			8.71
			(-1.16)			(0.23)			(0.71)

the fact that the value-weighted estimation reduces the weights on small stocks. Due to the lower value-weighted total trading costs and annual momentum returns, the value-weighted net momentum returns are consistent with the equally-weighted net momentum returns, with an average of -0.33% for value-weighted net return and -0.95% for equal-weighted net return after total trading costs; in addition, none of the value-weighted net momentum returns are positive and significant at the 5% level. In summary, using value-weighted and equally-weighted methods to estimate momentum returns and transaction costs does not alter the conclusion concerning the net momentum returns.

5.5. Analysis of the Observed Asymmetric Costs of the Winners and Losers

The results of Tables 5.2 and 5.4 show that trading costs are asymmetric for the winners and losers, the losers having higher trading costs than the winners. This section studies further the observed asymmetry by splitting each round-trip winner and loser trade into buyer-initiated trade and seller-initiated trades. As previously mentioned, the trade is defined as seller-initiated if the transaction price is less than the bid-ask midpoint; if not, it is defined as buyer-initiated. The rationale for splitting each round-trip trade into two one-trip trades comes from the fact that buyer- and seller-initiated trades have been found to have different impacts on prices (see Kraus and Stoll, 1972; Holthausen, Leftwich and Mayers, 1987; Chan and Lakonishok, 1993, 1995 and Keim and Madhavan, 1996). So an analysis of the one-trip effective spread might shed more light on the reasons behind the observed asymmetry between the transaction costs of winners and losers in Tables 5.2 and 5.4.

Figure 5.4 shows the average estimates of the half effective spreads on buyer- and seller-initiated trades for 3 winner portfolios, 3 loser portfolios,[29] and the average constituent of the FTSE 100 and AIM indices. It is clear that buying the average constituent of the FTSE100 index costs as much as selling it (0.63% and 0.64%, respectively). This conclusion does not, however, apply to small capitalization stocks, for which a seller-initiated trade on average costs 1.72%, which is 2.6 times as much as a buyer-initiated trade (which costs 0.66% on average). Likewise, the half effective spreads of seller-initiated trades are larger than the half effective spreads of buyer-initiated trades for both losers and winners. For example, buying a winner only costs 0.88% on average, while closing a long position in a winner costs slightly more (1.18%). The difference between the costs of buyer- and seller-initiated trades is even more pronounced for losers which happen to be extremely expensive to sell: selling a loser costs a massive 2.67% on average, while buying it back only costs 1.14%.[30] While buying winners is only slightly less expensive than buying losers (0.88% and 1.14%, respectively), the selling costs of winners and losers differ dramatically (1.18% and 2.67%, respectively). Clearly, the difference in trading costs that we observed between winners and losers in Tables 5.2 and 5.4 can be explained by the fact that the losers are particularly expensive to sell.

The results in Figure 5.4 for representative constituents of the FTSE100 and AIM indices show that the magnitude of the costs of seller-initiated trades depends on the

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[29] To conserve space, the results are only reported here for the momentum strategies with a 12 month holding period. The results from the other strategies are similar and are available from the authors upon request.

[30] Our results are consistent with Berkowitz, Logue and Noser (1988) who argue that the relatively higher cost of sells might be due to them being motivated by information and done in larger volumes and at greater speed than buys. Keim and Madhavan (1997) also report that the total cost of seller-initiated trades are larger than those of buyer-initiated trades and also attribute this finding to order quantities that are larger for sells than for buys in their sample.

market capitalization of the stock that is being traded. The smaller the stock, the more expensive it is to sell. This observation motivates our analysis of the relationship between transaction costs on buyer- and seller-initiated trades and the size of the winners and losers. To do that, we first sort the universe of stocks into winners and losers based on their past performance using, as previously, the 10% and 90% breakpoints. We then split each of the two extreme performers into three sub-portfolios based on the average market capitalization of the stock in the ranking period. We use the 30%-70% breakpoints and end up with 3 winner portfolios (Small-Winner, Medium-Winner and Big-Winner) and 3 loser portfolios (Small-Loser, Medium-Loser and Big-Loser).

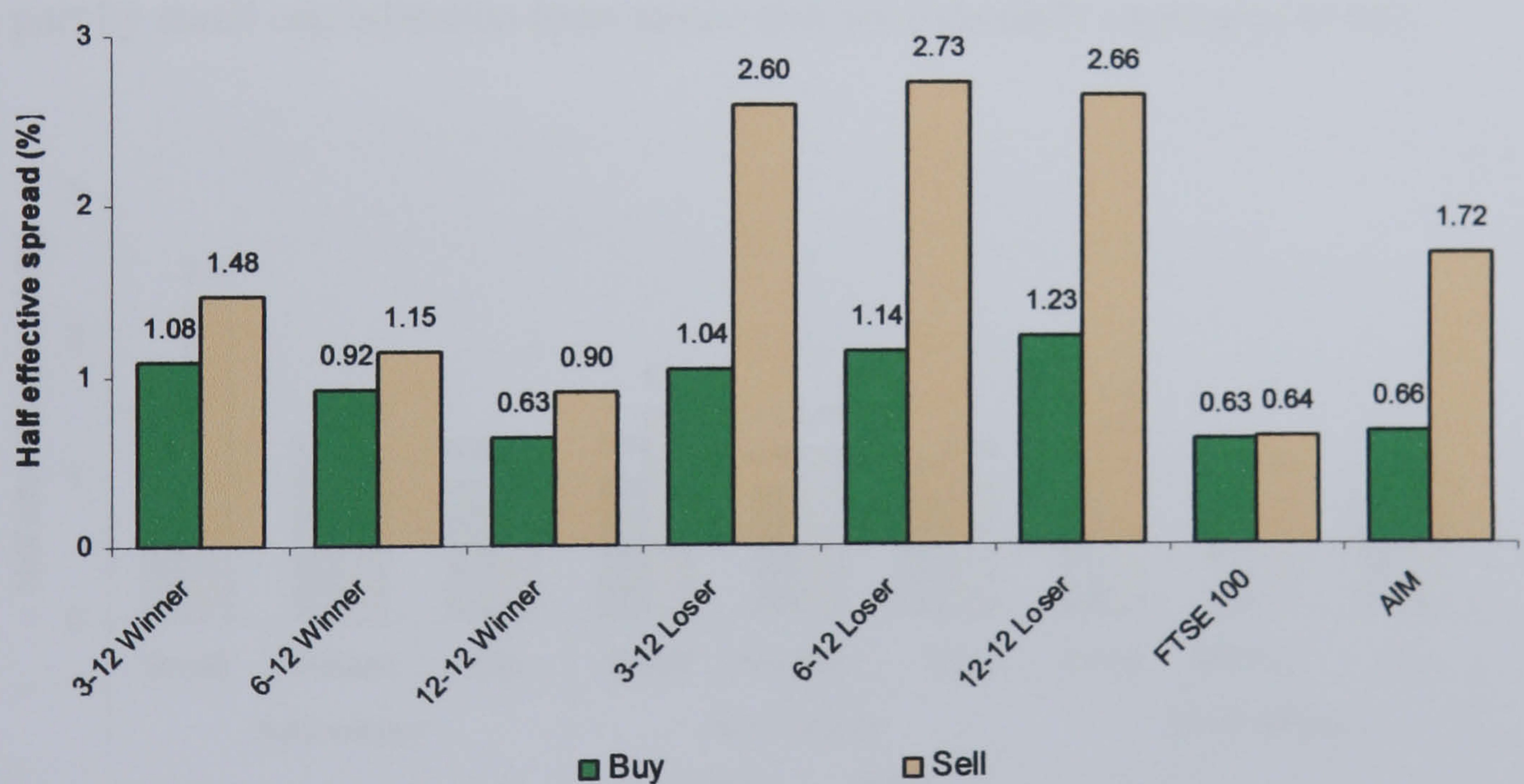

Figure 5.4. Average half effective spreads for buyer- and seller-initiated trades

Figures 5.5 and 5.6 report for different levels of market capitalization the average half effective spreads of buyer- and seller-initiated trades for the 3 winner and 3 loser portfolios with 12-month holding period. As reported for the FTSE100 and AIM indices in Figure 5.4, size does not have much impact on the cost of buying losers and winners. Buying small capitalization stocks costs on average 0.92% for winners and 1.26% for losers; buying large capitalization stocks costs on average 0.81% for winners and 1.07% for losers. So we can safely conclude that the market capitalization of a stock is not an important determinant of the cost of a buyer-initiated trade. The opposite conclusion applies to seller-initiated trades, for which we find an inverse relationship between size and costs. Indeed, selling small capitalization stocks on average costs 1.67% for winners and 4.80% for losers. The costs of selling large capitalization stocks is much lower (0.84% for winners and 1.57% for losers). We can therefore conclude that the difference in transaction costs between losers and winners that we observed in Tables 5.2 and 4.4 is driven at least in part by small capitalization loser stocks that are extremely expensive to sell.

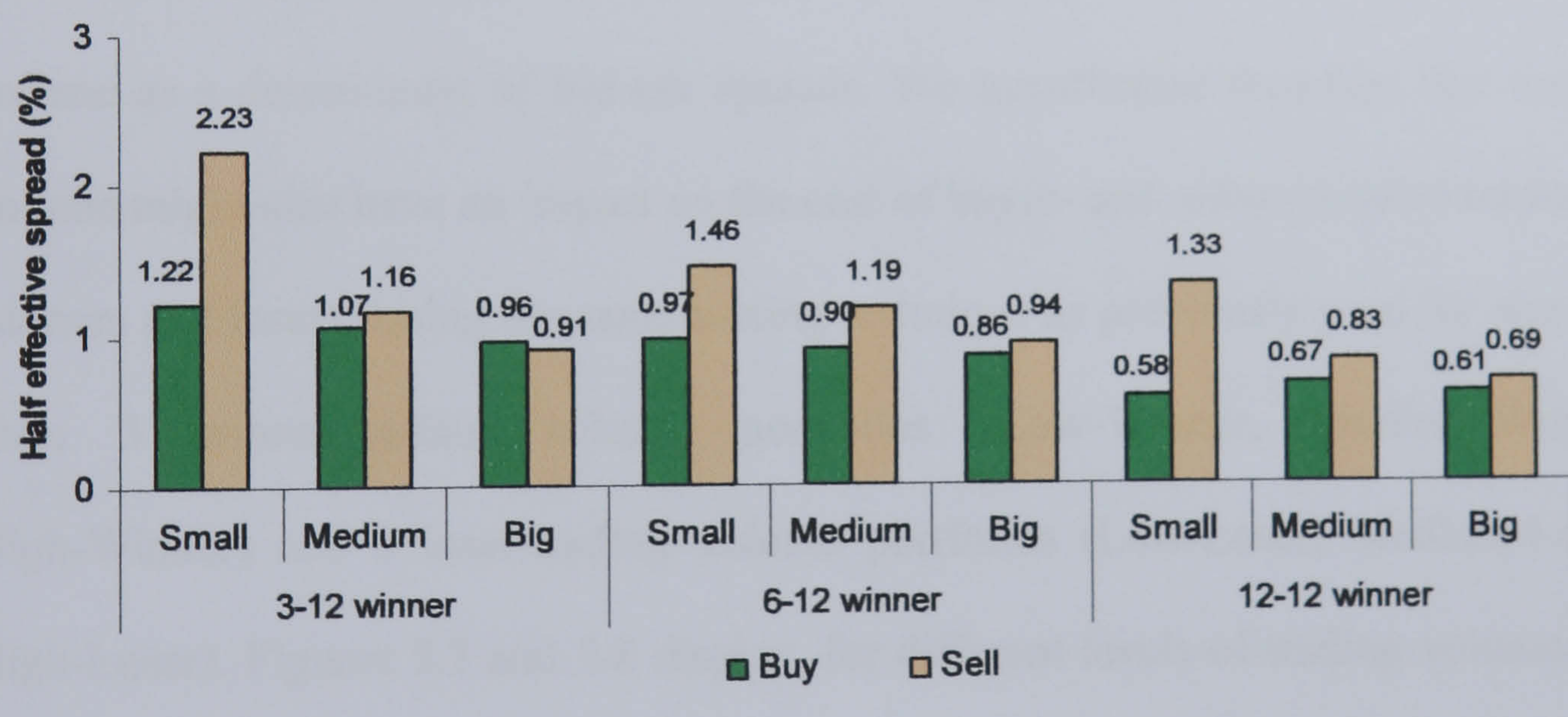

Figure 5.5. Average spreads of buyer-initiated and seller-initiated trades for the winners by size class.

Figure 5.6. Average spreads of buyer-initiated and seller-initiated trades for the losers by size class.

Chordia, Roll and Subrahmanyam (2000) also highlight the importance of trading volume as a determinant of bid-ask spreads. We hypothesize therefore that trading volume might also have an impact on the cost of buyer- and seller-initiated trades for winners and losers. Using the same sorting technique as previously used for size, we form 3 winner-trading volume portfolios (Low-Winner, Medium-Winner, High-Winner) and 3 loser-trading volume portfolios (Low-Loser, Medium-Loser, High-Loser). Figures 5.7 and 5.8 display, for different levels of trading volume, the average half effective spreads of buyer- and seller-initiated trades for the 3 winner and 3 loser portfolios with a 12-month holding period. When it comes to the losers, the evidence of an inverse relationship between size and the cost of seller-initiated trades seems to apply to trading volume as well. In effect, the cost of selling losers with low trading volume (3.73% on average) is 65% higher than the cost of selling losers with high trading volume (2.42%). To a lesser extent, the same negative relationship between volume and costs is reported for the seller-initiated trades of winners too: Closing a long position on a winner stock with low trading volume costs on average 1.23%; selling a winner with medium or high trading volume costs less (1.11% and 1.03%, respectively). The opposite applies to the cost of buyer-initiated trades. The cost of buying winners and losers with low trading volume equals 0.79% and 0.92%, respectively; which is slightly less than the cost of buying winners and losers with high trading volume (1.13% and 1.58%, respectively).[31]

To summarize, this section attempts to explain the difference in spreads observed between winners and losers in Tables 5.2 and 5.4 by relating the cost of buyer- and seller- initiated trades to the market capitalization and the trading volume of winners and losers. It appears that the relatively expensive trading costs of losers are mainly driven by the higher costs involved in selling small stocks with low trading volume. To a certain extent, the evidence also applies to the cost of seller-initiated trades for winners: the smaller the stock, the more expensive it is to close a long position in a winner. When it comes to the costs incurred in buyer-initiated trades, transaction costs for both winners and losers do not depend on the size of the stock and are positively related to its trading volume.

[31] Borrowing Keim and Madhavan's (1996) analysis, the result of a positive relation between volume and the cost of buyer-initiated trades could be due to the fact that large buyer-initiated trades are more informationally motivated than large seller-initiated trades since buyers have many potential stocks to choose from and sellers tend to sell, because of short-selling constraints, only the stocks they already own. So a large block purchase in a particular stock conveys a message of good news that drive stocks and spreads up, while a large block sale might be due to liquidity needs and not necessary result from bad news.

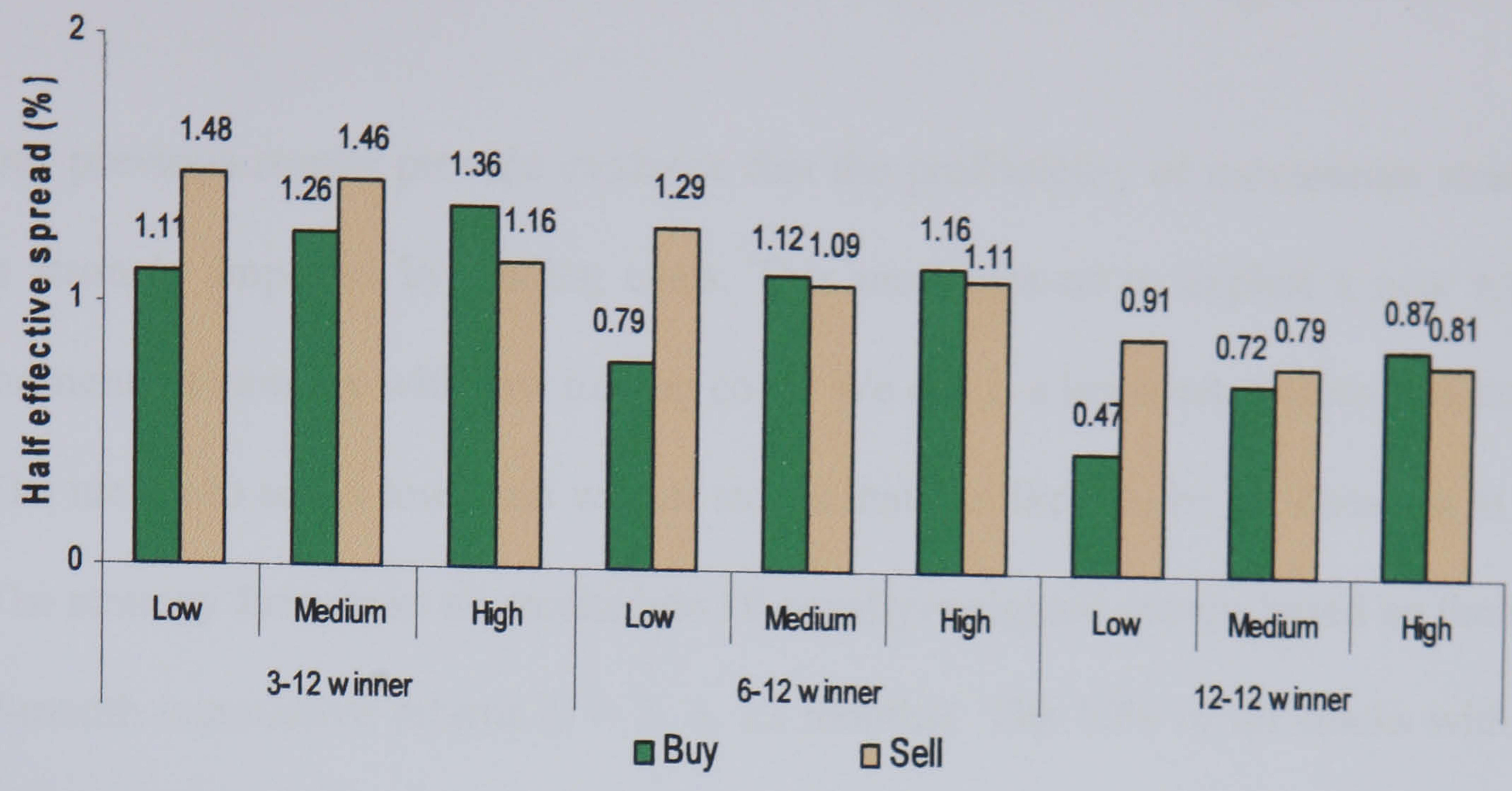

Figure 5.7. Average spreads of buyer-initiated and seller-initiated trades for the winners by trading volume class

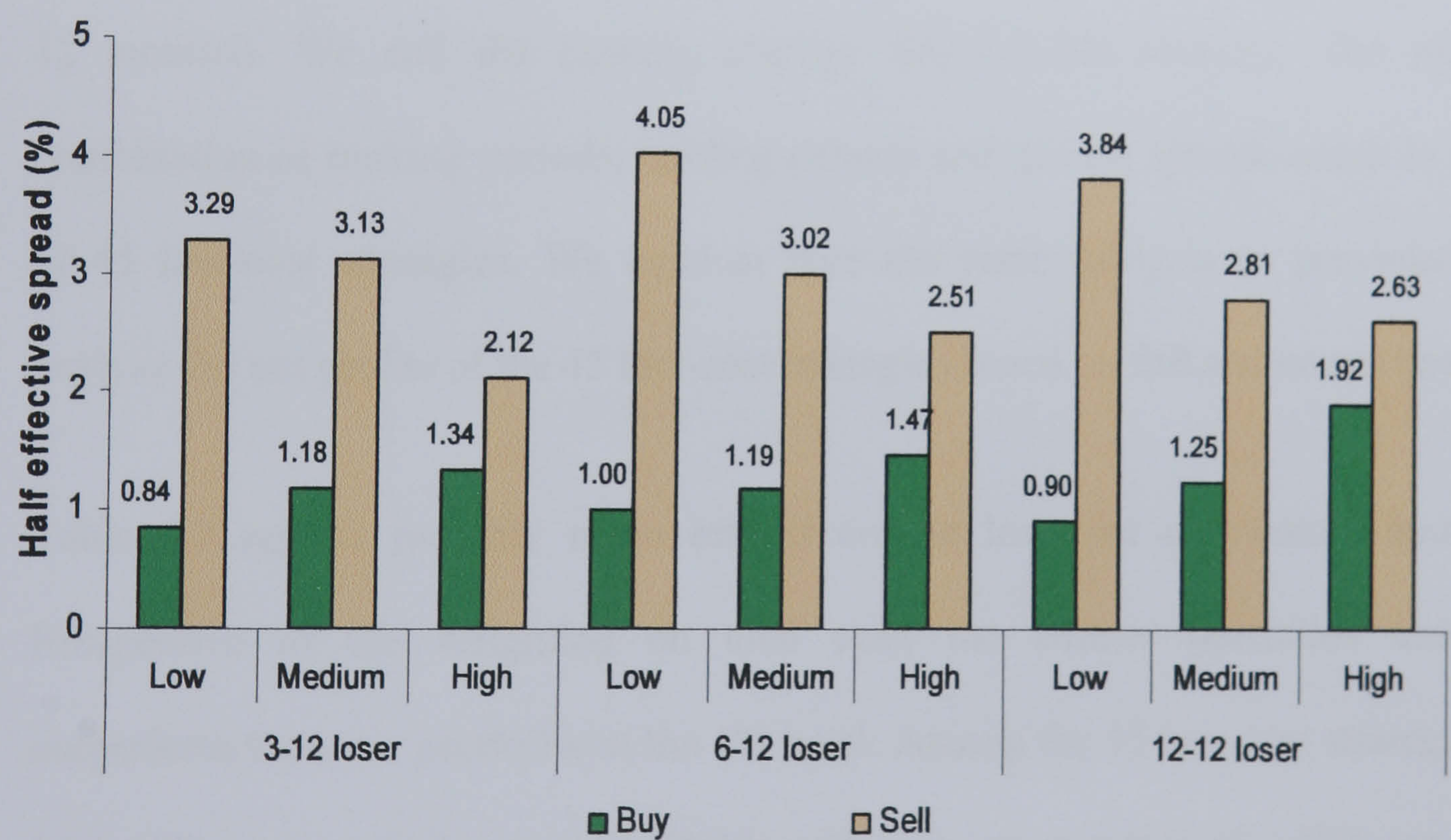

Figure 5.8. Average spreads of buyer-initiated and seller-initiated trades for the losers by trading volume class

5.6. The Profitability of Low-Cost Momentum Strategies

Our previous results provide evidence that the profitability of momentum strategies is strongly impeded by trading costs. This motivates us to exploit a new type of momentum strategy with low trading costs. We call it a low-cost momentum strategy. The idea is to select loser and winner stocks that are likely to be the cheapest to trade. The strategy first ranks all stocks into 10 equally-weighted groups based on their past *J*-month cumulative returns (*J* = 3, 6, 12 months). The 10% of all stocks with high cumulative returns are defined as winner stocks, and the 10% of all stocks with low cumulative returns are defined as loser stocks. Our low-cost momentum strategy then buys the *L*% (*L*% = 10%, 20%, 50%, 80% and 90%) of winner stocks, sells the *L*% of loser stocks that have the lowest total costs (measured as quoted spread plus commission) and holds the long-short portfolio over the next *K* months (*K* = 3, 6 and 12 months). We call the ensuing strategy the *J-K-L*% strategy. The resulting combination of ranking periods, holding periods and quoted spreads result in a total of 45 low-cost strategies. We conduct here the same analysis as previously and analyze the net profits of the 45 low-cost strategies based on full and actual turnover.

Table 5.7 reports monthly mean returns on the low-cost momentum strategies. Irrespective of the weighting on total cost, the winner portfolios uniformly outperform the loser portfolios at the 1% level. Among the 45 low-cost strategies, the 12-6-10% strategy is the most profitable with an average return of 2.67% per month and the 3-3-10% strategy yields the lowest average return at 1.45% per month. One source of concern however is the fact that the resulting low-cost portfolio for *L* = 10% might not be well diversified given the low number of stocks that are held on average in the long or short portfolios (9), but this is the price that must be paid for adopting a momentum strategy with an acceptable level of trading costs.

Table 5.8 reports the estimates of annual total trading costs for low-cost momentum strategies based on full turnover. The total trading costs are measured as quoted spread plus commission, stamp duty of purchases and short selling cost for losers. We find that the total trading costs can be substantially reduced from the standard relative-strength strategies of Table 5.2 to the low-cost strategies of Table 5.8. The conclusion is particularly valid for low values of L (10% and 20%); namely, when one shortlists only the most liquid winners and losers. For example, the annual total trading costs of the 6-3 strategy drop from 39.92% for the standard momentum strategies in Table 5.2 to 11.75% and 13.42% for the 6-3-10% and 6-3-20% low-cost strategies in Table 5.8. On average, the annual total trading costs based on quoted spread drop by 46% from 23.78% in Table 5.2 to 12.92% in Table 5.8.

Table 5.9 presents, for each of the 45 low-cost strategies, the mean proportions of winner and loser stocks that are retained in the same portfolio in the following holding period, along with estimates of total trading costs based, this time, on actual turnover. The results show that the lower L, the more likely it is that the constituents of the long-short portfolio will change hands from one holding period to the next. Across the 9 strategies for which L = 10%, only 5.62% of winner stocks and 8.35% of loser stocks are retained in the long-short portfolios on average from one holding period to the next. When L = 90%, the proportion of retained positions is much higher (at 20.77% for winner stocks and 23.97% for loser stocks on average). It follows that there might be a trade off between holding fewer stocks and rotating the portfolio more often.

Table 5.7. Monthly mean returns on low-cost momentum strategies

The table reports monthly mean return (%) on various low-cost momentum strategies. Winner and loser are equally-weighted non-overlapping portfolios containing *L*% (*L* = 10, 20, 50, 80 and 90) of winner and loser stocks with the lowest total costs (measured as quoted spread plus commission). Momentum is a portfolio that buys the resulting winners and short sells the resulting losers. *t*-statistics are in parentheses. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels for a two-sided test.

	Holding period of 3 months				Holding period of 6 months				Holding period of 12 months			
	Nber stocks	Winner	Loser	Momentum	Nber stocks	Winner	Loser	Momentum	Nber stocks	Winner	Loser	Momentum
Panel A: Ranking period of 3 months												
L = 10%	9	0.07	-1.38	1.45	9	0.11	-1.77	1.88	9	-0.12	-2.09	1.97
		(0.21)	(-2.77) [a]	(3.41) [a]		(0.30)	(-3.07) [a]	(3.82) [a]		(-0.24)	(-3.06) [a]	(3.18) [a]
L = 20%	18	0.09	-1.42	1.51	17	0.20	-1.66	1.85	16	0.16	-1.79	1.96
		(0.31)	(-3.38) [a]	(4.71) [a]		(0.58)	(-3.51) [a]	(5.15) [a]		(0.35)	(-3.17) [a]	(4.44) [a]
L = 50%	42	0.37	-1.47	1.84	42	0.43	-1.47	1.89	39	0.15	-1.72	1.87
		(1.33)	(-3.97) [a]	(7.08) [a]		(1.26)	(-3.48) [a]	(6.13) [a]		(0.33)	(-3.62) [a]	(4.89) [a]
L = 80%	66	0.39	-1.51	1.90	65	0.47	-1.50	1.96	61	0.06	-1.61	1.67
		(1.34)	(-4.03) [a]	(7.43) [a]		(1.35)	(-3.59) [a]	(6.61) [a]		(0.14)	(-3.39) [a]	(4.58) [a]
L = 90%	74	0.33	-1.48	1.81	74	0.44	-1.53	1.96	69	0.06	-1.66	1.72
		(1.13)	(-3.95) [a]	(7.38) [a]		(1.25)	(-3.65) [a]	(6.79) [a]		(0.12)	(-3.50) [a]	(4.82) [a]
Panel B: Ranking period of 6 months												
L = 10%	9	0.49	-1.52	2.02	9	0.46	-1.94	2.40	9	0.01	-2.34	2.35
		(1.64)	(-2.91) [a]	(4.01) [a]		(1.38)	(-3.46) [a]	(4.86) [a]		(0.03)	(-3.47) [a]	(3.70) [a]
L = 20%	17	0.47	-1.49	1.96	17	0.36	-1.68	2.04	16	0.03	-1.68	1.71
		(1.70) [c]	(-3.55) [a]	(5.33) [a]		(1.10)	(-3.47) [a]	(5.37) [a]		(0.08)	(-2.89) [a]	(3.58) [a]
L = 50%	41	0.63	-1.57	2.20	41	0.54	-1.55	2.10	39	0.14	-1.52	1.66
		(2.20) [b]	(-4.25) [a]	(7.77) [a]		(1.65)	(-3.73) [a]	(6.68) [a]		(0.33)	(-3.14) [a]	(4.40) [a]
L = 80%	64	0.62	-1.63	2.25	64	0.58	-1.59	2.18	61	0.04	-1.51	1.55
		(2.12) [b]	(-4.41) [a]	(8.07) [a]		(1.71) [c]	(-3.80) [a]	(7.05) [a]		(0.10)	(-3.12) [a]	(4.26) [a]
L = 90%	72	0.60	-1.64	2.24	72	0.54	-1.62	2.16	68	0.03	-1.58	1.61
		(2.02) [b]	(-4.42) [a]	(8.27) [a]		(1.58)	(-3.83) [a]	(7.18) [a]		(0.06)	(-3.23) [a]	(4.46) [a]
Panel C: Ranking period of 12 months												
L = 10%	9	0.36	-1.87	2.23	9	0.53	-2.15	2.67	8	0.01	-2.62	2.63
		(1.10)	(-4.01) [a]	(4.81) [a]		(1.66)	(-4.31) [a]	(5.77) [a]		(0.02)	(-4.42) [a]	(4.76) [a]
L = 20%	16	0.63	-1.83	2.46	16	0.53	-1.57	2.09	15	0.09	-1.81	1.90
		(1.95) [c]	(-4.51) [a]	(7.01) [a]		(1.67)	(-3.76) [a]	(6.05) [a]		(0.21)	(-3.62) [a]	(4.38) [a]
L = 50%	39	0.73	-1.57	2.30	39	0.56	-1.41	1.97	36	0.20	-1.55	1.75
		(2.52) [b]	(-4.39) [a]	(8.94) [a]		(1.79) [c]	(-3.54) [a]	(7.31) [a]		(0.51)	(-3.31) [a]	(5.79) [a]
L = 80%	61	0.73	-1.51	2.24	61	0.61	-1.43	2.04	56	0.20	-1.50	1.70
		(2.55) [b]	(-4.33) [a]	(8.92) [a]		(1.90) [c]	(-3.55) [a]	(7.81) [a]		(0.51)	(-3.16) [a]	(5.84) [a]
L = 90%	68	0.69	-1.54	2.23	68	0.58	-1.49	2.08	64	0.11	-1.53	1.64
		(2.38) [b]	(-4.38) [a]	(9.00) [a]		(1.79) [c]	(-3.65) [a]	(8.04) [a]		(0.28)	(-3.18) [a]	(5.57) [a]

Table 5.8. Estimates of trading costs based on full turnover – results for low-cost momentum strategies

The table reports annual total trading costs estimates (%) for 45 low-cost momentum strategies based on full turnover. Winner and Loser are equally-weighted non-overlapping portfolios containing $L\%$ ($L = 10, 20, 50, 80$ and 90) of winner and loser stocks with the lowest total costs (measured as quoted spread plus commission). Momentum is a portfolio that buys the resulting winners and short sells the resulting losers.

	Holding period of 3 months			Holding period of 6 months			Holding period of 12 months		
	Winner	Loser	Momentum	Winner	Loser	Momentum	Winner	Loser	Momentum
Panel A: Ranking period of 3 months									
L = 10%	4.75	7.01	11.76	2.40	4.25	6.64	1.24	2.90	4.14
L = 20%	5.30	8.32	13.62	2.68	4.91	7.59	1.42	3.23	4.65
L = 50%	7.73	12.42	20.15	3.91	6.95	10.87	2.10	4.19	6.29
L = 80%	11.13	17.26	28.39	5.70	9.40	15.10	3.07	5.47	8.54
L = 90%	12.95	20.08	33.03	6.67	10.85	17.52	3.62	6.20	9.83
Panel B: Ranking period of 6 months									
L = 10%	4.73	7.02	11.75	2.35	4.29	6.65	1.21	2.91	4.13
L = 20%	5.22	8.21	13.42	2.57	4.89	7.47	1.34	3.20	4.54
L = 50%	7.42	12.45	19.87	3.70	7.01	10.71	1.97	4.22	6.19
L = 80%	10.49	17.29	27.78	5.29	9.52	14.81	2.83	5.53	8.36
L = 90%	12.12	20.04	32.16	6.18	10.99	17.17	3.33	6.23	9.56
Panel C: Ranking period of 12 months									
L = 10%	4.66	6.81	11.47	2.31	4.16	6.47	1.16	2.89	4.05
L = 20%	5.09	8.15	13.24	2.51	4.85	7.36	1.27	3.21	4.48
L = 50%	6.98	12.39	19.37	3.47	6.97	10.44	1.77	4.25	6.02
L = 80%	9.76	17.14	26.90	4.85	9.44	14.29	2.47	5.54	8.01
L = 90%	11.12	19.99	31.10	5.56	10.92	16.48	2.82	6.31	9.12

Table 5.9. Estimates of trading costs based on actual turnover – results for low-cost momentum strategies

The table reports estimates of annual total trading costs (%) for various low-cost momentum strategies based on actual turnover. Winner and Loser are equally-weighted non-overlapping portfolios containing L% (L = 10, 20, 50, 80 and 90) of winner and loser stocks with the lowest total costs (measured as quoted spread plus commission). When actual turnover is measured, stamp duty on purchases (0.5% per purchase) and short selling costs for losers (1.5% per year) are also considered as part of trading costs. Momentum is a portfolio that buys the resulting winners and short sells the resulting losers. "Portfolio position retained" is the mean ratio of winners and losers that remain in the respective portfolios in the following period.

	Holding period of 3 months			Holding period of 6 months			Holding period of 12 months		
	Winner	Loser	Momentum	Winner	Loser	Momentum	Winner	Loser	Momentum
Panel A: Ranking period of 3 months									
Portfolio position retained (%)									
L = 10%	3.13	6.91		3.44	4.95		4.34	5.55	
L = 20%	4.60	8.27		5.66	7.27		3.91	6.42	
L = 50%	6.72	11.22		6.30	9.68		6.90	8.64	
L = 80%	10.11	15.36		10.88	14.04		10.61	12.57	
L = 90%	11.37	18.14		12.39	16.49		12.26	13.93	
Total trading costs based on actual turnover									
L = 10%	4.63	6.65	11.28	2.36	4.14	6.50	1.21	2.82	4.03
L = 20%	5.11	7.81	12.92	2.60	4.73	7.34	1.39	3.13	4.52
L = 50%	7.35	11.37	18.72	3.79	6.62	10.41	2.03	4.01	6.03
L = 80%	10.28	15.27	25.56	5.39	8.74	14.13	2.90	5.13	8.03
L = 90%	11.84	17.35	29.19	6.26	9.95	16.21	3.40	5.77	9.17
Panel B: Ranking period of 6 months									
Portfolio position retained (%)									
L = 10%	9.29	12.27		3.98	6.51		3.95	6.29	
L = 20%	16.96	18.72		4.89	7.88		4.92	6.82	
L = 50%	20.85	24.47		7.66	15.07		7.47	8.86	
L = 80%	29.84	34.36		11.99	14.32		9.91	11.98	
L = 90%	33.54	38.54		13.55	17.09		10.82	12.69	
Total trading costs based on actual turnover									
L = 10%	4.40	6.38	10.77	2.30	4.15	6.46	1.19	2.82	4.01
L = 20%	4.55	7.05	11.61	2.51	4.70	7.21	1.31	3.09	4.40
L = 50%	6.26	10.16	16.42	3.56	6.49	10.04	1.90	4.03	5.93
L = 80%	8.14	12.83	20.97	4.97	8.84	13.81	2.69	5.20	7.89
L = 90%	9.07	14.25	23.32	5.76	10.05	15.81	3.15	5.83	8.98
Panel C: Ranking period of 12 months									
Portfolio position retained (%)									
L = 10%	12.64	18.12		5.58	10.16		4.20	4.37	
L = 20%	19.18	25.52		10.05	13.14		3.89	11.25	
L = 50%	31.14	34.01		19.19	17.93		7.02	7.59	
L = 80%	43.62	46.31		29.02	28.59		13.20	11.70	
L = 90%	48.59	51.74		32.15	33.81		12.23	13.31	
Total trading costs based on actual turnover									
L = 10%	4.22	5.89	10.10	2.25	3.95	6.20	1.14	2.82	3.96
L = 20%	4.36	6.59	10.94	2.38	4.53	6.91	1.25	3.03	4.28
L = 50%	5.35	9.23	14.58	3.14	6.34	9.48	1.71	4.09	5.79
L = 80%	6.57	11.19	17.76	4.14	8.09	12.24	2.31	5.22	7.52
L = 90%	7.07	12.23	19.30	4.67	9.07	13.74	2.64	5.89	8.53

In Table 5.4, we noted that the 12-3 relative-strength strategy involves the least trading activity since it retains the highest proportions of winners and losers from one holding period to the next. Table 5.9 presents the same conclusion. For example, 31.14% (34.01%) of the time, the winners (losers) of the 12-3-50% strategy will remain in the winner (loser) portfolio in the following holding period. This suggests that based on full turnover implementing the 12-3-50% low-cost strategy can save over 30% of the costs involved on the purchase and sale of winners and losers. As a result, the total trading costs based on actual turnover of the 12-3 strategy drop from 19.27% for the standard momentum strategy in Table 5.4 to 10.10% and 10.94% in Table 5.9 for the 12-3-10% and 12-3-20% low-cost strategies, respectively. Overall, based on actual turnover, the low-cost momentum strategies that select 10% or 20% of winner and loser stocks with the lowest transaction costs are much less expensive than the standard momentum strategies of Table 5.4. Across the 9 *J-K* strategies the average yearly trading cost for L = 10% is only 7.04% versus 7.79% for L = 20% and 17.80% for L = 100% (in Table 5.4). So our low-cost strategies can reduce the total trading costs of standard momentum strategies by up to 60%.

Table 5.10 reports the net annual returns on low-cost relative-strength strategies once total trading costs based on full and actual turnovers are taken into account. While none of the standard momentum strategies generate positive net returns at the 5% level in Table 5.5, Table 5.10 shows that based on full turnover, 18 out of 45 low-cost strategies offer positive and significant net returns at the 5% level. When actual turnover is considered instead, 22 low-cost strategies have positive and significant net returns at the 5% level. The 12-12-10% low-cost strategy happens to be the most profitable (27.66% net annual return based on actual turnover, *t*-statistics of 4.16). The 3-3-90% strategy is the least profitable (average annual net return of

-7.48% based on actual turnover, *t*-statistic of -1.49). The performance of the strategies that shortlist the most liquid 10% and 20% winner and loser stocks is particularly noticeable. Based on actual turnover, the strategies with L = 10% and L = 20% generate average net returns of 19.10% and 15.53%, respectively.

Risk-adjusted returns of low-cost momentum strategies

Table 5.11 reports OLS estimates of the CAPM and Fama and French (FFM) models for the net monthly momentum returns on low-cost momentum strategies. Based on full turnover, 22 out of 45 alpha coefficients estimated from the CAPM and 30 out of 45 alpha coefficients estimated from the FFM are positive and significant at the 5% level. Based on actual turnover, 28 and 35 low-cost strategies have positive and significant alpha coefficients at the 5% level for the CAPM and the FFM, respectively. Consistent with the results in Table 5.10, the 12-12-10% low-cost momentum strategy generates the highest net abnormal return of 2.57% per month for the CAPM and 2.62% per month for the FFM (based on actual turnover). The 3-3-90% low-cost momentum strategy yields the lowest net abnormal return of -0.52% per month for the CAPM and -0.41% per month for the FFM (based on actual turnover). On average, the strategies with L = 10% generate net abnormal return of 1.60% from the CAPM and 1.69% from the FFM, which are in line with monthly net raw return of 1.59% reported in Table 5.10. The strategies with L = 20% earn average monthly net abnormal return of 1.33% from the CAPM and 1.45% from the FFM, which are similar to the monthly net raw return of 1.29% in Table 5.10. In summary, after taking account of market risk and Fama and French three risk factors, low-cost momentum strategies with L = 10% and L = 20% still can produce positive and significant net abnormal returns based on both full and actual turnovers.

Table 5.10. Estimates of net returns on low-cost momentum strategies

The table reports annual average net returns (%) on low-cost momentum strategies based on full and actual turnovers. The low-cost momentum strategy buys the L% of winners and short sells the L% of losers with the lowest total costs (measured as quoted spread plus commission). When actual turnover is measured, stamp duty on purchases (0.5% per purchase) and short selling costs for losers (1.5% per year) are also considered as part of trading costs. t-statistics are in parentheses. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels for a two-sided test.

	Holding period of 3 months		Holding period of 6 months		Holding period of 12 months	
Turnover	Full	Actual	Full	Actual	Full	Actual
Panel A: Ranking period of 3 months						
L = 10%	5.64	6.11	15.87	16.01	19.49	19.59
	(0.56)	(0.65)	(2.93) [a]	(2.96) [a]	(1.34)	(1.35)
L = 20%	4.56	5.26	14.65	14.91	18.83	18.96
	(0.76)	(0.90)	(2.79) [a]	(2.83) [a]	(1.63)	(1.64)
L = 50%	1.89	3.32	11.85	12.31	16.15	16.40
	(0.64)	(0.94)	(2.18) [b]	(2.26) [b]	(1.27)	(1.30)
L = 80%	-5.58	-2.75	8.48	9.45	11.55	12.06
	(-1.05)	(-0.39)	(1.83) [c]	(2.01) [b]	(0.94)	(0.98)
L = 90%	-11.32	-7.48	6.05	7.36	10.80	11.46
	(-2.40) [b]	(-1.49)	(1.44)	(1.69)	(0.93)	(0.99)
Panel B: Ranking period of 6 months						
L = 10%	12.45	13.43	22.19	22.37	24.09	24.20
	(1.59)	(1.75) [c]	(4.28) [a]	(4.32) [a]	(2.51) [b]	(2.52) [b]
L = 20%	10.10	11.92	17.06	17.32	16.01	16.15
	(1.90) [c]	(2.25) [b]	(3.49) [a]	(3.54) [a]	(1.93) [c]	(1.95) [c]
L = 50%	6.49	9.93	14.48	15.15	13.78	14.04
	(1.99) [b]	(2.76) [a]	(3.31) [a]	(3.45) [a]	(1.17)	(1.19)
L = 80%	-0.73	6.08	11.30	12.30	10.29	10.77
	(-0.18)	(1.74) [c]	(2.48) [b]	(2.69) [a]	(0.76)	(0.80)
L = 90%	-5.28	3.56	8.78	10.14	9.72	10.30
	(-0.93)	(1.09)	(1.88) [c]	(2.16) [b]	(0.72)	(0.78)
Panel C: Ranking period of 12 months						
L = 10%	15.29	16.66	25.62	25.89	27.57	27.66
	(2.90) [a]	(3.10) [a]	(3.35) [a]	(3.38) [a]	(4.15) [a]	(4.16) [a]
L = 20%	16.29	18.59	17.74	18.19	18.30	18.50
	(3.64) [a]	(4.08) [a]	(3.56) [a]	(3.64) [a]	(3.14) [a]	(3.18) [a]
L = 50%	8.24	13.03	13.22	14.18	14.96	15.18
	(2.01) [b]	(2.91) [a]	(2.53) [b]	(2.68) [a]	(2.34) [b]	(2.38) [b]
L = 80%	-0.02	9.13	10.20	12.26	12.38	12.87
	(0.37)	(1.95) [c]	(1.77) [c]	(2.09) [b]	(1.69)	(1.75) [c]
L = 90%	-4.37	7.43	8.42	11.16	10.55	11.14
	(-0.39)	(1.61)	(1.50)	(1.94) [c]	(1.49)	(1.57)

Table 5.11. Estimates of the CAPM and Fama and French models for the net returns on low-cost momentum strategies

The table reports coefficient estimates of the following CAPM and Fama and French model (FFM) for low-cost momentum strategies based on full and actual turnovers

$$r_{Pt} = \alpha + \beta_m (R_{mt} - R_{ft}) + \varepsilon_{Pt}$$

$$r_{Pt} = \alpha + \beta_m (R_{mt} - R_{ft}) + sSMB + hHML + \varepsilon_{Pt}$$

where r_{Pt} is either the excess returns on winner and loser portfolios or the return on the momentum portfolio, R_{mt} is the value-weighted return on the market portfolio of all assets, R_{ft} is the three-month Treasury bill rate. α (%) measures the abnormal performance of the portfolio; β_m measures the market risk of the portfolio, s and h are the portfolio loadings on the size and book-to-market value factors. The low-cost momentum strategy buys the L% (10%-90%) of winners and short sells the L% of losers with the lowest total costs (measured as quoted spread plus commission). When actual turnover is measured, stamp duty on purchases (0.5% per purchase) and short selling costs for losers (1.5% per year) are also considered as part of trading costs. White's heteroskedasticity robust t-statistics are in parentheses. Significance is denoted by superscripts at the 1% (^{a}), 5% (^{b}) and 10% (^{c}) levels for a two-sided test.

Turnover		Holding period of 3 months				Holding period of 6 months				Holding period of 12 months			
		Full		Actual		Full		Actual		Full		Actual	
		CAPM	FFM	CAPM	FFM	CAPM	FFM	CAPM	FFM	CAPM	FFM	CAPM	FFM
Panel A: Ranking period of 3 months													
L = 10%	α (%)	0.66	0.78	0.70	0.82	1.61	1.65	1.63	1.66	2.30	2.40	2.31	2.41
		(1.00)	(1.19)	(1.06)	(1.25)	(2.64) [a]	(2.64) [a]	(2.66) [a]	(2.66) [a]	(2.77) [a]	(2.88) [a]	(2.78) [a]	(2.89) [a]
	β	-0.32	-0.38	-0.32	-0.38	-0.38	-0.41	-0.38	-0.41	-0.41	-0.46	-0.41	-0.46
		(-1.92) [c]	(-2.19) [b]	(-1.93) [c]	(-2.19) [b]	(-2.12) [b]	(-2.32) [b]	(-2.12) [b]	(-2.32) [b]	(-1.74) [c]	(-1.91) [c]	(-1.74) [c]	(-1.91) [c]
	s		-0.07		-0.07		-0.08		-0.08		-0.05		-0.05
			(-0.33)		(-0.33)		(-0.35)		(-0.35)		(-0.20)		(-0.20)
	h		-0.44		-0.44		-0.12		-0.12		-0.39		-0.39
			(-1.64)		(-1.64)		(-0.42)		(-0.42)		(-0.94)		(-0.94)
L = 20%	α (%)	0.57	0.67	0.63	0.72	1.48	1.55	1.50	1.57	2.31	2.48	2.32	2.49
		(1.31)	(1.54)	(1.44)	(1.67)	(3.20) [a]	(3.42) [a]	(3.24) [a]	(3.47) [a]	(3.79) [a]	(4.29) [a]	(3.81) [a]	(4.31) [a]
	β	-0.26	-0.33	-0.26	-0.33	-0.37	-0.44	-0.37	-0.44	-0.40	-0.50	-0.40	-0.50
		(-2.07) [b]	(-2.71) [a]	(-2.07) [b]	(-2.71) [a]	(-2.71) [a]	(-3.32) [a]	(-2.71) [a]	(-3.33) [a]	(-2.22) [b]	(-2.84) [a]	(-2.22) [b]	(-2.84) [a]
	s		-0.20		-0.19		-0.27		-0.27		-0.24		-0.24
			(-1.50)		(-1.50)		(-1.69)		(-1.69)		(-1.58)		(-1.58)
	h		-0.29		-0.29		-0.17		-0.17		-0.59		-0.59
			(-1.74) [c]		(-1.74) [c]		(-0.91)		(-0.91)		(-2.28) [b]		(-2.28) [b]
L = 50%	α (%)	0.19	0.26	0.30	0.37	0.98	1.09	1.01	1.13	1.25	1.45	1.27	1.47
		(0.54)	(0.75)	(0.86)	(1.08)	(2.29) [b]	(2.69) [a]	(2.38) [b]	(2.78) [a]	(2.02) [b]	(2.59) [a]	(2.06) [b]	(2.63) [a]
	β	-0.27	-0.31	-0.27	-0.31	-0.40	-0.48	-0.40	-0.48	-0.23	-0.31	-0.23	-0.31
		(-2.60) [a]	(-3.04) [a]	(-2.61) [a]	(-3.05) [a]	(-3.58) [a]	(-4.15) [a]	(-3.58) [a]	(-4.15) [a]	(-1.35)	(-1.84) [c]	(-1.35)	(-1.84) [c]
	s		-0.11		-0.11		-0.18		-0.18		0.01		0.01
			(-0.94)		(-0.94)		(-1.27)		(-1.26)		(0.04)		(0.04)
	h		-0.23		-0.23		-0.38		-0.38		-0.78		-0.78
			(-1.62)		(-1.61)		(-2.06) [b]		(-2.06) [b]		(-2.82) [a]		(-2.82) [a]
L = 80%	α (%)	-0.41	-0.30	-0.18	-0.07	0.71	0.83	0.79	0.91	0.86	1.09	0.91	1.13
		(-1.17)	(-0.91)	(-0.51)	(-0.22)	(1.74) [c]	(2.16) [b]	(1.93) [c]	(2.37) [b]	(1.42)	(2.06) [b]	(1.49)	(2.14) [b]
	β	-0.25	-0.32	-0.25	-0.32	-0.40	-0.47	-0.40	-0.47	-0.27	-0.37	-0.27	-0.37
		(-2.63) [a]	(-3.27) [a]	(-2.64) [a]	(-3.27) [a]	(-3.95) [a]	(-4.41) [a]	(-3.95) [a]	(-4.41) [a]	(-1.68)	(-2.32) [b]	(-1.68)	(-2.32) [b]
	s		-0.14		-0.14		-0.13		-0.13		-0.01		-0.01
			(-1.15)		(-1.15)		(-0.97)		(-0.97)		(-0.09)		(-0.08)
	h		-0.35		-0.35		-0.42		-0.42		-0.89		-0.89
			(-2.50) [b]		(-2.47) [b]		(-2.13) [b]		(-2.12) [b]		(-3.20) [a]		(-3.20) [a]
L = 90%	α (%)	-0.83	-0.72	-0.52	-0.41	0.52	0.64	0.63	0.74	0.90	1.14	0.96	1.19
		(-2.50) [b]	(-2.29) [b]	(-1.56)	(-1.31)	(1.32)	(1.74) [c]	(1.60)	(2.04) [b]	(1.55)	(2.25) [b]	(1.64)	(2.36) [b]
	β	-0.24	-0.30	-0.24	-0.30	-0.36	-0.43	-0.36	-0.43	-0.24	-0.35	-0.24	-0.35
		(-2.59) [a]	(-3.27) [a]	(-2.61) [a]	(-3.27) [a]	(-3.65) [a]	(-4.23) [a]	(-3.65) [a]	(-4.23) [a]	(-1.57)	(-2.30) [b]	(-1.58)	(-2.30) [b]
	s		-0.16		-0.15		-0.15		-0.15		-0.06		-0.06
			(-1.36)		(-1.36)		(-1.21)		(-1.21)		(-0.36)		(-0.36)
	h		-0.36		-0.36		-0.40		-0.40		-0.91		-0.91
			(-2.74) [a]		(-2.70) [a]		(-2.16) [b]		(-2.15) [b]		(-3.45) [a]		(-3.45) [a]

Turnover		Holding period of 3 months				Holding period of 6 months				Holding period of 12 months			
		Full		Actual		Full		Actual		Full		Actual	
		CAPM	FFM	CAPM	FFM	CAPM	FFM	CAPM	FFM	CAPM	FFM	CAPM	FFM
Panel B: Ranking period of 6 months													
L = 10%	α (%)	0.62	0.84	0.70	0.92	1.53	1.62	1.55	1.64	1.85	1.96	1.86	1.97
		(0.83)	(1.17)	(0.94)	(1.29)	(2.31) [b]	(2.43) [b]	(2.34) [b]	(2.46) [b]	(2.39) [b]	(2.54) [b]	(2.40) [b]	(2.55) [b]
	β	-0.48	-0.66	-0.48	-0.66	-0.20	-0.27	-0.20	-0.27	-0.26	-0.30	-0.26	-0.30
		(-2.59) [a]	(-3.42) [a]	(-2.59) [a]	(-3.42) [a]	(-1.20)	(-1.62)	(-1.20)	(-1.62)	(-1.31)	(-1.45)	(-1.31)	(-1.45)
	s		-0.66		-0.66		-0.24		-0.24		0.02		0.02
			(-2.68) [a]		(-2.68) [a]		(-1.20)		(-1.20)		(0.07)		(0.07)
	h		-0.58		-0.58		-0.27		-0.27		-0.43		-0.43
			(-1.68)		(-1.67)		(-0.97)		(-0.97)		(-1.38)		(-1.38)
L = 20%	α (%)	0.61	0.78	0.76	0.93	0.61	1.32	1.18	1.34	1.29	1.49	1.30	1.50
		(1.20)	(1.60)	(1.48)	(1.90) [c]	(1.20)	(2.64) [a]	(2.33) [b]	(2.68) [a]	(2.00) [b]	(2.38) [b]	(2.01) [b]	(2.39) [b]
	β	-0.37	-0.49	-0.37	-0.50	-0.37	-0.38	-0.28	-0.38	-0.24	-0.36	-0.24	-0.36
		(-2.90) [a]	(-3.72) [a]	(-2.91) [a]	(-3.72) [a]	(-2.90) [a]	(-2.93) [a]	(-2.20) [b]	(-2.93) [a]	(-1.50)	(-2.10) [b]	(-1.50)	(-2.10) [b]
	s		-0.41		-0.41		-0.28		-0.28		-0.24		-0.24
			(-2.55) [b]		(-2.55) [b]		(-1.97) [b]		(-1.97) [b]		(-1.36)		(-1.36)
	h		-0.52		-0.52		-0.50		-0.50		-0.68		-0.68
			(-2.31) [b]		(-2.30) [b]		(-2.41) [b]		(-2.40) [b]		(-2.49) [b]		(-2.49) [b]
L = 50%	α (%)	0.51	0.59	0.78	0.87	1.22	1.37	1.28	1.42	1.09	1.32	1.11	1.34
		(1.38)	(1.69) [c]	(2.14) [b]	(2.47) [b]	(2.89) [a]	(3.46) [a]	(3.02) [a]	(3.60) [a]	(1.73) [c]	(2.36) [b]	(1.76) [c]	(2.40) [b]
	β	-0.27	-0.34	-0.28	-0.34	-0.30	-0.40	-0.30	-0.40	-0.18	-0.29	-0.18	-0.29
		(-2.74) [a]	(-3.31) [a]	(-2.75) [a]	(-3.31) [a]	(-2.61) [a]	(-3.32) [a]	(-2.62) [a]	(-3.32) [a]	(-1.07)	(-1.73) [c]	(-1.07)	(-1.73) [c]
	s		-0.20		-0.20		-0.24		-0.24		-0.09		-0.09
			(-1.65)		(-1.64)		(-1.71) [c]		(-1.71) [c]		(-0.51)		(-0.51)
	h		-0.26		-0.26		-0.48		-0.48		-0.87		-0.87
			(-1.53)		(-1.51)		(-2.81) [a]		(-2.80) [a]		(-2.97) [a]		(-2.97) [a]
L = 80%	α (%)	-0.02	0.11	0.53	0.65	0.99	1.14	1.07	1.22	0.71	0.99	0.75	1.03
		(-0.05)	(0.30)	(1.41)	(1.85) [c]	(2.28) [b]	(2.82) [a]	(2.47) [b]	(3.02) [a]	(1.08)	(1.75) [c]	(1.14)	(1.81) [c]
	β	-0.31	-0.39	-0.31	-0.40	-0.36	-0.45	-0.36	-0.45	-0.28	-0.43	-0.28	-0.43
		(-2.99) [a]	(-3.64) [a]	(-3.01) [a]	(-3.65) [a]	(-2.92) [a]	(-3.52) [a]	(-2.92) [a]	(-3.53) [a]	(-1.68)	(-2.51) [b]	(-1.68)	(-2.51) [b]
	s		-0.21		-0.21		-0.22		-0.22		-0.16		-0.16
			(-1.63)		(-1.62)		(-1.44)		(-1.44)		(-0.80)		(-0.80)
	h		-0.41		-0.41		-0.50		-0.50		-1.05		-1.05
			(-2.55) [b]		(-2.49) [b]		(-2.55) [b]		(-2.55) [b]		(-3.71) [a]		(-3.71) [a]
L = 90%	α (%)	-0.39	-0.26	0.32	0.45	0.79	0.93	0.90	1.04	0.78	1.08	0.83	1.13
		(-1.05)	(-0.74)	(0.85)	(1.30)	(1.85) [c]	(2.36) [b]	(2.11) [b]	(2.64) [a]	(1.17)	(1.89) [c]	(1.25)	(1.97) [b]
	β	-0.31	-0.40	-0.32	-0.41	-0.34	-0.44	-0.35	-0.44	-0.27	-0.44	-0.27	-0.44
		(-3.10) [a]	(-3.88) [a]	(-3.13) [a]	(-3.89) [a]	(-2.95) [a]	(-3.69) [a]	(-2.95) [a]	(-3.69) [a]	(-1.54)	(-2.46) [b]	(-1.54)	(-2.47) [b]
	s		-0.22		-0.22		-0.23		-0.23		-0.23		-0.23
			(-1.81) [c]		(-1.80) [c]		(-1.58)		(-1.58)		(-1.13)		(-1.13)
	h		-0.45		-0.45		-0.48		-0.48		-1.11		-1.11
			(-2.95) [a]		(-2.87) [a]		(-2.55) [b]		(-2.54) [b]		(-3.88) [a]		(-3.88) [a]

Turnover	Holding period of 3 months				Holding period of 6 months				Holding period of 12 months			
	Full		Actual		Full		Actual		Full		Actual	
	CAPM	FFM	CAPM	FFM	CAPM	FFM	CAPM	FFM	CAPM	FFM	CAPM	FFM
Panel C: Ranking period of 12 months												
L = 10% α (%)	1.02	1.12	1.13	1.24	1.91	1.90	1.93	1.92	2.56	2.62	2.57	2.62
	(2.03) [b]	(2.21) [b]	(2.25) [b]	(2.43) [b]	(3.40) [a]	(3.21) [a]	(3.44) [a]	(3.24) [a]	(3.92) [a]	(3.93) [a]	(3.94) [a]	(3.94) [a]
β	-0.06	-0.14	-0.06	-0.14	-0.08	-0.08	-0.08	-0.08	-0.03	-0.07	-0.03	-0.07
	(-0.58)	(-1.30)	(-0.59)	(-1.30)	(-0.53)	(-0.57)	(-0.53)	(-0.57)	(-0.20)	(-0.45)	(-0.20)	(-0.45)
s		-0.26		-0.26		-0.06		-0.06		-0.12		-0.12
		(-2.05) [b]		(-2.04) [b]		(-0.37)		(-0.37)		(-0.67)		(-0.67)
h		-0.33		-0.33		0.07		0.07		-0.16		-0.16
		(-1.49)		(-1.48)		(0.22)		(0.22)		(-0.50)		(-0.50)
L = 20% α (%)	1.12	1.25	1.31	1.44	1.39	1.40	1.43	1.44	1.54	1.59	1.56	1.60
	(2.93) [a]	(3.37) [a]	(3.42) [a]	(3.87) [a]	(3.13) [a]	(3.00) [a]	(3.21) [a]	(3.08) [a]	(2.76) [a]	(2.76) [a]	(2.79) [a]	(2.79) [a]
β	-0.03	-0.12	-0.04	-0.13	-0.08	-0.09	-0.08	-0.09	0.02	-0.01	0.02	-0.01
	(-0.36)	(-1.26)	(-0.37)	(-1.26)	(-0.70)	(-0.77)	(-0.70)	(-0.77)	(0.14)	(-0.09)	(0.14)	(-0.09)
s		-0.24		-0.24		0.01		0.01		-0.08		-0.08
		(-2.12) [b]		(-2.11) [b]		(0.06)		(0.06)		(-0.47)		(-0.46)
h		-0.44		-0.44		-0.05		-0.05		-0.15		-0.15
		(-2.74) [a]		(-2.73) [a]		(-0.21)		(-0.21)		(-0.52)		(-0.52)
L = 50% α (%)	0.57	0.70	0.96	1.09	1.01	1.12	1.08	1.20	1.11	1.19	1.13	1.21
	(1.95) [c]	(2.59) [a]	(3.27) [a]	(4.00) [a]	(3.06) [a]	(3.61) [a]	(3.29) [a]	(3.86) [a]	(2.83) [a]	(2.96) [a]	(2.87) [a]	(3.00) [a]
β	-0.11	-0.20	-0.12	-0.20	-0.12	-0.19	-0.12	-0.19	0.01	-0.04	0.01	-0.04
	(-1.43)	(-2.48) [b]	(-1.45)	(-2.48) [b]	(-1.33)	(-1.89) [c]	(-1.33)	(-1.89) [c]	(0.08)	(-0.34)	(0.08)	(-0.34)
s		-0.23		-0.23		-0.15		-0.15		-0.11		-0.10
		(-2.91) [a]		(-2.89) [a]		(-1.47)		(-1.46)		(-0.94)		(-0.94)
h		-0.43		-0.43		-0.39		-0.39		-0.26		-0.26
		(-3.50) [a]		(-3.45) [a]		(-2.41) [b]		(-2.40) [b]		(-1.14)		(-1.14)
L = 80% α (%)	-0.05	0.09	0.69	0.83	0.82	0.95	0.99	1.12	0.94	1.05	0.98	1.09
	(-0.15)	(0.32)	(2.24) [b]	(2.95) [a]	(2.38) [b]	(3.04) [a]	(2.86) [a]	(3.57) [a]	(2.37) [b]	(2.82) [a]	(2.47) [b]	(2.92) [a]
β	-0.13	-0.22	-0.13	-0.23	-0.16	-0.25	-0.17	-0.25	-0.16	-0.24	-0.16	-0.24
	(-1.45)	(-2.58) [b]	(-1.49)	(-2.60) [a]	(-1.59)	(-2.42) [b]	(-1.60)	(-2.43) [b]	(-1.42)	(-2.23) [b]	(-1.42)	(-2.23) [b]
s		-0.28		-0.28		-0.24		-0.24		-0.23		-0.23
		(-3.35) [a]		(-3.32) [a]		(-2.33) [b]		(-2.32) [b]		(-2.04) [b]		(-2.04) [b]
h		-0.43		-0.42		-0.43		-0.43		-0.36		-0.36
		(-3.90) [a]		(-3.80) [a]		(-2.83) [a]		(-2.82) [a]		(-2.20) [b]		(-2.20) [b]
L = 90% α (%)	-0.39	-0.25	0.57	0.70	0.66	0.81	0.88	1.03	0.80	0.94	0.85	0.98
	(-1.26)	(-0.90)	(1.86) [c]	(2.55) [b]	(1.91) [c]	(2.60) [a]	(2.55) [b]	(3.32) [a]	(2.02) [b]	(2.55) [b]	(2.14) [b]	(2.68) [a]
β	-0.16	-0.25	-0.16	-0.26	-0.17	-0.27	-0.18	-0.28	-0.18	-0.27	-0.18	-0.27
	(-1.89) [c]	(-3.06) [a]	(-1.94) [c]	(-3.08) [a]	(-1.65)	(-2.70) [a]	(-1.66)	(-2.70) [a]	(-1.54)	(-2.54) [b]	(-1.54)	(-2.54) [b]
s		-0.26		-0.26		-0.29		-0.29		-0.28		-0.28
		(-3.17) [a]		(-3.14) [a]		(-2.75) [a]		(-2.75) [a]		(-2.37) [b]		(-2.37) [b]
h		-0.45		-0.44		-0.46		-0.45		-0.42		-0.42
		(-3.94) [a]		(-3.85) [a]		(-2.99) [a]		(-2.98) [a]		(-2.44) [b]		(-2.44) [b]

5.7. Conclusions

The chapter examines the profitability of momentum strategies in the UK, taking into account the transactions costs involved in executing the required trades. We corroborate, for nine momentum strategies in the UK, the conclusions of Lesmond, Schill and Zhou (2004) for the 6-6 momentum strategy in the US. In particular, we find that the losers are more oriented towards stocks with lower market capitalization, lower price and lower trading volume than the winners and, thus, have higher total costs. An average round-trip quoted spread equals 2.21% for the winners and 3.76% for the losers. Based on effective spreads, round-trip transaction costs are only marginally smaller (1.90% for winners and 3.72% for losers). Once commissions, short selling costs and stamp duties are added, the average round-trip transaction cost based on the quoted spread rises to 3.77% for the winners and 6.71% for the losers. These estimates are far from the 2% round-trip cost reported in the early momentum literature which severely underestimated the actual cost of trading both the losers and winners in the UK. Net of these costs based on full or actual turnover, the profitability of relative-strength strategies proves to be an illusion.

Aside from providing confirmatory evidence for a range of momentum portfolios for the UK, we add our own contribution to the Lesmond, Schill and Zhou (2004) study in two ways. First, we investigate the reasons for the observed asymmetric pattern in trading costs between the winners and losers by splitting each round-trip trade into a buyer-initiated trade and a seller-initiated trade. While the trading costs of buyer-initiated trades are almost the same for the winners and losers, the trading costs of seller-initiated trades are asymmetric. On average, selling losers costs 2.3 times as much as closing a position in winners. This suggests that the asymmetry in trading costs between the winners and losers critically relates to the higher costs of selling the latter. We also relate the costs of buyer- and seller-initiated trades to the size and trading volume of the winners and losers. We find that the asymmetry in trading costs between the winners and losers is due to the higher cost of selling small capitalization loser stocks with low trading volumes. We note also that while size critically impacts the cost of selling the winners and losers, it does not affect the cost of buying them. Finally, for both the winners and losers, trading volume relates positively to the cost of buyer-initiated trades and negatively to the cost of seller-initiated trades.

Second, we derive and test the profitability, net of transaction costs, of so-called low-cost momentum strategies that select winner and loser stocks with the lowest total transaction costs. Interestingly, we conclude that, although standard momentum strategies are not profitable net of transaction costs, 22 out of 45 low-cost strategies produce, based on actual turnover, positive and significant net average returns. For example, the strategies that shortlist the 10%, 20% and 50% of winner and loser stocks with the lowest total transaction costs generate average net returns of 19.10%, 15.53% and 12.61%, respectively. Even after considering risk, low-cost momentum strategies with L = 10% and L = 20% still can earn positive and significant net abnormal returns based on both full and actual turnovers.

Chapter 6. Summary and Future Research

6.1. Summary

Momentum and value strategies are among the most controversial topics in financial literature. The evidence of momentum profits and the value premium has attracted a lot of attention by finance researchers since they strongly challenge both the EMH and the traditional CAPM. The explanations for these anomalies have been subject to considerable debate. Rational expectations argue that the profits are a compensation for risk and transaction costs, while behavioural economists interpret the profits as arising because investors make mistakes in the way they process information.

This study first examines momentum profits and the value premium by assuming that the variance of portfolio returns follows a GARCH process. The rationale for using the CAPM with a GARCH(1,1)-M specification is that the model allows for the impact of conditional information on the expected stock return caused by heteroskedasticity. Additionally, this model is able to capture the impact of time-varying idiosyncratic risk on the winner, loser, value and growth portfolios through time-varying total risk. These portfolios are sorted either by past performance or by book to market equity of stocks. Each portfolio has its own specific characteristics. Therefore, idiosyncratic risk, driven by these characteristics, may be a potential explanatory variable for the profits of momentum and value strategies.

Chapter 3 investigates whether momentum profits in the UK are a compensation for time-varying idiosyncratic risk. It shows that the CAPM and the FFM with a

GJR-GARCH-M specification can fully capture momentum profits. Thus, momentum profits are a compensation for exposure to time-varying idiosyncratic risk. Interestingly, both the GJR-GARCH(1,1) and the GARCH(1,1)-M specifications fail to account for the performance of momentum strategies. The profitability of momentum portfolios is explained by a combination of the time-varying risk premium and the asymmetric impact of good and bad news on the volatility of the momentum returns.

Chapter 3 also reveals that the impact of recent news on the volatility of the winners is more than it is on the volatility of the losers. Vice versa, the impact of distant news on the volatility of the losers is more than it is on the volatility of the winners. In addition, the volatility of the losers shows a higher level of persistence than that of the winners. Our results are consistent with the findings of Hong, Lim and Stein (2000) that for firms with no or low analysts coverage, bad news travels slower than good news and thus, the volatility of the losers may respond more slowly to news than that of the winners as the losers are more likely to disclose bad news and the winners are more likely to receive good news. We conjecture that the time-varying risk of companies with no or low analyst coverage depends on the nature of the information that has been disclosed: Good news is disclosed earlier, and impacts on volatility sooner, than bad news. Relative to the volatility of the winners, that of the losers also clearly shows a more asymmetric response to good and bad news. Negative return shocks increase the volatility of the losers more than they increase that of the winners.

Chapter 4 follows the same methodology used in Chapter 3 and investigates the relationship between time-varying idiosyncratic risk and the US post-1963 value premium through the conditional model with GARCH-M specifications. The results are in line with the findings in Chapter 3. That is the value premium can be fully captured by these specifications and the premium is a compensation for time-varying idiosyncratic risk. These findings are robust to different value and growth stocks defined by B/M, C/P and E/P ratios, and to the countries under view (US and UK).

Chapter 4 also finds that after taking account of total time-varying risk, the value portfolio does not have a higher market risk than the growth portfolio, although the market beta still has a strong explanatory power on the returns of the individual value and growth portfolio. This appears to support the findings of previous studies (see, for example, Jagannathan and Wang, 1996; Lettau and Ludvigson, 2001 and Adrian and Franzoni, 2005) that the conditional CAPM with time-varying beta performs well in explaining cross-sectional expected returns. On the other hand, the results show that the market betas are negative or insignificant for the momentum and HML portfolios. Therefore, Lewellen and Nagel (2006), Fama and French (2006) and Petkova and Zhang (2005) report that even after allowing betas to vary over time, the CAPM still fails to explain asset-pricing anomalies. The results in Chapter 4 are in support of the idea that the ability of time-varying total risk, in explaining the value premium, derives from the fact that it captures the time-varying idiosyncratic risk in the value and growth portfolios.

Fama and French (1996) conjectured that the value premium is priced as a risk factor because it is related to investment opportunities, a suggestion that is given credence empirically by Hahn and Lee (2006) and Petkova (2006) using financial variables that can capture such opportunities. The primary finding in this chapter, that the value premium is highly positively correlated with its time-varying volatility, is also consistent with this notion.

Chapter 5 examines the impact of trading costs on the profitability of momentum strategies through 9 combinations of ranking and holding periods in the UK. It shows that the losers consist mainly of stocks with low capitalization, low price and low trading volume in relation to the winners. Therefore, the average round-trip quoted spreads for the losers are much higher than those of the winners, which are underestimated by the previous momentum studies. The magnitude of trading costs can substantially reduce the net profits of momentum strategies. After taking account of total trading costs, momentum profit opportunities do not exist based on full turnover. Even with adjusted down trading costs based on actual turnover, momentum strategies still cannot produce positive net average returns at the 5% significant level. This chapter also analyzes the relationship between transaction costs on buyer- and seller-initiated trades and the market capitalization and trading volume of the winners and losers. The results reveal that both the market capitalization and trading volume of the winners and losers are negatively related to the cost of seller-initiated trades. Therefore, the relatively high trading costs of the losers are mainly driven by the high selling costs on small stocks with low trading volume.

Chapter 5 proposes a low-cost momentum strategy, which buys and sells the L% (L=10, 20, 50, 80, 90) of winner and loser stocks with the lowest total trading costs. The results show that based on actual turnover, 22 out of 45 low-cost momentum strategies can generate positive and significant net average returns. In particular, low-cost strategies, that trade on the 10% and 20% winner and loser stocks with the lowest total transaction costs, yield positive and significant net annual average returns of 19.10% and 15.53%, respectively.

6.2. Future Research

An increasing body of literature finds that idiosyncratic risk may be priced if investors do not hold a well-diversified portfolio (see, for example, Levy, 1978; Merton, 1987; Goyal and Santa-Clara, 2003 and Malkiel and Xu, 2001). Chapters 3 and 4 provide substantial evidence of the importance of time-varying idiosyncratic risk in explaining momentum profits and the value premium. This idea could also be applied to on the cross-section of expected returns. Size and B/M sorted portfolios consist of stocks that are highly correlated with each other. As a result, some idiosyncratic risks in these portfolios cannot be diversified away.

To examine the relationship between the cross-section of expected returns and time-varying idiosyncratic risk, one would use the Fama and French (1992) 100 value-weighted size and B/M sorted portfolios. Following the methodology employed in Chapters 3 and 4, one could assume that the variance of the cross-section of expected returns follows a GARCH-M process and examine whether these returns can be explained by time-varying idiosyncratic risk through a conditional model. More precisely the idea would then be to use the two-step methodology of Fama and McBeth (1973) in an attempt to find out if time-varying idiosyncratic risk is priced. Within this framework, one could also test whether size and B/M are still sources of priced risk once idiosyncratic risk is taken into account.

Another topic that attracts our attention is the relationship between industry momentum and time-varying idiosyncratic risk. Several studies report the existence of industry momentum, which is captured by investing in past winning industry portfolios and selling past losing industry portfolios. This strategy can be highly profitable (see, for example, Moskowitz and Grinblatt, 1999; Grundy and Martin, 2001 and Chordia and Shivakumar, 2002). Moskowitz and Grinblatt (1999) show that the performances of stocks within the same industry are more strongly positively correlated than stocks across industries. Therefore, industry portfolios are not perfectly diversified and time-varying idiosyncratic risk may contribute to industry momentum.

Chapter 3 shows that momentum profits can be fully captured by the conditional variance model without resorting to transactions costs and illiquidity issues that are the focus of Lesmond, Schill and Zhou (2004) or Sadka (2006). Sadka (2006) finds that the persistence of momentum profits can be partially attributed to compensation for liquidity risk. In Chapter 5, the magnitude of trading costs is found to play an important role in assessing the net profits of momentum strategies. It would be interesting in future research to explore whether momentum profits can be explained by liquidity risk. Following Chordia, Roll and Subrahmanyam (2000), research could use the trading costs and trading volume of stocks as proxies for liquidity and form liquidity mimicking portfolios to examine the impact of liquidity risk on the profitability of momentum strategies.

Chan and Lakonishock (1993 and 1995) and Keim and Madhavan (1997) report substantially variation in trading costs between different investment styles. In particular, investors who trade in value stocks have lower trading costs than those who trade in growth stocks. However, the results in Chapter 5 show that trading costs are high for stocks with small size, low price and low trading volume. Chen and

Zhang (1998) report that value stocks have characteristics of small size and low price. Therefore, we conjecture that value stocks may have higher trading costs than growth stocks. This is in conflict with the findings of existing studies and is an interesting area for future research.

References

Adrian, Tobias, and Francesco Franzoni, 2005, Learning about Beta: Time-Varying Factor Loadings, Expected Returns, and the Conditional CAPM, Federal Reserve Bank of New York Staff Report 254.

Ali, Ashiq, and Mark A Trombley, 2006, Short Sales Constraints and Momentum in Stock Returns, *Journal of Business Finance and Accounting* 33, 587-615.

Andersen, Torben G., Tim Bollerslev, Peter F. Christoffersen, and Francis X. Diebold, 2005, Volatility Forecasting, *Financial Institutions Center at The Wharton School, Working Papers*.

Ang, Andrew, and Joseph Chen, 2007, The CAPM Over the Long-Run: 1926-2001, *Journal of Empirical Finance* 14, 1-40.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The Cross-Section of Volatility and Expected Returns, *Journal of Finance* 61, 259-299.

Bali, Turan G., and Nusret Cakici, 2007, Idiosyncratic Volatility and the Cross-Section of Expected Returns, *Journal of Financial and Quantitative Analysis,* forthcoming.

Bali, Turan G., Nusret Cakici, Xuemin Yan, and Zhe Zhang, 2005, Does Idiosyncratic Risk Really Matter? *Journal of Finance* 60, 905-929.

Banz, Rolf W., 1981, The Relationship between Return and Market Value of Common Stocks, *Journal of Financial Economics* 9, 3-18.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A Model of Investor Sentiment, *Journal of Financial Economics* 49, 307-343.

Basu, Sanjoy, 1977, Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis, *Journal of Finance* 32, 663-682.

Basu, Sanjoy, 1983, The Relationship Between Earnings' Yield, Market Value and the Return for NYSE Common Stocks: Further Evidence, *Journal of Financial Economics* 12, 1983.

Bauwens, Luc, Sébastien Laurent, and Jeroen V. K. Rombouts, 2006, Multivariate GARCH Models: A Survey, *Journal of Applied Econometrics* 21, 79-109.

Bekaert, Geert, and Wu, Guojun, 2000, Asymmetric Volatility and Risk in Equity Markets, *Review of Financial Studies* 13, 1- 42

Berkowitz, S., D. Logue, and E. Noser, 1988, The Total Cost of Transactions on the NYSE, *Journal of Finance* 43, 97-112.

Bessembinder, Hendrik, and Herbert M. Kaufman, 1997, A Comparison of Trade Execution Costs for NYSE and NASDAQ-Listed Stocks, *Journal of Financial and Quantitative Analysis* 32, 287-310.

Bhandari, Laxmi Chand, 1988, Debt/Equity Ratio and Expected Common Stock Returns: Empirical Evidence, *Journal of Finance* 43, 507-528.

Bhardwaj, Ravinder K., and Leroy D. Brooks, 1992, The January Anomaly: Effects of Low Share Price, Transaction Costs, and Bid-Ask Bias, *Journal of Finance* 47, 553-575.

Bhojraj, Sanjeev, and Bhaskaran Swaminathan, 2006, Macromomentum: Returns Predictability in International Equity Indices, *Journal of Business* 79, 429- 451.

Black, Fischer, 1972, Capital Market Equilibrium with Restricted Borrowing, *Journal of Business* 45, 444-455.

Black, Fischer, 1976, Studies of Stock, Price Volatility Changes, *Proceedings of the 1976 meetings of the Business and Economics Statistics Section, American Statistical Association,* 177-181.

Black, Fisher, Michael Jensen, and Myron Scholes, 1972, The Capital Asset Pricing Model:Some Empirial Tests, in M.Jensen, ed.: *Studies in the Theory of Capital Markets* (Praeger, New York).

Blume, Marshall E., 1971, On the Assessment of Risk, *Journal of Finance* 26, 1-10.

Bodurtha, James N., and Nelson C. Mark, 1991, Testing the CAPM with Time-Varying Risks and Returns, *Journal of Finance* 46, 1485-1505.

Bollerslev, Tim, 1986, Generalized Autoregressive Conditional Heteroskedasticity, *Journal of Econometrics* 31, 307-327.

Bollerslev, Tim, Robert F. Engle, and Jeffrey M. Wooldridge, 1988, A Capital Asset Pricing Model with Time-Varying Covariances, *Journal of Political Economy* 96, 116-131.

Bollerslev, Tim and Jeffrey M. Wooldridge, 1992, Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time Varying Covariances, *Econometric Reviews,* 11, 143–172.

Brooks, Chris, Ales Cerny and Joelle Miffre, 2008, Optimal Hedging with Higher Moments, *EFA 2007 Liubljana Meetings Paper, Cass Business School Research Paper.*

Campbell, John Y., 1993, Intertemporal Asset Pricing without Consumption Data, *American Economic Review* 83, 487–512.

Campbell, John Y., 1996, Understanding Risk and Return, *Journal of Political Economy* 104, 298–345.

Campbell, John Y. and Ludger Hentschel, 1992, No News is Good News: An Asymmetric Model of Changing Volatility in Stock Returns, *Journal of Financial Economics* 31, 281-318.

Campbell, John Y., Martin Lettau, Burton G. Malkiel, and Yexiao Xu, 2001, Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk, *Journal of Finance* 56, 1-43.

Carhart, Mark M., 1997, On Persistence in Mutual Fund Performance, *Journal of Finance* 52, 57-82.

Chan, Kalok, Allaudeen Hameed, and Wilson Tong, 2000, Profitability of Momentum Strategies in the International Equity Markets, *Journal of Financial and Quantitative Analysis* 35, 153-172.

Chan, Louis K. C., Narasimhan Jegadeesh, and Josef Lakonishok, 1995, Evaluating the Performance of Value versus Glamour Stocks The Impact of Selection Bias, *Journal of Financial Economics* 38, 269-296.

Chan, Louis K. C., Narasimhan Jegadeesh, and Josef Lakonishok, 1996, Momentum Strategies, *Journal of Finance* 51, 1681-1713.

Chan, Louis K. C., and Josef Lakonishok, 1993, Institutional Trades and Intraday Stock Price Behavior, *Journal of Financial Economics* 33, 173-199.

Chan, Louis K. C., and Josef Lakonishok, 1995, The Behavior of Stock Prices Around Institutional Trades, *Journal of Finance* 50, 1147-1174.

Chan, Louis K. C., and Josef Lakonishok, 1997, Institutional Equity Trading Costs: NYSE versus Nasdaq, *Journal of Finance* 52, 713-735.

Chan, Louis K. C., and Josef Lakonishok, 2004, Value and Growth Investing: Review and Update, *Financial Analysts Journal* January/February, 71-86.

Chen, Hsiu-Lang, and Werner De Bondt, 2004, Style Momentum within the S&P-500 Index, *Journal of Empirical Finance* 11, 483-507.

Chen, Nai-Fu, Richard Roll, and Stephen A. Ross, 1986, Economic Forces and the Stock Market, *Journal of Business* 59, 383-403.

Chen, Nai-fu, and Feng Zhang, 1998, Risk and Return of Value Stocks, *Journal of Business* 71, 501-535.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2000, Commonality in Liquidity, *Journal of Financial Economics* 56, 3-28.

Chordia, Tarun, and Lakshmanan Shivakumar, 2002, Momentum, Business Cycle, and Time-Varying Expected Returns, *Journal of Finance* 57, 985-1018.

Chui, Andy C. W., Sheridan Titman, and K.C. John Wei, 2001, Momentum, Legal Systems and Ownership Structure: An Analysis of Asian Stock, *University of Texas at Austin, Working Paper.*

Conrad, Jennifer, Michael Cooper, and Gautam Kaul, 2003, Value versus Glamour, *Journal of Finance* 58, 1969-1995.

Conrad, Jennifer, and Gautam Kaul, 1998, An Anatomy of Trading Strategies, *Review of Financial Studies* 11, 489-519.

Christie, Andrew A., 1982, The Stochastic Behavior of Common Stock Variances: Value, Leverage, and Interest Rate Effects, *Journal of Financial Economics* 10, 407-432.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor Psychology and Security Market Under-and Overreactions, *Journal of Finance* 53, 1839-1886.

Daniel, Kent, and Sheridan Titman, 1997, Evidence on the Characteristics of Cross Sectional Variation in Stock Returns, *Journal of Finance* 52, 1-33.

Davis, James, Eugene F. Fama, and Kenneth R. French, 2000, Characteristics, Covariances, and Average Returns: 1927-1997, *Journal of Finance* 55, 389-406.

De Bondt, Werner F.M, and Richard H. Thaler, 1985, Does the Stock Market Overreact? *Journal of Finance* 40, 793-805.

De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, 1990, Positive Feedback Investment Strategies and Destabilizing Rational Speculation, *Journal of Finance* 45, 379-395.

Diavatopoulos, Dean, James S. Doran, and David R. Peterson, 2006, The Information Content in Implied Idiosyncratic Volatility and the Cross-Section of

Stock Returns: Evidence from the Option Markets. *Florida State University Working Paper.*

Dimson, Elroy, Stefan Nagel, and Garrett Quigley, 2003, Capturing the Value Premium in the United Kingdom, *Financial Analysts Journal* 59, 35-45.

Ellis, Mark, and Dylan C. Thomas, 2003, Momentum and the FTSE 350, *Journal of Asset Management* 5, 25-36.

Engle, Robert F., 1982, Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation, *Econometrica* 50, 987-1008.

Engle, Robert F., David M. Lillien, and Russell P. Robbins, 1987, Estimating Time Varying Risk Premia in the Term Structure: The ARCH-M Model, *Econometrica* 55, 391-407.

Fama, Eugene F., 1965, The Behavior of Stock Market Prices, *Journal of Business* 38, 34-105.

Fama, Eugene F., 1970, Efficient Capital Markets: A Review of Theory and Empirical Work, *Journal of Finance* 25, 383-417.

Fama, Eugene F., 1991, Efficient Capital Markets: II, *Journal of Finance* 46, 1575-1617.

Fama, Eugene F., 1998, Market Efficiency, Long-Term Returns, and Behavioral Finance, *Journal of Financial Economics* 49, 283-306.

Fama, Eugene F., and Kenneth R. French, 1992, The Cross-Section of Expected Stock Returns, *Journal of Finance* 47, 427-465.

Fama, Eugene F., and Kenneth R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics* 33, 3-56.

Fama, Eugene F., and Kenneth R. French, 1995, Size and Book-to-Market Factors in Earning and Returns, *Journal of Finance* 50, 131-155.

Fama, Eugene F., and Kenneth R. French, 1996, Multifactor Explanations of Asset Pricing Anomalies, *Journal of Finance* 51, 55-84.

Fama, Eugene F., and Kenneth R. French, 1998, Value versus Growth: The International Evidence, *Journal of Finance* 53, 1975-1999.

Fama, Eugene F., and Kenneth R. French, 2006, The Value Premium and the CAPM, *Journal of Finance* 61, 2163-2185.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, Return and Equilibrium: Empirical Test, *Journal of Political Economy* May/June, 607-636.

Ferson, Wayne E., and Campbell R. Harvey, 1991, The Variation of Economic Risk Premiums, *Journal of Political Economy* 99, 385-415.

Ferson, Wayne E., and Campbell R. Harvey, 1993, The Risk and Predictability of International Equity Returns, *Review of Financial Studies* 6, 527-566.

French, Kenneth R., G. William Schwert, and Robert F. Stambaugh, 1987, Expected Stock Returns and Volatility, *Journal of Financial Economics* 19, 3-30.

Fu, Fangjian, 2005, Idiosyncratic Risk and the Cross-Section of Expected Stock Returns, *EFA 2005 Moscow Meetings.*

Fuertes, Ana-Maria., Joelle Miffre, and Wooi H. Tan, 2008, Are Momentum Profits a Compensation for Non-normality in Equity Returns? *Applied Financial Economics*, forthcoming.

Ghysels, Eric, Pedro Santa-Clara, and Rossen Valkanov, 2005, There is a Risk-Return Trade-off After All, *Journal of Financial Economics* 76, 509-548.

Glosten, Lawrence R., Ravi Jaganathan, and David E. Runkle, 1993, On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks, *Journal of Finance* 48, 1779-1801.

Goyal, Amit, and Pedro Santa-Clara, 2003, Idiosyncratic Risk Matters! *Journal of Finance* 58, 975-1008.

Gregory, Alan, Richard D. F. Harris, and Maris Michou, 2001, An Analysis of Contrarian Investment Strategies in the UK, *Journal of Business Finance & Accounting* 28, 1193-1228.

Gregory, Alan, Richard D. F. Harris, and Maris Michou, 2003, Contrarian Investment and Macroeconomic Risk, *Journal of Business Finance & Accounting* 30, 213-255.

Griffin, John M., Xiuqing Ji, and J. Spencer Martin, 2003, Momentum Investing and Business Cycle Risk: Evidence from Pole to Pole, *Journal of Finance* 58, 2515-2547.

Grundy, Bruce D, and J. Spencer Martin, 2001, Understanding the Nature of the Risks and the Source of the Rewards to Momentum Investing, *Review of Financial Studies* 14, 29-78.

Hahn, Jaehoon, and Hangyong Lee, 2006, Yield Spreads as Alternative Risk Factors for Size and Book-to-Market, *Journal of Financial and Quantitative Analysis* 41, 245-269.

Hanna, J. Douglas, and Mark J. Ready, 2005, Profitable Predictability in the Cross Section of Stock Returns, *Journal of Financial Economics* 78, 463-505.

Harvey, Campbell R., 1989, Time-Varying Conditional Covariances in Tests of Asset Pricing Models, *Journal of Financial Economics* 24, 289-317.

Harvey, Campbell R., 1995, Predictable Risk and Returns in Emerging Markets, *Review of Financial Studies* 8, 773-816.

Haugen, Robert A., 1995. *The New Finance: The Case against Efficient Markets* (Prentice Hall, Englewood Cliffs, New Jersey).

Hentschel, Ludger, 1995, All in the Family Nesting Symmetric and Asymmetric GARCH Models, *Journal of Financial Economics* 39, 71-104.

Hirt, Geoffrey, and G.S. Pandher, 2005, Idiosyncratic Risk and Return across S&P 500 Stock, *Mimeo, Kellstadt Graduate School, DePaul University.*

Hon, Mark, and Ian Tonks, 2003, Momentum in the UK Stock Market, *Journal of Multinational Financial Management* 13, 43-70.

Hong, Harrison, Terence Lim, and Jeremy C. Stein, 2000, Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies, *Journal of Finance* 55, 265-295.

Hong, Harrison, and Jeremy C. Stein, 1999, A Unified Theory of Underreaction, Momentum Trading and Overreaction in Asset Markets, *Journal of Finance* 54, 2143-2184.

Jagannathan, Ravi, and Zhenyu Wang, 1996, The Conditional CAPM and the Cross-Section of Expected Returns, *Journal of Finance* 51, 3-53.

Jegadeesh, Narasimhan, 1990, Evidence of Predictable Behavior of Security Returns, *Journal of Finance* 45, 881-898.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance* 48, 65-91.

Jegadeesh, Narasimhan, and Sheridan Titman, 2001, Profitability of Momentum Strategies: An Evaluation of Alternative Explanations, *Journal of Finance* 56, 699-720.

Jensen, Michael C., 1978, Some Anomalous Evidence Regarding Market Efficiency, *Journal of Financial Economics* 6, 95-101.

Jiang, Xiaoquan, and Bong-Soo Lee, 2006, The Dynamic Relation Between Returns and Idiosyncratic Volatility, *Financial Management* 35, 43-65.

Johnson, Timothy C., 2002, Rational Momentum Effects, *Journal of Finance* 57, 585-608.

Karolyi, G. Andrew, and Bong-Chan Kho, 2004, Momentum Strategies: Some Bootstrap Tests, *Journal of Empirical Finance* 11, 509-536.

Keim, Donald B., 1990, A New Look at the Effects of Firm Size and E/P Ratio on Stock Returns, *Financial Analysts Journal* 46, 56-67.

Keim, Donald B., and Ananth Madhavan, 1996, The Upstairs Market for Large-Block Transactions: Analysis and Measurement of Price Effect, *Review of Financial Studies* 9, 1-36.

Keim, Donald B., and Ananth Madhavan, 1997, Transaction Costs and Investment Style: An Inter-exchange Analysis of Institutional Equity Trades, *Journal of Financial Economics* 46, 265-292.

Keim, Donald B., and Ananth Madhavan, 1998, The Cost of Institutional Equity Trades, *Financial Analysts Journal* 54, 50-69.

Knez, Peter J., and Mark J. Ready, 1996, Estimating the Profits from Trading Strategies, *Review of Financial Studies* 9, 1121-1163.

Korajczyk, Robert A., and Ronnie Sadka, 2004, Are Momentum Profits Robust to Trading Costs? *Journal of Finance* 59, 1039-1082.

Kothari, S. P., Jay Shanken, and Richard G. Sloan, 1995, Another Look at the Cross-Section of Expected Stock Returns, *Journal of Finance* 50, 185-224.

Lakonishok, Josef, Andrei Shleifer, and Robert Vishny, 1994, Contrarian Investment, Extrapolation, and Risk, *Journal of Finance* 49, 1541-1578.

La Porta, Rafael, Josef Lakonishok, Andrei Shleifer, and Robert Vishny, 1997, Good News for Value Stocks: Further Evidence on Market Efficiency, *Journal of Finance* 52, 859-874.

Lee, Charles M. C., and Mark J. Ready, 1991, Inferring Trade Direction from Intraday Data, *Journal of Finance* 46, 733-746.

Lee, Charles M. C., and Bhaskaran Swaminathan, 2000, Price Momentum and Trading Volume, *Journal of Finance* 55, 2017-2069.

Lehmann, Bruce N., 1990, Fads, Martingales, and Market Efficiency, *Quarterly Journal of Economics* 105, 1-28.

Lesmond, David A., Joseph P. Ogden, and Charles A. Trzcinka, 1999, A New Estimate of Transaction Costs, *Review of Financial Studies* 12, 1113-1141.

Lesmond, David A., Michael J. Schill, and Chunsheng Zhou, 2004, The Illusory Nature of Momentum Profits, *Journal of Financial Economics* 71, 349-380.

Lettau, Martin, and Sydney Ludvigson, 2001, Resurrecting the (C)CAPM: A Cross-Sectional Test When Risk Premia are Time-Varying, *Journal of Political Economy* 109, 1238-1287.

Levis, Mario, and Manolis Liodakis, 2001, Contrarian Strategies and Investor Expectations: The U.K. Evidence, *Financial Analysis Journal* 57, 43-56.

Levy, Haim, 1978, Equilibrium in an Imperfect Market: A Constraint on the Number of Securities in the Portfolio, *American Economic Review* 68, 643-658.

Levy, Robert A., 1971, On the Short-Term Stationarity of Beta Coefficients, *Financial Analysts Journal* 27, 55-62.

Lewellen, Jonathan, and Stefan Nagel, 2006, The Conditional CAPM Does Not Explain Asset-pricing Anomalies, *Journal of Financial Economics* 82, 289-314.

Lintner, John, 1965, The Valuation of Risky Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets, *Review of Economics and Statistics* 47, 13-37.

Litzenberger, Robert H., and Krishna Ramaswamy, 1979, The Effect of Personal Taxes and Dividends on Capital Asset Prices: Theory and Empirical Evidence, *Journal of Financial Economics* 7, 163-195.

Liu, Weimin, Norman Strong, and Xinzhong Xu, 1999, The Profitability of Momentum Investing, *Journal of Business Finance and Accounting* 26, 1043-1091.

Lo, Andrew W., and C. Craig MacKinlay, 1990, When are Contrarian Profits Due to Stock Market Overreaction? *Review of Financial Studies* 3, 175-205.

Loeb, Thomas, 1983, Trading Cost: The Critical Link between Investment Information and Results, *Financial Analysts Journal* 39, 39-43.

Loughran, Tim, 1997, Book-to-Market across Firm Size, Exchange, and Seasonality: Is There an Effect? *Journal of Financial and Quantitative Analysis* 32, 249-268.

Malkiel, Burton G., and Yexiao Xu, 2001, Idiosyncratic Risk and Security Returns, *AFA 2001 New Orleans Meetings*.

Mandelbrot, Benoit, 1963, The Variation of Certain Speculative Prices, *Journal of Business* 36, 392-417.

Markowitz, Harry, 1952, Portfolio Selection, *Journal of Finance* 7, 77-91.

Merton, Robert C., 1974, On the Pricing of Corporate Debt: The Risk Structure of Interest Rates, *Journal of finance* 29, 449-470.

Merton, Robert C., 1987, A Simple Model of Capital Market Equilibrium with Incomplete Information, *Journal of Finance* 42, 483-510.

Miffre, Joëlle, and Georgios Rallis, 2007, Momentum Strategies in Commodity Futures Market, *Journal of Banking and Finance* 31, 1863-1886.

Moskowitz, Tobias J., and Mark Grinblatt, 1999, Do Industries Explain Momentum? *Journal of Finance* 54, 1249-1290.

Nelson, Daniel B., 1991, Conditional Heteroskedasticity in Asset Returns: A New Approach, *Econometrica* 59, 347-370.

Newey, Whitney K., and Kenneth D. West, 1987, Hypothesis Testing with Efficient Method of Moments, *International Economic Review* 28, 777-787.

Ng, Lilian, 1988, Tests of the CAPM with Time Varying Covariances: A Multivariate GARCH Approach, *Journal of Finance* 46, 1507-1521.

Okunev, John, and Derek White, 2003, Do Momentum-Based Strategies Still Work in Foreign Currency Markets? *Journal of Financial and Quantitative Analysis* 38, 425-447.

Penman, Stephen H., 2007, Financial Statement Analysis and Security Valuation, *4th Edition*. New York: McGraw-Hill. ISBN 007-125432-3.

Petkova, Ralitsa, 2006, Do the Fama-French Factors Proxy for Innovations in Predictive Variables? *Journal of Finance* 61, 581-612.

Petkova, Ralitsa, and Lu Zhang, 2005, Is Value Riskier than Growth? *Journal of Financial Economics* 78, 187-202.

Poon, Ser-Huang, and Clive W. J. Granger, 2003, Forecasting Volatility in Financial Markets: A Review, *Journal of Economic Literature* 41, 478-539.

Rabemananjara, R., and J. M. Zakoian, 1993, Threshold ARCH Models and Asymmetries in Volatility, *Journal of Applied Econometrics* 8, 31-49.

Reinganum, Marc R., 1981, Misspecification of Capital Asset Pricing: Empirical Anomalies Based on Earnings' Yields and Market Values, *Journal of Financial Economics* 9, 19-46.

Reinganum, Marc R., 1983, The Anomalous Stock Market Behavior of Small Firms in January, *Journal of Financial Economics* 12, 89-94.

Roll, R., 1984, A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market, *Journal of Finance* 39, 1127-1139.

Rouwenhorst, K. Geert, 1998, International Momentum Strategies, *Journal of Finance* 53, 267-284.

Sadka, Ronnie, 2006, Momentum and Post-Earnings-Announcement Drift Anomalies: The Role of Liquidity Risk, *Journal of Financial Economics* 80, 309-349.

Schwert, G. William, and Paul J. Seguin, 1990, Heteroskedasticity in Stock Returns, *Journal of Finance* 45, 1129-155.

Sharpe, William F., 1964, Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk, *Journal of Finance* 19, 425-442.

Shleifer, Andrei, 2000. *Inefficient Markets - An Introduction to Behavioral Finance* (Oxford University Press, Oxford and New York).

Stoll, Hans R., 1989, Inferring the Components of the Bid-Ask Spread: Theory and Empirical Tests, *Journal of Finance* 44, 115-134.

Stoll, Hans R., 1995, The Importance of Equity Trading Costs: Evidence from Securities Firms' Revenues, in Schwartz R, ed.: *In Global Equity Markets: Technological, Competitive, and Regulatory Challenges* (New York University Salomon Center, New York).

Stoll, Hans R., and Robert E. Whaley, 1983, Transaction Costs and the Small Firm Effect, *Journal of Financial Economics* 12, 57-79.

Wang, Kevin Q., 2003, Asset Pricing with Conditional Information: A New Test, *Journal of Finance* 58, 161-195.

Wu, Xueping, 2002, A Conditional Multifactor Analysis of Return Momentum, *Journal of Banking and Finance* 26, 1675-1696.

Zhang, Lu, 2005, The Value Premium, *Journal of Finance* 60, 67-103.

List of Publications and Submissions

Publications

Li, Xiafei, Joelle Miffre, Chris Brooks and Niall O'Sullivan, 2008, Momentum Profits and Time-Varying Unsystematic Risk, *Journal of Banking and Finance* 32, 541-558.

Mazouz, Khelifa and Xiafei Li, 2007, The Overreaction Hypothesis in the UK Market: Empirical Analysis, *Applied Financial Economics* 17, 1101-1111.

Conference Paper

Li, Xiafei, Chris Brooks and Joelle Miffre, The Value Premium and Time-Varying Idiosyncratic Risk, is accepted for presentation at the European Financial Management Association 2008 Annual Conference.

Appendix 1

Barclays Stockbrokers Company Dealing Account - Rates & Charges (from http://www.stockbrokers.barclays.co.uk/?category=whatweoffer&usecase=landing48)

Commission Charges

Commission is charged per deal. Other charges and service restrictions may apply.

Online Commission - All investment types except non-IRS foreign securities, unit trusts and OEICs.

Deals per calendar month	Commission
1 – 5	£12
6 - 10	£7.50
11 and above	£6.95

Telephone Commission - All investment types except non-IRS foreign securities, bonds, unit trusts and OEICs.

Deal value	Commission
£0 - £1,000	£17.50
£1,001 - £2,000	£24
£2,001 - £4,000	£36
£4,001 - £20,000	£54
Over £20,000	£75

Commission will be negotiable on large size telephone deals (typically in excess of £100,000) for all Company Dealing Accounts opened after 30 January 2008.

The initial commission rate you pay in each quarter is determined by the number of deals you place in previous calendar quarters. Each time you hit a new tier, you will be switched to the lower commission rates with immediate effect. In order to remain at the new tier you must maintain the required number of deals per quarter. The calendar quarters run from January to March, April to June, July to September and October to December. The number of telephone and online deals you place are consolidated when calculating your deal count, but each method has its own commission rates.

Non-IRS Foreign Securities (telephone dealing only)

Deal value	
First £10,000	1.75%
Next £10,000	1.125%
Next £20,000	0.50%
Next £60,000	0.40%

Thereafter	0.30%
Minimum for US shares	£45
Minimum for non-US shares	£100

Automatic Dividend Reinvestment

Automatic dividend reinvestment purchases are charged at a flat rate commission of 1.0% (minimum £1, maximum £7.50).

Funds

The initial charge for buying funds through Funds Market is 1.5%. Other funds vary according to the fund manager.

There is no charge for selling Funds Market funds but there is a £15 charge per deal on the sale of non-Funds Market funds.

Taxes & Levies

Stamp duty or stamp duty reserve tax (SDRT) on all UK equity purchases is payable at the prevailing rate at the time of dealing.

The current rates are:

0.5% SDRT on all UK equity purchases settled through CREST, rounded up to the nearest 1p 0.5% stamp duty on all UK equity purchases not settled through CREST, rounded up to the nearest £5

Stamp duty on Irish registered stock is currently charged at 1%

The Panel of Takeovers and Mergers currently levy £1 on all UK equity transactions of £10,000 and over