Equity Style Investing

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Abstract

Despite the well documented benefits of equity style investing in today's financial markets, the academic view of the underlying cause for such benefits remains an ongoing debate. A number of theories have been proposed to explain why some asset classes earn better returns than others do under the same economic regimes. Rational finance links the outperformance of some stock groups to the equity characteristics that proxy for the common risk factors, behavioural finance, however, argues that mispricing resulting from irrational investor's sentiment to fundamentals plays a key role. Meanwhile, a variety of business cycle variables have also suggested to contain information useful in explaining the expected stock returns. The observed style returns change all the time with predictable time-varying components, reflecting the structural and cyclical shocks to the macroeconomy.

Motivated by the current ongoing controversy of anomaly versus risk compensation over interpreting equity style premiums, this thesis investigates how firm characteristics and business cycle conditions function separately to affect the style return dynamics based on the size and value-growth categorisations. It adds to the extant literature by explicitly examining the relative importance of the common risk factors versus firm-specific information as driving sources in the divergent equity style returns in the U.K. market. By identifying the dominant driving force that determines the relative style performance, it provides a further dimension to the current debate regarding the sources of style premiums and offers the choice of corresponding style investing strategies.

The divergent style returns and its time-varying nature offer astute investors the opportunity to implement active style management to enhance portfolio returns. Motivated by the benefits of capitalising on such style return cyclicality and in particular the availability and popularity of Exchange Traded Funds based on market segments in leading financial markets as investment vehicle that offers low cost and high liquidity, this thesis examines a dynamic long-short tactical trading strategy by applying a binomial approach to focus on the rotation between pairs of equity styles. By answering key questions of whether equity style cycles exist in the U.K. market and whether the return dynamics of such style momentum strategy is distinct from the price and industry momentum effects, it contributes to the literature by providing valuable empirical evidence to compare with other studies in different economic and institutional environments.

In response to the increasing popularity of using macro information to aid optimal style selection for the quant circles in the investment community, building on the methodology of Brandt and Santa-Clara (2006), this thesis approximates a solution of a mean-variance multi-style investor's optimal style investing problem incorporating the business cycle predictability. This approach is parsimonious as the optimal style weights are parameterised directly on a set of pervasive business cycle predictors. By exploring how the distributions of the expected style returns and the location or the shape of the optimal style allocations are affected by given shocks to the business cycles, this thesis contributes to the extant literature by demonstrating the transmission mechanism of how business cycle volatility affects equity style return volatility and in turn a mean-variance investor's optimal style allocation.

Declaration

I hereby declare that the content contained in this thesis has not been previously submitted, either in whole or in part, for a degree at this or other universities.

Wu Rong

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Dedications

To my father in the heaven, Xiangjing Rong

To my mother, Sanzhuang Ping

Your love, support, encouragement and positive attitude towards education as well as the optimistic spirit when facing hardship has inspired me throughout my life

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Chapter 1

Introductions

1.1 Equity style

Human beings have the unique behaviour of classifying objects into different categories (Wilson and Keil (1999)). When facing complex environment we are able to simplify the decision-making process based on such categorisation. For example, a product displayed in a supermarket can be classified as *luxury* or *necessity,* a customer can decide whether to purchase it or not given his budget constraint. When talking about a person's occupation, one can be classified as '*golden collar'*, '*white collar'* or '*blue collar'*, depending on the nature of his work involved. Similarly, a country can be classified as '*developed*' or '*developing*' based on the average overall wealth its people have and the current stage of its economy development. A capital market can also be classified as '*developed*' or '*emerging*' depending on whether the underlying economy needs growing liquidity, stability, infrastructure and other positive features. The mechanism of categorisation can help us to better understand the underlying objects because objects within the same category share common characteristics.

The idea of classification of objects into categories is also pervasive in the financial markets. The investable assets in the marketplace can be broadly classified into several groups as differentiated by the characteristics like return patterns or risk factors. Within each asset class there also exist some subgroups that share properties similar to their major asset class but are unique along specific dimension. For example, investors can separate the assets from each other by classifying them as bonds, stocks, real estate and cash etc. Assets can also be further sub-categorised within each category (e.g. bonds can be subdivided into government bonds or corporate bonds; stocks can be sub-classified as value and growth, etc). In the investment community, 'style' refers to such classification of assets by market segments, and 'equity style' refers to systematic classification among stocks in the equity market. Style is by no means fixed, as time goes by due to market innovation or research discovery, new styles may evolve and old styles may die off[1].

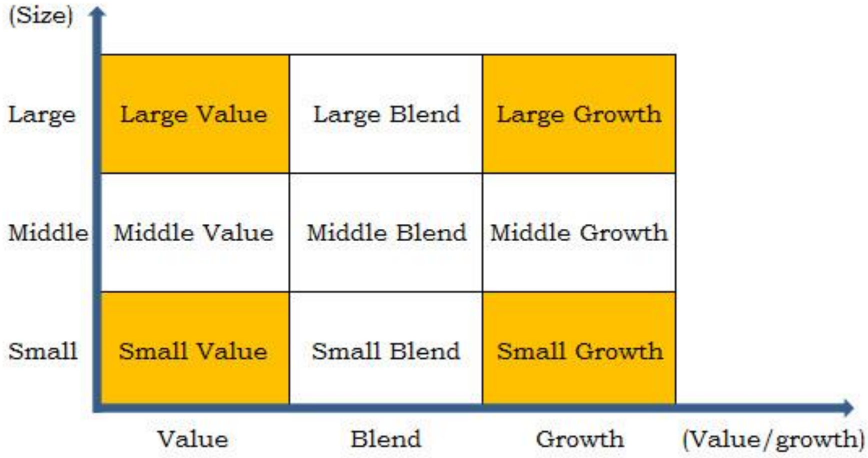
A number of descriptors can be used in empirical research to define equity styles. Firm characteristics like market values that lie in the size dimension and valuation multipliers in the value and growth dimension are most commonly used. While it is intuitive to subdivide the stocks according to their market capitalisations, categorising the stocks into the broad group of value and growth is perhaps more natural because value and growth stocks tend to follow different return patterns and therefore counterbalance each other. Moreover, the dispersion of value and growth returns is perhaps more likely driven by economic fundamentals. Hence value and growth stocks are often considered as two different asset classes. In addition to the common value-growth styles, stocks can also be classified according to their past performance and the *winners* and *losers* are identified.

[1] Barberis and Shleifer (2003) suggest two possible reasons for the emergence of new styles: financial innovations (e.g. inflation-related bonds) and the detection of outperformance of one asset group over another (e.g. momentum effect). On the other hand, some old styles are no longer available to investors due to change of the market condition. For example, inflation-linked bonds used to be attractive to investors in a high inflation economy, such products die off when the economy turns into deflation states.

Indeed, the concept of style is well recognised in today's global equity markets. There are many index providers to offer equity style indexes as benchmarks to serve the investment community. Over the past decade leading financial markets have witnessed the availability and popularity of Exchange Traded Fund (ETF) and the introduction of style index futures that offer low trading cost and high liquidity for investors.

Figure 1-1 shows a typical equity style box that is widely used by market practitioners. This figure provides a visual representation of the major investment characteristics of stocks in the market. Such 'equity style box' was first created by Morningstar to define the risk-return structures of stocks. The equity style box is comprised of nine categories with the underlying investment features defined by two dimensions. Horizontally, all stocks in the market can be divided into three categories: value, blend (i.e. a value/growth mix) and growth. Vertically, stocks are divided into three sizes based on their market capitalizations, representing small, medium and large, respectively. Since different category represents different risk-return profiles, investors with dedicated risk-return preference could generally confine their stocks to a specific category or combination of categories.

Figure 1-1 Equity style box



1.2 Equity style investing

Equity style investing refers to the investment strategy based on the common stock classifications. Despite the introduction as a new investing concept in 1980s, the idea of style investing is by no means novel. The classic works of equity style analysis can be traced back to 1934 when Benjamin Graham and David Dodd published their groundbreaking book 'Security Analysis' and set out the concept of value investing. In this book, Graham and Dodd argue that some fundamental criteria like the intrinsic value, the future value and the market factors should be considered when evaluating a stock value. Similarly, John Burr Williams develops the concept of fundamental analysis. His book 'The Theory of Investment Value' published in 1938 introduces the theory of dividend based valuation approach. While Graham and Dodd (1934) advocate that investors should buy value stocks because the future growth of growth stocks tends to be exaggerated and hence uncertain, Thomas Rowe Price, Jr., on the other hand, publishes a paper entitled 'Picking Growth Stocks' in 1939. Price argues that buying growth stocks could offer hedge against the inflation because the earnings and dividends of growth stocks could be expected to grow faster than the overall economy. Contrast with Graham who is regarded by many to be the 'father of value investing'[2], Price is best known for developing the growth stock style of investing and is regarded as 'father of growth investing'. Apart from value-growth style investing, the momentum investing is characterised as to buy the past winners and to sell the past losers (Jegadeesh and Titman (1993)), while contrarian investing does the opposite (DeBont and Thaler (1985)).

The exploration of style investing has gained growing popularity over the past decades. Since mid-80's U.S. institutional investors have been found to follow some pre-defined investment strategies with specific market segments (*c.f.* Ahmed *et al.* (2002)). While value and growth investing are regarded as two most important investment styles, the most popular style investing is perhaps to combine value and growth with firm size to capture the interactions of basic style dimensions. For instance, strategies based on the combination of large value stocks, large growth stocks, small value stocks and small growth stocks. Such strategies could capture the interactions of different styles effects and could arguably yield better returns[3].

One reason for style investing being well established and gained its popularity is perhaps due to its simplicity in the investment process. Money managers face the complex and ever changing investment

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[2] Graham's work has remained influential in nearly half century in the investment industry. The merit of value investing is perhaps best demonstrated by Graham's most famous student Warren Buffett.

[3] Asness (1997) documents a strong relation between value and momentum effects. It is found that value premiums are strongest among loser stocks (low momentum) but are weakest among winner stocks (high momentum). Likewise, momentum is particular strong among growth stocks.

environment, they often experience the maze of investment choices given an overwhelming amount of assets available in the investment opportunity set. The classification of the investible assets into some categories simplifies the manager's decision-making problem when dealing with asset allocation and therefore making the investment process less intimidating (Mullainathan (2002)). This is because instead of having to screen thousands of individual stocks for the investing portfolio, managers could simply make the dynamic asset allocation decision among the style level (Barberis and Shleifer (2003)). Indeed, formal market segmentation has become an integral part of today's asset management industry. Recent studies find that professional money managers follow specific investment styles (*c.f.* Brown and Goetzmann (1997), Fung and Hsieh (1997b), Chan *et al.* (2002)), and the control of investment style is regarded as a critical aspect of investment monitoring and decision-making process.

1.3 Motivations and objective for the research

The concept of equity style and style investing offers a good example of the exchange of brilliant ideas between academic research and the investing practice. Despite the apparent simplicity of asset allocation process, manager's incentive for engaging in equity style investing also stems from capitalising on the time-varying return differentials across equity styles. Institutional investors such as pension and endowment funds act as fiduciaries and therefore accept substantial responsibilities and assume significant liabilities. These investors often follow specific styles that determine the construction of their portfolios and generate unique return patterns compared to the benchmark. Such investment return patterns are caused by diverse behaviours of different asset classes. Financial markets have long observed the style return differentials as well as the tremendous swings of equity style dynamics. For example, over the past 70 years, while the US small-cap stocks outperform in the long-run, the large-cap stocks are able to beat their small counterpart during 1950s and 1980s. The US value and growth stocks also perform differently over the past three decades. Value investing outperform during 1970s and 1980s, followed by the dominance of growth stocks during the 1990s. More recently, the market has again seen that value stocks outperform again since year 2000. Evidence of the divergence of style returns is also reported in other equity markets outside the US. Overall, empirical evidence generally suggests that over the long term small-cap and value investing have been more advantageous in most equity markets around the world, but there can be periods where the size and value-growth returns reverses dramatically.

Style analysis adds to arsenal of portfolio management tools, and the dynamics of equity style returns have introduced the new risk-return structure for active portfolio management. But to have capitalised on its time-varying nature, money managers would need to not only identify the underlying driving forces that determine the relative style performance, but also to capture the mechanisms through which those underlying forces work. Most importantly, successful active managers must be able to capture the dynamic properties of those driving forces to forecast the future style trends. Over the past years, although the benefits of style investing have been well recognised globally, the academic view of the underlying cause for such benefits is open to debate. There is still no general consensus as why some asset groups are able to earn better returns than others do under the same economic regime. Since style investing is based on asset classification, arguably a sensible categorisation of assets should be based on the characteristics that relate to the asset's cross-sectional expected returns. In an efficient market where the price of stocks reflects all relevant information, style investing should not be more profitable than any other portfolios containing the arbitrary subset of stocks. Furthermore, if investors do not diversify across styles then any portfolios based on single styles would not be mean-variance efficient. Hence equity style investing maybe fundamentally risky, and the evidence of style premium would suggest that either the markets are inefficient or the traditional asset pricing models are misspecified. Previous studies suggest equity characteristics such as the market capitalisation and book-to-market ratios (BM) are closely associated with the cross-sectional expected stock returns (Fama and French (1992, 1996)). However, the mechanism of how such characteristics work remains controversial. Rationalist such as Fama and French (1993, 1996, 1998) argue that size and BM are risk factors[4], Behaviourist, on the other hand, argue that mispricing resulting from investor's sentiment unrelated to the fundamentals plays the key role. Meanwhile, a variety of business cycle variables have also found to contain useful information in interpreting the expected stock returns. Hence the observed differentials of style return should be time-varying and related with shocks from the macro economy.

Chapter 3 is motivated by the empirical findings regarding the relationship between stock returns, equity characteristics and the business cycle fluctuations. The use of the business cycle framework is motived by the strong *a priori* relationship between stock returns and the business cycle conditions. Traditional financial theories link

[4] Daniel and Titman (1997) contend that these characteristics are irrelevant to the covariance structure of stock returns.

the value of stocks to future cash flows. The dividend discount model argues that the present value of a stock equals to the sum of the discounted expected future dividends. The parameters involved in the valuation process, namely, the expected future cash flows, the market risk premium, the market risk exposure and the term structure of interest rates share a common component, the business cycles (Dahlquist and Harvey (2001)). Hence equity style returns evolves over time, reflecting the cyclical and structural fluctuations in the business cycles. The objective of Chapter 3 is to examine the *relative importance* of the style driving sources that determines the differentials of style returns in the UK market. This chapter would contribute to the extant literature by explicitly examining how firm-specific characteristics and the business cycle conditions function separately to affect the dynamics of stock performance based on the size and value-growth categorisations. Specifically, it addresses a central question: what is the dominant driving force that affects the relative style performance, the firm characteristics or the business cycle risk? The empirical findings in Chapter 3 shed new light on the understanding of the source of equity style performance and add a further dimension to the current literature of anomaly versus risk compensation debate for explaining equity style premiums.

The divergence of equity style returns evolve all the time with cyclical nature. Over the time there are styles moving in and out of favour by investors according to their relative performance driven by changes of economic, financial and political conditions. There is no single style or a mix of styles dominating under all market states. Foir example, Fama and French (1992), Eleswarapu and Reinganum (1993), Dichev (1998), Chan *et al.* (2000), Horowitz *et al.* (2000a, b), Amihud (2002) and Roll (2003) and many other studies all document that the size effect cease to exist since 1980s in the U.S. markets. Likewise, Dimson and Marsh (1999), Michou *et al.* (2010) report that no size effect exists in the U.K. market in later 1980s. Internationally, Barry *et al.* (2002) also fail to find the size effect in global emerging markets. Most recently, Fama and French (2012) show that no size premium exist in North America, Europe, Japan and Asia Pacific markets since 1990. These findings suggest that striving to one predominant style investing strategy over the entire investing horizon is by no means efficient. Furthermore, a natural question also arises whether equity style cycles do exist. Arguably, if equity style cycles exist and has long duration, smart investors could implement the active investment strategy based on style cycles by identifying the turning point of the leading styles and transitioning portfolio holding to next prevailing market segments to enhance returns.

Active investment strategies have been very popular in professional manager circles in the investment community. One objective of such strategies is to protect investors against negative effects caused by prolonged period of poor economic conditions. The fundamental idea is to follow some heuristic methods to select specific stocks or asset classes according to the changing market conditions. Motivated by the potential benefits of such active portfolio management based on the cyclicality of the relative style returns, Chapter 4 investigates a dynamic style rotation trading strategy. Prior research has confirmed the value of price-driven investment strategies at the stock level. For example, the momentum strategies of Jegadeesh and Titman (1993) and the contrarian investing of DeBont and Thaler (1985) are well documented in the literature. However, momentum strategies along the style level have not been extensively studied. Papers such as Beinstein (1995), Fan (1995), Fisher *et al.* (1995), Sorensen and

Lazzara (1995), Kao and Shumaker (1999), Levis and Liodakis (1999), Asness *et al.* (2000), Ahmed and Lockwood (2002) and Lucas *et al.* (2002), among others, explore the benefit of style rotations. However, as Chen and De Bondt (2004) point out, by and large these studies do not give clear details of the specific trading strategies derived from the information of equity style cycles. Chapter 4 contributes to the literature by providing valuable empirical evidence to compare with other findings in different economic and institutional environments. The study in Chapter 4 aims to answer 2 central questions: (1) whether U.K. equity style cycles exist and hence investors can profit from the information of style cycles and (2) whether the return pattern of style momentum is distinct from price and industry momentum effects documented in the literature. The findings in this chapter could help investors better understand the 'style effect' in the cross-sectional expected stock returns. It also offers a practical approach for passive investors to enhance investing returns. Passive investors do not aim to 'beat the market' and therefore generally take indexation strategy. However, the relative fixed composition of the market index results in constant overall style exposures that is inefficient under changing market conditions. Style momentum trading strategy based on ETF (exchange traded funds) of style benchmarks can be used to enhance index returns. Since the style momentum hedge portfolios are generally market neutral they of little market risk if there is any. Style ETF generally has low transaction cost and high liquidity, as a result, the long-short style ETF momentum hedged portfolio could be designed to overlay with the underlying indexation strategy to eliminate its least efficient style exposures and generate additional alphas.

The style momentum strategy in chapter 4 is a quantitative adaptive style investing in essence. The advantage for such strategy is that its trading signal is quantitatively generated by data set and hence free of investors' sentiment when being implemented. The strategy is self-financed as it longs the winner style and shorts the loser style in the same time. However, while both the long and the short side of the portfolio are not limited to contain only one style, they generally take the same weight in order to satisfy the condition of self-finance. This makes style momentum strategy less attractive to some multi-style investors who have more expertise to some specific asset classes and are therefore more ambitious for their portfolio structure. Meanwhile, the construction of style momentum does not explicitly consider the underlying economic driving force that determines the relative style returns; in particular it does not account for the trade-off between style returns and risks from a mean-variance investor's perspective. Hence style momentum is not optimal for some specific investors.

Chapter 5 is motivated by the identified gap in the literature about the optimal multi-asset investing over the business cycles. There is substantial evidence suggesting that the distributions of expected stock returns are time-varying with predictable components derived from business cycle variables. For example, early foundation papers such as Fama and Schwert (1977), Campbell (1991), Harvey (1991), and Campbell and Ammer (1993) use dividend yield and interest rate to model stock return dynamics. The significant explanatory ability of business variables in determining stock returns can also be found in early papers like Schwert (1989). Existing literature has generally recognised the benefits of considering business cycle predictors on asset allocation process on the stock level. For instance, Kandel and Stambaugh (1996) show that research variables predicting stock returns also have significant impact on a myopic portfolio setting. Avramov and Chordia (2006a, 2006b) demonstrate that a real-time optimising investor can benefit from incorporating business cycle information to their asset allocation between stocks and cash or investment strategies of 'fund of mutual funds'. However, the portfolio choice implications of business cycle effect in prior studies often focus primarily on the time-varying nature of stock return distributions driven by business cycle predictors, while the role such predictors play on determining optimal multi-style allocation is less directly explored. Arguably, if a multi-style investor believes that business cycle variables can predict the conditional distributions of equity style returns, the expected style returns and the variance structure to be predicted are endogenous to the investor's preference due to model specification. Hence, in order to capture the changing investment opportunities associated with business cycle regimes, the investor should focus primarily on identifying how the same exogenous state variable directly predicts the ultimate style investing choices, i.e. the optimal weight in the style investing portfolio.

Chapter 5 contributes to the literature by applying an optimisation framework to test several equity style investing strategies based on business cycle information and examine their *ex ante* in-sample and *ex post* out-of-sample performance. This chapter aims to answer two questions: (1) which economic variable or a combination of economic variables should track when implementing equity investing based on market segments; (2) if business cycle predictor variable *X* changes, should the investor invest more or less in *Y* style? Answers to these questions would give multi-style investors like 'fund of hedge funds' managers an intuitive manner to understand their asset allocation process when incorporating business cycle predictability.

1.4 Basic findings in each chapter

The empirical study in Chapter 3 concludes that the underlying driving forces affecting the dynamics of relative style performance are indeed much controversial. Overall, the relative performance of small vs. large stocks and the value vs. growth characterised by price to cash-flow ratios (PC) and market to book value ratios (MTBV) are mainly driven by the cross-sectional *mispricings* in the context of a multifactor business cycle model. This suggests that the relative outperformance of small-cap stocks and PC- and MTBV-sorted value stocks may be driven by investors' irrational trading behaviour that results from cognitive biases like underreaction to firm-specific news. By contrast, the divergent returns of value and growth stocks sorted by the dividend yield are attributed to the cross-sectional differences in *conditionally expected returns* predicted by the business cycle model. Hence the outperformance of investing in stocks with high dividend yield is mainly captured by the predicted risk premias, and therefore should be the compensation for bearing business cycle risk.

The test results in Chapter 3 would also suggest that, while on the individual stock level the relative performance of stocks sorted on PC and MTBV are not driven by the business cycle risk, on the portfolio level the business cycle model could partly capture the time-series expected value premiums. Hence equity characteristics PC, DY and MTBV should contain information in predicting the time-variation in expected style returns. These results are consistent with findings of empirical studies regarding the time-series relations among expected returns, risk and equity characteristics (e.g. Fama and French (1993, 1996), Kothari and Shanken (1997), and Chan *et al.* (1998)).

The profitability of style momentum strategy documented in Chapter 4 indicates the existence of equity style cycles in the U.K. market. Since assets behave differently during various stages of a market cycle, investing strategies to buy stocks in current in-favour (winner) styles could continue to outperform those in current out-of-favour (loser) styles for periods up to 12 months or possibly longer. Style momentum payoffs tend to increase with longer ranking periods but decrease with longer test periods, implying that the outperformance of winner styles are more persistent once more information is collected in the ranking period, while such style return differentials generally reverse at longer horizon. Consistent with the literature, style momentum effect demonstrate strong independent explanatory power for the future individual stock's expected returns, and style momentum is distinct from the price momentum of Jegadeesh and Titman (1993) and industry momentum of Moskowitz and Grinblatt (1999) documented in the literature.

The empirical test results in Chapter 5 find that, consistent with the literature, investors tend to significantly long value stocks or small-cap stocks, and short growth stocks or large stocks in their optimal style allocation process. It is suggested that the conditional style investing incorporating business cycle effects and the unconditional style investing disregarding business cycles is very much different. Sceptical investors disregarding business cycle predictability are generally quite conservative for their overall net equity exposures compared to the *Doctrinaires* who maintain strong prior beliefs about the business cycle information. The *Doctrinaires* are found to often take extreme weights to some styles financed by leverage, possibly because they believe the return differential of styles can be estimated using business cycle predictors and therefore extreme exposures can be reduced at bad times when expected returns are low or volatility is high.

Chapter 5 also demonstrates that business cycle predictors affect the conditional equity style returns and the optimal style investing in quite a different mechanism. For example, the role of default spread plays in the style allocation process is less significant despite of its significance in determining the expected return distributions. It is predicted that positive shocks to the short-term interest rate would induces investors to move to small-cap stocks and move away from large stocks despite the lower expected returns for small stocks and higher expected returns for large stocks are estimated by such shocks. In addition, a positive innovation to short-term interest rate would lead investors to tilt towards growth stocks, which matches their higher expected returns signalled by changes of interest rate. The dividend yield also predicts the style allocation along both size and value dimensions. While this predictor has more significant and positive impact on return distributions for small-cap stocks and value stocks than for large-cap stocks or growth stocks, a positive shock to short-term interest rate would induce investors to tilt towards large stocks or growth stocks and tilt away from small stocks or value stocks. The term spread also exerts significant impact on the style allocation process. A positive shock to the term spread would induce investors to overweight small-cap stocks or growth stocks in general.

Overall, Chapter 5 concludes that business predictors such as short term interest rate, term spread, dividend yield and default spread exert a strong influence on the shape or location of a mean-variance investor's optimal style investing frontier. Investors who can capitalise on the conditional business cycle information consistently beat those disregarding business cycle influence, both in-sample and out-of-sample.

1.5 Research structure

The remainder of the thesis is structured as follows: Chapter 2 reviews the literature. Starting from the equity style investing history, this chapter first reviews the firm characteristics documented to be related to the cross-sectional average stock returns. Since investors categorise stocks based on firm characteristics, some typical style investing advocated by such characteristics are explained and the time-series of the style performance over the business cycles are analysed. Chapter 2 also reviews some competing explanations for typical style premiums as advocated by traditional and behavioural finance. Following the time-varying style return dynamics, the benefits of style rotation strategies are reviewed. In response to the business cycle effect in the predictability of style return dynamics, the optimal style allocation in a mean-variance framework is also extensively reviewed.

Chapter 3 examines the relative importance of the style driving sources that determines the differentials of style returns in the UK market. Using U.K. stock data, this chapter explicitly tests how firm-specific characteristics and the business cycle conditions function separately to drive the dynamics of stock performance based on the categorisation of size and value-growth dimensions. Specifically, Chapter 3 aims to answer a central question: what is the dominant driving force to determine the relative style performance, the firm characteristics or the business cycle risk?

Chapter 4 investigates an adaptive tactical style investing problem by applying a binomial approach to focus on the shifting between pairs of equity styles. At each given point of time investors extrapolate the relative expected performance of different asset classes like value versus growth stocks or small versus large stocks according to their past performance and bet 100% of investing on the 'winner' style financed by shorting the 'loser' style. By exploring the profitability of style momentum the evidence of equity style cycles in the U.K. stock market is examined. More importantly, by examining the profitability of such style momentum strategies after controlling for the stock-level momentum and the industry-level momentum effects, Chapter 4 further tests whether style effects are unique in affecting the cross-section of stock returns.

In response to the increasing popularity of using macro information to aid optimal style selection for the quant circles in the investment community, based on the methodology of Brandt and Santa-Clara (2006), this chapter approximates the solution of a mean-variance multi-style investor's optimal style rotation question incorporating the business cycle predictability. The approach is parsimonious as the optimal style weights are parameterised directly on a set of pervasive business cycle predictors. By exploring how the directions of the expected style returns as well as the location and shape of the optimal style allocations are affected by given shocks to business cycle variables, Chapter 5 demonstrates how business cycle volatility affects asset return volatility and in turn investor's optimal style allocation.

Finally, Chapter 6 concludes the thesis and offers recommendations in the areas for relevant future research.

Chapter 2

Literature Review

2.1 Introduction

The research of equity styles began in 1970s when the investment community began to gather and analyse market data and money managers. Financial analysts have long observed clusters of stocks with similar characteristics and performance patterns in the U.S. markets. Early studies such as King (1966) and Farrell (1975) use cluster analysis to identify natural groupings of stocks and portfolios. They find that some groups of stocks and portfolios with similar characteristics demonstrate similar return patterns. Other studies such as LeClair (1974) suggest that groups of fund managers with similar investment philosophies could also lead clustering portfolio returns. The most prominent study in the context of investment style and mutual fund performance analysis was conducted by Sharpe (1988, 1992). Sharpe developed a returns-based technique that is rooted in analysing the covariance structure in manager return patterns. It is proposed that managers with different styles would behave differently and this behaviour could be determined by looking at the underlying fund's 'effective asset mix' in terms of a predefined set of style indices. In addition to Sharpe's returns-based approach to assess the style characteristics of a portfolio, the portfolios-based approach based on the actual holdings is also popular in the investment industry. For example, Grinblatt and Titman (1989) employs the quarterly holdings of a sample of mutual funds to construct an estimate of their gross returns. Daniel *et al.* (1997) also evaluate the portfolio performance based on the characteristics of stocks held by the portfolios. In their study, the benchmarks are constructed from the returns of some passive portfolios matched with stocks held in the underlying portfolio based on market value, book-to-market ratios and past relative returns.

The heightened attention of style and style investing in today's investment community is perhaps driven by several motives. First, academic studies suggest that investment style shapes the pattern of portfolio returns more than any other factors in the investment process. It is argued that the philosophy of *how to select stocks* trumps *what individual stocks are selected* in determining the overall portfolio performance. Brinson *et al.* (1986) document that asset allocation decision accounts for about 90% of the return variations in large pension funds. Likewise, Hansen (1992) argues that return differentials due to investment style accounts for approximately 60% of the performance over short and medium term. More specifically, Sharpe (1992) proposes that 90% of the performance of equity funds is due to the overall style of the fund, the remaining 10% is due to the individual characteristics of the specific securities hold.

Second, in recent years, money managers have been required by the consultants and trustees to identify their investment styles. For marketing purposes, fund managers generally define their fund products into different style classifications to meet different investors with dedicated risk preference. Hence in today's asset management industry, style has been widely recognised as a tool for portfolio management and performance evaluation. Style analysis is important for portfolio management as it can simplify the portfolio selection problem and the process of diversification (*c.f.* Barneby *et al.*

(1986), Mullainathan (2000)). Hence professional money managers can benefit from the style analysis to build portfolios, while plan sponsors or individual investors can obtain information regarding the managers' area of expertise and therefore become more knowledgeable about how to allocate their money across funds with different investment styles.

2.2 The dimension of equity styles

The concept of equity style in the stock markets can be defined as a systematic classification by market segments sharing distinguishing characteristics. Such characteristics can be quantified by a number of descriptors like measures of return volatility, the firm size, values of corporate growth rate and the quality of the underlying company etc. These common factors are recognisable components of equity portfolio styles box widely accepted in the investment community (e.g. Morningstar equity style box). Correspondingly, equity style investing can take different forms based on the underlying framework.

A popular style investing approach is to form portfolios based on firm characteristics. Style investing based on firm-specific characteristic factors uses firm size or other valuation multiples as criteria to sort stocks to construct portfolios. In addition to the general category-based methods, investors may also follow positive feedback trading according to the relative returns, namely to long (short) past winners and short (long) past losers based on the stock's performance. Such momentum or contrarian investing is well recognised in the market practice. Characteristic related and feedback investing strategies aim to exploit and benefit from market deficiency. The massive existence of anomalies in the financial markets implies that investors chasing such strategies may have good opportunity to add value through efficient style rotations. Today, equity style investing such as value, growth, contrarian and momentum are familiar and well-considered concepts in the asset management industry. The following sections conduct an extensive review regarding these investing strategies.

2.3 Size, value and growth investing

The stock market as a whole can be broadly divided into different types of stocks based on their similarities along some dimensions like firm values, valuation multiples and risk exposures etc. The size (measured by the market capitalisation) and value-growth (defined by valuation multiplier) are earliest style categories recognised in the investment community. Although stocks can be sorted based on other dimensions, to categorise the stock universe into the broad category of value and growth class is more natural because empirical studies generally suggest that the return differentials to these stocks are more likely driven by the economic fundamentals.

While it is intuitive to understand that small and large stocks differ in that they have different market values, the characteristics of value and growth stocks can differ in a number of ways. Value and growth stocks generally share common characteristics of valuation multiples. Value stocks generally have relatively low prices as compared with the underlying fundamentals. Such stocks normally have low price-to-earning (PE) ratios, price-to-book (PB) ratios or price-to-cash flow (PC) ratios and high book-to-market ratios (BM). Value stocks also have higher dividend yield (DY) and lower price-to-net tangible asset ratio. In contrast, growth stocks have opposite characteristics, such stocks typically have high PE, PB or PC and low BM values relative to their stock prices, they also tend to have lower dividend yield or higher price-to-net tangible asset ratio.

A large financial literature relates stock returns with firm-specific characteristics. Since the introduction of asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), academic researchers find that CAPM cannot fully explain the stock returns with market risk along. Researchers have therefore identified factors other than market risk to interpret the stock returns. The published papers document that firm-specific characteristics like size and value-growth descriptors are significantly related to expected stock returns. Early pioneering works of Basu (1977) and Banz (1981) use PE ratios and firm size to explore the cross-section of average stock returns on U.S. equities and document the evidence of 'PE effect' and 'size effect'. Chan *et al.* (1991) find the explanatory power of book-to-market (BM) ratio to the Japanese stock returns. Studies such as Rosenberg *et al.* (1985), Lakonishok *et al.* (1994) find that other factors, such as cash flow-to-price ratio and the past sales growth rate, are also significant to stock returns. The prominent study of Fama and French (1992, 1993) use a multifactor asset pricing model supplementing the standard market risk premium with factors related to the firm size and BM ratio and find that their three-factor model can capture large fractions of the variability of cross-sectional average stock returns in the U.S. stock markets. These papers and many others have served to deepen our understanding in the role that firm characteristics played in explaining the average stock returns in the international framework[5]. The pervasive influence of these empirical findings has

[5] Partial list of other papers in this literature includes Ball (1978), Sharpe (1982), Chen *et al.* (1986), Bhandari (1988), Jaffe *et al.* (1989), Capaul *et al.* (1993), Breen and Korajczyk (1995), Chan *et al.* (1995) and Kothari *et al.* (1995), among many others.

been such that it is now a common practice to define the investment styles along two basic dimensions, namely the small-large and value-growth, in today's asset management industry.

A considerable literature exists to explore the relative performance of basic equity style investing in the global stock markets. The general findings are, first, investing in smaller firm stocks tend to outperform over the long-run but with higher risk than investing in the large-cap stocks. For example, over the period of 1926 to 2002, investing in small-cap companies could outperform large-cap strategy by almost 5% annually despite of the large stocks' dominance during 1950s and 1980s in the U.S stock markets (State Street Research (2003)).

Second, over the past decades and in the long-run, value investing tends to generate higher returns than growth strategy on most equity markets around the world. The reward to value investing is more pronounced for small-cap stocks, but it is also present in large-cap companies. Chan *et al.* (1991) first document that the return spread between the Japanese value and growth stocks defined by BM ratios is 1.1% per month. In the U.S. markets, Fama and French (1992) show value portfolios generate average monthly returns of 1.83% as compared to 0.30% of the growth portfolios. They also find that the size of value stocks with higher BM ratios on average tend to be smaller than growth stocks. Capaul *et al.* (1993) argue that the value premiums are pervasive in the international market, and Fama and French (1998) provide similar findings that a global value investing outperform the global growth investing for 7.6% annually from 1975-1995. Lakonishok *et al.* (1994) also document the outperformance of value investing on NYSE and AMEX stocks sorted by different valuation descriptors. They report that value portfolios sorted by BM ratios outperform the growth counterparts by 10.5% annually over the five years after formation, and such superior returns persisted if using different valuation criteria like PE ratios or PC ratios. Besides, the average size-adjusted value investing return is 3.5%, indicating a 7.8% spread relative to the growth strategy. Other studies like La Porta (1996), Daniel and Titman (1997), Barber and Lyon (1997) and Lewellen (1999) also provide similar evidence of the outperformance of small and value stocks in the U.S markets, and Gregory et al. (2001) report the outperformance of value strategies using U.K. stock data for the period 1975 to 1998.

2.4 Explanations for size and value premiums

Although the existence of size and value premium is relatively uncontroversial, there is much debate about the underlying reason behind it. The explanations regarding the size and value premiums split in the academic community.

For the size premium, some papers argue that small stocks tend to have high liquidity risk. For example, Amihud and Mendelson (1986) find that the size effect is linked to liquidity risk (measured as bid-ask spread) and therefore conclude that the size effect is largely a liquidity effect. Similarly, Liu (2006) argues that small-cap stocks perform better because they have low liquidity and hence investing in such smaller firms require higher returns for the compensation of bearing liquidity risk. Vassalou and Xing (2004), on the other hand, link the default risk to the size effect. They argue that small firms with highest default risk can earn high returns hence size premium can be viewed as a default risk effect. More recently, Zhang (2006) links the size premium to 'information uncertainty' provided to investors about small stock's volatile fundamentals. Overall, these explanations are based on the classical financial theory that smaller firms are riskier than larger firms in general and hence conclude the outperformance of small-cap investing is driven by underlying sources of risk.

There are some competing theories to explain why value investing outperforms growth investing in general. Fama and French (1992, 1993, 1995) argue that value premium is the compensation for the higher risk of value stocks that is not explained by Capital Asset Pricing Model (CAPM). With the use of the multifactor asset pricing model in the context of Merton (1973), they link the higher returns of value stocks to exposure to the financial distress. The risk-based explanation is supported by authors like Liew and Vassalou (2000), Cooper *et al.* (2001), Lettau and Ludvigson (2001) and Petkova and Zhang (2003) and Vassalou and Xing (2004). Lakonishok *et al.* (1994), however, do not support that value stocks are fundamentally risky. Lakonishok *et al.* (1994) compare value and growth stock performance under different economic conditions. They find that value stocks still outperform growth stocks in bad economic states and when the marginal utility of wealth is high. Hence it is concluded that value stocks actually have lower downside risk than growth stocks. Lakonishok *et al.* (1994) therefore suggest mispricing is the cause for the outperformance of value stocks. La Porta (1996) also argue that value investing works because expectations about future growth in earnings are too optimistic. Investors undervalue the value stocks and overvalue the growth stocks and the reward of value investing results from the correction of such mispricing. The mispricing story about value premium is also supported by Haugen and Baker (1996) and Daniel and Titman (1997) in a behavioural finance framework.

There is another interpretation for the value premium which rests on the data-snooping hypothesis and poses a tough challenge to style investing. Lo and MacKinglay (1990) argue that the findings of value premium is due to data mining. Thus the methodological issue of sample selection bias causes the relative returns between value and growth strategies (*c.f.* Kothari *et al.* (1995), Conrad *et al.* (2003)). Banz and Breen (1986) and Kothari *et al.* (1995) also suggest that 'survivorship bias' may contribute to the observed value premium. Since some authors exclude delisted/dead companies in the year-to-year test and therefore fail to take into consideration the risk of financial distress for value stocks. Hence the cross-sectional return differences across stocks might be a statistical fluke.

2.5 Contrarian and Momentum investing

Parallel to style investing based on the classification of firm-specific characteristics, the implementation of investing strategies based on the correlations of asset returns is very popular. The properties of the short-term positive autocorrelation and long-term negative serial correlation of stock returns are well documented in the literature. This academic finding forms the theoretical basis for contrarian and momentum investing widely recognised in the market. Contrarian investing of De Bondt and Thaler (1985, 1987) is to buy stocks that have performed poorly and sell stocks that have performed well in the past period. This strategy ignores the market trend and only focuses on the stocks which are considered to be mispriced. De Bondt and Thaler (1985, 1987) document that stocks experienced poor performance over a 3-5 years period subsequently outperform those that have previously performed well, and vice versa. The contrarian strategies of buying past losers and selling past winners can earn average profit of 25% over 3-year period. While this strategy is a relative long-run investing, Jegadesh (1990) and Lehman (1990) also find that it works in the short-term. Although studies on contrarian investing are initially based on the U.S. markets, it has also been widely investigated across continents both in developed markets and emerging markets. For example, in the U.K. market, Lonie and Lonie (1991), MacDonald and Power (1991) and Dissanaike (1997) document the abnormal returns from contrarian strategies based on monthly returns of UK stocks. Rouwenhorst (1998), Bildik and Gulay (2007), Galariotis (2004) and Antoniou *et al.* (2005) find similar results. These studies all suggest that contrarian investing can generate economically significant profits.

However, similar to value premium, there is no general consensus regarding the cause of this profitability. De Bondt and Thaler (1985) interpret the contrarian profit being driven by investors' overreaction to good and bad news, while Chan (1988) argues it is caused by the instability of risks for winner and loser stocks. Apart from the above explanations, there are schools of other thoughts such as the size effect (Clare and Thomas (1995)), January effect (Zarowin (1990) and the stock market microstructure bias (Conrad and Kaul (1993).

In contrast to contrarian strategy, momentum investing comes in various guises. Price momentum and earnings momentum are two of the most common types. Unlike contrarian strategy that exploits the long-run reversals of stock returns, the price momentum is based on the continuation of short-term and intermediate of cross-sectional stock returns. Such strategy follows the 'trends' to buy the past 'winners' and sell the past 'losers'. The usual justification for this investing strategy is that the performance of both overall market and individual stocks is largely driven by investors' sentiment which itself follows trends. Jegadeesh and Titman (1993) use stocks on the NYSE and AMEX markets to form self-financed portfolios and find that buying stocks with high returns over the previous 3-12 months and selling stocks with low returns over the same time period perform well in the following 12 months. When dealing with data, ten equally weighted deciles portfolios are constructed according to the ranking of returns in the past 3 to 12 months. The 'winner' is defined as the top deciles portfolios and 'loser' is identified as the bottom deciles. In their later study, Jegadeesh and Titman (2001) extend the dataset to 1998 and show that the initial results still held, suggesting that their initial findings are robust to the criticism of data-snooping.

Momentum profit is not only found in the individual stock level, but is also observed in the industry and country level. Moskowitz and Grinblatt (1999) document the large abnormal returns for industry momentum of buying past winner industries and selling past losing industries. Asness *et al.* (1997) also test the momentum strategies in industry portfolios and country portfolios. Furthermore, Lewellen (2002) finds that momentum strategy based on size and book-to-market portfolios are at least as profitable as individual stock momentum. The profitability of momentum strategy is not only identified in the U.S. markets, but in international markets as well. For example, in the U.K. market, Liu *et al.* (1999) document the profitability of momentum strategies over the period 1977-96. They argue that UK momentum effects are robust across two sub-samples in their dataset. Based on a different data sample source, Hon and

Tonks (2003) also find that UK momentum effects exist in the sub-sample 1977-96, but not in the earlier 1955-76 period. Other studies such as Rouwenhourst (1998) and Bird and Whitaker (2003) all document the momentum effect in the European markets during periods of 1980-1995 and 1990-2002, respectively. Furthermore Richards (1997) find the monthly momentum profit in international markets from 16 countries during the period of 1970-1995. Overall, these studies would suggest that price momentum is a worldwide phenomenon in the investment marketplace.

The earnings momentum investing is based on the assumption that the reported earnings of a firm is a major source of information to which its underlying stock prices react. Ball and Brown (1968) suggest that the change in a company's earnings from one reporting period to the next would cause a consistent movement in stock prices, and the post announcement earnings drift is also found to be relevant. This suggests that investment strategies based on earnings momentum are likely to be rewarded. Earnings momentum strategy forms the investing portfolios based on the direction and the magnitude of analysts' earnings forecasts. Bird and Whitaker (2003) implement such strategy in major European markets for the periods of 1990-2002. They show that across the markets the performance of the quintile portfolios formed using the direction of 'agreement' as the criterion is significant for a period of up to 12 months, and the performance differentials between the low and high momentum portfolios is 7.5% annually. However, the performance of the portfolios based on the magnitude of the earnings forecast revisions is much weaker and inconsistent.

The profitability of momentum strategies seem to be at odds with the efficient market hypothesis since asset pricing models such as CAPM and Fama and French (1993) three-factor model all fail to explain it. The academic view for the source of momentum profits is divided. A number of influential theoretical papers have sought to explain momentum effects based on cognitive biases in the behavioural finance framework. For example, De Bondt and Thaler (1985), Jegadeesh and Titman (1995), Daniel *et al.* (1998) propose the overreaction hypothesis. They argue that investors tend to overreact to news (both bad and good) and such overreaction could lead past losers to be underpriced and past winners to be overpriced, therefore resulting in better returns and worse returns for the losers and winners in the future, respectively. On the other hand, papers like Hong and Stein (1999) favour the underreaction hypothesis. They contend that momentum effect is related to underreaction since the positive autocorrelations of stock returns over short periods may reflect the slow transition of firm-specific news into its underlying stock prices. Specifically, stock prices may underreact to firm-related news like earnings announcements. If the underlying news is good in nature, stock prices may keep going up after the initial positive reaction. Conversely, stock prices will continue to fall down following the initial negative reaction when receiving the bad news. In addition to the overreaction and underreaction propositions, Barberis *et al.* (1998) argue that momentum is caused by irrational investors' underreaction to corporation news because investors suffer from representativeness bias and conservatism.

Recently, in addition to these behavioural explanations, Chordia and Shivakumar (2002) link the momentum effect to business cycles. They find some evidence that momentum profits can be attributed to business cycle conditions and be predicted by lagged macroeconomic variables. However, this risk-based explanation is challenged by Griffin *et al.* (2003). Cooper *et al.* (2004) also argue that profits to momentum strategies depend critically on the state of the market, thus market state is the sort of conditioning information that is relevant for predicting the profitability of the momentum investing.

While the studies for properties of long-term and short-term stock return reversals have been well undertaken, previous researches focus primarily on the price and earnings side, rather than style side. Recently, a number of empirical studies provide the evidence for reversals on the style level. Barberis and Shleifer (2003), for example, propose a theoretical style-level positive feedback trading model in an economy with two types of investors: Switchers (positive feedback traders) and Fundamental Traders (arbitrageurs). They assume that Switchers invest in styles that have performed well in the recent past and their behaviour could trigger style level momentum. In contrast, Fundamental Traders build portfolios by buying recent losers that look cheaper according to the estimated cash flows information. This model would imply that asset returns are less correlated than cash flows. Moreover, when an asset is classified into a style, its correlation with other assets already in that style would increases. Hence regardless of its cash flow characteristics, when a stock is admitted as a constituent in an index, the underlying stock becomes more correlated with that index. The conclusions of this model are supported by Teo and Woo (2004). Teo and Woo investigate the style effects in the cross-section of stock returns in the U.S. markets and find the evidence for style-level reversals, style-level momentum and positive feedback trading at the style level. Likewise, and perhaps more prominently, Chen and De Bondt (2004) investigate the style momentum payoffs for large U.S. companies in the S&P-500 index over the period 1977-2000. They find that Style momentum effect is distinct from the price and industry momentum, and investors pursuing strategies of buying stocks with past winner characteristics and selling stocks with past loser characteristics could outperform for periods up to one year and possibly longer.

2.6 The cyclicality of style returns and macro cycle

Style investing is a common investment strategy advocated by both fundamental and technical investors. But just like other strategies it can suffer during certain investment periods. It is observed that the performance of small size stocks and value stocks go through cycles, and such cycles may not coincide with the overall stock market. The time-variation or cyclical nature of style performance and volatility has raised many interests from both the academics and practitioners. Studies show that the size premium varies over time or disappears for some periods. Fama and French (1992), Eleswarapu and Reinganum (1993), Dichev (1998), Chan *et al.* (2000), Horowitz *et al.* (2000a, b), Amihud (2002) and Roll (2003), among others, document that the size effect has diminished or cease to exist since 1980s in the U.S. markets. Similarly, Dimson and Marsh (1999), Michou *et al.* (2010) show that no size effect is found in the U.K. market in later 1980s. Internationally, Barry *et al.* (2002) also fail to find the size effect in global emerging markets. Most recently, Fama and French (2012) find that no size premium exist in any of the 4 global markets (i.e. North America, Europe, Japan and Asia Pacific) for 20 years investing period since 1990. A number of other studies also suggest that the size premium demonstrates cyclical nature. For example, Horowitz *et al.* (2000a) find that the size effect changes over time and it is more pronounced in one period but not for the other or it can even reverse.

While the findings of value premium are relevant from a perspective of the long horizon, over short investment periods the performance of value investing is not reliable and also time-varying (Oertmann (1999)). The tech rally in 1990s and the recent market turmoil in 2007 are perhaps two episodes for the poor performance of value investing (*c.f.* Owyong (2011). Empirical findings generally suggest that the annual value-growth return pread can vary considerably with respect to both signs and magnitudes (*c.f.* Arshanapalli *et al.* (1998), Lucas *et al.* (2002)). Oertmann (1999) and Zhang (2005) also find that the U.S. value premium and the volatility of value-growth style investing returns are closely related with market states and business cycles. Likewise, Zhang *et al.* (2008) establish a strong link between size and value premium with macroeconomic state in the context of U.K. market.

2.7 Time-varying style returns and business cycle variables

The economic interpretations for above mentioned time-variation of equity style returns are twofold. The first focuses on the behaviour of market participants such as noise traders and speculators. There is large literature reporting that speculative trading behaviour causes fads, bubbles or even market crashes. The second explanation relates stock price movements to the macroeconomic fundamentals. The expected stock returns evolve over time in response to cyclical and structural changes in macro-economy. However, macroeconomic conditions do not affect all stocks in the same manners. Different stocks tend to behave differently in various stages of a business cycle.

For example, consumer staple (known as defensive stocks) generally have inelastic demand and are therefore not much affected by peaks and troughs of the business cycle. There are other stocks, however, can lead the economic cycle and are quite sensitive to the state of the economy. For instance, capital goods yield good performance during the recovery phrase, while luxury stocks generally offer best returns during boom time in the business cycles.

Bolten and Weigand (1998), DeStefano (2004) demonstrate that the determinants of stock value defined by the equity valuation models can possess time-varying patterns related with business cycles. Indeed, the relative performance of equity styles has been observed to be closely associated with the cyclicality of macro-economy. The rationale behind such divergent performance of style investing stems from the different sensitivity of asset value or return determinants to different business conditions. It is suggested that the returns of small stocks investing is more pronounced during recessions. Similarly, Kwag and Lee (2006) argue that the benefit of value investing is even greater during periods of contraction than expansion. Indeed, value stocks tend to be more sensitive to the cyclical strength of the overall business environment. They generally outperform growth stocks when the macro-economy changes from the sustained period of weakness to transitions into an accelerated recovery period. Conversely, growth stocks are favoured by investors in a slowing economy states and are therefore more likely to be able to beat value stocks when the economy transitions into a period of steady growth or simply begins to weaken.

There is overwhelming evidence to suggest that some business cycle pervasive variables such as the changes in GDP rate, inflation rate, the slope of the yield curve or the term structure of the interest rates and the default premium are important economic variables to determine future stock returns. Recent literature on the relation between stock returns and business cycles have focused on 4 variables due to their indicator nature that predict the future business cycle fluctuations. The 4 underlying variables are 1) the short-term interest rate; 2) the dividend yield on the overall market; 3) the default spread and 4) the term spread.

The short-term interest rate (*yld* hereafter) can be proxied by the yield on the 3-month T-bills. Fama and Schwert (1977), Fama (1981) show that this variable is negatively related to the future market returns. More specifically, Choi and Jean (1991) find that the risk relating to *yld* for small stocks is a significant source of the investing risk, while *yld* risk for large stocks is 'negative'. Choi and Jean (1991) argue that the variable *yld* explains a significant portion of the size premium for the NYSE and AMEX stocks.

The dividend yield on the overall stock market (*div* hereafter) is one of the oldest variables recognised to affect the expected stock returns. Studies such as Keim and Stambaugh (1986), Cambell and Shiller (1988), Fama and French (1988), Hodrick (1992) and Nelson and Kim (1993) all show that dividend yield is associated with slow mean reversion in stock returns over the business cycles. Fama (1990) argues that stock prices are low relative to the dividends when the discount rate and expected returns are high, and vice versa. More recently, Ait-Sahalia and Brandt (2001) argue that *div* should forecast returns on the basis of the present value formula (since *div* does not appear to predict dividend growth).

The default spread (*def* hereafter) is measured by the yield spread between the lower-yield to higher-yield bond. This variable measures the credit market conditions, a change in *def* can be generally interpreted to signal the market's revisions of expectation of worsening credit market conditions. The use of *def* is motivated by the studies of

Stock and Watson (1989) and Bernanke (1990). By doing the horse race research in predicting future business conditions, these authors find that a variable similar to *def* does the best job. Hence the variable *def* is a leading indicator of the state of the economy.

Keim and Stambaugh (1986) use *def* to predict stock and bond returns. Chen *et al.* (1986) find that *def* is an indicator to the business cycles. They argue that the *def* is likely to be high when the economy is in good condition, and vice versa. Likewise, Fama and French (1989) and Fama (1990) show that *def* tracks the long-term business cycle conditions and therefore captures variations in expected returns within the business cycles. Daniel and Torous (1991) further suggest that the variable *def* contains information about future production volatility. Jagannathan and Wang (1996) also report that this variable may capture investor's hedging concerns associated with time-varying risk premia.

Chan and Chen (1991), Gertler and Gilchrist (1994) and Perez-Quiros and Timmermann (2000) suggest that small and large size stocks have different accessibility to credit markets. Compared to the large firms, small firms are vulnerable to the variation of credit market conditions over the business cycles. Fama and French (1992, 1995) contend that value stocks tend to have high financial leverage and cash flow problems than growth stocks. Hence it is expected that *def* may be closely related to the size and value premiums.

The term spread (*term* hereafter) is defined as the long-term interest rate minus the short-term interest rate. This variable can be poxied by the spread between the yield of long-term government bond and the yield of 3-month T-bills. *term* is considered as one of the most widely used indicators for market's expectation about future interest rates, it also arguably captures the hedging demands to investors associated with changes in interest rates. The term spread tends to decreases in an expanding economy as short-term rates generally rise more the long-term rates. Conversely, *term* generally increases when economy is in contraction (Lucas *et al.* (2002)). Indeed, Fama and French (1989), Hahn and Lee (2006) all show that the slope of the yield curve moves in tandem with the business cycle fluctuations. They show that the term spread tends to be low near business cycle peaks and be high when the economy troughs. Daniel and Torous (1991) also provide evidence that this variable is primarily informative about the future growth prospects. Overall, it is argued that positive shocks to the term spread happen at bad times while the negative shocks happen at good times. Since the expected stock returns are low when the economy peaks and high when the economy troughs, the variable *term* positively predicts expected returns by the effect on the expected company earnings and in term the value of the stock in the context of the dividend discount or cash-flow discount valuation models. Chen (1991) use the term spread to predict excess returns. Recent study of Ait-Sahalia and Brandt (2001) confirms that *term* is positively related with expected returns.

In summary, the above 4 variables are standard macro-economic variables containing rich information of business cycle risks. The predictability of these variables is due to their business cycle indictors that contain information about the current and future economic conditions. In particular, *def* and *term* have long been regarded as proxies for credit market conditions and the stance of monetary policy, indicating that innovations in these variables would capture changes in the financial market's expectation regarding future credit market conditions and the interest rates environment, and would ultimately transitions to the expectations of company earnings and the stock value in the dividend discount or cash-flow discount valuation framework.

2.8 Equity multi-style rotation strategy

The existence of the cyclicality of style returns and business cycle effect highlights the importance of capitalising on the time-varying characteristics of style returns and volatility in the investment process. Such dynamics of stock returns and its relationship with the underlying macroeconomic variables that vary over business cycles would represent significant opportunity as well as significant risks for investors. The evidence of relative style returns under different economy regimes indicates that investors who successfully exploit the variability of multi-style premiums based on different market conditions are likely to be able to obtain better performance than active strategies based on single style investing only. Although some previous studies suggest that the ability to beat a benchmark by market timing or style timing remains debatable (*c.f.* Henriksson (1984), Connor and Korajczyk (1991), Ferson and Schadi (1996), Chan *et al.* (2004)), and the implication of style timing strategies is constrained by the inherent difficulties (*c.f.* Levis (2003)), in market practice, however, investors still have strong incentives to capitalise on the benefit of style rotations in the multi-period asset allocation process.

Style rotation strategies have been attractive to money managers as potential source of adding value. Such strategy could be arguably implemented by, but not limited to, the use of an adaptive approach. A business cycle model usually uses economic variables to determine an economic state, such variables are latent in essence and hence the forecasted outcome as which state would prevail at each point of time can only be drawn on an adaptive manner. Quantitative-based adaptive trading techniques have already raised many interests from academics in the literature (*c.f.* Rabatin (1997), Hung *et al.* (2003), Chiu and Xu (2004)). In the context of the equity style investing, the adaptive style rotation model forecasts the equity style performance dynamics and identify the leading style trends, rather than on the individual stocks, in the current market state and opportunistically shifting to the most productive style. By striving to invest a number of top-performing stock groups in leading market segments in a specific period of time, the objective of adaptive style allocation is to achieve enhanced style investing returns via a more rewarding form of diversification.

There is a growing literature exploring the dynamic trading strategies based on the equity style cycle and the corresponding style switching in a given point of time. Birch (1995) shows plan sponsors can use style cycle information to manage equity style exposures. Reinganum (1999) demonstrates the massive economic benefits of controlling the variability of size premiums to improve returns as compared to the by-and-hold and rebalanced fixed-weighted investing strategies. Kao and Shumaker (1999) simulate the performance of three timing strategies based on asset classification (e.g. stocks versus cash, size and value-growth stocks) in the U.S. markets. They use a set of macroeconomic variables like yield curve, real bond yield, corporate credit spread, high yield spread, estimated GDP growth rate and earning yield gap for their business forecasting model to forecast subsequent year's value-growth performance. Kao and Shumaker (1999) find that the rotation strategies based on stocks versus cash, small-cap stocks and large stocks could historically provide more opportunities to outperform the timing strategies based on value and growth stocks. Kao and Shumaker (1999) demonstrate that, based on the monthly rebalancing, a perfect selection by market values could add 20%-27% spread to the market returns, while perfect foresight timing between value and growth stocks could achieve 24%-34% higher return than market average. Other relevant studies including Fan (1995), Sorensen and Lazzara (1995), Avramov (2002), Bauer and Molenaar (2002) and Amenc *et al.* (2003), they also have documented evidence of predictability in style returns and the corresponding style rotation strategies.

In the U.K. market, Levis and Liodakis (1999) examine the style rotation strategies based on size and value-growth dimensions for the period of 1968-1997. They demonstrate that a hypothesised investor who could perfectly identify the size premium turning points would generate average annual return of 34%. An accuracy of 60%-70% for the investor's forecasting ability would be sufficient to beat the small size long only investing or buy-and-hold passive investing. Similarly, with a perfect foresight to identify value and growth style turning points, the value-growth rotation strategy would have earned annual returns of 29%. More recently, Clare *et al.* (2010) investigate the UK momentum-based multi-style rotation strategy. They argue that simple momentum style rotation strategy could outperform the complicated quantitative multi-style rotation strategy based on set of forecasting variables. Overall, these studies and many others generally conclude that since expected returns on leading market segments present predictable time-varying components over the business cycles, rotation strategies across equity styles could offer a substantial opportunity to outperform the market averages.

2.9 Optimal style allocation incorporating return predictability

Empirical finance documents the evidence of time-varying expected returns with predictable components across styles. The important implication of such return predictability is that active investors may wish to engage style rotation strategies to enhance returns. To model expected returns, traditional finance generally links expected returns with the condition risk premium by previous observable information set. One of the popular approaches to model the time-varying expected return patterns is to allow the information set to contain some economic pervasive variables that have been identified as return predictors by previous research[6]. Campbell and Viceira (2005) argue that the stock return predictability can have a strong impact on the variance and covariance structures of asset returns which is relevant for buy-and-hold investors with fixed investment horizons. Brant (2010) observes that following the recent empirical evidence of such predictable time-varying return distributions, optimal portfolio selection problems has once again been in the forefront of financial research. For example, Kandel and Stambaugh (1996) show that from an *ex ante* perspective variables predicting the distributions of the moments of stock return exert significant impact on a tactical portfolio allocation. Brennan and Schwartz (1996), Brennan *et al.* (1997) and Barberis (2000) examine the impact of predictability to the myopic versus dynamic portfolio choice problems. Ferson and Siege (2001) derive the optimal portfolio weights for mean-variance

[6] Solnik (1993) argues there are three approaches to model expected returns: the first is to contain past returns in the information set. The second is to contain the first and second moments in the information set, and the third is to use economic variables like *yld*, *def*, *term* and *div* as discussed in previous sections. Studies such as Harvey (1991) show the strong explanatory power of such variables to both U.S. and none U.S. equity risk premia.

investors assuming that the moments of stock returns are known functions of state variables. More recently, Avramov and Chordia (2006a, 2006b) find that a real time optimising investor benefits from incorporating business cycle information to the asset allocation between stocks and cash, and investment strategies such as 'fund of mutual funds' can also benefit from capitalising on the predictable time-varying dynamics over the business cycles.

Asset allocation is the key factor in determining the performance of long-term investments. Brinson et al. (1986) show that the decision of how to allocate assets accounts for about 90% of the performance variations for large pension funds. Likewise, the prominent study of Sharpe (1992) suggests that 90% of the performance of equity funds is due to the overall style of the fund, while the remaining 10% is due to the individual characteristics of the specific securities hold. From a money manager's perspective, for a solid strategy to decide an appropriate asset allocation, it requires first to consider on which level, tactical or strategic.

There is fundamental difference between tactical asset allocation and strategic asset allocation framework. Strategic asset allocation is mainly driven by the long-term return-risk assumptions for various asset classes. It specifies the overall weight of various styles in a portfolio to satisfy investor's risk-return preference in a lengthy investment period. However, the change of investor's life style will eventually impact the underlying risk tolerance and in turn his strategic asset allocation decision. Hence the risk-return profile for strategic asset allocation should be evaluated periodically once the investment landscape experience fundamental change. Unlike strategic framework, tactical asset allocation takes into account the short-term market conditions and is therefore designed to identify the possibility to tilt strategic asset allocations according to the changes in the investment opportunity set. Hence the underlying drivers for tactical asset allocation are valuation, momentum or contrarian, investor's sentiment and business cycle effect etc. Overall, the strategic asset allocation is the establishment of a long-term investment objective, while the tactical asset allocation determines how to adjust strategic asset allocation by exploiting inefficiencies in equilibrium values among asset classes. A solid investment strategy must highlight the role of both frameworks from the very beginning.

The optimal strategic and tactical asset allocations are perhaps most relevant for delegated asset management. As mentioned previously, institutional investors like pension funds and endowment funds act as fiduciaries and generally accept substantial responsibilities and assume significant liabilities. van Binsbergen *et al.* (2008) argue that the asset allocation of such investors are mainly structured around asset classes. As a result the fund's Chief Investment Officer (CIO), who acts in the best interest of his beneficiaries, would pick asset manager who is specialised in a single style or delegates the portfolio decision to such specialists. Therefore the asset allocation decisions are made in two stages, namely CIO's strategic allocation to different styles represented by different style managers and the individual style manager's tactical allocation within his style[7]. The CIO usually has long-term investment horizon and his objective is to minimise the utility cost from the misalignments of incentives induced by the above two-step allocations by optimising the investment weights to

[7] The reason why the CIO in the asset management firm should hire such multi-style managers can be justified by Sharp (1981) who argues that the decision to employ different managers is to exploit their specialisation or to diversify among managers (i.e. style diversifications).

different style managers in a mean-variance framework. In contrast, the individual style manager, however, is motived to maximise his remuneration on a relatively short horizons. van Binsbergen *et al.* (2008) argue that if asset returns are predictable, the CIO's optimal style manager choice problem depends on his investment horizon and requires being tactically optimised. This introduces the hedging demands from the difference between the strategic and tactical style portfolio weights in response to changes in the future investment opportunity set.

A variety of theoretical solutions have been explored in the literature to solve the optimal portfolio choice problem incorporating return predictability. Brandt and Santa-Clara (2006) point out that most techniques are out of reach for ordinary investors since close-form solutions are not always available. Over the years the mean-variance paradigm of Markowitz (1952) is the major workhorse of portfolio optimisation. When solving the optimal portfolio choice problem, prior studies generally first estimate the conditional moments with state variables and then apply traditional Markowitz approach. This methodology raise concerns such as rigid assumptions between moments of returns and state variables to safeguard covariance matrix and massive number of parameters be estimated. Michaud (1989) argues this will inevitably results in notoriously noisy and unstable test results. Recently, Brandt (1999) develops a framework to bypass the procedure of estimating the joint distributions of conditional stock return but directly estimate the optimal portfolio weights based on the state variables. Ait-Sahalia and Brandt (2001) argue that the predictability of expected returns and the covariance structure is difficult to be translated into portfolio selection advice because the two moments may be predicted by different variables.

Moreover, a variable may be both significant for predicting the variations of expected return and variance but such variations offset therefore it is not useful for determining optimal portfolio weights. Based on that, Brandt and Santa-Clara (2006) propose an approximation to solve the CIO's problem by introducing managed and timing portfolios in the asset space. This approach is easy to apply by investors in the traditional static Markowitz paradigm.

Chapter 3

Equity Style Drivers: Business Cycle Risk versus Firm-specific Characteristics

3.1 Introduction

Over the past decades a large number of empirical studies provide evidence to show that certain firm characteristics can profitably differentiate among stocks. For example, Banz (1981) first reports the size premium that stocks with small market capitalisation can earn higher risk-adjusted returns than those with large market values. Defined as having higher earnings-to-price ratios (E/P), Basu (1983) first documents that value stocks could generate higher absolute and risk-adjusted returns than growth stocks. The outperformance of value stocks (often called the value premium) is also found when value stocks are defined by different firm characteristics such as book-to-market ratios (BM), price to cash-flow ratios (PC) or dividend-yield (DY) (*c.f.* Fama and French (1993, 1998); Lakonishok *et al.* (1994)). These results are robust across U.S. and international markets. Parallel to the findings of divergent return patterns across different equity groups, the concept of style-based investment strategy has evolved in the U.S. markets. For instance, around 1980s, institutional investors such as pension funds start to engage in style investing by searching the best style managers to build portfolios that can capitalise on the relative style performance within the investment cycles. The premise of style investing is that investors allocate their asset along style level rather on the individual stock level. Since asset categorisation based on firm characteristics provides common structure in the complex investment environment, the idea of style investing has gained growing popularity in today's financial markets because it simplifies money managers' decision-making process and makes the investment process less intimidating (*c.f.* Mullainathan (2002), Barberis and Shleifer (2003)).

Recent research of style investing has shifted from providing empirical evidence on the existence of relative style returns to the investigations of various components and theory-based interpretations of relative style performances. While the benefit of style investing is less controversial, it remains an ongoing debate why some stock groups can generate higher average returns than others in a given period of time. Rational asset pricing theory argues that stock markets are efficient and the outperformance of one style over another is not abnormal but rather represents compensation for higher non-diversifiable systematic risks. Chan *et al.* (1985) and Huberman *et al.* (1987) show that the relative returns of small and large stocks are due to their different sensitivities to the risk factors important for pricing assets. Fama and French (1993) document that value premium is related to a distinct distress factor proxied by firm leverage or the book-to-market ratio. As a result the outperformance of value stocks would suggest they are fundamentally riskier than growth stocks. In contrast to the traditional rational-based explanations, behavioural finance links the divergence of style returns to the mispricing of some asset groups caused by investors' cognitive biases unrelated to economic fundamentals. Lakonishok *et al.* (1994), for example, argue that value stocks and growth stocks are not properly priced in stock markets. The outperformance of value stocks is driven by investors' systematic judgement errors to believe that the past growth rate for growth stocks would persist far in the future. Value and growth returns reverse when investors subsequently receive surprises regarding the financial results for the two styles. Hence the reason for value premium is driven by investor's cognitive biases rather than due to the compensation for higher systematic risks. Apart from the rational and behavioural frameworks for the size and value premiums, papers such as Daniel and Titman (1997) propose other school of characteristic-based interpretation. They contend that the cross-sectional variations in expected returns between stocks with different characteristics are not due to there being risk factors associated with Fama and French (1993) three factors, but rather from characteristics themselves. Hence the size and value premiums are caused by their underlying firm-specific characteristics instead of different loadings on the risk factors underpinning the asset pricing dynamics.

A growing number of empirical studies demonstrate that the observed variations on returns across some equity styles are related to the dispersions of cross-sectional expected returns. Conrad and Kaul (1998) and Berk *et al.* (1999) argue that stocks with high (low) expected returns tend to achieve high (low) realised returns. These studies have highlighted the importance of the macroeconomy in determining such cross-sectional variations in expected stock returns. There are strong *a priori* grounds to relate stock returns to the business cycle conditions. Finance theory provides a suggestive correlation between stock price and economic states. For example, the dividend discount valuation model suggests that the present value of a stock equals to the aggregate discounted expected future dividends received. There are 4 parameters involved when evaluating the value of a stock, namely, the expected future cash flows, the market risk premium, the market risk exposure and the term structure of interest rates. Dahlquist and Harvey (2001) point out that these variables share a common component, the business cycles. Indeed, a firm's ability to generate cash flows and its risk exposure often differs in different phases of the economic cycles. The market risk premium is low when the economy peaks and high when it troughs. The term structure of interest rates (the yield curve) is the leading indicator of business cycle volatility that determines a firm's cost of capital. Bolten and Weigand (1998) demonstrate how the underlying parameters in a basic dividend discount valuation model vary and are affected by different states of the economy.

Chan and Chen (1991) and Fama and French (1993) propose that the returns of distressed stocks are especially sensitive to economic states and are driven by many of the same macroeconomic factors such as variations over time in bankruptcy costs and the accessibility to credit markets. Bernanke and Gertler (1989), Gertler and Gilchrist (1994), Kiyotaki and Moore (1997), and Hahn and Lee (2006) show that changing credit market conditions can exert different effects on risks and expected returns across styles. Berk *et al.* (1999) provide a theoretical model in which the value of a firm is the sum of its existing assets that generate cash flows and the value of an option that makes positive net present value investment in the future. Their model suggests that the expected return of a firm is jointly determined by the current interest rate, the firm's systematic risks of its existing assets and the number of active projects. Thus expected returns vary across firms with changes in interest rate and the number of old projects that are dead and replaced. Consistent with these studies, authors such as Perez-Quiros and Timmermann (2000) document asymmetries in the variation of small and large firms' risk characteristics over the economic regimes. Vassalou and Xing (2004) find that the size and value premiums are intimately related to the default risk, which is related to macroeconomic factors and varies with the business cycles (*c.f.* Denis and Denis (1995)). More recently, Zhang (2005) suggests that value and growth firms have different ability in investing (disinvesting) in good (bad) times and therefore the dispersion of risk between value and growth stocks is high in bad times, while the risk differential is low or even negative in good times. Black and McMillan (2005) also show that value and growth stocks exhibit asymmetric responses to the shocks in macroeconomy across the business cycles. Value stocks tend to be more responsive to changes in macroeconomic conditions than growth stocks, and such responsiveness increases during economic contractions.

In a recent paper, Chordia and Shivakumar (2002) investigate the influence of time-variations in risk premia on the momentum effect of Jegadeesh and Titman (1993). The momentum effect suggests that if stocks are classified by their past performance, the winner group continues to earn higher returns than the loser group in medium term. Using a parsimonious set of macroeconomic variables in a multifactor business cycle model framework, Chordia and Shivakumar (2002) find that momentum profits can be attributed to the higher *conditional expected returns* predicted by business cycle model. Thus the relative return differentials of the two asset classes can be interpreted as the compensation for bearing the business cycle risks rather than the diversifiable firm-specific risks. Griffin *et al.* (2003) also study whether global momentum profits could be attributed to macroeconomic risks. They employ the model of Chen *et al.* (1986) to regress the momentum returns on contemporaneous macroeconomic variables but fail to find a direct relation between macroeconomic risks and momentum profits. More recently, Avramov and Chordia (2006a) develop a framework extending that of Brennan *et al.* (1998) to test whether asset pricing models can explain size, value and momentum effects. In their paper, the factor loadings of a given asset pricing model change with characteristics such as firm size and BM ratios as well as with business cycle conditions. Avramov and Chordia (2006a) show that when beta is allowed to vary with size, BM and macroeconomic variables, the size and value premiums are often explained and the momentum effect can be captured by model mispricing that varies with macroeconomic variables, suggesting the risk-based explanation for size and value premiums and a potential business cycle related explanation for the impact of momentum on the cross-section of stock returns. Overall, the majority of recent studies generally suggest that economic exogenous forces dominate in affecting equity style return dynamics over time, and the reason why some stocks offer average higher returns than others is because they bear higher time-varying macroeconomic risks. Hence stock price evolves over time, reflecting the cyclical and structural changes in the aggregate economy.

While rational, behavioural and characteristic-based theories are able to explain the divergent equity style return patterns, the relative importance of such theories has not been carefully studied in the extant literature. From an investor's perspective, the observed time-varying relative equity style returns is of obvious importance as it introduces opportunities for active portfolio manager to tactically invest in some specific asset classes in certain periods of investment cycles. However, to successfully implement such equity style rotation strategy, one must be able to not only identify the underlying driving forces that determine the relative style returns, but also to capture the mechanisms through which those forces work. Understanding the relative importance of such competing theories is important since different interpretations would suggest different driving forces that underlie style return dynamics and consequently provide different practical guidance for active portfolio management.

This chapter contributes to the literature by empirically investigating the relative importance of common risk factors versus the firm-specific information as driving sources of equity style return differentials. The objective of this chapter is to answer a central research question: what is the dominant factor that affects size and value premiums, common risk factors or the firm-specific information? Answers to this question tells rational and behavioural theories apart because a common structure to the divergent style return could point towards a rational risk-based interpretation, while the firm-specific based finding is more likely to be within the behavioural framework.

To pursue this research question, Chapter 3 builds some simple style trading strategies and examines the underlying sources determining the profitability of such style investing in the U.K. stock market. The study of the U.K. market is motivated by the fact that despite being one of the most influential financial markets, the U.K. experience of style investing has lagged considerably behind that of the U.S. (Williams (2004)) and therefore needs careful research. Although style investing develops from and still dominates in the U.S. stock markets, given the fact that such investing is based on sound and observable characteristics that are theoretically as relevant as they are in the U.S. context, the fundamental rule of style investing is arguably the same in the U.K with different economic and institutional environment.

This chapter develops and employs the methodology used in Chordia and Shivakumar (2002) to investigate the relative importance of common risk factors versus firm-specific information as sources of size and value premiums in the U.K. stock market. Over a sample period of January 1980 to December 2004, all U.K. stocks are categorised into size and value-growth groups according to firm characteristics such as market value (MV), market-to-book ratios (MTBV), price to cash flow ratios (PC) and dividend yields (DY). Based on asset classification, simple long-short style investing strategies are tested and their return dynamics over the business cycles are examined. Using firm characteristics to categorise stocks is pervasive in the financial market. Empirical research consistently finds robust cross-sectional relation between average stock returns and equity characteristics. More importantly, it is found that stocks with similar characteristics tend to move together. Huberman *et al.* (1987) find that returns of stocks within the same size range tend to comove and respond to risk factors in similar ways. Berk *et al.* (1999) argue that firms with same characteristics are affected by the same state variables relating to systematic risks and expected returns. Hence firms share similar characteristic tend to have the same underlying pervasive forces affecting stock returns. These studies point to the rationale of simple asset allocation strategies focusing on specific asset classes that share similar characteristics.

In response to the popularity in recent studies to link macroeconomic effects with the observed cross-sectional variation on stock returns, Chapter 3 also models expected stock returns conditional on shocks originating in a set of pervasive economic variables that relate to the business cycles. To examine whether business cycle risks contribute to the realised return differentials, style investing strategies are tested based on both the *predicted* and *unpredicted* part of the business cycle model. Specifically, 2 hypothecations are tested:

1. *If business cycle risk is the major driving force to the cross-sectional variations on stock returns, style spreads should be substantially decreased after controlling for the exposures to the predicted macroeconomic risk premias;*
2. *If mispricing (firm-specific information) is the major source that underlies the relative style returns, controlling for the business cycle effect would not cause material changes for the observed style spreads. Rather, simple style investing strategies based on business risk adjusted returns would generate significant profits.*

Since equity characteristics under consideration explain significant cross-sectional variation in average stock returns, rational pricing theory would argue that such firm characteristics are proxy for risk factors or the information of mispricing, or alternatively they are cross-sectionally correlated with the underlying factor loadings. In order to better understand the mechanism that explains the cross-sectional variation in mispricing of the business cycle model, the contemporaneous relations between equity characteristics, common risk factors and the mispricing from the business cycle model are also cross-sectionally examined using model pricing errors as dependent variable on equity characteristics augmented with estimated loadings on asset pricing models such as CAPM and Fama and Fench (1993) three-factor model.

The empirical results in this study uncover interesting time variations in equity style returns and shed further light on the ongoing debate regarding the underlying driving forces determining the relative style performance. Consistent with previous findings in the literature, significant size and value premiums are found in the U.K. stock market. Such style premiums are more pronounced in periods when the economy is in bad times, suggesting that indeed small stocks and value stocks are more sensitive to bad economic conditions. However, further results suggest that the underlying driving forces differ with respect to different characteristics considered to category stock groups. Specifically, it is suggested that the divergent performance for stocks sorted by DY is mainly driven by different exposures to common business cycle factors, indicating that the value premium on DY is compensation for bearing business cycle risks. Consistently, equity characteristics and loadings on common risk factors of CAPM or Fama and French (1993) three-factor model do not capture the pricing errors of the business cycle model. In contrast, the size premium and value premiums based on PC or MTBV are less likely due to direct compensation for bearing business cycle risks, rather they are mainly affected by the firm-specific components unpredicted by the business cycle model, suggesting that the outperformance of small stocks and value stocks based on firm characteristics PC and MTBV result from investors' consistently underreact to firm-specific information within the style. Moreover, the mispricing of the business cycle model is mainly related to common risks of CAPM or Fama and French (1993) three-factor loadings, but not the firm characteristics. Hence the null hypotheses that market capitalisation, PC and MTBV do not proxy for risk factors or have no cross-sectional correlations with the risk factor loadings can be rejected.

Overall, the findings in Chapter 3 generally support the rational risk-based theory that equity style premiums reflect compensation for risk, although such risk may or may not directly relate to the business cycle fluctuations. The findings in this chapter provide practical guidance for active portfolio management. Portfolio managers who pursue style investing by allocating their funds to characteristic-based asset groups to capitalise on the dynamic divergent style returns have to understand the different risk-related mechanism behind the observed style spreads. For example, if style premiums are driven by macroeconomic risks, active style management should aim to timing the business cycle. Conversely, if risks outside the business cycle drive the mispricing as the main cause of style spreads, style timing should focus on identifying the stock groups related to investors' trading behaviour.

The remainder of Chapter 3 is organised as follows. The next section introduces the empirical model specifications and the hypothesis to be tested. Section 3 describes the data, the firm characteristic variables and the methodology of building style portfolios. Section 4 presents the detailed empirical test results and discussions. Finally Section 5 summarises and concludes this chapter.

3.2 Econometric framework

In a risk-based multifactor economy, suppose there are N stocks to be priced and M macroeconomic variables containing useful information important for pricing the stocks and are observable by investors. If the market is efficient and in the absence of arbitrage, the N stocks are priced by the pricing kernel, m_t, such that:

$$E_t[R_{t+1}m_{t+1}] = 1_N \tag{1}$$

Where 1_N is a $N \times 1$ vector of ones, R_{t+1} is the $N \times 1$ vector of gross returns of the N stocks in time period $t+1$, and m_{t+1} is the scalar stochastic discount factor (pricing kernel). Assuming that the pricing kernel can be proxied as a linear multivariate function of a set of pricing factors, i.e

$$m_{t+1} = a_t + b_t' \tilde{f}_{t+1} \tag{2}$$

Here a_t and b_t are time-varying coefficients that are adapted to information set of M macroeconomic variables at given time t. Assuming that a_t and b_t are linear functions of the M macroeconomic variables:

$$\begin{aligned} a_t &= a' Z_t \\ b_t &= b Z_t \end{aligned} \tag{3}$$

Where a and b are $M \times 1$ and $N \times M$, respectively. Z_t is a $M \times 1$ vector of M macroeconomic variables that are observed at time t-1. Hence:

$$m_{t+1} = a' Z_t + (bZ_t)' \tilde{f}_{t+1} \tag{4}$$

Thus, at each point of time t, the expected return of an individual stock can be related to the conditional covariance of returns with the measure of the pricing kernel. The pricing kernel is proxied by a linear and multivariate structural function based on the M macroeconomic variables, implicitly allowing the time variations in the exposure to macroeconomic variables over the business cycles.

Equation (4) is a dynamic multifactor model and both theoretical and empirical studies support the use of such dynamic multifactor pricing models. The motivation to use a conditional framework is that in a dynamic world the pricing kernel of assets are likely to be time-varying in responding to different information set (Wu, 2002). The multifactor approach is also empirically motivated. Justified for a century of empirical analysis, the fragility of single factor asset pricing model such as CAPM is well recognised. CAPM summarises the expected asset return with a single beta measurement that relates to the comovement with the overall market. Thus higher expected returns should suggest higher betas that act as compensation for higher common risk exposures. The extant literature has however identified asset groups that offer better returns than others but do not necessarily have higher CAPM betas. For example, Fama and French (1996) show that small stocks and value stocks do not have higher market betas, suggesting the major failure of CAPM in explaining the cross-sectional variations in average returns. Hence, as Cochrane (2000) points out, at least since Merton (1971, 1973) asset pricing theory recognises the use of additional factors of the source of priced risks beyond the movement of market portfolio to explain why some assets earn higher returns than others.

Given the foregoing and in the spirit of Chordia and Shivakumar (2002), for each individual stock, the expected returns conditional on the M macroeconomic variable set Z_t can be specified as:

$$E(R_{i,t+1} \mid Z_t) = \lambda_{i0} + \sum_M \beta_{i,M,t+1} \lambda_{i,M,t+1}(Z_t) \qquad (5)$$

This chapter uses 4 macroeconomic variables as the instruments to proxy the pricing kernel. These variables are:

- *div* - the dividend yield on the overall market;
- *def* - the default spread measured by the yield spread between the lower- to higher- yield bond;
- *term* - the term spread measured by the differential between the yield of long-term government bond and the yield of 3-month T-bills;
- *yld* - the short-term interest rate proxied by the yield on the 3-month T-bills.

Thus Z = (*div, yld, term, def*) and it is easy to show:

$$\lambda_{i,M,t+1} = \alpha_{i,k0} + \alpha_{i,M1} div_t + \alpha_{i,M2} yld_t + \alpha_{i,M3} term_t + \alpha_{i,M4} def_t \qquad (6)$$

Therefore, the one-period-ahead predicted stock return is obtained from the following regression:

$$R_{i,t} = c_{i,0} + c_{i,1} div_{t-1} + c_{i,2} yld_{t-1} + c_{i,3} term_{t-1} + c_{i,4} def_{t-1} + e_{i,t} \qquad (7)$$

Where $c_{i,0} = \lambda_{i0} + \sum_M b_{i,M} a_{M0}$ and $c_{i,j} = \sum_M b_{i,M} a_{M,j}$, for $j = 1, 2, \cdots, M$ (M = 4).

The selection of these 4 variables is motivated by the criteria noted in Campbell (1996) that proxies for state variables of time-varying investment opportunities should be chosen based on their ability to forecast market returns and explain the patterns of cross-sectional average asset returns. Prior studies on the relation between stock returns and the business cycles have focused on these 4 variables due to their indicator nature that relate to the business cycle fluctuations. For example, Fama and Schwert (1977), Fama (1981) show that the yield on the 3-month T-bills is negatively related to future market returns. The dividend yield on the overall market is perhaps one of the oldest variables recognised to affect the expected stock returns. Fama (1990) shows that stock prices are low relative to the dividends when the discount rate and expected returns are high, and vice versa. Keim and Stambaugh (1986), Cambell and Shiller (1987) and Fama and French (1988) also show that dividend yield is associated with slow mean reversion in stock returns in the business cycles.

The importance of default spread and term spread in explaining stock returns is also well documented. Keim and Stambaugh (1986) use the default spread to predict stock and bond returns. Chen et al. (1986) find that the default spread is an indicator to the business cycle. They argue that the default spread is likely to be high when the economy is in good condition, and vice versa. Likewise, Fama and French (1989) and Fama (1990) show that the default spread tracks the long-term business cycle conditions and captures the variations in expected returns within the business cycles. Daniel and Torous (1991) further show that the default spread contains information about future production volatility.

Fama and French (1989) find that the term spread is also closely related to the business cycles. They argue that this variable tends to decrease near peaks of business cycles and increases when the economy troughs. Daniel and Torous (1991) provide evidence that the term spread is primarily informative about future growth prospects. Chen (1991) also use the default and term spread to predict excess returns and contends that the predictability of these variables is due to their business cycle indictors that contain information about the current and future economic conditions.

Overall, the above 4 variables are standard macroeconomic variables containing rich information of the business cycle risks. In particular, the default and term spread variables have long been used as proxies for credit market conditions and the stance of monetary policy, suggesting that innovations in these variables would capture revisions in the market's expectation about future credit market conditions and interest rates. Given that small and large size stocks have different accessibility to credit markets (*c.f.* Chan and Chen (1991); Gertler and Giichrist (1994)), and that value stocks tend to have high financial leverage and cash flow problems than growth stocks (Fama and French (1992, 1995)), it is expected that the default spread would be good state variable capturing the cross-sectional variations in average returns of size and value-growth stocks. Furthermore, this variable may also capture investor's hedging concerns associated with time-varying risk premia (Jagannathan and Wang (1996)). Similarly, since the term spread is one of the most widely used proxies for market's expectation about future interest rates, it is also expected to capture the hedging concerns to investors associated with changes in interest rates.

While most prior studies use these macroeconomic variables to do empirical tests on the portfolio level, recently there are some studies to implement the same framework but on the individual stock level. Avramov and Chordia (2006a) argue that the use of individual stocks reduces the data-snooping biases raised by Lo and MacKinlay (1990) and can avoid the loss of information in the portfolio sorting process suggested by Litzenberger and Ramaswamy (1979). Recent paper of Chordia and Shivakumar (2002) use these macroeconomic variables to investigate the influence of time variation in risk premia on momentum returns. They first estimate individual stock returns using these variables and subsequently sort stocks based on these predicted returns to investigate if momentum effect still exists. Chordia and Shivakumar (2002) find that momentum profits based on predicted returns are substantially reduced, suggesting that momentum profits could be attributed to higher conditional expected stock returns and hence can be interpreted as compensation for bearing business cycle risks.

This chapter employs a similar methodology to that used in Chordia and Shivakumar (2002). Each month Equation (7) is used to predict the one-month-ahead expected returns for individual stocks. The parameters of Equation (7) are estimated using a rolling window based on previous 60-month observed (realised) returns. To obtain the meaningful estimates, only stocks with at least 24-month return observations are included during the parameter estimation procedure. The estimated coefficients of Equation (7) are then used to predict the one-month-ahead expected returns of the underlying stocks.

Under a rational asset pricing framework, any abnormal returns are caused by risk factors. Equation (7) states that expected stock returns are driven by conditional shocks to macroeconomic variables. Given the evidence of significant size and value premiums found in the U.K. stock market, the following two hypotheses can be tested:

- *Null hypothesis: if business cycle risks are the major driving force to such divergent stock returns, it is expected that return differentials across styles should be substantially decreased once controlling for the exposures to these macroeconomic variables.*
- *Null hypothesis: if firm-specific components are the major sources that underlie the relative returns across different stock groups, controlling for the business cycle effect should not cause material changes for the observed style spreads. Hence simple style investing strategies based on the unexplained parts (i.e. the pricing error) of Equation (7) should generate significant payoffs.*

3.3 Data and methodology

3.3.1 Data description

While U.S. markets data are widely used to develop ground theory, test asset pricing models and investigate the cross-sectional and time-series returns across different asset classes, this chapter will focus on the U.K. stock market only. The study of U.K. market is less covered in the extant style investing literature, and this chapter will be able to provide additional evidence to compare with other studies in different economic and institutional environments. The source of stock prices and firm characteristic information are obtained from the Datastream. The sample in this study spans from December 1979 to December 2004 [8]. Stocks that are denominated by foreign currencies are excluded because their returns are also affected by foreign exchange rate fluctuations. All delisted (dead or suspended) stocks are retrieved and added back to the sample when they were "alive" in a specific time period. The firm characteristics used to classify stocks into size or value-growth groups are market capitalisations (MV), price to cash flow ratios (PC), market to book ratios (MTBV) and dividend yield (DY). These variables represent a firm's fundamental characteristics and are generally found to be associated with the variations on average stock returns. In market practice, many investors also use these variables to classify stocks into different size and value-growth styles to simplify their asset allocation process. The definition of these variables in Datastream is as follows:

- MV: market capitalisation. It is equal to the share price multiplied by the number of ordinary shares in issue displayed in millions of units of British pounds (£).
- PC: price to cash flow ratios. It is the price divided by the adjusted price cash earnings per share for the appropriate financial year end, which is adjusted for any exception and extraordinary profits or losses.
- MTBV: market value to book value ratios. This is the ratio of the market value divided by the net book value. Essentially it is the inverse of book-to-market ratio (BM).

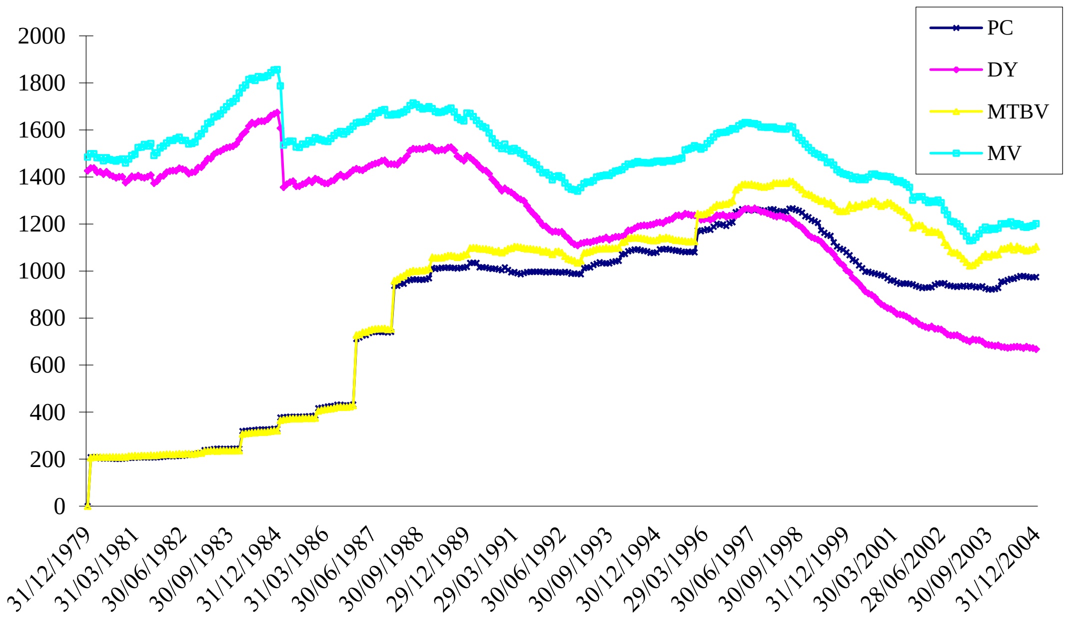
[8] This study was conducted in 2005-2006, thus the most recent available sample data for the research was up to December 2004.

- DY: the dividend yield. It is the dividend per share as a percentage of the share price. In Datastream the underlying dividend is calculated as the anticipated payment over the following 12 months and maybe calculated on a rolling 12-month basis. Special or one-off dividends are generally excluded.

Figure 3-1 depicts the time-series number of stocks that have positive values for a given firm characteristic value in the sample period. It is suggested that for a given month not every stock has all the 4 characteristic information available in Datastream. Most stocks have market value information but roughly only half of the stocks have readily available dividend yield data. Hence style investing based on different characteristic variables would have different sample size.

Figure 3-1 Number of stocks based on the available firm characteristics in the sample

The time-series number of stocks with positive firm characteristic values is plotted over the period 1979:12 to 2004:12. It is shown that for a given month, not every stock has all the 4 variable information used in the study.



As mentioned in previous section, the 4 macroeconomic variables used in this study are default risk premium (*def*), dividend yield (*div*), the term spread (*term*) and short-term interest rate (*yld*). *def* is the yield spread between the lower- to higher- bond and is measured as the yield on corporate bonds less the yield on long-term U.K. government bonds. *div* is the dividend yield on the overall market index as proxied by the Datastream U.K. market index. *term* is the difference between the 20-year gilt and 3-month Treasury bill yields and the short-term interest rate *yld* is proxied by the 3-month Treasury bill yield. Table 3.1 presents the correlation matrix of these variables.

Table 3-1 Correlation Matrix of the Macro Variables

This table shows the correlation matrix between the macro variables used in the study. Panel A reports the raw correlations. In Panel B the variable *yld*1 is the innovations of the raw *yld* regressed on variables *def*, *div* and *term*, representing the raw *yld*'s explanatory part orthogonal to variable *def*, *div* and *term* in regression (7).

Panel A Raw Correlation Matrix				
	def	*yld*	*div*	*term*
def	1	0.1628	0.0907	-0.2311
yld	0.1628	1	0.7746	-0.5908
div	0.0907	0.7746	1	-0.0859
term	-0.2311	-0.5908	-0.0859	1
Panel B New Correlation Matrix				
	def	*yld1*	*div*	*term*
def	1	0.0000	0.0907	-0.2311
yld1	0.0000	1	0.0000	0.0000
div	0.0907	0.0000	1	-0.0859
term	-0.2311	0.0000	-0.0859	1

Panel A shows that the variable *yld* is highly correlated with *div* and *term*, while correlations among other variables are relatively low. The correlation between variables *yld* and *div* is 0.7746 and the correlation of *yld* with *term* and *def* is -0.5908 and 0.1628, respectively. The observed high correlations between *yld* and other variables suggest that Equation (7) may suffer from multicollinearity problem. To eliminate this problem, the variable *yld* is regressed on other three variables (*def, div, term*) and the innovation of the regression, *yld*1, is used to replace the original variable *yld* in Equation (7), representing its explanatory power that is orthogonal to *def*, *div* and *term*. This process is mainly econometrically motivated. For notation purpose, the variable *yld1* will still be noted *yld* later. After this procedure, as reported in Panel B the correlations between the 4 variables become reasonably low.[9]

3.3.2 Style portfolio construction

To match the minimum 24 months observation of stock returns, the empirical tests in this chapter are based on data after January 1982. Starting from January 1982 to December 2004, at the end of each month, all U.K. non-financial stocks are categorised into quintiles in ascending order according to their firm characteristics as measured by the previous J-month average values of the style variables[10]. Stocks that are newly listed during the previous J months or those with negative characteristic values will be excluded in the study. Following the literature all financial stocks are also excluded because Fama and French (1996) argue that the financial ratios of such stocks may not have the usual meanings as non-financial stocks do. Besides, all the dead or suspended stocks are added back to the sample when they are still "alive" in each point of time. Each month stocks are sorted into 5 quintiles, quintile 1 (Q1) has the lowest value of characteristic values and quintile 5 (Q5) has the highest values of average characteristics. The number of stocks in Q1 and Q5 is identical and

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[9] It is worth noting, however, that the empirical results are qualitatively the same in this study should this procedure is not applied.

[10] One may well be concerned that whether the strategies discussed here are practically applicable given the fact that companies only disclose the financial reports on a quarterly or semi-annually basis. Arguably, this sort of 'information lag' should not be a problem for institutional investors. Institutional investors do their investment research based on proprietary or outsourced database and arguably information in that database will be updated timely. The use of the average value of past J-month information also smooths the possible data error or outliers, making the ranking more reliable.

hedge portfolios are constructed by longing Q1 stocks and shorting Q5 stocks (for research variable DY, the hedge portfolio is to long Q5 and to short Q1). The hedge portfolios are built in two ways, i.e. the equally-weighted (EW) and the value weighted (VW) schemes [11]. Correspondingly, the returns of the two schemes are reported for different quintiles to provide useful insight of constituent stocks' return patterns. The hedge portfolios are rebalanced in K months after formation and monthly hedge portfolio returns are calculated following the 'overlapping' principle proposed by Jegadeesh and Titman (1993). Specifically:

1. At every month end, all stocks are ranked into 5 quintiles according to their average firm characteristic values over the previous J months, time $t-J+1$ to t where t is the current month. Portfolios Q1-Q5 for different characteristic variables are formed based on equally-weighted and value weighted schemes.

2. Style portfolio returns are measured in every month for the next K months after formation, $t+1$ to $t+K$. The return of Q1 (Q5) portfolio in period $t+1$ is the average of the returns to the top (bottom) quintile portfolios formed at $t, t-1, \cdots, t-K+1$ in period $t+1$. Thus the return to the Q1 (Q5) asset class is the average return to the K Q1 (Q5) portfolios formed consecutively over the previous K months.

3. The returns of hedge portfolios (J, K) are the average return to the self-financing portfolio Q1-Q5 over the entire sample periods.

[11] The two weighting schemes help identify the basic interaction between size and value-growth styles because value weighted returns are biased to large-cap stocks and the equally-weighted returns are biased to small-caps.

For every style variable, the average performance of hedge portfolios based on a combination of formation and testing period (J,K) = 6, 12, 24 and 36 months in the entire sample periods are reported. Thus for a combination of (J,K) strategy, a total of $C_j^1 \times C_k^1 = j \times k$ tests will be considered. The longer formation and testing period helps to investigate the return patterns in a long-term perspective.

Table 3-2 summarises the characteristics of quintile portfolios based on formation periods of 6, 12, 24 and 36 months. On the value-growth dimension, value stocks can be generally defined as stocks with low price to cash flow ratios (Q1 of PC), low market-to-book value ratios (Q1 of MTBV) or high dividend yields (Q5 of DY). The opposite is for growth stocks. It is shown that these firm characteristics provide consistent style definitions, i.e. stocks with low PC generally have higher DY and lower MTBV. On the size dimension, it seems that the size differential between large and small stocks is very large. Q1 stocks are mainly genuine small companies, while Q5 stocks are all blue chips. It is also recognised that small size stocks have higher PC ratios than those in other quintiles, and DY in both small and large quintiles are much higher than those in other quintiles. Besides, it is suggested that value stocks tend to have small firm size as compared to growth stocks.

Table 3-2 Time-series average equity characteristics of quintile portfolios

This table shows the time-series average characteristics of style portfolios classified by equity characteristics PC, DY, MTBV and MV based on formation period J = 6, 12, 24 and 36 months. The sample period is from January 1982 to December 2004. The sample size for different characteristic variable is different.

Research Variable	Quintiles	Formation period (J)															
		J = 6				J = 12				J = 24				J = 36			
		PC	DY	MTBV	MV (m)	PC	DY	MTBV	MV (m)	PC	DY	MTBV	MV (m)	PC	DY	MTBV	MV (m)
PC	Q1(L)(Value)	4.18	5.43	1.72	342.7	4.48	5.30	1.69	389.6	4.87	5.19	1.73	473.0	5.22	5.11	1.80	582.8
	Q2	6.30	5.08	1.96	515.7	6.59	5.05	2.04	528.9	7.01	5.06	2.17	579.5	7.18	5.05	2.22	580.1
	Q3	8.22	4.51	2.58	618.8	8.36	4.53	2.54	662.8	8.61	4.54	2.63	726.0	8.88	4.57	2.64	836.2
	Q4	13.08	3.84	3.44	883.4	12.38	3.88	3.50	922.0	11.14	3.95	3.32	1037.4	11.11	4.03	3.40	1168.3
	Q5 (H)(Growth)	25.93	3.55	4.63	832.2	25.35	3.58	4.53	916.4	23.48	3.62	4.15	1053.7	22.17	3.62	4.03	1173.6
DY	Q1(L)(Growth)	30.91	1.64	4.88	1016.1	24.70	1.75	4.93	1101.9	22.03	1.92	4.88	1225.5	25.54	2.07	4.56	1313.5
	Q2	18.64	3.07	3.12	989.8	23.09	3.17	2.99	1040.5	25.27	3.34	2.82	1152.8	20.60	3.47	2.73	1323.6
	Q3	14.87	4.26	2.39	751.4	15.11	4.32	2.34	770.7	14.05	4.41	2.42	822.8	11.09	4.48	2.54	843.0
	Q4	15.15	5.68	2.25	567.1	11.62	5.67	2.24	562.0	9.25	5.66	2.15	595.2	9.36	5.55	2.06	660.0
	Q5 (H)(Value)	13.60	8.29	1.70	346.1	13.75	8.04	1.80	355.2	10.67	7.67	2.02	360.0	10.84	7.48	2.17	367.8
MTBV	Q1(L)(Value)	11.53	5.76	0.75	228.6	11.24	5.53	0.78	243.7	10.51	5.28	0.83	251.8	10.30	5.10	0.87	287.3
	Q2	18.62	5.42	1.20	382.3	18.05	5.34	1.23	398.6	16.59	5.21	1.28	454.6	12.12	5.15	1.33	479.6
	Q3	35.05	4.85	1.70	500.4	31.12	4.86	1.72	516.7	22.67	4.87	1.75	559.6	14.89	4.87	1.80	640.8
	Q4	25.30	4.00	2.54	760.4	23.40	4.07	2.53	835.5	17.34	4.19	2.53	933.6	18.60	4.27	2.54	1029.2
	Q5 (H)(Growth)	25.90	3.05	6.11	806.5	27.73	3.14	5.84	847.7	30.65	3.30	5.50	970.1	23.55	3.41	5.26	1081.1
MV	Q1(L)(Small)	28.39	9.97	3.69	5.2	25.98	9.71	3.14	5.7	22.88	8.46	2.81	6.6	19.16	7.17	2.52	7.6
	Q2	33.14	5.26	2.49	15.4	36.69	5.05	2.42	16.7	25.96	4.99	2.35	19.4	13.34	4.98	2.40	22.2
	Q3	25.51	4.70	2.92	39.5	25.33	4.68	2.95	43.2	25.10	4.68	3.14	50.5	25.34	4.70	3.20	58.4
	Q4	23.32	4.24	3.52	129.6	22.57	4.26	3.43	140.8	21.34	4.32	3.37	163.7	18.51	4.39	3.32	187.5
	Q5 (H)(Large)	12.98	7.53	3.98	1664.0	12.75	7.77	4.00	1769.3	12.59	8.25	3.86	1957.9	12.44	8.69	3.91	2147.2

3.4 Empirical results

3.4.1 The returns of simple style investing strategies

Table 3-3 documents the average monthly returns during the K-month holding periods spanning from January 1982 to December 2004 for simple style investing strategies that buy and sell different stock groups based on past J-month firm characteristics and subsequently hold for K months.[12] For brevity, only formation and testing periods of (6, 12) and (12, 6) months are reported (for other formation and holding periods the results are qualitatively similar). Since style portfolios are built using the overlapping method, there may be autocorrelations in the time-series average returns. Hence the t ratios in brackets are calculated using Newey-West (1987) heteroscedasticity and autocorrelation consistent variance with lags equal to K, the testing periods.[13]

Table 3-3 suggests that, consistent with the literature, there is strong evidence of divergent style return patterns in the U.K. stock market. For example, during January 1982 to December 2004, on average U.K. value stocks outperform growth stocks at 1.66% (PC), 0.80% (DY) and 1.24% (MTBV) per month in the subsequent 12 months if stocks are classified using past 6-month characterises and returns are calculated using equally-weighted scheme. This is in contrast to value-weighted premiums of 1.28% (PC), 0.83% (DY) and 0.97% (MTBV). Moreover, if instead the stocks are categorised according to the past 12-month characteristics, equally-weighted average monthly value premiums in the subsequent 6 months after portfolio formation would be 1.82%

[12] To match the return prediction that requires at least 24 months observations, the tests are based on data starts from January 1982 rather than January 1980.

[13] Using Fama-MacBeth (1973) approach will overstate the test statistics because of the autocorrelations of the returns series. It is reasonable to assume the lags equals to the number of the holding periods K because there are K portfolios involved in the calculation of monthly holding returns.

(PC), 0.88% (DY) and 1.36% (MTBV) as compared to 1.30% (PC), 0.82% (DY) and 1.00% (MTBV) of value weighted scheme. It is noted that in the same period the equally-weighted size premiums based on (6, 12) and (12, 6) are 0.90% and 0.97% respectively as compared to value weighted size premiums of 0.90% and 1.06% respectively. The value and size premiums are economically significant, and in most scenarios the style premiums within the subperiods are also significant.

Table 3.3 also reveals some evidence of seasonality in style return patterns. Since the January effect is the most important calendar anomaly observed in the stock market, to better understand the style return properties, Table 3-3 also reports the January-only and non-January-only average returns. It can be seen that the size premium and value premiums based on PC and MTBV are more pronounced in January than those in non-January months, while the value premium based on DY is less evident to show such January effect.

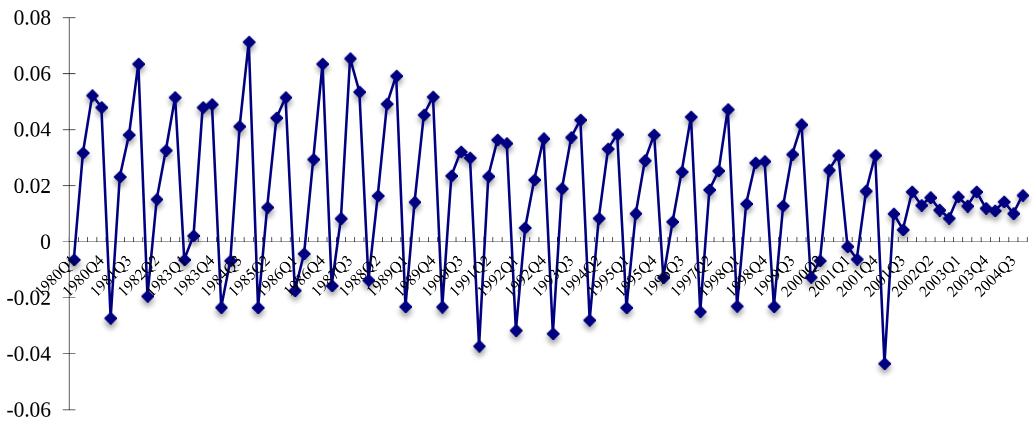
The interaction of styles is also evident in table 3.3. It is shown that equally-weighted value premiums are generally higher than value weighted premiums, suggesting that in this U.K. data set value stocks generally have much smaller market values than growth stocks, which is consistent with results showed in Table 3-2.

3.4.2 Style returns and the business cycles

While Table 3-3 offers some evidence for the style return differentials classified by different equity characteristics in the U.K. stock market, a question to ask is whether there are variations in style returns within the different stages in the business cycles. To pursue this question, the dynamics of U.K. economy are first analysed in the sample period. Given the lack of official data to define and identify the business cycle turning points for the U.K. economy, this section follows the traditional definition to define economic recession as two consecutive quarters of decline in real GDP growth. Graph 3.2 depicts the times-series of U.K. quarterly GDP growth over the period of January 1980 to December 2004.

Figure 3-2 U.K. GDP quarterly growth rate (1980:01-2004:12)

This graph depicts the time-series of U.K. real GDP growth rate over the period from January 1980 to December 2004. Data are obtained from the Datastream. According to the traditional definition of economic recession, 4 U.K. recession periods are identified, i.e. 1984:01-1984:06, 1986:01-1986:06, 2000:01-2000:06 and 2001:01-2001:06. The rest periods can be regarded as expansions.



During the sample period, the U.K. economy has arguably experienced 4 economic recessions and 5 expansions. Specifically, during 1984:01-1984:06, 1986:01-1986:06, 2000:01-2000:06 and 2001:01-2001:06 the U.K. economy has seen two consecutive declines in real GDP growth rate, hence these periods are identified as recessions, and the rest are regarded as expansionary periods. It is also noted that as similar to the U.S., the recessionary periods have short durations than expansionary periods.

Table 3-4 reports the style investing returns in different economic states. For brevity only results based on formation and testing periods (12, 6) are reported. Style returns during recessionary periods are much volatile as compared to returns in expansionary periods. Style investing returns in recessionary periods are larger than those in expansionary periods, suggesting that on average return U.K. value premiums are larger when the economy is in bad regimes. The average equally-weighted value premiums during recessions are 2.81% (PC), 2.44% (DY) and 3.09% (MTBV) as compared to 1.72% (PC), 0.73% (DY) and 0.87% (MTBV) in expansions based on sorting of different firm characteristics. The returns based on value weighted scheme are also supportive of this finding. Coincidentally, the size premium is also found to be more pronounced during recessions. These results are consistent with recent empirical findings such as Kwag and Lee (2006) who suggest that the benefit of value investing is even greater during periods of contraction than expansion.

The higher premiums of small and value stocks during the economic recessional periods is intriguing. On the one hand, rational risk-based explanations may argue that such style premiums results from great risk associated with holding small and value stocks, especially in bad economic times. Chan and Chen (1991) and Gertler and Gilchrist (1994) argue that small firms are in distress or young, poorly collateralised that have limited access to credit markets. Fama and French (1992, 1995) claim that value firms tend to have high financial leverage and cash flow problems. Hence naturally size and value premiums should be higher in recessional periods, reflecting the vulnerability of small and value stocks to bad economic regimes over the business cycles. Consistently, Black and McMillan (2005) show that the responsiveness of value stocks to changes in economic conditions increase during contractions. Zhang (2005) argues that value and growth firms have different ability in investing (disinvesting) in good (bad) times and the dispersion of risk between value and growth stocks is high in bad times, while the risk differential is low or even negative in good times. Thus value stocks are riskier than growth stocks, especially in bad times when the price of risk is high. Petkova and Zhang (2006) also contend that value stocks are more (less) risky than growth stocks in bad (good) times when the expected risk premium is high (low). These studies suggest that on a rational framework size and value premiums emerge as bearing for higher business cycle risks.

On the other hand, however, in a consumption-based asset pricing framework, small and value stocks are not more risky because they are able to offer relative better returns when investors' marginal utility of wealth is high. Conventional asset pricing model such as CAPM assumes that investors only care about the performance of their portfolios. In essence, typical investors would be concerned with both the investment returns and their end of period wealth. Barberis and Thaler (2003) argue that stocks failing to pay out at bad times but instead pay out at good times are risky because during bad times investors' marginal utility of wealth is high. Hence it is suggested that the higher returns of size and value stocks are the result of market underreaction to stocks in such specific asset classes. Obviously, while both competing arguments sound interesting, it is impossible to disentangle them without further investigation.

Table 3-3 Profit of Simple Style Investing (J, K) = (6, 12) and (12, 6)

At the end of each month, all UK non-financial stocks are classified into quintiles in ascending order according to their previous J-month company characteristics. The quintile portfolios are formed using equally-weighted (EW) and value weighted (VW) schemes. The number of stocks in Q1 and Q5 is identical. All portfolios are held in the following K month after formation and the average monthly returns over the K-holding period are calculated using "overlapping portfolios" methodology proposed by Jegadeesh and Titman (1993). The zero-cost hedge portfolios are formed as to long Q1 stocks and to short Q5 stocks for research variable PC, MTBV and MV. For research variable DY, the hedge portfolio is to long Q5 and short Q1.The table reports average monthly returns in 12 and 6-month holding period for the long, short and the hedge portfolios based on 6 and 12-month company characteristics respectively. The column titled "%>0" gives the percentage of positive hedge portfolio returns. The t ratios in brackets are calculated based on the Newey-West (1987) heteroscedasticity and autocorrelation consistent standard errors with lags equal to K testing periods. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

		Equally-weighted Portfolios												Value-weighted Portfolios											
(J,K)	Periods	Non-January (%)				January only (%)				All the periods (%)				Non-January (%)				January only (%)				All the periods (%)			
		Q1	Q5	Q1-Q5	%>0	Q1	Q5	Q1-Q5	%>0	Q1	Q5	Q1-Q5	%>0	Q1	Q5	Q1-Q5	%>0	Q1	Q5	Q1-Q5	%>0	Q1	Q5	Q1-Q5	%>0
Panel A: Portfolios based on PC																									
(6,12)	01/1982-12/1993	2.27	0.88	1.39	77.0	6.92	2.78	4.14	100.0	2.64	1.03	1.61	78.8	1.71	0.85	0.86	61.9	5.46	2.05	3.42	81.8	2.01	0.94	1.07	63.5
	t-value	(4.60)***	(2.13)**	(5.96)***		(4.34)***	(2.16)**	(4.79)***		(5.32)***	(2.53)**	(7.30)***		(4.36)***	(2.27)**	(3.78)***		(3.44)***	(1.86)*	(2.02)**		(5.14)***	(2.86)***	(4.81)***	
	01/1994-12/2004	1.98	0.29	1.69	80.0	3.34	1.95	1.38	60.0	2.09	0.42	1.66	78.4	1.59	0.20	1.39	67.0	1.49	-1.23	2.72	80.0	1.59	0.09	1.50	68.0
	t-value	(6.70)***	(0.50)	(4.06)***		(4.97)***	(1.58)	(1.16)		(7.42)***	(0.73)	(3.76)***		(5.25)***	(0.37)	(2.82)***		(1.64)	(-0.89)	(3.36)***		(5.25)***	(0.16)	(3.11)***	
	01/1982-12/2004	2.10	0.54	1.56	78.9	5.61	2.73	2.88	81.8	2.38	0.72	1.66	79.2	1.62	0.49	1.13	64.4	3.72	0.72	3.00	81.8	1.79	0.51	1.28	65.8
	t-value	(7.23)***	(1.56)	(6.72)***		(5.14)***	(2.99)***	(3.62)***		(7.91)***	(2.08)**	(6.96)***		(6.62)***	(1.54)	(4.29)***		(3.58)***	(0.77)	(3.25)***		(7.14)***	(1.64)	(5.02)***	
(12,6)	01/1982-12/1993	2.33	0.73	1.60	79.3	7.06	3.06	4.01	100.0	2.69	0.91	1.78	80.9	1.64	0.75	0.88	63.6	4.89	2.65	2.24	90.0	1.88	0.90	0.99	65.6
	t-value	(4.16)***	(1.59)	(6.58)***		(4.16)***	(2.11)**	(5.77)***		(4.79)***	(1.97)**	(7.86)***		(3.66)***	(1.71)*	(3.25)***		(2.93)***	(2.61)***	(1.70)*		(4.4)***	(2.17)**	(3.96)***	
	01/1994-12/2004	2.11	0.29	1.82	76.4	3.88	2.32	1.56	55.6	2.24	0.44	1.80	74.8	1.73	0.18	1.55	66.4	1.92	-0.87	2.79	77.8	1.74	0.10	1.64	67.2
	t-value	(5.07)***	(0.44)	(4.05)***		(5.50)***	(1.60)	(1.06)		(5.64)***	(0.70)	(3.96)***		(3.88)***	(0.35)	(2.99)***		(2.29)**	(-0.55)	(2.57)**		(4.04)***	(0.20)	(3.22)***	
	01/1982-12/2004	2.16	0.43	1.73	78.9	5.71	2.84	2.87	81.0	2.45	0.62	1.82	79.1	1.62	0.42	1.21	65.3	3.32	0.92	2.40	81.0	1.76	0.46	1.30	66.5
	t-value	(6.37)***	(1.13)	(7.23)***		(5.16)***	(2.87)***	(3.62)***		(7.20)***	(1.68)*	(7.72)***		(5.40)***	(1.28)	(4.35)***		(3.30)***	(0.93)	(3.06)***		(6.07)***	(1.46)	(4.87)***	
Panel B: Portfolios based on DY																									
(6,12)	01/1982-12/1993	0.84	1.78	0.95	70.6	3.59	4.71	1.12	72.7	1.06	2.02	0.96	70.8	0.87	1.35	0.48	55.6	-1.08	4.97	6.05	72.7	0.71	1.64	0.93	56.9
	t-value	(2.10)**	(3.27)***	(4.38)***		(3.43)***	(3.25)***	(1.80)*		(2.69)***	(3.61)***	(4.14)***		(2.59)***	(2.43)**	(1.17)		(-0.29)	(3.25)***	(1.55)		(1.38)	(3.16)***	(1.74)*	
	01/1994-12/2004	0.53	1.19	0.67	56.5	1.68	1.89	0.21	60.0	0.62	1.25	0.63	56.8	0.42	1.36	0.94	55.7	-0.37	-0.33	0.04	70.0	0.36	1.23	0.87	56.8
	t-value	(0.88)	(3.98)***	(1.35)		(1.41)	(2.95)***	(0.22)		(1.04)	(4.19)***	(1.33)		(0.73)	(4.92)***	(1.42)		(-0.27)	(-0.33)	(0.05)		(0.64)	(4.52)***	(1.40)	
	01/1982-12/2004	0.65	1.45	0.80	63.2	2.95	3.72	0.78	68.2	0.84	1.64	0.80	63.6	0.63	1.23	0.60	55.1	-0.63	2.69	3.32	72.7	0.52	1.35	0.83	56.5
	t-value	(1.88)*	(4.66)***	(3.18)***		(3.59)***	(3.92)***	(1.38)		(2.42)**	(4.99)***	(3.21)***		(1.94)*	(4.32)***	(1.66)*		(-0.32)	(2.27)**	(1.51)		(1.41)	(4.68)***	(2.11)**	

Table 3-3 (continued)

Panel B: Portfolios based on DY																									
(12,6)	01/1982-12/1993	0.76	1.79	1.03	71.9	3.62	4.90	1.28	70.0	0.98	2.03	1.05	71.8	0.90	1.10	0.20	54.5	-2.37	4.76	7.13	80.0	0.65	1.38	0.73	56.5
	t-value	(1.66)*	(3.12)***	(4.30)***		(3.02)***	(2.88)***	(1.59)		(2.16)**	(3.50)***	(4.17)***		(2.05)**	(2.11)**	(0.53)		(-0.56)	(2.75)***	(1.52)		(1.13)	(2.76)***	(1.29)	
	01/1994-12/2004	0.52	1.28	0.77	58.2	2.07	2.36	0.28	55.6	0.63	1.37	0.73	58.0	0.28	1.46	1.17	60.0	0.49	-0.49	-0.98	33.3	0.30	1.31	1.01	58.0
	t-value	(0.80)	(2.92)***	(1.55)		(1.51)	(3.14)***	(0.27)		(1.02)	(3.33)***	(1.55)		(0.49)	(3.72)***	(1.75)*		(0.29)	(-0.40)	(-0.86)		(0.54)	(3.38)***	(1.58)	
	01/1982-12/2004	0.59	1.47	0.88	65.3	2.91	3.84	0.92	66.7	0.78	1.66	0.88	65.4	0.57	1.16	0.59	56.2	-1.05	2.36	3.41	61.9	0.44	1.25	0.82	56.7
	t-value	(1.59)	(4.16)***	(3.43)***		(3.28)***	(3.65)***	(1.44)		(2.14)**	(4.73)***	(3.55)***		(1.64)	(3.60)***	(1.60)		(-0.49)	(1.86)*	(1.33)		(1.15)	(4.06)***	(2.02)**	
Panel C: Portfolios based on MTBV																									
(6,12)	01/1982-12/1993	2.09	0.88	1.21	67.5	6.56	3.20	3.36	72.7	2.45	1.07	1.38	67.9	1.93	1.05	0.88	61.9	5.73	1.74	3.99	72.7	2.23	1.11	1.13	62.8
	t-value	(4.11)***	(2.16)**	(5.09)***		(3.53)***	(2.33)**	(2.14)**		(4.53)***	(2.76)***	(5.68)***		(4.91)***	(3.51)***	(2.72)***		(3.04)***	(1.46)	(1.85)*		(5.18)***	(3.93)***	(2.98)***	
	01/1994-12/2004	1.41	0.34	1.08	65.2	2.90	2.40	0.50	70.0	1.53	0.50	1.03	65.6	1.19	0.38	0.81	53.9	0.63	-0.49	1.12	60.0	1.14	0.31	0.84	54.4
	t-value	(3.89)***	(0.45)	(1.85)*		(3.91)***	(1.60)	(0.36)		(4.28)***	(0.67)	(1.73)*		(3.11)***	(0.72)	(1.96)**		(0.49)	(-0.43)	(1.47)		(2.84)***	(0.65)	(2.13)**	
	01/1982-12/2004	1.73	0.57	1.16	67.2	5.34	3.18	2.16	72.7	2.03	0.78	1.24	67.7	1.50	0.68	0.83	58.3	3.44	0.85	2.59	68.2	1.66	0.69	0.97	59.1
	t-value	(5.42)***	(1.39)	(3.88)***		(4.30)***	(3.12)***	(1.98)**		(5.91)***	(1.94)*	(4.03)***		(5.22)***	(2.31)**	(3.24)***		(2.62)***	(0.98)	(2.19)**		(5.22)***	(2.51)**	(3.59)***	
(12,6)	01/1982-12/1993	2.18	0.76	1.42	74.4	6.35	3.60	2.75	70.0	2.50	0.97	1.52	74.0	2.11	0.97	1.14	66.9	5.09	2.40	2.69	70.0	2.34	1.08	1.26	67.2
	t-value	(3.90)***	(1.61)	(6.08)***		(3.25)***	(2.48)**	(2.17)**		(4.38)***	(2.08)**	(6.27)***		(4.46)***	(2.44)**	(3.76)***		(2.79)***	(2.18)**	(1.82)*		(5.04)***	(2.85)***	(3.81)***	
	01/1994-12/2004	1.54	0.34	1.19	64.5	3.27	3.09	0.18	66.7	1.67	0.55	1.12	64.7	1.27	0.53	0.74	50.0	1.10	-0.11	1.21	66.7	1.25	0.48	0.77	51.3
	t-value	(3.46)***	(0.41)	(1.90)*		(4.48)***	(1.74)*	(0.10)		(3.98)***	(0.68)	(1.76)*		(2.51)**	(1.09)	(1.46)		(0.74)	(-0.08)	(1.21)		(2.48)**	(1.05)	(1.57)	
	01/1982-12/2004	1.80	0.48	1.32	71.1	5.22	3.46	1.75	71.4	2.08	0.72	1.36	71.1	1.61	0.68	0.93	59.9	3.04	1.22	1.82	66.7	1.73	0.72	1.00	60.5
	t-value	(5.14)***	(1.07)	(4.27)***		(4.17)***	(3.14)***	(1.66)*		(5.86)***	(1.64)	(4.33)***		(4.69)***	(2.26)**	(3.33)***		(2.44)**	(1.42)	(2.13)**		(5.03)***	(2.54)**	(3.56)***	
Panel D: Portfolios based on MV																									
(6,12)	01/1982-12/1993	2.26	1.24	1.02	61.9	5.14	4.28	0.86	54.5	2.49	1.49	1.01	61.3	1.94	1.12	0.82	54.8	5.12	2.40	2.72	72.7	2.19	1.22	0.97	56.2
	t-value	(2.96)***	(3.65)***	(1.74)*		(3.11)***	(3.62)***	(0.77)		(3.27)***	(4.35)***	(1.82)*		(2.66)***	(3.02)***	(1.24)		(3.19)***	(1.56)	(1.59)		(3.02)***	(3.24)***	(1.50)	
	01/1994-12/2004	1.13	0.74	0.39	49.6	4.29	-0.43	4.72	70.0	1.38	0.65	0.74	51.2	1.07	0.61	0.46	53.0	3.86	-0.43	4.29	70.0	1.30	0.53	0.77	54.4
	t-value	(2.05)**	(1.74)*	(1.07)		(2.89)***	(-0.52)	(3.43)***		(2.32)**	(1.55)	(1.74)*		(1.99)**	(1.54)	(1.13)		(2.79)***	(-0.29)	(2.04)**		(2.25)**	(1.38)	(1.56)	
	01/1982-12/2004	1.68	0.97	0.71	56.3	5.25	2.19	3.05	63.6	1.97	1.07	0.90	56.9	1.48	0.84	0.64	54.7	4.96	1.17	3.79	72.7	1.77	0.87	0.90	56.1
	t-value	(3.48)***	(3.63)***	(2.01)**		(4.29)***	(2.24)**	(2.63)***		(3.98)***	(3.85)***	(2.59)***		(3.24)***	(3.17)***	(1.63)		(4.29)***	(1.06)	(2.71)***		(3.75)***	(3.21)***	(2.21)**	
(12,6)	01/1982-12/1993	2.31	1.16	1.15	61.2	5.00	4.24	0.76	50.0	2.51	1.40	1.12	60.3	2.00	0.99	1.01	58.7	5.20	1.76	3.44	70.0	2.25	1.05	1.20	59.5
	t-value	(3.07)***	(2.89)***	(2.05)**		(2.88)***	(3.24)***	(0.67)		(3.42)***	(3.46)***	(2.13)**		(2.71)***	(2.41)**	(1.64)		(3.02)***	(1.00)	(1.71)*		(3.11)***	(2.54)**	(1.95)*	
	01/1994-12/2004	1.20	0.77	0.43	53.6	5.03	-0.07	5.10	66.7	1.49	0.71	0.78	54.6	1.20	0.58	0.62	55.5	4.78	0.18	4.60	77.8	1.47	0.55	0.92	57.1
	t-value	(1.92)*	(1.52)	(0.99)		(3.09)***	(-0.07)	(3.30)***		(2.32)**	(1.47)	(1.61)		(1.85)*	(1.54)	(1.22)		(3.12)***	(0.10)	(1.80)*		(2.22)**	(1.48)	(1.68)*	
	01/1982-12/2004	1.69	0.92	0.77	57.0	5.30	2.09	3.22	61.9	1.97	1.01	0.97	57.4	1.53	0.74	0.79	56.2	5.19	0.97	4.22	76.2	1.82	0.76	1.06	57.8
	t-value	(3.48)***	(2.96)***	(2.19)**		(4.14)***	(2.05)**	(2.62)***		(4.10)***	(3.32)***	(2.78)***		(3.19)***	(2.76)***	(2.02)**		(4.28)***	(0.82)	(2.71)***		(3.82)***	(2.84)***	(2.66)***	

Table 3-4 Style Investing Returns Classified by Business Cycles

Style portfolios are formed based on different research variables as described in Table 3-3. This table presents the average style premiums based on past 12-month firm characteristics and subsequently held for 6 months. The holding period is classified into various expansionary and contractionary periods as defined by the quarterly real U.K. GDP growth. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Returns (%)	PC	%>0	DY	%>0	MTBV	%>0	MV	%>0		PC	%>0	DY	%>0	MTBV	%>0	MV	%>0
Panel A: Equally-weighted scheme (J = 12, K = 6)																	
Expansionary Period									Contractionary Period								
01/1982-12/1983	1.63	81.8	1.48	81.8	1.05	72.7	1.78	81.8	01/1984-06/1984	1.11	33.3	1.18	83.3	3.21	66.7	1.61	66.7
t-value	(2.63)***		(4.67)***		(1.48)		(2.70)***		t statistics	(0.69)		(2.05)*		(1.29)		(1.33)	
07/1984-12/1985	1.61	77.8	1.04	77.8	2.23	72.2	1.09	55.6	01/1986-06/1986	2.63	100.0	2.36	100.0	2.82	100.0	3.62	100.0
t-value	(3.70)***		(3.57)***		(3.28)***		(1.69)*		t statistics	(7.20)***		(4.31)***		(3.74)**		(2.99)*	
07/1986-12/1999	1.59	81.5	0.40	60.5	0.81	69.1	0.78	55.6	01/2000-06/2000	0.55	50.0	0.71	50.0	-0.64	50.0	1.04	33.3
t-value	(9.64)***		(2.03)**		(3.73)***		(2.31)**		t statistics	(0.23)		(0.28)		(-0.18)		(0.27)	
07/2000-12/2000	3.04	66.7	2.36	66.7	3.41	66.7	-0.77	16.7	01/2001-06/2001	6.94	100.0	5.51	83.3	6.97	83.3	1.36	66.7
t-value	(1.17)		(1.03)		(1.40)		(-0.67)		t statistics	(5.27)***		(3.51)**		(3.08)*		(0.99)	
07/2001-12/2004	2.12	76.2	1.40	66.7	1.90	76.2	1.13	59.5									
t-value	(3.77)***		(2.66)***		(3.07)***		(1.66)*										
Mean	1.72	79.9	0.73	64.0	1.18	70.7	0.87	56.5	Mean	2.81	70.8	2.44	79.2	3.09	75.0	1.91	66.7
t-value	(10.38)***		*4.13)***		(5.82)***		(3.28)***		t statistics	(3.07)*		(2.99)*		(2.39)*		(1.80)	
Panel B: Value weighted scheme (J = 12, K = 6)																	
Expansionary Period									Contractionary Period								
01/1982-12/1983	1.74	63.6	0.52	54.5	2.19	63.6	1.05	72.7	01/1984-06/1984	0.82	50.0	3.77	83.3	2.63	66.7	2.31	66.7
t-value	(1.17)		(0.35)		(2.12)**		(1.41)		t statistics	(0.53)		(3.22)*		(1.24)		(1.16)	
07/1984-12/1985	0.36	55.6	3.39	55.6	2.42	77.8	1.97	61.1	01/1986-06/1986	0.50	66.7	-1.28	50.0	2.13	83.3	4.05	100.0
t-value	(0.39)		(1.16)		(4.13)***		(1.66)*		t statistics	(0.27)		(-1.35)		(2.75)*		(3.38)**	
07/1986-12/1999	0.81	66.0	0.01	53.7	0.62	60.5	0.76	54.9	01/2000-06/2000	2.52	83.3	0.66	50.0	-1.52	33.3	1.47	50.0
t-value	(3.17)***		(0.04)		(2.16)**		(2.10)**		t statistics	(1.09)		(0.21)		(-0.58)		(0.31)	
07/2000-12/2000	2.53	66.7	3.18	50.0	0.60	50.0	0.10	66.7	01/2001-06/2001	6.01	83.3	7.24	66.7	3.59	83.3	1.62	66.7
t-value	(0.84)		(1.10)		(0.18)		(0.07)		t statistics	(2.50)*		(1.97)		(2.69)*		(1.19)	
07/2001-12/2004	2.67	71.4	1.53	66.7	1.20	50.0	1.24	54.8									
t-value	(3.51)***		(1.99)**		(1.19)		(1.66)*										
Mean	1.19	66.1	0.64	56.1	0.93	59.8	0.93	56.5	Mean	2.46	70.8	2.59	62.5	1.71	66.7	2.36	70.8
t-value	(4.72)***		(1.76)*		(3.30)***		(3.15)***		t statistics	(2.32)*		(1.92)		(1.79)		(1.85)	

3.4.3 Predicted and unpredicted returns across styles

The empirical results in the previous section suggest that the relative style returns based on firm characteristics PC, DY, MTBV and MV may be caused by the business cycle risks or investors' underreaction to specific asset classes. This section explores the relative importance of the predicted and unpredicted component from the business cycle model in explaining the style return premiums.

Recall that Equation (7) predicts the one-month-ahead single stock returns. The predicted return of stock i for a given point of time t is:

$$\hat{R}_{i,t} = \hat{c}_{i,1}div_{t-1} + \hat{c}_{i,2}yld_{t-1} + \hat{c}_{i,3}term_{t-1} + \hat{c}_{i,4}def_{t-1} \quad (8)$$

Where $\hat{c}_{i,j}$ $(j = 1,2,3,4)$ is the vector of estimated coefficients obtained from a time-series recursive regression based on the 60-month rolling window that contains stocks with at least 24 months return data.

Equation (8) stands for exact pricing specification and the unpredicted return portion of Equation (7) is $\hat{c}_{i,0} + e_{i,t}$, representing stock returns adjusted for the business cycle risk. The estimated intercept of Equation (7) is excluded from the explained portion of Equation (7). Chordia and Shivakumar (2002) argue that this time-varying intercept may capture some of the return patterns in the formation periods and therefore could lead to control for the cross-sectional variations in average returns that are unrelated with the business cycles.

To better understand the dynamics of predicted and unpredicted stock returns around the portfolio formation point, Figure 3-3 plots the median predicted and unpredicted returns for stocks within quintiles 1, 3 and 5. The quintiles are formed the same as in Table 3-3. For brevity only styles based on formation and testing period (12, 6) are presented. For a given stock i in each month t, the model parameters are estimated using equation (7) based on the observations from months $t-19$ to $t-1$. Using the estimated coefficients, the predicted returns for that stock from time period $t-18$ to $t+5$ are recorded and the above procedures are repeated until all the stocks in that quintile are covered. If economic exogenous forces are the key factor affecting equity style returns over time, one would expect to see that the business cycle model predicts stock returns in a consistent and systematic way.

Figure 3-3 suggests that the predicted and unpredicted stock returns from the business cycle model seem to vary systematically across different quintiles. For quintiles sorted on characteristics PC and MTBV, the predicted portions are systematically lower for value stocks (Q1) than for growth stocks (Q5) around the formation period, and the unpredicted returns of value stocks appear to be systematically larger than growth stocks before and after the formation point. Such systematic patterns are strongest for size quintiles. This suggests that the macroeconomic variables are unable to capture the divergent return patters of stocks across quintiles sorted on PC, MTBV and MV. Instead, the pricing errors, namely the business cycle risk-adjusted returns, point to the right sign of observed size and value premiums.

However, stocks sorted on equity characteristics DY seem to tell a different story. The predicted returns of value stocks in DY quintiles are always larger than growth stocks before and in the formation period, and the unpredicted returns of value stocks are smaller than growth stocks. Although the business cycle model predicts that small size value stocks of high dividend yield do not outperform in the testing period, larger size value stocks could comfortably outperform growth stocks. Moreover, consistent with the evidence of strong value premium based on realized returns of DY quintiles, business cycle risk adjusted value premiums in the testing periods are negative, indicating that the business cycle model could indeed capture the dynamics of relative stock returns across DY quintiles.

In summary, given the evidence of significant size and value premiums based on the realised stock returns, it is tempting to conclude that the relative returns for stocks in quintiles sorted on firm characteristic of PC, MTBV and MV are mainly determined by the unpredicted portions of the business cycle model, while the divergent style return for stocks sorted by characteristics of DY are captured by Equation (7). Hence value premiums based on characteristics PC and MTBV, and the size premium in the U.K. stock market are likely due to the mispricing of stock prices relative to common risk factors. But the outperformance of value stocks characterised by high DY values is likely to be driven by business cycle conditions, and therefore such value premium may be interpreted as the compensation for bearing business cycle risks.

Figure 3-3 Median predicted and unpredicted returns around formation period

In each month t, all U.K. non-financial stocks are classified into 5 quintiles in ascending order based on the average previous J-month characteristics PC, DY, MTBV and MV. Each stock must have at least 24-month observations and the expected return of individual stock is estimated by Equation (7) using a set of economic pervasive variables relating to the business cycles. This Figure depicts the median predicted and unpredicted returns of quintile portfolios Q1, Q3 and Q5 for the 6-month holding period around the 12-month formation period (i.e. from t-18 to t+5 month, J = 12, K = 6). It is suggested that the unpredicted return components from the business cycle model vary systematically across quintiles based on PC, MTBV and MV, while the business cycle model captures the variations on average returns in DY quintiles.

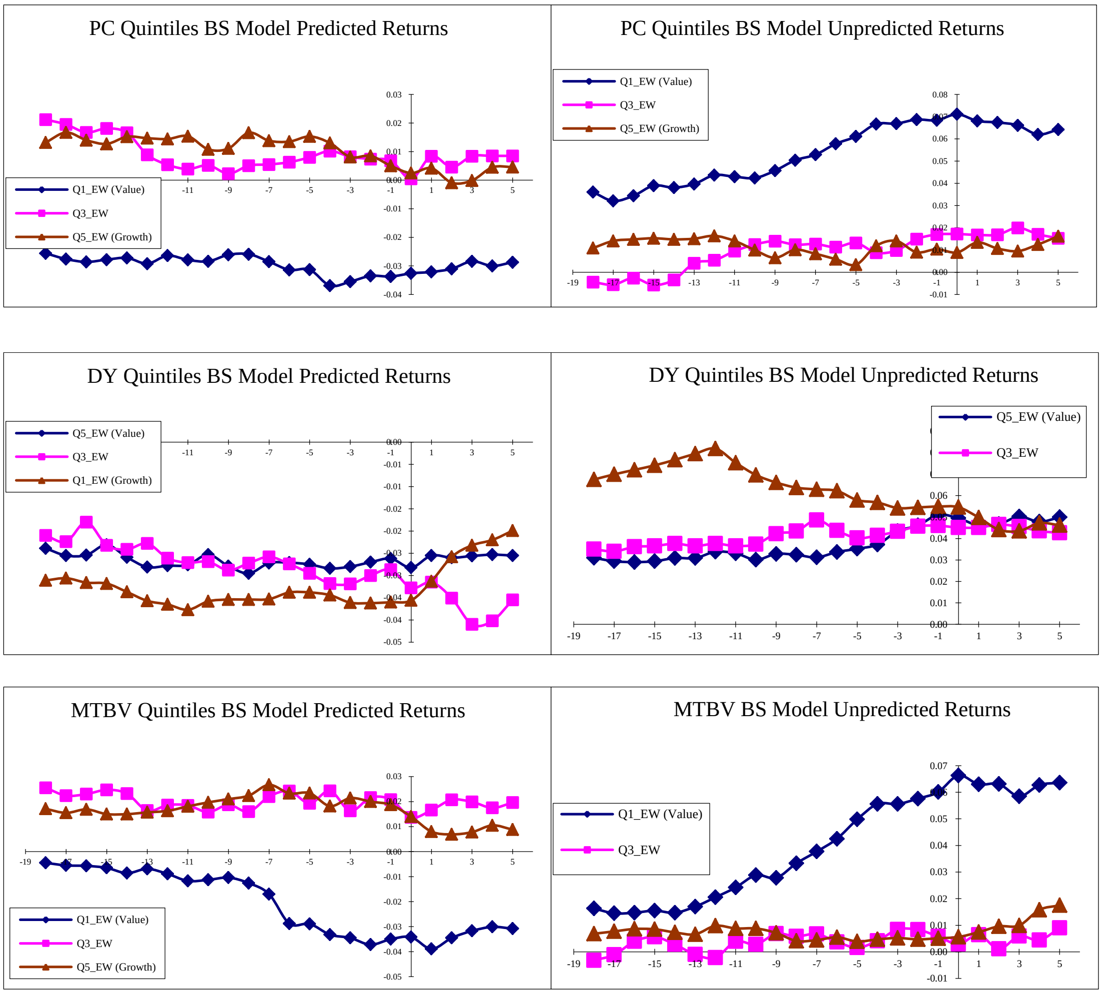
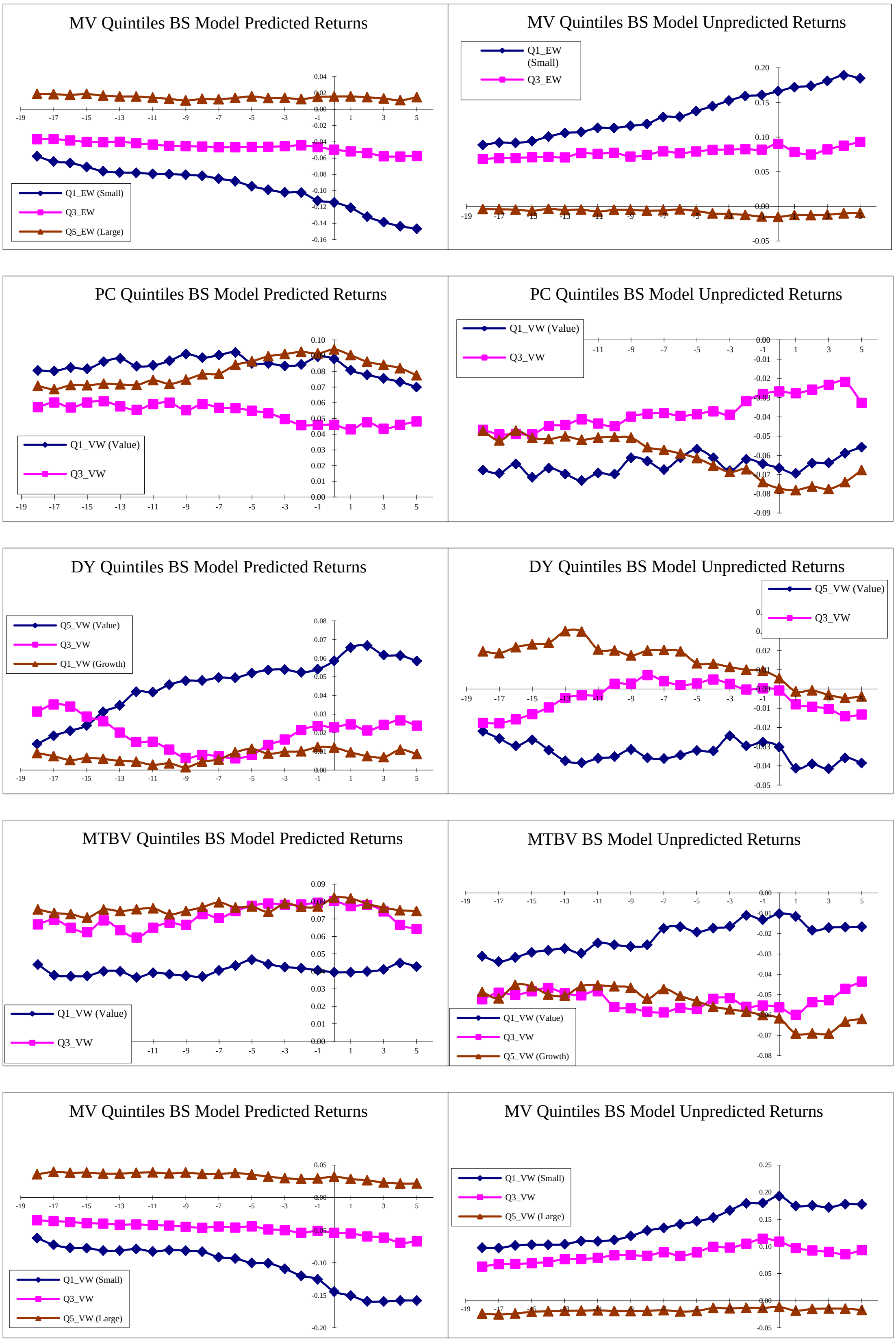


Figure 3-3 (continued)



3.4.4 Style premiums after adjusting for the predicted returns from the business cycle model

Given the evidence on the profitability of simple style investing strategies, this section examines how the predicted and unpredicted returns from Equation (7) are related to the U.K. size and value premiums in more detail.

If business cycle risk is the only exogenous driving force to determine such divergent style return patterns, arguably controlling for business cycle effects could substantially reduce the return differentials across styles. Hence the hedge portfolio returns would not be significant if the predicted ability of Equation (7) is already accounted for. For this investigation, the same simple style investing strategies as described in Section 3.3.2 are implemented. However, to control for the business cycle effect impounded in stock returns, when calculating the hedge portfolio returns in the K-month testing period, the observed (realised) stock returns are replaced with the unpredicted returns (i.e. intercept plus residual) from the business cycle model. As mentioned in Section 3.4.3, the intercept of Equation (7) is not included in the predicted return part because this time-varying component may capture the cross-sectional information that is not related to the business cycle. Table 3-5 presents the hedge portfolio returns using the predicted and unpredicted stock returns in the K-month testing period, representing style premiums after controlling for the firm-specific information and business cycle effects, respectively.

The predicted and unpredicted returns from the business cycle model play a very different role in affecting the relative performance of stocks in extreme quintiles based on different equity characteristics. First, for stocks sorted on characteristics PC, MTBV and MV, controlling for the mispricing from regression (7) generally reduces style premiums, and the number of months with positive hedge portfolio returns is reduced sharply. For example, consider the (6,12) strategy, after controlling for the unpredicted returns (i.e. use Equation (8) to calculate the hedge portfolio returns), in the 12-month testing period the percentage of outperformance of small stocks declines from 57.4% to 12.2% in the entire sample period. Similarly, the outperformance of value stocks decreases from 79.2% (PC) and 67.7% (MTBV) to 46.1% (PC) and 33.8% (MTBV), respectively. Such return patterns also exhibit in both January and non-January months. Hence, after controlling for the pricing errors of the business cycle model, the return differentials between stock group Q1 and Q5 decrease in most sample periods and are no longer significant. It is also noted that the value premium for MTBV stocks or size premium becomes negative after controlling the model mispricing, suggesting that model pricing errors are responsible for the observed returns spread. In contrast, however, consistent with Figure 3-3, value premiums based on characteristics DY seem to tell a different story. Controlling for the unpredicted returns from Equation (7) decreases the value premium and leads to the opposite sign.

Second, even after controlling for the business cycle risk, there is still MTBV-based value premium found, and the size premium is even more pronounced. The number of months with positive style spreads is still reasonably high. While there is no PC-based value premium during subperiod January 1994 to December 2004, 59% of the months see higher returns of value stocks relative to growth stocks. This suggests that business cycle effects are unlikely the dominant factors that affect the size premium and value premiums based on stocks sorted on PC and MTBV. However, the business cycle model seems to capture the divergent performance of stocks across DY quintiles. Controlling for the explained portion of Equation (7) would result in growth premium instead. Overall, consistent with Figure 3.3, Table 3-5 suggests that in the U.K. market, common stocks sharing similar characteristics tend to commove together. The size premium and value premiums based on equity characteristics PC and MTBV are not captured by the business cycle. On the contrary, business cycle fluctuations are able to capture the cross-sectional average return of extreme stocks characterised by DY.

The finding of different underlying mechanism driving value premiums on firm characteristics is intriguing. The characteristic variables used to classify assets are price-related financial ratios and empirical literature has found that such characteristics are associated with the cross-sectional average returns (e.g. Stattman (1980); Rosenberg *et al.*, (1985); Fama and French (1992, 1996); Lakonishok *et al.* (1994)). Given significant size and value premiums found in this study, asset pricing theory would well argue that these firm characteristics proxy for a risk factor in returns. Alternatively they provide information about stock mispricing. Arguably, as Chordia and Shivakumar (2002) suggests, if the exposures to the risk factors of each stock are well known and the pricing model is empirically well specified, sorting can take place on either the risk premiums or the pricing errors instead of raw returns. A risk-based explanation can be rejected if these sorts on pricing errors still exhibit style premiums, or style spreads disappear when the sorting is on the predicted risk premiums. For this reason, the preliminary results in this section would suggest that firm characteristics PC, MTBV and MV may proxy for mispricing from the business cycle model, while DY is a proxy of business cycle risk factor.

However, if Equation (7) accurately describes the stock returns, and PC, MTBV and MV are cross-sectionally associated with the factor loadings, the variation in expected returns across stocks based on these characteristics would still be consistent with traditional finance theory. Thus style premiums on such characteristics still reflect compensation for risk. Chan and Chen (1991) and Fama and French (1993) argue that size and BM proxy a distress factor that explains the variation in average stock returns. Berk (1995, 1996) shows that in the cross-section, market value or BM is theoretically inversely related to expected returns. Liew and Vassalou (2000) find that the size and the BM factors forecast GDP output growth, indicating that they are already business cycle variables. A number of other studies including Estrella and Hardouvelis (1991) and more recently Ang *et al.* (2004) all document that such price variables that forecast returns also forecast macroeconomic activity. If such characteristic variables have already impounded business cycle risk information, sorting stocks into quintiles on these variables is an abundant procedure simply because all stocks in the universe have been already properly sorted (just like in a single quintile of similar business cycle risk premia). Hence the cross-sectional variation in returns across stock groups cannot be business cycle risk related, and hence are unpredictable by the business cycle model.

Table 3-5 Style Investing Returns Adjusted for Macro Variables and Firm-specific Component from Model

Stock returns are predicted by $R_{i,t} = c_{i,0} + c_{i,1}div_{t-1} + c_{i,2}yld_{t-1} + c_{i,3}term_{t-1} + c_{i,4}def_{t-1} + e_{i,t}$, def is the default spread, yld is the three-month T-bill yield, div is the overall market dividend yield and $term$ is the term spread. The parameters of the model are estimated by a 60-month rolling window containing stocks with minimum 24 months return observations. The one-month-ahead predicted and unpredicted portion of this equation is used to replace the observed stock returns in the K-testing period to calculate the firm-specific-controlled and business-cycle-controlled value and size premiums. The t ratios in brackets are calculated using Newey-West (1987) heteroscedasticity and autocorrelation consistent variance with lags equal to K, the testing periods. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Equally-weighted Hedge Portfolio Returns (%)		Style premium based on predicted returns						Style premium based on unpredicted returns						Raw style premium					
		Non-Jan		Jan only		All periods		Non-Jan		Jan only		All periods		Non-Jan		Jan only		All periods	
	Periods	Q1-Q5	%>0	Q1-Q5	%>0	Q1-Q5	%>0	Q1-Q5	%>0	Q1-Q5	%>0	Q1-Q5	%>0	Q1-Q5	%>0	Q1-Q5	%>0	Q1-Q5	%>0
PC (6,12)	01/1982-12/1993	-1.26	49.2	-0.53	54.5	-1.20	49.6	2.66	60.3	4.61	54.5	2.82	59.9	1.39	77.0	4.14	100.0	1.61	78.8
	t-value	(-0.62)		(-0.18)		(-0.59)		(1.28)		(1.53)		(1.34)		(5.96)***		(4.79)***		(7.30)***	
	01/1994-12/2004	3.71	43.0	1.18	36.4	3.50	42.4	-2.03	57.9	0.43	63.6	-1.83	58.3	1.69	80.0	1.38	60.0	1.66	78.4
	t-value	(0.72)		(0.24)		(0.71)		(-0.41)		(0.10)		(-0.39)		(4.06)***		(1.16)		(3.76)***	
	01/1982-12/2004	1.18	46.2	0.33	45.5	1.11	46.1	0.36	59.1	2.52	59.1	0.54	59.1	1.56	78.9	2.88	81.8	1.66	79.2
	t-value	(0.42)		(0.11)		(0.41)		(0.13)		(0.95)		(0.21)		(6.72)		(3.62)		(6.96)	
PC (12,6)	01/1982-12/1993	-1.42	47.1	-2.09	40.0	-1.47	46.6	3.01	61.2	6.04	60.0	3.24	61.1	1.60	79.3	4.01	100.0	1.78	80.9
	t-value	(-0.73)		(-0.86)		(-0.78)		(1.49)		(1.51)		(1.64)		(6.58)***		(5.77)***		(7.86)***	
	01/1994-12/2004	3.92	41.3	0.70	27.3	3.65	40.2	-2.06	59.5	1.12	72.7	-1.80	60.6	1.82	76.4	1.56	55.6	1.80	74.8
	t-value	(0.83)		(0.14)		(0.82)		(-0.46)		(0.27)		(-0.43)		(4.05)***		(1.06)		(3.96)***	
	01/1982-12/2004	1.25	44.2	-0.63	33.3	1.10	43.3	0.47	60.3	3.46	66.7	0.71	60.8	1.73	78.9	2.87	81.0	1.82	79.1
	t-value	(0.48)		(-0.20)		(0.45)		(0.19)		(1.16)		(0.30)		(7.23)***		(3.62)***		(7.72)***	
DY★ (6,12)	01/1982-12/1993	1.83	61.9	2.29	63.6	1.87	62.0	-0.92	51.6	-1.19	63.6	-0.94	52.6	0.95	70.6	1.12	72.7	0.96	70.8
	t-value	(0.92)		(0.87)		(0.96)		(-0.45)		(-0.39)		(-0.47)		(4.38)***		(1.80)*		(4.14)***	
	01/1994-12/2004	7.17	70.2	5.59	72.7	7.04	70.5	-6.48	30.6	-5.16	36.4	-6.37	31.1	0.67	56.5	0.21	60.0	0.63	56.8
	t-value	(2.14)**		(1.67)*		(2.17)**		(-2.14)**		(-1.79)*		(-2.19)**		(1.35)		(0.22)		(1.33)	
	01/1982-12/2004	4.45	66.0	3.94	68.2	4.41	66.2	-3.64	41.3	-3.18	50.0	-3.61	42.0	0.80	63.2	0.78	68.2	0.80	63.6
	t-value	(2.20)**		(1.79)*		(2.26)**		(-1.90)*		(-1.43)		(-1.95)*		(3.18)***		(1.38)		(3.21)***	
DY[1] (12,6)	01/1982-12/1993	1.69	57.0	2.24	70.0	1.73	58.0	-0.67	52.9	-0.96	60.0	-0.69	53.4	1.03	71.9	1.28	70.0	1.05	71.8
	t-value	(0.93)		(0.74)		(0.99)		(-0.36)		(-0.27)		(-0.38)		(4.30)***		(1.59)		(4.17)***	
	01/1994-12/2004	7.72	66.1	5.65	72.7	7.55	66.7	-6.97	35.5	-5.04	27.3	-6.81	34.8	0.77	58.2	0.28	55.6	0.73	58.0
	t-value	(2.41)		(1.45)		(2.47)		(-2.35)		(-1.48)		(-2.42)		(1.55)		(0.27)		(1.55)	
	01/1982-12/2004	4.71	61.6	4.03	71.4	4.65	62.4	-3.82	44.2	-3.10	42.9	-3.76	44.1	0.88	65.3	0.92	66.7	0.88	65.4
	t-value	(2.47)**		(1.56)		(2.56)**		(-2.10)**		(-1.19)		(-2.16)*		(3.43)***		(1.44)		(3.55)***	

Table 3-5 (continued)

Equally-weighted Hedge Portfolio Returns (%)		Style premium based on predicted returns						Style premium based on unpredicted returns						Raw style premium					
		Non-Jan		Jan only		All periods		Non-Jan		Jan only		All periods		Non-Jan		Jan only		All periods	
	Periods	Q1-Q5	%>0	Q1-Q5	%>0	Q1-Q5	%>0	Q1-Q5	%>0	Q1-Q5	%>0	Q1-Q5	%>0	Q1-Q5	%>0	Q1-Q5	%>0	Q1-Q5	%>0
MTBV (6,12)	01/1982-12/1993	-3.86	27.8	-4.55	27.3	-3.92	27.7	5.09	77.0	7.89	81.8	5.31	77.4	1.21	67.5	3.36	72.7	1.38	67.9
	t-value	(-2.28)**		(-2.33)**		(-2.38)**		(2.88)***		(2.38)**		(2.99)***		(5.09)***		(2.14)**		(5.68)***	
	01/1994-12/2004	-0.76	41.3	-2.13	27.3	-0.87	40.2	1.86	59.5	3.16	81.8	1.97	61.4	1.08	65.2	0.50	70.0	1.03	65.6
	t-value	(-0.13)		(-0.31)		(-0.15)		(0.34)		(0.51)		(0.37)		(1.85)*		(0.36)		(1.73)*	
	01/1982-12/2004	-2.34	34.4	-3.34	27.3	-2.42	33.8	3.51	68.4	5.52	81.8	3.67	69.5	1.16	67.2	2.16	72.7	1.24	67.7
	t-value	(-0.77)		(-0.94)		(-0.82)		(1.21)		(1.53)		(1.31)		(3.88)***		(1.98)**		(4.03)***	
MTBV (12,6)	01/1982-12/1993	-3.64	28.1	-3.51	30.0	-3.63	28.2	5.07	76.9	6.25	70.0	5.16	76.3	1.42	74.4	2.75	70.0	1.52	74.0
	t-value	(-2.45)**		(-1.58)		(-2.52)**		(3.30)***		(1.94)*		(3.41)***		(6.08)***		(2.17)**		(6.27)***	
	01/1994-12/2004	0.80	42.1	-2.69	18.2	0.51	40.2	0.43	58.7	3.56	81.8	0.69	60.6	1.19	64.5	0.18	66.7	1.12	64.7
	t-value	(0.15)		(-0.35)		(0.10)		(0.09)		(0.50)		(0.14)		(1.90)*		(0.10)		(1.76)*	
	01/1982-12/2004	-1.42	35.1	-3.08	23.8	-1.55	34.2	2.75	67.8	4.84	76.2	2.91	68.4	1.32	71.1	1.75	71.4	1.36	71.1
	t-value	(-0.51)		(-0.73)		(-0.58)		(1.05)		(1.19)		(1.15)		(4.27)***		(1.66)*		(4.33)***	
MV (6,12)	01/1982-12/1993	-14.12	21.4	-13.46	27.3	-14.07	21.9	15.18	80.2	14.37	81.8	15.11	80.3	1.02	61.9	0.86	54.5	1.01	61.3
	t-value	(-4.08)***		(-2.62)**		(-4.16)***		(4.55)***		(2.86)***		(4.62)***		(1.74)*		(0.77)		(1.82)*	
	01/1994-12/2004	-17.43	6.6	-13.63	9.1	-17.11	6.8	17.86	91.7	18.80	90.9	17.94	91.7	0.39	49.6	4.72	70.0	0.74	51.2
	t-value	(-3.53)***		(-3.03)***		(-3.64)***		(3.59)***		(3.66)***		(3.77)***		(1.07)		(3.43)***		(1.74)*	
	01/1982-12/2004	-15.74	14.2	-13.55	18.2	-15.56	14.5	16.49	85.8	16.58	86.4	16.50	85.9	0.71	56.3	3.05	63.6	0.90	56.9
	t-value	(-5.24)***		(-4.03)***		(-5.40)***		(5.56)***		(4.59)***		(5.75)***		(2.01)**		(2.63)***		(2.59)***	
MV (12,6)	01/1982-12/1993	-15.63	18.2	-16.36	20.0	-15.69	18.3	16.79	82.6	17.13	80.0	16.82	82.4	1.15	61.2	0.76	50.0	1.12	60.3
	t-value	(-5.82)***		(-3.22)***		(-5.99)***		(6.48)***		(3.32)***		(6.61)***		(2.05)**		(0.67)		(2.13)**	
	01/1994-12/2004	-19.13	5.8	-14.96	9.1	-18.78	6.1	19.55	92.6	20.38	90.9	19.62	92.4	0.43	53.6	5.10	66.7	0.78	54.6
	t-value	(-4.19)***		(-2.99)***		(-4.36)***		(4.27)***		(3.55)***		(4.51)***		(0.99)		(3.30)***		(1.61)	
	01/1982-12/2004	-17.38	12.0	-15.63	14.3	-17.24	12.2	18.17	87.6	18.83	85.7	18.23	87.5	0.77	57.0	3.22	61.9	0.97	57.4
	t-value	(-6.54)***		(-4.42)***		(-6.81)***		(6.90)***		(4.86)***		(7.21)***		(2.19)**		(2.62)***		(2.78)***	

★Note: for style based on DY, the hedge portfolios are Q5 – Q1.

3.4.5 Style premiums regressed on macroeconomic variables

Previous section suggests that U.K. size and value premiums on characteristics PC and MTBV sorted stocks are mainly driven by firm-specific mispricing rather than the conditional macroeconomic risk factors, one may be concerned with the explanatory power of the business cycle model under consideration. Equation (7) is based on the individual stock level. Prior studies such as Ferson and Harvey (1991, 1998 and 1999) have focused on the portfolio level to relate with the macroeconomic variables. Avramov and Chordia (2006a) argue that the use of individual stocks in a model reduces the data-snooping biases of Lo and MacKinlay (1990) and avoids the loss of information in the portfolio sorting process of Litzenberger and Ramaswamy (1979). Equation (7) is based on the assumption that the exposures to the risk factors of each stock are known, and hence the pricing errors can be used to examine the model's explanatory ability. The null hypothesis of a rational risk-based explanation can be rejected if after controlling for the predicted risk premiums there are still significant return divergence exhibited across styles. However, rejecting the risk-based interpretation may also be caused by failing to properly identifying the underlying risk factors. In particular in the individual stock level, the exposures to the risk factors are in general unknown and can be hard to estimate (Swinkels, 2004).

To have a better understanding regarding the relation between the style spreads based on such characteristics and the macroeconomic conditions, this section directly examines the relation between style spreads for stocks classified by different characteristics PC, DY, MTBV and MV with the macroeconomic variables as described in Equation (7):

$$r_{i,t} = c_{i,0} + c_{i,1}div_{t-1} + c_{i,2}yld_{t-1} + c_{i,3}term_{t-1} + c_{i,4}def_{t-1} + e_{i,t} \qquad (9)$$

Where r_i (i = 1, 2, 3, 4) is the hedge portfolio returns based on characteristic variables PC, DY, MTBV and MV.

To allow for the time-varying nature impounded in Equation (9), the parameters are estimated using the previous 60-month rolling window that contains stocks with at least 24 months return observations. The estimated coefficients from (9) are then used to forecast the one-month-ahead style spreads. Identical to Equation (7), each month the unpredicted portion of regression (9) is calculated as the sum of the intercept and residuals. To account for the possible autocorrelations caused by the rolling windows, the t-statistics are calculated based on Newey-West (1987) heteroscedasticity and autocorrelation consistent standard errors. Given the evidence of size and value premiums found in previous sections, it is hypothesized that, if Equation (9) fails to capture the business cycle effect in the expected style spreads, the pricing error of Equation (9) is expected to be significantly positive.

Table 3-6 reports the time-series average of the intercept and the style spreads that are predicted and unpredicted by Equation (9) in different sample periods. The time-series average of the coefficients of the macroeconomic variables is also presented. For comparison the raw hedge portfolio returns are also listed. Panel A presents the results for the regressions without including the January dummy variable, while Panel B includes the January dummy to consider the seasonality of style premiums.

Table 3-6 Style Investing Profits Regressed on the Business Cycle Variables

Style portfolios are formed in the same manner as in Table 3.3. This table reports the average coefficients for the regression:

$$r_{i,t} = c_{i,0} + c_{i,1}div_{t-1} + c_{i,2}yld_{t-1} + c_{i,3}term_{t-1} + c_{i,4}def_{t-1} + e_{i,t}$$

where r_i (i = 1, 2, 3, 4) represents hedge portfolio returns based on characteristic variables PC, DY, MTBV and MV. The predictor variables are the default spread, the yield on the three-month T-bill, the dividend yield on the overall U.K. market and the term spread, respectively. A January dummy is also included in Panel B that takes a value of 1 in January and 0 in other months. For each month t, the parameters are estimated by using payoffs in month t-60 through t-1. A minimum of 24 months data are required for the estimation period. The unpredicted part of the regression is equal to the sum of the intercept and residuals, and "%>0" gives the percentage of the positive unpredicted returns. The t ratios in the brackets are calculated based on the Newey-West (1987) heteroscedasticity and autocorrelation consistent standard errors with lags equal to 6. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Panel A: Regression Excludes the January Dummy J, K = (12,6)										
Period	Raw	Predicted	Unpredicted	%>0	Intercept	DEF	YLD	DIV	TERM	R-Sqr
Hedge portfolio returns (Q1-Q5) based on PC										
01/1982-12/1993	0.018	0.027	-0.008	45.4	-0.009	-0.791	0.119	0.776	-0.132	0.094
t-value	(7.86)***	(5.624)***	(-1.241)		(-1.665)*	(-10.267)***	(1.124)	(8.590)***	(-4.877)***	
01/1994-12/2004	0.018	0.018	0.001	41.4	-0.001	2.100	0.599	0.020	0.355	0.115
t-value	(3.96)***	(0.828)	(0.040)		(-0.043)	(5.340)***	(2.721)***	(0.025)	(1.264)	
01/1982-12/2004	0.018	0.019	0.000	46.3	-0.002	0.739	0.241	0.278	0.190	0.107
t-value	(7.72)***	(1.552)	(-0.015)		(-0.134)	(2.215)***	(1.838)*	(0.621)	(1.209)	
Hedge portfolio returns (Q5-Q1) based on DY										
01/1982-12/1993	0.010	-0.026	0.036	75.9	0.037	-0.687	0.201	-0.415	-0.135	0.103
t-value	(4.17)***	(-3.170)***	(4.338)***		(4.862)***	(-3.338)***	(2.328)**	(-2.806)**	(-3.724)***	
01/1994-12/2004	0.007	0.061	-0.054	25.6	-0.056	2.345	0.803	1.167	0.890	0.186
t-value	(1.55)	(3.553)***	(-3.370)***		(-3.460)***	(5.143)***	(2.889)***	(2.253)**	(4.193)***	
01/1982-12/2004	0.009	0.019	-0.010	48.8	-0.011	0.865	0.550	0.425	0.381	0.134
t-value	(3.55)***	(1.540)	(-0.854)		(-0.876)	(2.343)**	(3.426)***	(1.329)	(2.660)***	
Hedge portfolio returns (Q1-Q5) based on MTBV										
01/1982-12/1993	0.015	-0.025	0.041	69.4	0.046	0.215	0.136	-0.646	-0.118	0.080
t-value	(6.27)***	(-1.353)	(1.999)**		(2.276)**	(3.038)***	(1.102)	(-1.651)*	(-1.598)	
01/1994-12/2004	0.012	0.075	-0.063	30.1	-0.067	2.881	1.446	1.685	0.485	0.188
t-value	(1.76)*	(2.288)**	(-2.073)**		(-2.141)**	(3.969)***	(4.442)***	(1.726)*	(1.799)*	
01/1982-12/2004	0.014	0.024	-0.011	55.0	-0.011	1.549	0.647	0.497	0.285	0.134
t-value	(4.33)***	(1.120)	(-0.518)		(-0.512)	(3.384)***	(3.253)***	(0.825)	(1.795)*	
Hedge portfolio returns (Q1-Q5) based on MV										
01/1982-12/1993	0.011	-0.188	0.199	100.0	0.202	-0.832	0.860	-4.017	0.273	0.387
t-value	(2.13)**	(-13.530)***	(17.835)***		(21.166)***	(-2.574)**	(4.931)***	(-15.370)***	(3.380)***	
01/1994-12/2004	0.008	-0.183	0.191	87.2	0.196	0.578	0.815	-6.096	0.748	0.233
t-value	(1.61)	(-3.730)***	(3.893)***		(3.993)***	(0.662)	(1.079)	(-3.798)***	(1.966)**	
01/1982-12/2004	0.010	-0.202	0.212	97.5	0.216	-0.483	0.396	-5.555	0.671	0.301
t-value	(2.78)***	(-7.889)***	(8.399)***		(8.513)***	(-0.999)	(1.117)	(-6.412)***	(3.490)***	

Table 3-6 (Continued)

Panel B: Regression Includes the January Dummy J, K = (12,6)											
Period	Raw	Predicted	Unpredicted	%>0	Int	JAN	DEF	YLD	DIV	TERM	R-Sqr
Hedge portfolio returns (Q1-Q5) based on PC											
01/1982-12/1993	0.018	0.038	-0.018	43.5	-0.019	0.027	-0.824	0.165	0.948	-0.205	0.216
t-value	(7.86)***	(3.726)***	(-1.776)*		(-1.920)*	(8.500)***	(-6.999)***	(1.991)*	(4.716)***	(-5.027)***	
01/1994-12/2004	0.018	0.026	-0.007	36.8	-0.009	0.006	1.951	0.622	0.317	0.359	0.169
t-value	(3.96)***	(1.315)	(-0.390)		(-0.489)	(1.687)*	(4.457)***	(3.086)***	(0.439)	(1.312)	
01/1982-12/2004	0.018	0.028	-0.010	44.2	-0.011	0.014	0.689	0.306	0.516	0.152	0.176
t-value	(7.72)***	(2.388)**	(-0.852)		(-0.963)	(4.962)***	(2.014)**	(1.248)	(1.248)	(0.973)	
Hedge portfolio returns (Q5-Q1) based on DY											
01/1982-12/1993	0.010	-0.023	0.033	75.0	0.035	0.005	-0.663	0.198	-0.379	-0.152	0.127
t-value	(4.17)***	(-2.503)***	(3.616)***		(3.982)***	(2.599)***	(-3.309)***	(2.093)**	(-2.216)**	(-4.452)***	
01/1994-12/2004	0.007	0.067	-0.059	24.8	-0.062	0.008	2.129	0.797	1.367	0.913	0.220
t-value	(1.55)	(3.775)***	(-3.572)***		(-3.674)***	(2.110)**	(4.524)***	(2.792)***	(2.559)**	(4.344)***	
01/1982-12/2004	0.009	0.023	-0.014	47.9	-0.014	0.004	0.826	0.570	0.528	0.379	0.154
t-value	(3.55)***	(1.781)*	(-1.126)		(-1.140)	(2.334)**	(2.263)**	(3.390)***	(1.579)	(2.639)***	
Hedge portfolio returns (Q1-Q5) based on MTBV											
01/1982-12/1993	0.015	-0.010	0.025	70.4	0.030	0.020	0.261	0.174	-0.373	-0.189	0.140
t-value	(6.27)***	(-1.026)	(2.266)***		(2.869)***	(3.296)***	(3.514)***	(2.011)**	(-1.767)*	(-2.053)**	
01/1994-12/2004	0.012	0.078	-0.066	30.1	-0.070	0.001	2.731	1.407	1.815	0.496	0.222
t-value	(1.76)*	(2.434)**	(-2.227)**		(-2.297)**	(0.234)	(3.744)***	(4.496)***	(1.902)*	(1.854)*	
01/1982-12/2004	0.014	0.033	-0.020	53.8	-0.020	0.008	1.530	0.664	0.678	0.253	0.173
t-value	(4.33)***	(1.669)*	(-1.041)		(-1.007)	(2.060)**	(3.366)***	(3.534)***	(1.191)	(1.553)	
Hedge portfolio returns (Q1-Q5) based on MV											
01/1982-12/1993	0.011	-0.188	0.200	100.0	0.203	-0.003	-0.898	0.888	-4.005	0.287	0.394
t-value	(2.13)	(-14.001)***	(18.648)***		(22.969)***	(-1.105)	(-2.608)**	(5.269)***	(-15.99)***	(3.452)***	
01/1994-12/2004	0.008	-0.150	0.158	74.4	0.162	0.052	0.012	1.197	-4.962	0.807	0.353
t-value	(1.61)	(-3.792)***	(3.979)***		(4.103)***	(15.420)***	(0.015)	(2.001)**	(-3.975)***	(2.303)**	
01/1982-12/2004	0.010	-0.185	0.195	96.7	0.199	0.022	-0.672	0.688	-4.973	0.690	0.352
t-value	(2.78)***	(-9.291)***	(9.977)***		(10.188)***	(5.350)***	(-1.458)	(2.505)**	(-7.812)***	(3.817)***	

Consistently, it is found that business cycle variables do not explain the size premium in the U.K. market. It is shown that all intercepts of size portfolios are significantly positive over all sample periods, and the unpredicted portion of the size premium is statistically significant regardless whether the January effect is considered or not. Besides, the coefficients for variable *div* are always significantly negative in different testing periods, and those for *def* are significantly negative during period 1993:01-2004:12, suggesting that in market conditions with high dividend yields on aggregate level and small default spreads, small stocks tend to underperform large stocks. The negative coefficients on default spread and the overall market dividend yield should imply that controlling for these two variables could increase the size premium.

However, the business cycle effect has some ability in explaining value premiums on the portfolio level. All coefficients on the macroeconomic variables are positive based on whole sample periods although some may be noisy in subperiods. The unexplained portions of the regression are not significantly positive, and the percentage of positive signs is less than 50% on characteristics PC and DY. The dummy variables in Panel B are generally significant in different testing periods too. Thus both size and value premiums exhibit some kind of January effect, which is consistent with Table 3-3. It is shown that adding January dummy variable generally increases the explanatory ability of macro variables. The t-ratios are higher in absolute value and the R^2 are higher in Panel B as compared to those in Panel A.

It is interesting to see that the default spread has largest coefficients compared to other variables. It also remains as the only variable that is significant regardless whether to consider January effect. Since default spread measures the credit market conditions, an increase in this variable is commonly interpreted to signal the market's expectation of worsening credit market conditions. Chan and Chen (1991) and Perez-Quiros and Timmermann (2000) suggest that small firms are more vulnerable to variation of credit market conditions over the business cycle. Hence there should be interaction between value premiums and the size premium. Further, Fama and French (1989) and Hahn and Lee (2006) show that the term spread tends to be low near business cycle peaks and high near troughs. Hence, consistent with Table 3.4, Equation (9) predicts that value premiums are higher in an economic environment with higher short-term interest rates, wider default spread and higher term spreads, which is typically the case in economy recessions.

Overall, while previous sections find that on the individual stock level the relative performance of stocks sorted on PC and MTBV are not driven by the business cycle risk, this section suggests that on the portfolio level the business cycle model partly explains the time-series expected value premiums. Hence equity characteristics PC, DY and MTBV contain information in predicting the time-variation in expected style returns. This result is consistent with findings of recent empirical studies to focus on the time-series relations among expected returns, risk and equity characteristics. For example, Kothari and Shanken (1997) and Pontiff and Schall (1998) find that DY and BM forecast stock returns at the aggregate level. Similarly, Lewellen (1999) reports that BM predicts economically and statistically time-variation in expected returns at the portfolio level. These studies aim to distinguish between risk and characteristics stories and generally support the risk-based argument.

In order to examine whether the early results are not unique to a specific subperiod and to provide a robustness tests for Equation (7), the monthly hedge portfolio returns are also regressed on the macro variables in each of the 5-year subperiods. The length of the subperiod is based on comprise to obtain meaningful estimated parameters and to capture the time-varying properties in stock returns. For brevity, Table 3-7 only reports the test results based on formation and testing period (12, 6). All regressions are carried out independently and the t-ratios in the brackets are calculated using the Newey-West (1987) heteroscedasticity and autocorrelation consistent standard errors with lags equal to 6. Panel A excludes the January dummy variable and in Panel B a January dummy variable is included that takes value of 1 in January and 0 otherwise.

Regardless whether to consider the January effect, the intercepts from the regression based on the size premium tend to have higher absolute values relative to the value portfolios, suggesting that the explanatory power of Equation (9) is weaker for the size premium than for value premiums. It is noticed that the regression coefficients on variable *def* and *term* are consistently positive for value premiums in post-1993 subsamples (except for term based on PC in 2003-2004). Also the R^2 are much higher when considering the January effect. Overall, the results are consistent with those of Table 3-6 and it is safe to conclude that the early results are not driven by specific sample periods.

In summary, the empirical results in this section show that the underlying driving forces affecting the style spreads are much controversial. The size premium and the value premiums on company characteristics PC and MTBV are mainly driven by the cross-sectional pricing error from the multifactor business cycle model, suggesting that the outperformance of small stocks and PC- and MTBV-based value stocks may be caused by investors' irrational trading behaviour to such stock groups that results from cognitive biases such as underreaction to firm-specific news. Conversely, the divergent return patterns between value and growth stocks on DY is attributed to the cross-sectional differences in conditionally expected returns predicted by the business cycle model, and therefore is the compensation for bearing business cycle risk.

Table 3-7 Style Investing Returns Regressed on Macroeconomic Variables: 5-year Subperiod Results (J, K) = (6, 12)

Style portfolios are formed in the same manner described in Table 3.3. This table reports the average coefficients for the regression: $r_{i,t} = c_{i,0} + c_{i,1}div_{t-1} + c_{i,2}yld_{t-1} + c_{i,3}term_{t-1} + c_{i,4}def_{t-1} + e_{i,t}$, where r_i (i = 1, 2, 3, 4) represents hedge portfolio returns of characteristic variables PC, DY, MTBV and MV based on a five-year subperiods and the lagged value of a set of economic pervasive variables. Panel A excludes the use of January dummy variable that takes the value 1 for January and 0 otherwise. Panel B includes such January dummy variable. The regressions are carried separately for each subperiods and the t-ratios in the brackets are calculated based on the Newey-West (1987) heteroscedasticity and autocorrelation consistent standard errors with lags equal to 6. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Panel A: Business Cycle Model Excludes January Dummy												
	Subperiods	Intercept	t(intercept)	DEF	t(def)	YLD	t(yld)	DIV	t(div)	TERM	t(term)	R^2
PC	1983-1987	-0.017	(-0.361)	-0.552	(-2.112)**	0.415	(0.884)	0.873	(0.879)	-0.210	(-1.200)	0.076
	1988-1992	0.007	(0.172)	-1.481	(-1.124)	-0.580	(-1.528)	0.569	(0.599)	-0.182	(-1.084)	0.167
	1993-1997	0.024	(0.723)	1.631	(2.739)***	-0.092	(-0.162)	-0.510	(-0.525)	0.055	(0.143)	0.137
	1998-2002	-0.107	(-0.839)	3.119	(1.732)*	2.010	(1.845)*	3.811	(0.954)	1.156	(1.958)*	0.130
	2003-2004	0.185	(1.134)	2.424	(2.109)**	-1.497	(-0.695)	-6.507	(-1.107)	-0.772	(-1.467)	0.257
DY	1983-1987	0.022	(0.406)	-0.168	(-0.873)	0.233	(0.387)	-0.171	(-0.149)	-0.021	(-0.187)	0.051
	1988-1992	0.038	(1.325)	-2.174	(-2.507)**	0.382	(0.677)	-0.199	(-0.301)	-0.395	(-3.109)	0.101
	1993-1997	-0.021	(-0.213)	2.274	(1.601)	-0.948	(-1.15)	0.341	(0.121)	0.054	(0.073)	0.173
	1998-2002	-0.148	(-0.923)	3.558	(1.824)*	2.525	(1.639)	4.801	(0.956)	1.259	(1.943)*	0.170
	2003-2004	0.103	(0.834)	4.609	(2.29)**	0.470	(0.3)	-4.310	(-0.924)	2.385	(2.4)**	0.272
MTBV	1983-1987	0.023	(0.420)	0.274	(0.800)	0.121	(0.207)	-0.185	(-0.161)	-0.462	(-2.226)**	0.034
	1988-1992	0.024	(0.620)	-0.481	(-0.425)	0.346	(0.819)	-0.187	(-0.248)	-0.016	(-0.114)	0.049
	1993-1997	0.098	(1.061)	1.010	(0.700)	-0.834	(-0.906)	-2.825	(-1.113)	0.858	(1.252)	0.150
	1998-2002	-0.301	(-1.464)	5.746	(2.342)**	3.538	(2.022)**	9.379	(1.451)	0.660	(0.844)	0.154
	2003-2004	0.078	(0.213)	0.827	(0.406)	-0.304	(-0.069)	-2.503	(-0.187)	0.388	(0.35)	0.024
MV	1983-1987	0.162	(1.175)	-0.041	(-0.077)	0.919	(0.655)	-3.346	(-1.149)	0.130	(0.260)	0.360
	1988-1992	0.218	(2.939)***	-4.947	(-1.897)*	1.030	(1.636)	-3.094	(-2.289)**	-0.079	(-0.217)	0.302
	1993-1997	0.038	(0.339)	4.710	(2.597)***	1.404	(1.242)	-1.744	(-0.588)	-0.193	(-0.288)	0.178
	1998-2002	0.269	(1.547)	-3.184	(-2.062)**	-1.202	(-0.604)	-7.577	(-1.321)	2.180	(5.016)***	0.187
	2003-2004	1.151	(1.636)	-4.227	(-0.801)	-12.217	(-1.457)	-41.316	(-1.583)	11.243	(3.935)***	0.445

Table 3-7 (Continued)

Panel B: Business Cycle Model Includes January Dummy														
	Subperiods	Intercept	t(intercep	JAN	t(Jan)	DEF	t(def)	YLD	t(yld)	DIV	t(div)	TERM	t(term)	R^2
PC	1983-1987	0.000	(-0.009)	0.035	(2.291)**	-0.44	(-1.687)**	0.228	(0.507)	0.447	(0.407)	-0.281	(-1.815)*	0.238
	1988-1992	0.006	(0.139)	0.014	(1.893)*	-1.680	(-1.281)	-0.446	(-1.176)	0.659	(0.703)	-0.157	(-0.957)	0.194
	1993-1997	0.025	(0.720)	-0.003	(-0.432)	1.665	(2.778)***	-0.118	(-0.201)	-0.516	(-0.523)	0.045	(0.118)	0.141
	1998-2002	-0.119	(-0.895)	0.008	(0.398)	3.152	(1.767)*	2.154	(1.749)*	4.221	(1.003)	1.160	(1.989)**	0.132
	2003-2004	0.184	(1.077)	-0.012	(-2.943)**	1.628	(1.112)	-1.521	(-0.666)	-6.264	(-1.024)	-0.626	(-1.202)	0.280
DY	1983-1987	0.028	(0.489)	0.011	(2.473)**	-0.132	(-0.642)	0.173	(0.279)	-0.308	(-0.260)	-0.044	(-0.366)	0.075
	1988-1992	0.039	(1.272)	-0.009	(-1.088)	-2.041	(-2.138)**	0.293	(0.456)	-0.259	(-0.368)	-0.412	(-3.149)**	0.113
	1993-1997	-0.023	(-0.226)	0.009	(1.358)	2.175	(1.466)	-0.872	(-1.049)	0.359	(0.127)	0.084	(0.112)	0.187
	1998-2002	-0.132	(-0.756)	-0.010	(-0.77)	3.515	(1.762)*	2.339	(1.365)	4.270	(0.776)	1.253	(1.920)*	0.172
	2003-2004	0.099	(0.706)	-0.030	(-2.91)***	2.705	(1.372)	0.413	(0.235)	-3.727	(-0.682)	2.732	(2.929)***	0.340
MTBV	1983-1987	0.039	(0.673)	0.035	(1.437)	0.386	(1.221)	-0.066	(-0.107)	-0.612	(-0.492)	-0.534	(-2.789)**	0.123
	1988-1992	0.025	(0.633)	-0.005	(-1.327)	-0.403	(-0.35)	0.293	(0.622)	-0.223	(-0.289)	-0.026	(-0.183)	0.056
	1993-1997	0.096	(1.038)	0.011	(1.363)	0.892	(0.596)	-0.743	(-0.805)	-2.803	(-1.104)	0.894	(1.326)	0.172
	1998-2002	-0.279	(-1.354)	-0.015	(-0.833)	5.683	(2.311)**	3.267	(1.826)*	8.606	(1.332)	0.651	(0.827)	0.157
	2003-2004	0.079	(0.216)	0.005	(0.66)	1.167	(0.476)	-0.294	(-0.067)	-2.607	(-0.196)	0.325	(0.288)	0.026
MV	1983-1987	0.156	(1.164)	-0.013	(-1.016)	-0.082	(-0.158)	0.986	(0.723)	-3.192	(-1.134)	0.156	(0.318)	0.365
	1988-1992	0.218	(2.924)***	0.000	(-0.009)	-4.944	(-2.004)**	1.028	(1.731)*	-3.095	(-2.299)**	-0.079	(-0.214)	0.302
	1993-1997	0.032	(0.270)	0.040	(2.495)**	4.294	(2.200)**	1.725	(1.422)	-1.668	(-0.537)	-0.068	(-0.106)	0.273
	1998-2002	0.205	(1.498)	0.043	(1.228)	-3.009	(-2.163)**	-0.443	(-0.268)	-5.413	(-1.193)	2.205	(4.508)***	0.243
	2003-2004	1.168	(2.191)**	0.124	(8.275)***	3.773	(0.846)	-11.979	(-1.995)**	-43.763	(-2.205)**	9.782	(3.302)***	0.637

3.4.6 Contemporaneous relations between equity characteristics, common risk factors and the pricing error of the business cycle model

In the previous sections a set of macroeconomic variables are used to model the expected stock returns. Such variables are state variables that have forecasting power for future investment opportunities that represents the slope of the yield curve and the conditional distribution of stock returns. By decomposing stock returns into predicted and unpredicted components from the business cycle model, it is suggested that the value premium based on equity characteristics DY is mainly captured by the predicted risk premias, while value premiums based on characteristics PC and MTBV and the size premium may result from the model mispricing unrelated to the business cycle, and may be best described by investors' underreaction to the firm-specific information in behavioural finance.

The different mechanisms company characteristics predict the cross-sectional average stock returns is intriguing. The characteristics used in this study are price-related variables. The empirical literature suggests that these variables are associated with the variation on average stock returns. Fama and French (1989) emphasize that the price variables that forecast returns are correlated with business cycles. In addition, authors such as Estrella and Hardouvelis (1991) and more recently Ang *et al.* (2004) document that the price variables that forecast returns are also able to forecast economic activity. If the business cycle model is empirically well specified, rational asset pricing argues that the evidence of strong size and value premiums would suggest that the underlying characteristic proxies for risk factor. Alternatively it should proxy for the information of mispricing. However, as discussed in section 3.4.4, the existence of style premiums on firm characteristics would still be consistent with traditional finance theory if the underlying characteristic associated with higher average returns is cross-sectionally correlated with risk factors. Under this condition, the style premium simply reflects compensation for risk.

Given the seeming evidence that macroeconomic variables do not capture the style premiums on firm characteristics PC, MTBV and MV in this chapter, it is motivated to examine what underlies the mispricing of the business cycle model. Under the assumptions that 1) the multifactor asset pricing model is well specified; 2) significant style premium found on the underlying characteristic based on raw stock returns; and 3) the underlying characteristic neither proxies for the risk factor nor has the cross-sectional correlation with the risk factor loadings in the asset pricing model, it follows that the style premium is mainly driven by the cross-sectional pricing errors, which are determined by other factors orthogonal to risk factors in the asset pricing process. Moreover, if such factors predict stock returns, one would expect to see a significant correlation between the mispricing and the underlying characteristic. Now consider factors such as the underlying firm characteristic, the CAPM beta and the loadings on Fama and French (1993) three factors, the null hypothesis of business cycle risk proxy story or correlation with risk factor argument can be rejected if these factors do not predict the cross-sectional pricing errors of the business cycle model.

For this investigation, this section examines the contemporaneous relations between the equity characteristics, common risk factors and the business cycle adjusted returns from Equation (7). Thus cross-sectional regressions are tested for individual stock i in each month t starting from January 1982 to December 2004. The cross-sectional OLS regression takes the form of:

$$R^{*}_{i,t} = c_{0,t} + \sum_{j=1}^{J} c_j Z_{i,j,t} + e_{i,t} \tag{10}$$

Where $R^*_{i,t} = R_{i,t} - \hat{R}_{i,t} = \hat{c}_{i,0} + e_{i,t}$ stands for the pricing error from regression (7) and acts as the dependent variable in regression (10). Z_t is a vector of firm characteristics including the log of market value, the log of the value-growth style indicators (PC, DY and MTBV), the CAPM beta, the loadings on Fama-French three factors. To be consistent with the estimation of Equation (7), the CAPM beta for the underlying stock is estimated using a rolling window of its previous 24-60 month observations. Thus stocks must have at least 24-month return data to be considered. The loadings on Fama-French three factors are obtained using exactly the same methodology as CAPM betas.

Equation (10) links the time-series data with the cross-sectional data and some of the independent variables are observed while others are estimated. A combination of firm characteristics and risk factor loadings is used as regressors in Equation (10), yielding a total of 11 regressions (except for size portfolios)[14]. In each month, regression (10) is estimated and the vector of monthly estimators of c_m obtained. The average time-series of such estimated c_m and the Newey-West (1987) heteroscedasticity and autocorrelation consistent standard errors with lags of 36 are calculated to obtain the t-ratios[15].

Table 3-8 reports the result for such cross-sectional regressions. Panel 1 is the result for stocks with size information only. Only the CAPM betas or the loading on Fama and French market risk factor significantly tracks the variation on the cross-sectional average pricing

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[14] Only the market value (MV) and the underlying characteristic variables (PC, DY and MTBV) used to sort stocks will be used in regression (10). This is because not every stock has all the four available characteristic values. Due to this reason, for size portfolios, characteristic variables PC, DY and MTBV are not included, hence yielding only 5 cross-sectional regressions in each month.

[15] It is reasonable to use 36 as the number of lags in the Newey-West (1987) test. U.K. listed companies generally disclose the financial results on a quarterly basis. The time-series test of return series (not reported here) suggests that in most cases there are autocorrelations up to around 40 months.

errors from the business cycle model. When augmented by stock's market value information or using market value alone as independent variable, the intercepts become significant, suggesting that firm characteristic MV does not predict the average pricing errors, although it does have the correct sign.

Panel 2 and 4 report the results for stocks with characteristic PC and MTBV. Notice that the size information is also included in the regression because of its availability. Consistent with Panel 1, the pricing errors from the business cycle model is explained by the CAPM betas, or the market risk exposure and/or SMB but not HML of Fama and French three factor model. Augmenting equity characteristics or using such characteristics along as regressors will result in significant intercepts, indicating that company characteristic variable PC and MTBV do not explain the mispricing of the business cycle model. It is also noted that SMB or MV has the right sign to demonstrate the size effect impounded in pricing errors. The sign of PC is correct while that of MTBV is relatively noisy. Interestingly, the coefficients on HML factor are all negative (but not significant), suggesting that the mispring of business model is perhaps more severe for growth stocks. This result is consistent with recent research such as Finn *et al.* (1999) who argue that equity mispricing is mostly on the short side (growth stocks).

The results in Panel 4 based on characteristic DY tell a very different story. Although the sign of DY is correct, the regression intercepts are all significant regardless which set of variables is combined as regressors. This is consistent with the argument that DY-based value premium is mainly captured by business cycle risk, and hence common factors such as CAPM beta and the loading on Fama and French market factor do not explain the model mispricing. Naturally, since DY is associated with average returns, it does not track the cross-sectional variation on pricing errors.

In summary, it is suggested that in the U.K. stock market the value premium on firm characteristic DY is compensation for the business cycle risk and hence DY is a proxy for macroeconomic risk factor in stock returns. While the size premium and value premiums on firm characteristic PC and MTBV are not directly captured by the business cycle effects, under the assumption that the underlying multifactor business cycle model accurately describes stock returns, they are mainly driven by factors that are unrelated with the business cycle risk. Specifically, this chapter finds that the pricing errors are cross-sectionally captured by exposures to other common risk factors such CAPM betas or loadings on market factor or SMB of Fama and French (1993) three-factor model. Moreover, equity characteristics PC, MTBV and MV have no explanatory ability in such mispricing when augmented or used alone as independent variables. Given the fact that these variables are associated with the cross-sectional variation on average stock returns, the null hypothesis that these variables do not proxy for risk factors or have no cross-sectional correlation with the factor loadings can be rejected. Overall, the empirical research in this chapter supports the rational risk-based argument that style premium reflect compensation for risk, although such risk may not directly business cycle related.

Table 3-8 Regressions of unpredicted stock returns on firm characteristics and risk factors

Stock returns are modelled by

$$R_{i,t} = c_{i,0} + c_{i,1}div_{t-1} + c_{i,2}yld_{t-1} + c_{i,3}term_{t-1} + c_{i,4}def_{t-1} + e_{i,t}.$$

def is the default spread of the lower and higher yield bond. *yld* is the short-term interest rate proxied by the 3-month Treasury bill yield. *div* is the dividend yield on the overall market and *term* is the term spread representing the difference between the 20-year gilt and 3-month Treasury bill yield. The parameters of the above regression are estimated by 60-month rolling window samples containing stocks with minimum 24 months of observations. In each month and cross-sectionally, all the one-month-ahead unpredicted returns from the above regression (i.e. the estimated intercept plus the residual) of individual stocks are regressed on a combination of a set of equity characteristics such as the market capitalisation (MV), the price to cash flow ratios (PC), the dividend yield (DY), the market to book ratios (MTBV) and the common risk factor loadings such as CAPM beta and the Fama-French three-factor loadings. The CAPM beta and the loadings for Fama-French three factors of an individual stock are also estimated using a 60-month rolling window with stocks having minimum 24 months of observations. The table below presents the regression results and the t-ratios in the brackets are calculated using the Newey-West (1987) heteroscedasticity and autocorrelation consistent standard errors with lags equal to 36. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Panel 1: Stocks with MV								
Model	Constant	Beta(CAPM)	Beta(FF)	Beta(SMB)	Beta(HML)	Ln(MV)		R^2
1	0.032	0.337						0.081
	(1.178)	(3.638)***						
2	0.024		0.304	0.014	-0.071			0.165
	(1.109)		(3.557)***	(0.536)	(-1.157)			
3	0.085	0.322				-0.028		0.09
	(2.733)***	(3.520)***				(-3.873)***		
4	0.252					-0.065		0.021
	(2.910)***					(-3.732)***		
5	0.038		0.301	0.014	-0.071	-0.007		0.17
	(1.721)*		(3.507)***	(0.527)	(-1.162)	(-1.185)		
Panel 2: Stocks with Price to cash flow ratios (PC)								
Model	Constant	Beta(CAPM)	Beta(FF)	Beta(SMB)	Beta(HML)	Ln(MV)	Ln(PC)	R^2
1	-0.016	0.387						0.098
	(-0.550)	(4.630)***						
2	0.000		0.357	0.024	-0.031			0.185
	(-0.014)		(4.479)***	(0.816)	(-0.703)			
3	0.061	0.349				-0.055	0.04	0.119
	(1.590)	(4.540)***				(-3.963)***	(1.537)	
4	0.099	0.348				-0.054		0.114
	(2.155)**	(4.550)***				(-3.925)***		
5	-0.045	0.387					0.029	0.103
	(-1.625)	(4.609)***					(1.104)	
6	0.255					-0.096		0.035
	(2.686)***					(-3.855)***		
7	0.041						0.029	0.005
	(0.892)						(1.147)	
8	0.212					-0.097	0.048	0.04
	(2.539)***					(-3.863)***	(1.826)*	
9	0.046		0.335	0.023	-0.032	-0.028	0.014	0.197
	(1.545)		(4.470)***	(0.777)	(-0.765)	(-2.532)**	(0.620)	
10	0.062		0.335	0.024	-0.033	-0.03		0.193
	(1.591)		(4.475)***	(0.804)	(-0.777)	(-2.816)***		
11	-0.011		0.357	0.024	-0.03		0.011	0.189
	(-0.430)		(4.461)***	(0.789)	(-0.698)		(0.496)	

Panel 3: Stocks with Price to Dividend yield (DY)								
Model	Constant	Beta(CAPM)	Beta(FF)	Beta(SMB)	Beta(HML)	Ln(MV)	Ln(DY)	R^2
1	0.055	0.181						0.059
	(2.496)**	(2.580)***						
2	0.061		0.187	-0.001	-0.042			0.104
	(2.664)***		(2.680)***	(-0.052)	(-1.248)			
3	0.204	0.163				-0.044	-0.106	0.079
	(4.357)***	(2.378)**				(-4.138)***	(-4.334)***	
4	0.133	0.166				-0.037		0.070
	(3.933)***	(2.409)**				(-3.957)***		
5	0.101	0.18					-0.087	0.066
	(3.652)***	(2.562)**					(-4.367)***	
6	0.196					-0.051		0.017
	(2.998)***					(-3.661)***		
7	0.146						-0.095	0.008
	(2.943)***						(-4.061)***	
8	0.272					-0.058	-0.119	0.027
	(3.361)***					(-3.820)***	(-4.112)***	
9	0.179		0.172	-0.002	-0.037	-0.034	-0.087	0.118
	(4.275)***		(2.544)**	(-0.114)	(-1.211)	(-3.806)***	(-4.814)***	
10	0.122		0.176	-0.001	-0.041	-0.029		0.112
	(3.734)***		(2.573)**	(-0.051)	(-1.255)	(-3.546)***		
11	0.099		0.184	-0.002	-0.039		-0.071	0.109
	(3.687)***		(2.661)***	(-0.095)	(-1.212)		(-4.652)***	

Panel 4: Stocks with Market-to-book ratios (MTBV)								
Model	Constant	Beta(CAPM)	Beta(FF)	Beta(SMB)	Beta(HML)	Ln(MV)	Ln(MTBV)	R^2
1	0.010	0.356						0.106
	(0.234)	(4.343)***						
2	0.013		0.337	0.054	-0.040			0.204
	(0.424)		(4.370)***	(2.343)**	(-0.757)			
3	0.123	0.320				-0.062	0.060	0.125
	(1.951)*	(4.445)***				(-3.209)***	(2.120)**	
4	0.120	0.320				-0.054		0.118
	(1.860)*	(4.429)***				(-3.122)***		
5	0.006	0.358					0.021	0.111
	(0.149)	(4.332)***					(1.042)	
6	0.259					-0.093		0.030
	(2.261)**					(-3.203)***		
7	0.088						-0.003	0.006
	(1.233)						(-0.149)	
8	0.256					-0.101	0.064	0.037
	(2.269)**					(-3.230)***	(2.148)**	
9	0.064		0.317	0.053	-0.042	-0.025	0.018	0.215
	(1.380)		(4.500)***	(2.300)**	(-0.790)	(-1.493)	(0.598)	
10	0.060		0.316	0.054	-0.042		-0.023	0.211
	(1.268)		(4.503)***	(2.336)**	(-0.787)		(-1.545)	
11	0.015		0.340	0.053	-0.041		0.004	0.209
	(0.440)		(4.360)***	(2.334)**	(-0.756)		(0.154)	

3.5 Summary and conclusions

Expected returns vary over time and across asset groups. The size and value premium are widely referred to market anomalies, but the precise paradigm for which they present an anomaly is far from clear. The interpretations of the relative performance across styles remain an ongoing debate in the financial literature. Rational asset pricing theory argues that style spreads are compensation for the risk, behavioural finance links style premiums to mispricing of assets groups caused by investors' irrational trading behaviour that are unrelated to fundamentals. This chapter contributes to the literature by investigating the relative importance of common risk factors and the firm-specific information in explaining the return differentials across equity styles. Understanding the relative importance of the underlying driving forces that affect the relative performance across asset classes is of obvious interest for portfolio managers and those who pursue style investing. This is because different driving forces would point to the different guidelines for investors to capitalise on the relative style performance to enhance their investment returns.

In this chapter, a set of equity characteristics PC, DY, MTBV and MV are considered to classify stocks into size, value and growth styles. The reason to use these firm characteristics is that prior studies suggest they explain significant cross-sectional variation in average stock returns, and hence at given each point in time they convey information about the expected returns relative to other stocks. Consistent with the general findings in the literature, significant size and value premiums are found in the U.K. stock market over the period of 1980:01-2004:12, which suggests the applicability to apply simple equity style investing strategies. Moreover, it is found that the size premium and value premiums tend to be more pronounced during recessionary periods, indicating that small size and value stocks perform better as compared to large stocks and growth stocks in bad economic conditions. Such better performance of value stocks in unfavourable stages in the business cycle is also consistent with prior findings in the literature.

In response to the recent popularity to link macroeconomic effects with the observed cross-sectional variation on average stock returns, this chapter follows the methodology of Chordia and Shivakumar (2002) to examine the relative importance of common risk factors and the firm-specific information in affecting stock returns across styles. A multifactor business cycle model is employed to model the expected stock returns to the response of shocks originating in a set of parsimonious economically-motivated variables. Based on the role of the predicted risk premias and the pricing errors in the observed style premiums, it is suggested that the size premium and value premiums on firm characteristics of PC and MTBV are likely related to the unpredicted component of the business cycle model. Plausibly, U.K. size premium and value premiums on PC and MTBV are not driven by the economic exogenous forces that affect stock returns over time within the business cycle. Rather, they should be related to the idiosyncratic information unrelated to business cycles that may cause investors to underreact when doing trading, which is best described in behavioural finance. However, the value premium on characteristic DY seems to represent compensation for bearing business cycle risks. The divergent returns for stocks sorted on DY is mainly driven by the predicted component from the business cycle model, and the outperformance of value stocks disappear after controlling the predicted risk premias.

The finding of different sources driving the divergent stock returns across styles characterized by PC, MTBV and DY is intriguing. The characteristic variables under consideration are price-related ratios and are associated with the variation on average stock returns. Such firm characteristics are correlated with business cycles (Fama and French (1989)), or are able to forecast economic activity (Estrella and Hardouvelis (1991), Ang *et al.* (2004)). If the multifactor business cycle model is empirically well specified, rational asset pricing argues that the evidence of style premiums would suggest that the underlying characteristics proxy for risk factors or information of mispricing. But the existence of style premiums on firm characteristics would still be consistent with traditional finance theory should the underlying characteristics associated with higher average returns are cross-sectionally correlated with risk factors. Under this condition, the style premiums still simply reflect the compensation for risk.

By examining the contemporaneous relations between characteristics, common risk factors and the mispricing from the business cycle model, This chapter finds that the pricing errors are cross-sectionally captured by exposures to other common risk factors such CAPM betas or loadings on market factor or SMB of Fama and French (1993) three-factor model. Equity characteristics of PC, MTBV and MV demonstrate no incremental explanatory ability in such mispricing. Hence the null hypothesis that MV, PC and MTBV do not proxy for risk factors or have no cross-sectional correlations with the risk factor loadings can be rejected. Overall, the empirical findings in this chapter tend to support the rational risk-based argument that equity style premiums reflect compensation for risk, although such risk may or may not directly business cycle related.

The findings in this chapter shed further light on the understanding of equity style returns and provide guidance for portfolio management in the investment practice. Investors should understand while different firm characteristics can be considered to identify value and growth stocks, the underlying mechanisms of the value premiums may be different. Although such premiums all reflect compensation of risk, stocks sharing some specific characteristics may be more vulnerable to the direct business cycle risks, while others are less directly affected by macroeconomic conditions. To capitalize on the relative style returns, active managers need to identify the underlying driving forces that determine the relative style performance. More importantly, managers need to capture the mechanisms through which those underlying forces work. In the context of style investing, if portfolios are based on characteristics that proxy for macroeconomic risks, arguably active style management should aim to timing the business cycle. In contrast, for asset allocation based on characteristics that are less directly related to the business cycle fluctuations, style management should aim to pick up stock groups that have information relate to investors' irrational behaviour in their trading process. The divergence of equity style returns evolves all the time; there is no single style or mix of styles dominating under all market states. Since timing business cycles is difficult, active portfolio management naturally aim to identify stocks that have high average returns and commove together. Perhaps due to this reason, recent studies in finance find that institutional investors follow distinct investment styles (e.g. Brown and Goetzmann (1997), Fung and Hsieh (1997), Chan *et al.* (2002)). It will be interesting to examine whether astute investors can profit from the information of equity style cycles as represented by current popular investment styles, which provides motivation for the research in Chapter 4.

Chapter 4

Equity Style Momentum Strategies

4.1 Introduction

Recent studies in finance suggest that institutional investors follow distinct investment styles (e.g. Brown and Goetzmann (1997); Fung and Hsieh (1997); Chan *et al.* (2002)). The heightened attention of investment style is driven by several motives. Armott *et al.* (1989) argue that investment style dominates equity return patterns in the investment process. Money manager's philosophy of selecting stocks trumps individual stock selection in determining overall performance. Brinson *et al.* (1986) propose that the decision of asset allocation accounts for about 90% of the variations in large pension funds. Similarly, Hansen (1992) argues that different investment styles account for approximately 60% of the performance over short and medium term. More specifically, Sharpe (1992) shows that over 90% of the superior performance of a typical equity investment fund can be attributable to its investment style, only less than 10% is due to the individual characteristics of the specific securities hold. Since assets in a typical style category share common characteristics that are generally related to the expected returns, investors are motivated to implement style investing to simplify the problem of their investment choice.

Considerable evidence suggests that both individual and institutional investors pursue style investing in stock markets. Kumar (2009) shows that U.S. individual investors demonstrate style-switching trading behaviour based on relative style performance, and such style trading behaviour is unrelated to fundamental factors or the expected stock returns. Style investing is arguably more attractive to pool investing such as investment fund mandates because agents generally manage large amount of funds but face the maze of investment opportunities given an overwhelming amount of assets available in the marketplace. Indeed, institutional investors such as pension and endowment funds generally accept substantial responsibilities and assume significant liabilities for their beneficiaries. These agents act as fiduciaries and tend to follow specific investment philosophy based on the contract that leads to a unique process of building portfolios. Style-based investing is attractive to such investors because it helps organise and simplify their portfolio construction process. By chasing specific investment style to make dynamic asset allocation decision at the style level rather than individual stock level, manager's investment practice becomes less intimidating (Barberis and Shleifer (2003)). Perhaps for this reason, popular styles like value versus growth and small versus large are widely followed in the global equity markets. On the other hand, the concept of investment style has also been utilized to help fund sponsors evaluate managers' area of expertise and help them to be more knowledgeable about how to allocate assets across funds with different investment styles. Hence, paralleling with the popularity of equity style investing and the growth of institutional investors, many style benchmarks are created to help evaluate money manager's performance with dedicated investment styles. Today, leading financial markets have witnessed the popularity of Exchange Traded Fund (ETF) based on equity styles and the introduction of style index futures contract that offer low cost and high liquidity to serve the investment community.

The time-varying nature of equity style performance is well recognised in the equity markets. For example, U.S. small size stocks earn significant larger returns during 1971-80 than between 1981-90 (Ibboston and Sinquefeld (1995)), and growth stocks perform exceptionally well but value stocks do extremely poorly despite good earnings news during 1998-99 (Chen and De Bondt (2004)). The divergence of equity style returns evolves all the time, there is no single style or mix of styles dominating under all market conditions. Such time-varying equity style return dynamics attracts investors to consider the benefit of tactical style rotations in the portfolio performance enhancement. Arguably, if style cycles exist and can last for a long duration, there is potential success for systematic tactical asset allocation strategies once investors are able to identify the turning points of the style cycles. Birch (1995) demonstrates that in principle how perfect tactic asset allocation could be implemented based on style cycle information. Other studies like Beinstein (1995), Fan (1995), Fisher *et al.* (1995), Sorensen and Lazzara (1995), Kao and Shumaker (1999), Levis and Liodakis (1999), Asness *et al.* (2000) and Lucas *et al.* (2002) explore the benefit of style rotations. However, as Chen and De Bondt (2004) point out, by and large these researches do not detail the specific trading strategies derived from the information of style cycles. The implementation of successful style rotation strategies requires that investors are able to correctly predict the potential style trends in the future. Given the yet not fully clear economic forces that underlie the divergent style returns, forecast-based active timing models often have difficulty in doing a good job. Previous studies such as Henriksson (1984), Ferson and Schadt (1996), and Chan *et al.* (2002) suggest that active money managers have neither market timing nor style timing ability.

Style momentum investing is a style-level positive feedback trading strategy based on the information of investment style evolution to buy winner styles and to sell loser styles following the past relative style performance. Unlike forecast-based timing models, the trading signal is determined by the relative style performance over the previous period of time. The strategy is adaptive in nature because the trading signal is based on information that is readily available at the end of each time period instead of a forecast procedure.

Style momentum strategy in particularly appeals to pool investing such as investment fund mandates with large amount of assets under management. As mentioned previously, managers understand the importance of investment style and are motivated to implement style investing to simplify their asset allocation problems. It is recognised that although managers have good reason to explicitly designate style exposures for their fund products, they face strong incentives to chase current in-favour investment styles to attract fund inflows for better compensation. Although some studies such as Davis (2001) find that mutual funds are unable to generate persistent abnormal returns, as Chen and De Bondt (2004) observe empirical evidence suggests a positive linkage between fund performance and money flows. For example, Sirri and Tufano (1998) and Jain and Wu (2000) document that mutual fund investors base their purchase decisions on the underlying fund's prior performance information. Equity mutual funds that show continued historical good performance attract more money into the funds. Cooper *et al.* (2005) argue that some funds even change their names to chase current in-favour investment styles, and such name changes appear to stop the money outflow. Other studies such as Choe *et al.* (1999) and Froot *et al.* (2001) also show that foreign institutional investors tend to buy into countries with good recent stock market performance. It is found that manager's incentive to chase in-favour styles can result in what is called the style drifts in the investment practice. DiBartolomeo and Witkowski (1997) argue that during the 1990s many equity funds in the U.S. markets are mislabelled because their return patterns do not match what would have been suggested by the investment styles described in their fund prospectus. The popularity of style investing and investors' style chasing behaviour is perhaps best described by Barberis and Shleifer (2003) in the behavioural finance framework.

The theoretical style investing model of Barberis and Shleifer (2003) proposes that investors chase a particular style with higher relative returns in a market with positive feedback style-level investors (switchers) and fundamental traders (arbitrageurs), The trading behaviour of style-chasing investors would bid stock prices away from fundamentals and subsequently prices revert to fair value. Thus the style-switching trading behaviour plays an important role in the return generating process and affects the cross-sectional variations of stock returns. Hence the evolution of equity style cycles conveys useful information in predicting future stock returns.

The style investing model of Barberis and Shleifer (2003) predicts some interesting and empirically testable results. One of which is that style-level momentum strategy is profitable. A growing number of studies have provided evidence that is consistent with the predictions of Barberis and Shleifer (2003). For example, on country level, Chan *et al.* (2000) find significant excess momentum returns for a sample of 38 countries as well as a subsample of 16 developed countries, indicating that momentum exists if treating country as investable assets[16]. Haugen and Baker (1996) track returns on a number of investment styles and show that a strategy that tilts to styles with relative good performance could earn higher risk-adjusted returns. Moskowitz and Grinblatt (1999) and O'Neal (2000) show the evidence of momentum strategies based on the industry categorisation. They also assert that a large portion of individual price momentum of Jegadeesh and Titman (1993) is attributed to the industry momentum effect[17] . Lewellen (2002) examines the momentum strategies based on the sorting of industry, size and book-to-market ratios (BM). The author finds that the well-diversified size and BM portfolios exhibit momentum effect as strong as the individual price and industry momentum. Chordia and Shivakumar (2002) also find significant industry momentum and Swinkels (2002) finds evidence for the industry momentum in Europe. Using weekly data, Pan *et al.* (2004) find industry momentum generates significant profits for short horizons of less than 4 weeks. More closely relates to this chapter, Chen (2003) investigates the profitability of momentum strategies based on firm characteristics of market value (MV), BM and dividend-yields (DY). It is found that a hedged strategy of buying past winner characteristic portfolio and selling past loser characteristic portfolio yields 0.782% per month in the following three months after portfolio formation. Such profits are distinct from price and industry momentum. Moreover, Chen and De Bondt (2004) uncover evidence of

[16] Richard (1997) investigates momentum and contrarian strategies at the country index level. The author finds that the momentum return of 0.57% per month at the 6-month holding period but it is not statistically significant. Asness et al. (1997) also successfully apply momentum strategy for country portfolios. The findings of Bhojraj and Swaminathan (2001) are qualitatively consistent with the results of Chan *et al.* (2000).

[17] Several other studies have come to different conclusions. For example, Grundy and Martin (2001) argue that price and industry momentum are two separate phenomena.

style momentum effect within S&P-500 index. Their study covers all firms within the S&P-500 index since 1976 and finds that winner style continues to outperform loser style for periods up to 12 months or probably longer, and style momentum is a unique phenomenon that is different from price and industry momentum documented in the literature.

Chapter 4 is motived by the dynamic U.K. relative equity style returns found in Chapter 3 and the potential success of systematic active style rotation strategies documented in the context of U.S. market data in the literature. This chapter builds on the methodology in papers of Chen (2003), and Chen and De Bondt (2004) to test the characteristic-based equity style momentum strategies in the U.K. stock market. It is recognised that so far there are very limited relevant research for the U.K. market in the current literature. Chapter 4 therefore contributes to the literature by offering comparison test results in a different institutional and market environment relative to the U.S. data. The objective of Chapter 4 is to answer the following questions:

1) Do equity style cycles exist in the U.K. stock market?
2) If style cycles do exist, can investors profit from the information of style cycles?
3) Are the return patterns of equity style momentum investing unique? Namely, is style momentum effect distinct from price momentum of Jegadeesh and Titman (1993) and industry momentum of Moskowitz and Grinblatt (1999) documented in the literature?

To pursue these questions, during sample period of 1980-2003 and on the annual basis, all U.K. non-financial stocks with meaningful firm characteristics of PC, BM and DY are partitioned alone two dimensions of the market value and the value-growth axis. For each characteristic this two-way independent sorting yields 9 style portfolios for the style momentum strategy. The 9 style portfolios are ranked according to their previous 3- to 12-month returns. The empirical results in this chapter suggest that stocks in current in-favour (winner) styles continue to outperform those in out-of-favour (loser) styles for periods up to 12 months or possibly longer. Specifically, a monthly average return differential between the extreme styles for (3, 3) PC-based style portfolios is 0.48%, and the spreads for BM- and PC-based style portfolios are 0.57% and 0.74%, respectively.[18] In contrast, a typical (12, 6) strategy yields average monthly profit of 0.62%, 0.27% and 0.62% for PC-, BM- and DY-based portfolios, respectively. Style momentum payoffs generally increase with longer ranking periods and decrease with longer test periods, suggesting that the outperformance of winner styles are more persistent once more information is added in the ranking period. However, style spreads reverse at longer horizon.

While Chapter 4 documents the profitability of style momentum strategies in the U.K. market, one may argue that such profit is simply the miracle of price momentum of Jegadeesh and Titman (1993) or industry momentum documented by Moskowitz and Grinblatt (1999). This is because stocks in current in-favour (out-of-favour) styles may also be categorised into the winner (loser) portfolios based on past individual stock returns, or winner (loser) industries according to the industry performance. Thus the style continuations observed may be due to a concentration of winner (loser) stocks within winner (loser)

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[18] A (J, K) style momentum strategy means that style portfolios are ranked according to past J-month performance and then the strategy is tested for the following K months period.

styles whose returns persist in test periods. To disentangle the style, price and industry momentum effects, three methods are applied. First, style momentum payoffs are recalculated after adjusting for the price or industry momentum effects on individual stock level. Next, a two-way independent sorting is used to avoid the problems criticised by Berk (2000) when distinguishing the explanatory ability for future returns from two variables that are perceived to be correlated. Finally, monthly Fama-MecBeth (1973) cross-sectional regressions are fitted to examine the explanatory power of three momentum effects. The results suggest that, consistent with the literature, style momentum has strong independent explanatory power for the future individual stock returns, and style momentum is distinct from price and industry momentum.

The profitability of style momentum poses challenge to traditional financial theories based on rational agents and frictionless markets. Conventional risk-based approach such as Fama and French (1993) three-factor model does not capture all the variations in the returns of firm characteristic-based style momentum in this study. It is shown that differences in market risk (betas) of long and short side of the hedge portfolios do not cause style momentum profits. The three-factor model appears to strengthen, rather than explain, the style momentum returns. The intercept of the regression suggests that risk-adjusted return differentials between the winner and loser styles are in some cases larger than raw return spreads, and controlling for the factors exposures can actually increase style momentum returns. Based on this, it is argued that from a conventional risk-adjusted sense, style momentum strategy may not be necessary risky.

The structure of Chapter 4 is organised as follows. The next section discusses the theoretical framework for momentum strategy. Section 3 describes the sample data and methodology. Section 4 explains the characteristics of equity style portfolios based on firm attributes PC, BM and DY. Section 5 reports the payoffs of style momentum strategy. Section 6 analyses the interaction of style, price and industry momentum and examine whether style momentum is distinct from price and industry momentum. Section 7 evaluates the performance of style momentum trading using Fama and French (1993) three-factor models. Finally, section 8 summaries and concludes.

4.2 General framework of momentum trading

It is useful to first begin with a general framework to understand the nature of the risks and the source of the rewards to momentum investing on individual stock level. The momentum effect is typically defined as a positive relation between the return of the underlying stock in a certain period of time with its lagged return, both relative to cross-sectional sample average returns. Mathematically, momentum exists if

$$E[\frac{1}{N}\sum_{i=1}^{N}(r_{i,t-1}-r_{m,t-1})(r_{i,t}-r_{m,t})]>0 \qquad (1)$$

where $r_{i,t}$ is the return of stock i in period t, $r_{m,t}$ is the average return of the sample and N is the number of stocks in the sample.

A momentum strategy based on individual stocks ranks stocks according to their past returns. There are several research methods in the literature aiming to capture the momentum effect but they differ somewhat in their implementations, and hence may affect the empirical outcomes. Papers such as Jegadeesh and Titman (1993) use the decile-based method to include only top (bottom) 10% of the stocks in the ranking on past returns from the winner (loser) portfolio in the analysis. The advantage of using decile strategy is that portfolio weights of the stocks are equal for both top and bottom performers, thus extreme weighting schemes are excluded. Arguably the decile-based strategy is more consistent with the concept of style investing because style-based investors make asset allocations along style level instead of individual stocks level. Hence they do not distinguish between stocks in the style regarding the weightings.

Studies such as Lo and MacKinlay (1990) use a different approach often referred as WRSS to detect momentum effect. Analogue of Equation (1), the zero-investment hedge portfolio longs stocks that outperform the sample mean and financed by the short positions of stocks that underperform relative to the sample average. The portfolio weights of WRSS depend linearly on the absolute value of deviations of the stock's return from the cross-sectional mean, and momentum effect can be estimated by calculating the excess portfolio returns based on time-series stock returns. The average excess return of s WRSS strategy is

$$\frac{1}{T}\sum_{i=1}^{N} R_{p,t}^{e} = \frac{1}{TN}\sum_{t=1}^{T}\sum_{i=1}^{N} w_{i,t-1}(r_{i,t} - r_{m,t}) \tag{2}$$

$$w_{i,t-1} = \frac{1}{N}(r_{i,t-1} - r_{m,t-1}) \tag{3}$$

The WRSS strategy invests most in the stocks with the most extreme performance, capturing the belief that extreme price movements are often followed by extreme movements. Despite the smooth weighting patters, WRSS could potentially lead to long and short positions that contain only smallest stocks listed, resulting in large idiosyncratic components in the momentum portfolios.

This chapter uses the decile-based strategy throughout the analysis but the following discussion is based on WRSS scheme. Prior studies suggest that the two methods yield empirical outcomes that are highly correlated. For example, Jegadeesh and Titman (1993) note that the correlation between the momentum effect based on their decile scheme and that of WRSS strategy is 0.95. Unlike the decile-based strategy, the WRSS weighting scheme in Equation (3) can be conveniently used to decompose the profit of momentum trading strategy, and hence provides useful insight in the understanding of the mechanism of style momentum strategy.

In the context of WRSS, consider an economy containing 2N stocks for simplicity and assume investors buy or sell stocks at time t based on their performance from time *t-2* to *t-1*. Assume that the performance of a stock *i* is determined relative to the average performance of all stocks in the sample. Following Lehmann (1990), Lo and MacKinlay (1990), the expected return of the stock-level momentum strategy in the next period *t+1* is given by

$$\begin{aligned}
&E[\sum_{i=1}^{2N} w_{i,t} r_{i,t+1}] \\
&= \frac{1}{2N}[E\sum_{i=1}^{2N}(r_{i,t} - r_{m,t}) r_{i,t+1}] \\
&= \frac{1}{2N}\sum_{i=1}^{2N} E(r_{i,t} r_{i,t+1}) - \frac{1}{4N^2}\sum_{i,j=1}^{2N} E(r_{i,j} r_{j,t+1}) \\
&= \frac{1}{2N}\sum_{i=1}^{2N} Cov(r_{i,t}, r_{i,t+1}) - \frac{1}{4N^2}\sum_{i,j=1}^{2N} Cov(r_{i,t}, r_{j,t+1}) + \frac{1}{2N}\sum_{i=1}^{2N}(\mu_i - \mu_m)^2
\end{aligned} \tag{4}$$

where μ_i is the unconditional expected return of stock i and μ_m is the mean return (unconditional) of the market portfolio containing N stocks.

Equation (4) suggests that the stock-level momentum profit may be driven by three factors: the serial correlation of the underlying stock i, the serial (cross) correlations between stock i and its peers, and the cross-sectional dispersion in unconditional expected returns. There is no general consensus as which factor dominants because different papers assume different assumptions to stock price dynamics and in turn the return generating process. For example, Conrad and Kaul (1998) assume a random walk with drift for stock price. The authors provide empirical evidence to hypothesise that the dispersion in unconditional expected stock returns explains momentum profit. However, Jegadeesh and Titman (2001) show that such hypothesis would imply that momentum returns should increase linearly with the length of the test period, which is unlikely the case. Jegadeesh and Titman (1993) assume that stocks can be priced by a single factor model, based on their decomposition that is similar to Equation (4), they conclude that autocorrelation in idiosyncratic returns drives the momentum effect. More recently, studies like Moskowitz and Grinblatt (1999), Lewellen (2002), Chan *et al.* (2000), Bhojraj and Swaminathan (2001) and Nijman *et al.* (2004) either assume multifactor models to explain the cross-section of stock returns, or relax the assumption for the return generating process to investigate the underlying driving forces that affect momentum returns.

In the behavioural model of Barberis and Shleifer (2003), style-based investors (switchers) are assumed to allocate their funds at style level, and the amount of fund they allocate to that style is determined by the underlying style's relative performance to others. Barberis and Shleifer (2003) propose that, in the presence of switchers, Equation (4) is strictly positive (Proposition 6, p195), suggesting that stock-level momentum is profitable.

Now consider style-level momentum. Suppose that all 2N stocks can be grouped into 2 styles, X and Y, for a given firm characteristic. It should suffice to consider only 2 styles here because as Barberis and Shleifer (2003) argue many styles come in natural pairs. Stocks with high firm attributes constitute one style, while those with low values form the twin. Small size stocks versus large-cap stocks and value stocks versus growth stocks are typical examples of twin styles. Assume further that each style has N stocks and each stock belongs to one and only one of the 2 styles. A style momentum strategy buys style with good performance and sells style that perform poorly. Following Barberis and Shleifer (2003), the weights of stocks in the long-short hedge portfolio are

$$w_{i,t} = \frac{1}{4N}(R_{X,t} - R_{Y,t}), i \in Y \tag{5}$$

$$w_{j,t} = \frac{1}{4N}(R_{Y,t} - R_{X,t}), j \in Y \tag{6}$$

where $R_{X,t}$ and $R_{Y,t}$ is the return of style X and Y in period t, respectively. The expected return of a style momentum strategy is therefore given by

$$
\begin{aligned}
&E(\sum_{i=1}^{N} w_{i,t} r_{i,t+1} + \sum_{j=N+1}^{2N} w_{j,t} r_{j,t+1}) \\
&= E[\sum_{i=1}^{N} \frac{1}{4N} (R_{X,t} - R_{Y,t}) r_{i,t+1} + \sum_{j=N+1}^{2N} \frac{1}{4N} (R_{Y,t+1} - R_{X,t+1}) r_{j,t+1}] \\
&= \frac{1}{4} E[(R_{X,t} - R_{Y,t})(R_{X,t+1} - R_{Y,t+1})]
\end{aligned} \tag{7}
$$

This is equal to the expected return of the stock-level momentum.

4.3 Data descriptions and methodology

The empirical test in this chapter uses all stocks in the U.K. stock market. Previous related studies such as Lewellen (2002), Chen (2003), and Chen and De Bondt (2004) mainly focus on the U.S. data in their analysis. However as at the time of writing there are so far no studies in the literature to investigate whether the general findings of prior studies also apply in developed markets like the U.K. based on all the stocks in the market[19]. Hence Chapter 5 provides useful insight in the understanding of the style-level strategy based on data set outside the U.S. in a different market and institutional environment.

In this study, monthly U.K. stock prices and equity characteristic information are collected from *Thomson Financial Datastream* over the sample period of January 1980 to December 2003. Similar to Chapter 3, the equity characteristic variables used to categorise stocks into

[19] Aarts and Lehnert (2005) also test the style momentum strategy in the U.K. market, but their sample is based on ftse 300 Index and therefore provides less insight as whether there is style momentum effect in the U.K. stock market given a small sample size. Clare et al. (2010) also test the U.K. style momentum, but they use ftse 350 Growth Index and the ftse 350 Value Index as proxies for the growth stocks and the values stocks, and ftse100 and ftse small-cap Index to proxy for the large-cap and the small-cap stocks, respectively.

different style portfolios are price-to-cashflow ratios (PC), book-to-market ratios (BM), dividend-yields (DY) and market value (MV)[20] .The use of these firm attributes to identify styles is partly justified by Kothari and Shanken (1997), Chan *et al.* (1998), and Berk *et al.* (1999). Kothari and Shanken (1997) find that both BM and DY track the time-series of expected stock returns in 1926-1991. Chan *et al.* (1998) assert that MV, BM and DY are most important fundamental variables. Berk *et al.* (1999) argue that firm-specific characteristics relate to the underlying state variables that determine firm's systematic risk and expected returns. Hence firms with the same characteristics tend to have the same underlying pervasive forces affecting stock returns, implying that equity style portfolios based on such characteristics could price individual stock returns. This chapter forms value and growth portfolios based on research variable PC, BM and DY. The reason for the use of these variables for a broad value-growth style momentum is to test its robustness.

At the end of December each year, all U.K. stocks are divided into 2 parts based on one firm characteristic value X (X = PC, BM, DY, respectively). Stocks in Part 1 all have X > 0 and stocks in Part 2 all have X <= 0. Only stocks denominated by local currency (£) are included in the analysis and those denominated by foreign currencies are excluded from the sample. Following the literature, stocks that belong to financial sectors are also excluded because their firm attributes do not have the same meanings as non-financial stocks do (Fama and French (1996)). Since the style variables used in this study are price-related ratios that relate to cash flow news, stocks in Part 2 (named as P10) are NOT studied as these stocks either do not have

[20] The definition of these variables can be seen in Chapter 3.

meaningful firm attribute values, or simply do not have such data in data source at hand. Therefore only stocks in Part 1 are covered throughout the study in this Chapter. For each firm characteristic variable, all stocks in Part 1 are ranked independently by their end-of-year MV and X in ascending order and are further allocated to 3 equal-sized MV and 3 equal-sized X groups, resulting 9 (intersection) style portfolios (P1-P9). Firms with share price <= £1 at the time of portfolio formation are excluded to avoid the influence of extreme price movements in low price stocks.[21] After style portfolio formation at the end of each year, the style category of a stock belongs to (i.e. P1-P9) is fixed for the next 12 months, regardless whether the firm's characteristic value X changed in the following year. If a firm is delisted during a year, the proceeds from the sale of the stock are invested equally in other firms in the portfolio. Hence there is no survival-bias in the sample and in essence the style portfolios are rebalanced annually.

Figure 4-1 Equity style investing box

MV				
Large-cap	**P9**	**P8**	**P7**	
Mid-cap	**P6**	**P5**	**P4**	
Small-cap	**P3**	**P2**	**P1**	PC
	Value	Blend	Growth	

MV				
Large-cap	**P7**	**P8**	**P9**	
Mid-cap	**P4**	**P5**	**P6**	
Small-cap	**P1**	**P2**	**P3**	BM, DY
	Growth	Blend	Value	

Figure 4-1 illustrates 9 style portfolios based on independent two-way

[21] Chen and De Bondt (2004) only test BM based style portfolios and their P10 group is for those do not have DY values. They also exclude stocks with price < $1. It is noteworthy that by construction the number of stocks in each style portfolio P1-P9 is not identical.

sorting of the size and value-growth dimensions. These portfolios are small-cap growth (SG), small-cap blend (SB), small-cap value (SV), mid-cap growth (MG), mid-cap blend (MB), mid-cap value (MV), large-cap growth (LG), large-cap blend (LB) and large-cap value (LV). These style portfolios are consistent with the investment style concept widely applied by practitioners in the market. For example, the Morningstar style classification system categorises investment funds into small, mid-cap, large size, or growth, blend and value. The interaction of these styles forms 9 cells in the style box. Morningstar style definition is widely followed as many funds name their products after the Morningstar style analogue. Some style benchmarks such as S&P/BARRA indexes, S&P 500, Mid-Cap 400, and Small-Cap 600 are also sorted by BM to create additional style indexes such as S&P 500 Growth, S&P 500 Value, Mid-Cap 400 Growth, Mid-Cap 400 Value, Small-Cap 600 Growth, and Small-Cap 600 Value. It is noteworthy that the style portfolio created here are also implemental in market practice[22].

4.4 Characteristics of equity style portfolios

Table 4-1 characterises the 9 style portfolios. For comparison purpose, statistics for stocks in Part 2 (named as P10) are also displayed. The sample size based on PC, BM and DY sorting is different because not all stocks have all available data for these variables.

[22] One may be concerned with the availability of the company characteristic values at the end of each December since firms release their financial reports on a quarterly or semi-annually basis. Institutional investors generally do their investment research based on proprietary or outsourced database and information in such database is updated timely to reflect the firm’s latest financial status.

It is suggested that the firm characteristics of most style portfolios (P1-P9) vary dramatically over time. From 1980 to 2000, the average PC ratio of SG and MG style portfolios (based on PC, hereafter SG-PC, MG-PC and etc.) increases and peaks in year 2000. Coincidentally, the average BM ratios for stocks in BM-based portfolios and the average DY ratios for stocks in DY-based portfolios tend to demonstrate a decline trend before 2000. At the end of 2003, LG companies have an average PC ratio 29.76, BM ratios 0.21 and DY 1.65, while stocks in SV portfolios have average PC, BM and DY ratios of 4.39, 1.96 and 10.34, respectively. The statistics represents the cross-sectional average percentile rank of 85%, 36% and 18% based on PC, BM and DY respectively for LG portfolios, and 43%, 78% and 83% for SV portfolios in 2003. It is noted that the PC ratios are more influenced by the size of the stock than BM and DY ratios do. For example, the average PC ratios are much higher for stocks in SG than in LG from 1980 to 2003, while the ratios of BM and DY are less volatile for the two style portfolios. Thus suggests that PC portfolios may demonstrate more size effects.

At the end of 2003, LG-PC, LG-BM and LG-DY style portfolios have average market value around £3.16 billion, £2.50 billion and £ 4.19 billion, respectively. In contrast, the average market value of SV-PC, SV-BM and SV-DY portfolios are only £11.1 million, £6.3 million and £17.1 million, respectively. Table 4-1 also reports the statistics based on 5-year interval from 1980 to 2000 and the average percentile rank of stocks in each style portfolio. As of end of year 2003, the average stocks in LG-PC, LG-BM and LG-DY style portfolios are larger in size than 85%, 82% and 89% of all stocks respectively in the market; this is in contrast to the rank of 95%, 95% and 78% respectively in year-end 1980. Meanwhile, stocks in the SV-PC, SV-BM and SV-DY portfolios are larger in size than 22%, 15% and 29% other stocks in end of year 2003, while the statistics is 55%, 52% and 9% in 1980, respectively.

Table 4-1 also presents the time-series average market value of each style portfolio relative to the cumulated value of all stocks. It shows that the data vary dramatically over time. At the end of 2003, for company attribute PC, large-cap stocks tend to be sorted into large blend portfolio (LB, P8) followed by large growth styles (LG, P9). The average market value of LB-PC and LG-PC portfolios represent 47% and 24% of the market value of all stocks. On the other hand, stocks sorted on BM are biased to LG and LB portfolios. LG-BM and LB-BM style portfolios count for 37% and 29% of the market value, respectively. As for characteristic value DY, similar to PC sorting, stocks tend to be classified into LB and LG portfolios and they represent 40% and 28% of the market value of all stocks, respectively.

Interestingly, there seems to be a trend that over time more and more stocks become growth-oriented based on PC and BM sorting from 1980 to 2000. Large growth portfolios defined by PC, BM and DY all dominant in terms of the size as a fraction of the summed value of all stocks in the market, partly reflecting the peak of the bubble for growth stocks in year 1999-2000. This is also evidenced by the extreme variations in average PC ratios for stocks in SG-PC (564.28) and MG-PC (278.12) portfolios in year 2000.

Table 4-2 documents the average monthly performance of passive style portfolio (P1-P9) based on PC, BM and DY during January 1980 to December 2003. For comparison purpose, stocks in Part 2 are treated a portfolio named P10. All returns are calculated using value weighted schemes. It can be seen that the sample sizes are different since not all stocks have all firm characteristic data in the database. Hence, the time-series average number of stocks in P1-P9 portfolios is 810, 926 and 1283 based on PC, BM and DY sorting, respectively. Correspondingly, the average number of stocks assigned to P10 is 830, 715 and 356. Hence all style portfolios are fully diversified in general sense.

Consistent with previous studies such as Gregory *et al.* (2001) for U.K. market data, equity style portfolios demonstrate strong divergent return patterns. In general, value style portfolios earn higher returns than growth portfolios regardless how value and growth style is defined, and returns are lower for large-cap stocks. But the magnitude of value premium varies depending on different style descriptors. It is also evident that stocks perform exceptionally better in January (except for LG portfolios). Moreover, amongst P1-P9 styles based on different firm characteristic variables, small value portfolios are found to have performed best and large growth portfolios done worst in 2 out of 3 outcomes. For example, SV-PC style earns average monthly returns of 2.5%, and that for SV-BM and SV-DY is 1.92% and 1.65% respectively. This is in sharp contrast to returns of 0.74% (LG-PC), 0.86% (LG-BM) and 0.68% (LG-DY). It is noted that along the size dimension for PC- and BM-based styles, the average spread between small and large size value portfolios are larger than that between growth portfolios of different size. But it is opposite for styles based on DY, which suggests that along the size dimension the return spread between growth portfolios is larger than that of value portfolios.

While SV portfolios generally earn highest returns, the reported time-series standard deviations would suggest that such portfolios are not necessarily the most risky ones. On the other hand, although LG portfolios have lowest returns, they are not necessarily less volatile. For example, the time-series volatility for SV-PC, SV-BM and SV-DY is 5.25%, 5.09% and 4.72%, respectively, as compared to that of 5.09% (LG-PC), 4.96% (LG-BM) and 5.06% (LG-DY).

Table 4-2 also reports the time-series average cross-sectional standard deviation of returns for stocks within each style portfolio. Chen and De Bondt (2004) argue that this statistics represents a measure of "stock-picker's risk". The results in Table 4-2 for P1-P9 suggests that on average the returns offered by individual stocks in SG-PC, SG-BM and SV-DY are much wider than those in LB-PC, LB-BM and LB-DY portfolios. Moreover, the statistics is larger for SV portfolios than LG portfolios regardless which style variables used, indicating that stocks in SV portfolios have higher cross-sectional volatility than stocks in LG styles. Besides, P10 stocks have shown to have the widest cross-sectional variation in returns.

Figure 4-2 illustrates the time-series variations in the annual returns for SV and LG style portfolios based on PC, BM and DY. The returns are calculated in the same way as in Table 4-2 but are annualised. Figure 4-2 shows both the qualitative and quantitative similarity for the return patterns of value and growth styles based on different style variables. Figure 4-3 presents the dynamics of annual value and growth style returns and the value premium. The value (growth) style returns are calculated as the average of SV (SG), MV (MG) and LV (LG) portfolio returns, and the value premium is the spread between value and growth returns. Similarly, the small-cap premiums are calculated as the return spread between small size portfolios and the large size portfolios, which are the average of SG (LG), SB (LB) and SV (LV), respectively. Figure 4-3 suggests that indeed in the long-term value stocks beats growth stocks although there are short periods that the two style returns reversal. This also applies to small-cap stocks that exhibit long-term better performance relative to large-caps. It is evident that a combination of the two style effects seems to be able to yield an even larger style premium, namely, the return spread between SV and LG styles seems to have larger upper side spread but not necessarily larger downside reversals. These results are consistent with the empirical studies regarding the size effect in the literature. For example, Hoeowitz *et al.* (2000a) document that the observed size premium is not linear across all stocks but is concentrated only in smaller firms. Likewise, Fama and French (2008) observe that the size premium is the strongest among U.S. tiny firms based on data from 1963-2005. Fama and French (2012) also find that value premiums differ across size dimension, specifically, value premiums decrease with size.

Overall, the empirical findings in Table 4-2 and Figure 4-2, 4-3 are consistent with recent study of Berk *et al.* (1999). Berk *et al.* (1999) argue that the same firm characteristics tend to have the same state variables affecting the systematic risks and expected returns. If styles capture the underlying driving forces that determine the asset returns, style portfolio should have explanatory ability in predicting individual returns, and the cross-sectional dispersion of systematic risks across all stocks within a style is lower. The results in this section suggests that firm attributes PC, BM and DY capture the basic economic driving forces that describe the asset return dynamics.

Table 4-1 Characteristics of equity style investing portfolios

9 style portfolios are formed at the end of each year between 1980 and 2003. All stocks that do not have positive characteristic value X (X = PC, BM, DY) or do not have X data are assigned to portfolio 10. The remaining stocks are independently ranked according to market value (MV) and characteristic X. Portfolio P1-P9 represents 9 MV-X portfolios as the intersections of 3 MV-based and 3 X-based groups. This table reports average market values (in £ million) and firm attribute value X every five years over the period of 1980 to 2003. The cross-sectional average percentile rank of the stocks in each portfolio and the time-series average market value of each style portfolio as a percentage of the cumulated value of all stocks in the P1-P9 are displayed.

		PC						BM						DY					
Style	Year	1980	1985	1990	1995	2000	2003	1980	1985	1990	1995	2000	2003	1980	1985	1990	1995	2000	2003
P1 Small Growth	Average style variable values	17.72	27.76	34.65	41.97	564.28	74.12	0.66	0.32	0.32	0.22	0.2	0.2	3.3	2.03	2.92	1.76	1.38	1.61
	cross-sectional average percentile rank	0.85	0.84	0.86	0.87	0.86	0.88	0.24	0.2	0.3	0.34	0.27	0.36	0.19	0.18	0.18	0.17	0.16	0.17
	Market value	17.6	33.63	6.41	11.82	11.37	11.7	19.69	32.79	5.76	13.31	10.5	7.69	1.45	3.96	5.31	11.68	13.33	22.58
	cross-sectional average percentile rank	0.56	0.57	0.2	0.19	0.2	0.23	0.62	0.6	0.18	0.21	0.19	0.18	0.11	0.16	0.17	0.19	0.23	0.35
	% of value of all stocks	0.21	0.22	0.12	0.1	0.05	0.11	0.18	0.26	0.07	0.08	0.06	0.08	0.15	0.12	0.11	0.12	0.05	0.13
P2 Small Blend	Average style variable values	4.62	6.7	6.42	8.88	8.8	9.1	1.41	0.68	0.85	0.52	0.57	0.55	7.19	4.29	6.09	3.69	3.68	3.49
	cross-sectional average percentile rank	0.53	0.47	0.52	0.52	0.63	0.64	0.59	0.46	0.55	0.48	0.44	0.5	0.47	0.45	0.45	0.45	0.45	0.47
	Market value	21.42	31.2	6.94	14.17	15.25	12.79	16.02	31.59	5.6	13.53	9.27	7.84	1.45	4.22	5.9	14.16	13.28	20.82
	cross-sectional average percentile rank	0.62	0.59	0.21	0.22	0.24	0.25	0.55	0.6	0.18	0.22	0.17	0.18	0.11	0.18	0.19	0.22	0.22	0.33
	% of value of all stocks	0.32	0.3	0.08	0.14	0.11	0.09	0.19	0.22	0.09	0.15	0.08	0.07	0.17	0.15	0.11	0.2	0.09	0.12
P3 Small Value	Average style variable values	2.46	3.68	3.25	4.92	4	4.39	4.06	3.07	1.89	1.29	1.71	1.96	14.16	8.55	15.22	20.77	9.12	10.34
	cross-sectional average percentile rank	0.23	0.18	0.28	0.27	0.43	0.43	0.86	0.79	0.81	0.74	0.78	0.78	0.81	0.8	0.82	0.78	0.81	0.83
	Market value	16.68	24.87	6.6	12.21	12.71	11.13	14.93	22.91	4.89	10.15	8.34	6.33	1.3	3.56	5.25	12.54	13.79	17.1
	cross-sectional average percentile rank	0.55	0.52	0.2	0.2	0.21	0.22	0.52	0.5	0.15	0.17	0.15	0.15	0.09	0.15	0.17	0.2	0.22	0.29
	% of value of all stocks	0.34	0.37	0.16	0.23	0.12	0.11	0.44	0.36	0.15	0.22	0.13	0.11	0.22	0.18	0.18	0.22	0.12	0.14
P4 Middle Growth	Average style variable values	15.18	15.89	35.72	21.55	278.12	169.13	0.61	0.3	0.37	0.21	0.19	0.22	3.14	1.92	3.15	1.86	1.33	1.62
	cross-sectional average percentile rank	0.84	0.83	0.81	0.8	0.86	0.87	0.21	0.19	0.33	0.33	0.26	0.36	0.17	0.17	0.19	0.18	0.16	0.17
	Market value	73.64	112.66	33.54	76.59	101.11	84.35	63.87	108.18	30.13	73.29	61.36	47.54	7.48	18.33	31.82	74.09	113.44	127.4
	cross-sectional average percentile rank	0.82	0.78	0.51	0.56	0.59	0.59	0.8	0.77	0.49	0.55	0.5	0.49	0.39	0.47	0.5	0.55	0.61	0.66
	% of value of all stocks	1.2	1.32	0.51	0.94	0.74	0.8	1.26	1.19	0.58	1.15	0.62	0.53	0.95	0.74	0.74	1.15	0.77	0.96

Table 4-1 (continued)

Style	Year	PC						BM						DY					
		1980	1985	1990	1995	2000	2003	1980	1985	1990	1995	2000	2003	1980	1985	1990	1995	2000	2003
P5 Middle Blend	Average style variable values	4.59	7.2	6.53	9.05	9.16	9.17	1.41	0.66	0.79	0.49	0.55	0.56	7.09	4.16	6.12	3.67	3.74	3.49
	cross-sectional average percentile rank	0.53	0.52	0.53	0.53	0.64	0.65	0.6	0.45	0.53	0.47	0.43	0.51	0.47	0.44	0.46	0.45	0.45	0.47
	Market value	73.8	111.7	36.45	73.3	92.07	86.49	65.73	110.3	27.64	67.88	63.64	47.96	6.61	19.21	29.74	71.97	103.35	141.58
	cross-sectional average percentile rank	0.82	0.78	0.53	0.55	0.57	0.59	0.8	0.78	0.48	0.53	0.51	0.49	0.37	0.48	0.49	0.54	0.59	0.67
	% of value of all stocks	1.51	1.2	0.76	1.01	0.58	0.75	1.25	1.32	0.59	0.93	0.61	0.63	0.85	0.75	0.77	1.05	0.53	0.93
P6 Middle Value	Average style variable values	2.63	4.22	3.64	5.56	4.28	4.83	2.39	1.12	1.7	1.15	1.27	1.16	13.44	7.67	11.63	6.99	7.86	11.05
	cross-sectional average percentile rank	0.25	0.22	0.31	0.31	0.44	0.44	0.82	0.71	0.78	0.72	0.71	0.72	0.78	0.75	0.77	0.75	0.79	0.78
	Market value	78.97	104.11	32.41	64.38	81.92	82.59	71.55	91.17	25.62	57.67	51.04	43.11	6.17	17.18	28.9	68.64	86.34	123.22
	cross-sectional average percentile rank	0.82	0.77	0.51	0.52	0.55	0.59	0.81	0.75	0.46	0.5	0.47	0.47	0.35	0.45	0.48	0.53	0.56	0.65
	% of value of all stocks	0.95	0.94	0.57	0.68	0.64	0.73	0.91	0.69	0.49	0.55	0.51	0.49	0.81	0.64	0.72	0.83	0.62	0.77
P7 Large Growth	Average style variable values	32.07	16.06	19.44	18.71	41.2	29.76	0.59	0.34	0.37	0.21	0.17	0.21	3.01	1.94	2.98	1.81	1.23	1.65
	cross-sectional average percentile rank	0.83	0.82	0.79	0.81	0.88	0.85	0.21	0.21	0.33	0.33	0.26	0.36	0.17	0.17	0.18	0.18	0.15	0.18
	Market value	602.11	988.6	910.76	1447.6	5443	3157.9	762.95	1261.5	875.22	1597.3	2897.7	2504.8	270.97	975.94	1459.2	2210.8	6133.1	4193.2
	cross-sectional average percentile rank	0.95	0.92	0.82	0.83	0.87	0.85	0.95	0.92	0.81	0.82	0.82	0.82	0.78	0.82	0.83	0.85	0.88	0.89
	% of value of all stocks	11.48	12.78	18.72	22.98	50.67	24.18	16.7	14.77	23.71	27.64	40.94	36.6	42.87	44.28	42.55	35.1	51.03	28.42
P8 Large Blend	Average style variable values	4.51	7.18	6.86	9.2	8.79	9.17	1.41	0.67	0.78	0.48	0.52	0.53	6.8	4.18	6.13	3.58	3.73	3.5
	cross-sectional average percentile rank	0.52	0.51	0.55	0.54	0.63	0.65	0.59	0.45	0.52	0.46	0.42	0.49	0.45	0.44	0.46	0.43	0.45	0.47
	Market value	302.24	882.01	868.96	1663.8	3620.2	4303.7	361.79	968.87	810.01	1865	2587.3	2115.6	275.54	600.57	1220.3	2502.1	4376.3	5136.6
	cross-sectional average percentile rank	0.93	0.92	0.83	0.85	0.87	0.88	0.93	0.91	0.8	0.84	0.83	0.82	0.79	0.82	0.84	0.86	0.88	0.89
	% of value of all stocks	4.06	9.68	18.42	22.01	29.88	46.97	7.41	11.34	17.94	26.58	28.7	29.42	38.53	25.49	37.14	34.38	32.36	40.24
P9 Large Value	Average style variable values	2.87	4.13	3.9	5.68	4.84	5.33	2.31	1.08	1.56	0.9	1.14	1.03	13.21	9.42	9.66	44.84	6.55	5.55
	cross-sectional average percentile rank	0.27	0.22	0.32	0.31	0.46	0.46	0.82	0.7	0.77	0.66	0.67	0.69	0.76	0.76	0.72	0.72	0.72	0.75
	Market value	756.45	1536.3	914.1	2214	1095.2	1300.9	290.77	897.38	589.91	971	3069.5	2308.9	151.86	845.8	770.09	1949.3	1492.1	2735.9
	cross-sectional average percentile rank	0.94	0.92	0.81	0.84	0.85	0.86	0.92	0.9	0.78	0.81	0.81	0.83	0.76	0.82	0.81	0.85	0.86	0.9
	% of value of all stocks	11.22	11.24	11.07	16.45	4.19	10.76	2.46	6.35	5.92	6.92	14.19	16.46	13.41	24.14	10.92	24.4	4.93	15.41
P10 Variable NA	Average style variable values	-0.78	-0.25	-8.48	-11	-36.28	-35.57	0	0	-0.33	-0.23	-0.38	-1.08	0	0	0	0	0	0
	cross-sectional average percentile rank	0.1	0.03	0.14	0.13	0.2	0.19	0.01	0.01	0.15	0.22	0.15	0.21	0	0	0	0	0	0
	Market value	59.95	199.48	513.52	696.72	375.73	386.84	60.88	202.93	630.78	806.57	1509	1130.7	15.74	63.96	185.13	74.41	227.52	214.99
	cross-sectional average percentile rank	0.34	0.36	0.39	0.39	0.36	0.31	0.34	0.37	0.43	0.4	0.38	0.37	0.17	0.24	0.28	0.3	0.38	0.33
	% of value of all stocks	68.72	61.94	49.59	35.46	13	15.49	69.18	63.51	50.46	35.79	14.15	15.62	2.06	3.51	6.76	2.53	9.51	12.87

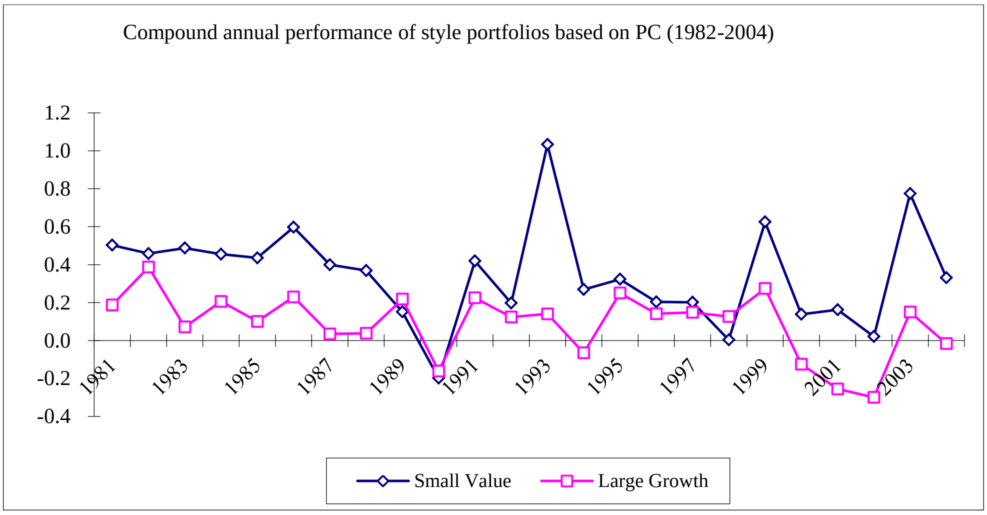
Table 4-2 the performance of simple equity style investing

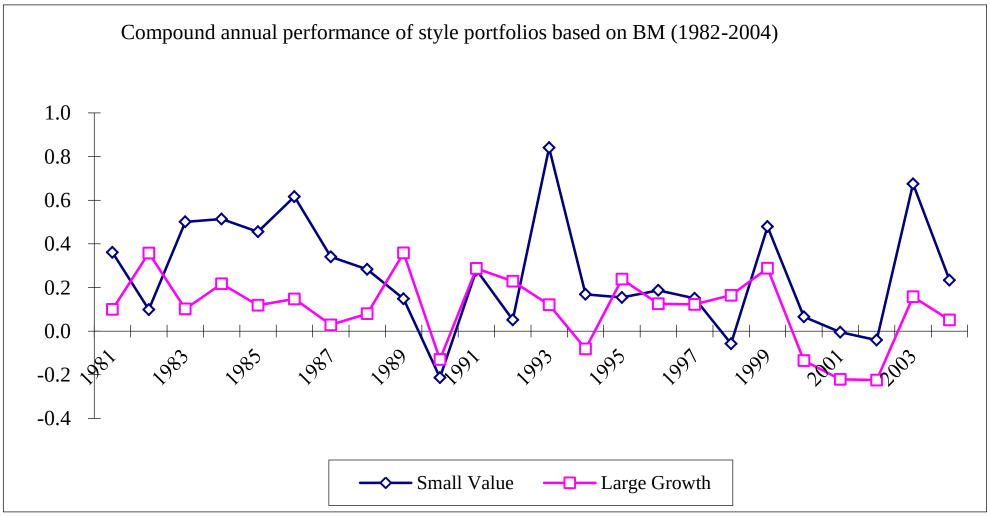
Style portfolios (P1-P9) are formed at the end of each year based on firm characteristics PC, BM and DY between 1980 and 2003. P10 stocks are those that do not have meaningful characteristic values. This table reports the average monthly returns (%) earned by these portfolios during January 1982 to December 2003. The time-series averages of (1) monthly value-weighted average portfolio returns; (2) portfolio returns for January only; (3) portfolio returns for February through December; and (4) the monthly cross-sectional standard deviations of stock returns within each style portfolio are presented. Finally, the corresponding time-series standard deviations and the time-series average number of stocks in each portfolio are also reported.

Style portfolios		Value-weighted Returns	Time-series std of returns	Jan only	Feb - Dec	Cross-sectional std of stocks in portfolio	Time-series std of cross-sectional std	Average # of stocks
Panel A style portfolios based on PC								
P1	small_growth	0.82	5.27	3.01	0.62	13	5.96	76
P2	small_blend	1.69	4.78	4.13	1.46	11.29	5.08	69
P3	small_value	2.5	5.25	6.29	2.16	12.37	4.69	125
P4	middle_growth	0.51	5.72	2.53	0.33	10.51	3.72	90
P5	middle_blend	1.46	5.14	4.27	1.2	8.83	2.67	98
P6	middle_value	2.05	5.5	6.36	1.66	10	3.26	82
P7	large_growth	0.74	5.09	0.71	0.74	9.09	3.29	104
P8	large_blend	1.34	4.83	2.32	1.26	7.57	2.07	104
P9	large_value	1.66	5.39	2.71	1.56	8.27	2.47	62
P10	PC < 0 or NA	0.77	5.15	2.53	0.61	16.46	5.87	830
Panel B style portfolios based on BM								
P1	small_growth	0.9	6.11	4.83	0.54	14.75	7.54	64
P2	small_blend	1.31	5.29	4.1	1.06	13.24	6.06	83
P3	small_value	1.92	5.09	5.45	1.6	13.91	5.58	161
P4	middle_growth	0.8	6.05	3.37	0.57	11.93	5.37	109
P5	middle_blend	1.07	5.33	4.06	0.8	10.31	3.94	110
P6	middle_value	1.91	5.68	5.43	1.59	10.69	4.14	91
P7	large_growth	0.86	4.96	0.99	0.85	9.28	3.6	135
P8	large_blend	1.22	4.96	2.13	1.14	8.42	2.65	117
P9	large_value	1.63	6.04	3.23	1.48	8.81	3.32	56
P10	BM < 0 or NA	0.9	4.75	2.24	0.78	15.65	5.47	715
Panel C style portfolios based on DY								
P1	small_growth	1.22	4.61	3.74	0.99	13	4.97	118
P2	small_blend	1.5	4.26	3.38	1.33	11.69	3.3	127
P3	small_value	1.65	4.72	3.96	1.44	13.25	4.11	182
P4	middle_growth	0.82	4.96	3.36	0.59	10.55	3.16	148
P5	middle_blend	1.16	4.48	3.76	0.93	9.78	2.75	144
P6	middle_value	1.5	5.35	4.23	1.25	11.16	3.21	137
P7	large_growth	0.68	5.06	-0.24	0.76	9.87	3.32	161
P8	large_blend	1.15	4.36	1.41	1.12	8.17	2.1	158
P9	large_value	1.73	4.81	2.76	1.63	9.61	3.66	108
P10	DY <= 0 or NA	0.25	7.4	4.99	-0.19	18.77	6.2	356

Figure 4-2 the time-varying returns in annual SV, LG style portfolio

This figure demonstrates the dynamics in the annual returns earned by small-cap value, large-cap growth style portfolios since 1982.





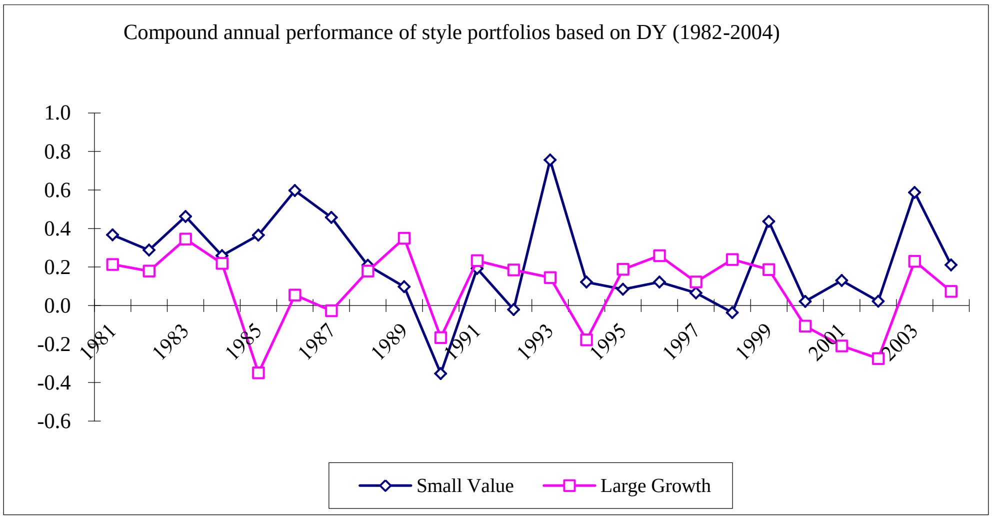
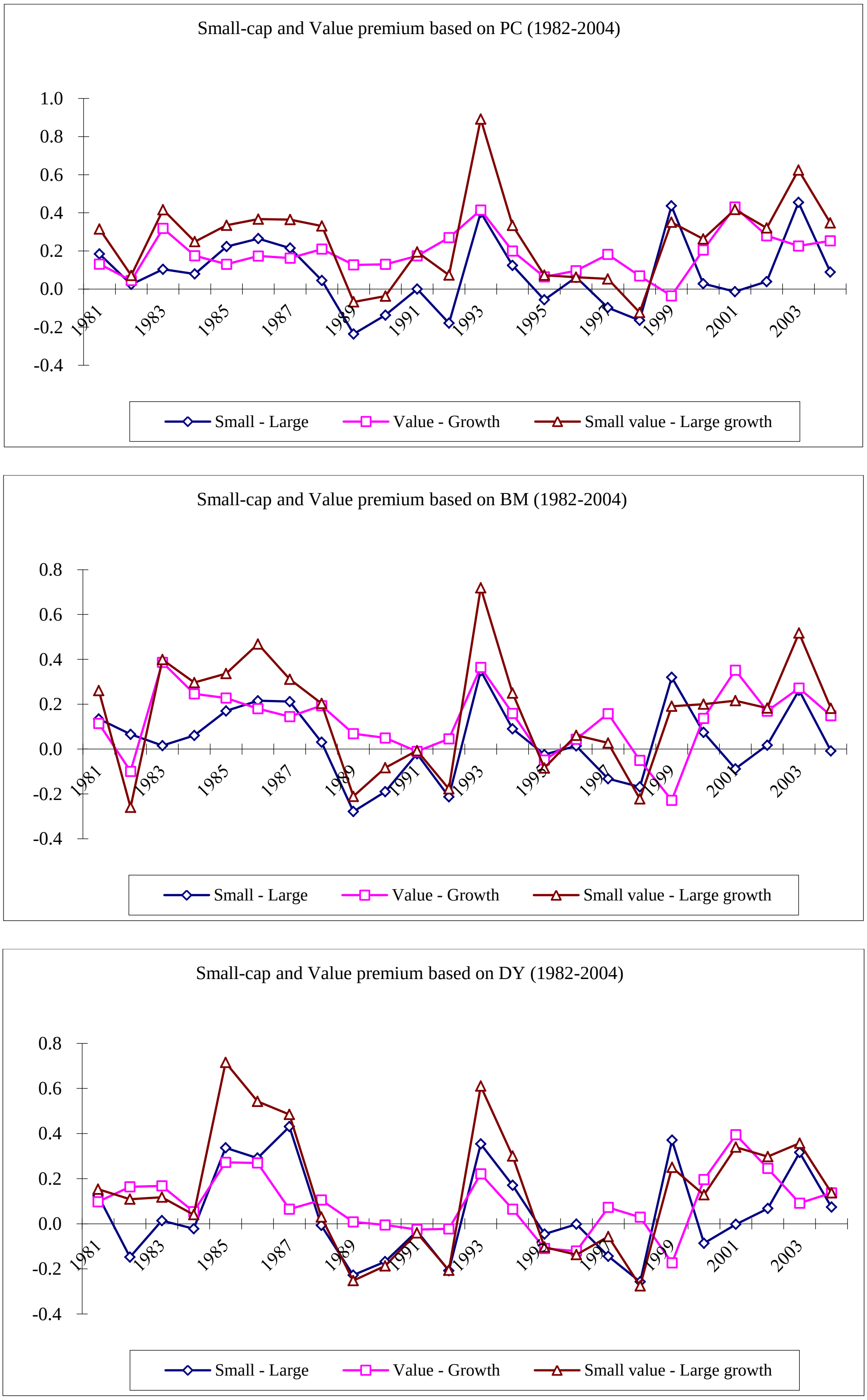


Figure 4-3 Size and value premiums dynamics

This figure shows the annual small-cap spreads and value premiums between 1982 and 2004, as well as the annual return differential between the small-cap value and large-cap growth portfolios.



4.5 The profitability of style momentum strategies

If there are equity style cycles in the U.K. stock market and it is of long duration, then smart investors can engage in the style rotation strategy to capitalise on the divergence of style returns. This section explores the profitability of such tactical trading strategies that incorporates the information of investment style evolution.

A style momentum strategy is to buy stocks in styles that perform well in the past and to sell stocks in styles that do poorly recently. The fundamental idea for such strategy can be justified by investors' behavioural trading as in Barberis and Shleifer (2003) and the rational framework such as Berk *et al.* (1999). In essence, style momentum is a positive feedback adaptive trading model based on equity style cycles.

Starting from January 1982, 9 style portfolios (P1-P9) based on firm characteristics X (X = PC, BM and DY) are ranked every month by their performance in the past j months (j = 3, 6, 12). The formation of these style portfolios are described in section 3. Hedge portfolios are formed to buy the top one (or top two) winner style portfolio(s) and to sell the corresponding bottom one (or bottom two) loser portfolio(s). The hedge portfolios are held for k test periods (k = 3, 6, 9, 12, 24, or 36 months). The test for the style momentum strategy builds on the "overlapping method" proposed by Jegadeesh and Titman (1993). Specifically:

- At every month end t, rank all style portfolios (P1-P9) according to their value weighted compound returns over the previous j months, $t-j+1$ to t and identify the winner and loser styles. Form hedge portfolios based on top and bottom one or two styles (i.e. winner and loser) using equally weighted scheme.
- Measure the return to each of the hedge portfolios in every month for the next k months after formation, $t+1$ to $t+k$ or $t+2$

to $t+k+1$ if there is one month skipped after hedge portfolio formation to avoid short term price reversals.

- The return to the winner (loser) styles in period $t+1$ is the average of the returns to the winner (loser) style portfolios identified at time point $t, t-1, \ldots, t-k+1$ in period $t+1$. If a month's gap is left, the return at period $t+1$ is the average of the returns to the winner (loser) style portfolios at $t-1, t-2, \ldots, t-k$. Hence, the return to the winner (loser) style portfolios is the average return to the k winner (loser) styles identified consecutively over the previous k months.

- The returns to the style momentum strategy $(j,k,0)$ or $(j,k,1)$ if a month's gap is allowed is the mean return to the self-financing portfolios of winner-minus-loser styles over the entire sample.

Table 4-3 reports the equally weighted average monthly returns for winner and loser styles as well as the style momentum payoffs over the sample period 1982:01-2004:12. Panel A and B use 2 extreme style portfolios to construct hedge portfolios, while Panel C and D use 4 style portfolios to form hedge portfolios. Panels A and C report the k test period returns when there is no time gap between the rank and test periods, while Panels B and D report the test result when skipping one month after hedge portfolio formation.

The results suggest that the PC- and DY-based style momentum strategy is profitable at least up to 12 months and possibly longer according to the 3-, 6- and 12-month sorting. Style momentum effect is a bit shorter based on a 12-month ranking period and two extreme BM-based style portfolios in the test. When using two extreme styles, a style momentum based on characteristics variable PC and the 3-month ranking period and the 3-month test period without skipping a month (hereafter SM-PC (3,3,0)) yields the average monthly return of 48 basis point (abbreviated as 'BPS' hereafter), while the SM-PC

(3,12,0), SM-PC (12,3,0) and SM-PC (12,12,0) strategies generate monthly average performance of 34 BPS, 98 BPS and 33 BPS, respectively. In comparison to PC-based results, the SM-BM (3,3,0), SM-BM (3,12,0), SM-BM (12,12,0) and SM-BM (12,12,0) strategies yield 57 BPS, 29 BPS, 63 BPS and 19 BPS monthly returns, respectively, and the SM-DY(3,3,0), SM-DY (3,12,0), SM-DY (12,3,0) and SM-DY (12,12,0) strategies have respective monthly performance of 74 BPS, 47 BPS, 77 BPS and 45 BPS. These returns are significant at conventional level (except for SM-BM (12,12,0)).

For a robust check, results are also presented when skipping one month between ranking period and test period. Lo and MacKinlay (1990) and Jagadeesh and Titman (1995) show that portfolios can exhibit positive serial correlation due to lead-lag effect. Jagadeesh (1990) also show the effect of bid-ask spread in the return calculations. To mitigate such effects on the style portfolios, Panel B and D report the style momentum returns when skipping one month.

It can be seen that except for SM-BM strategy, the style momentum profits are still significant in short and intermediate term up to 9 months. Using four extreme styles instead of two slightly improve the style momentum performance but such change is not material (Panel C). It is noteworthy that the returns for hedge portfolios are always positive because the holding periods are overlapping. The style momentum payoffs are strong over intermediate horizons and they generally increase for longer rank periods and decrease when the test periods become longer. The long-term reversal of style momentum returns is consistent with the story of Barberis and Shleifer (2003).

While style momentum based on firm characteristic variable PC, BM and DY are all profitable, their return magnitude varies. It is evident that the returns and the duration of style momentum are weaker and shorter for BM-based strategy as compared to PC- and DY-based styles, suggesting that the mispricing of styles based on BM factor are less severe relative to styles base on PC and DY. This may imply that the information content contained in characteristics BM is much efficient. Fama and French (1992) argue that BM is a risk factor relating to the variations in cross-sectional expected stock returns. It is plausible that because investors understand the widely accepted three-factor model and use it to pricing asset values, the misspricing occurs less severe on style level based on BM sorting.

It is interesting further to examine how different style portfolios (P1-P9) perform on the quarterly and annually basis. One may ask if winner and loser styles cluster in a few stocks with certain characteristics, and/or what the cumulative quarterly or annual profit would be if an investor follows the different investment styles represented by P1-P9 portfolios.

Table 4 displays the best and the worst styles and the corresponding cumulative returns based on 3-month and 12-month rank periods starting from 1982 to 2004. It is evident that value styles tend to be the winner style and growth style tend to be the loser style, in particularly when the ranking period is longer, which is consistent with general findings that value strategy works at long-term. For example, for styles based on PC, SV portfolio has been the winner in 20 out of 92 ranks, and LG portfolio been the loser style in 19 out of 92 ranks according to quarterly sorting. If sorting is based on past 12 months, SV is the winner in 49 out of 92 and LG being the loser in 26 out of 92 ranks. Similar findings apply to BM and DY based style portfolios. This findings that momentum profits differ across stocks with certain characteristics are consistent with the literature. Previous studies show that momentum returns are higher for small stocks (Hong et al. (2000)), and stocks with high market-to-book ratios (Daniel and Titman (1999)). More recently, Fama and French (2012) also document that momentum returns differ across size groups. Specifically, momentum returns decrease from smaller to large stocks.

Table 4-3 The profitability of style momentum strategies

Starting in January 1982, 9 style portfolios (P1-P9) are ranked every month by their performance in the past *J* months (*J = 3, 6, 12)*. Hedge portfolios are formed to buy the top (or the top two) winner style portfolio(s) and to sell the corresponding loser portfolio(s). The hedge portfolios are held for K test periods (*K*=3, 6, 9, 12, 24, or 36 months). This table reports the equally weighted average returns per month. Panel A and B use two style portfolios to form the long-short hedge portfolios, while Panel C and D use 4 style portfolios to construct hedge portfolios. Panels A and C report the K test period returns when there is no time gap between the rank and test periods, while Panels B and D report the test result when skipping one month.

	Style portfolios based on PC						Style portfolios based on BM						Style portfolios based on DY					
	K = 3	K = 6	K = 9	K = 12	K = 24	K = 36	K = 3	K = 6	K = 9	K = 12	K = 24	K = 36	K = 3	K = 6	K = 9	K = 12	K = 24	K = 36
Panel A Hedge portfolio holds two style portfolios																		
J = 3																		
Winner	0.016	0.016	0.016	0.016	0.014	0.014	0.017	0.016	0.016	0.016	0.015	0.015	0.016	0.016	0.015	0.015	0.015	0.014
Loser	0.011	0.011	0.011	0.012	0.013	0.014	0.012	0.012	0.012	0.013	0.013	0.014	0.009	0.01	0.01	0.01	0.012	0.012
Hedge portfolio	0.005	0.005	0.004	0.003	0.001	7E-04	0.006	0.004	0.003	0.003	0.002	0.001	0.007	0.006	0.005	0.005	0.003	0.002
t - ratios	2.443	3.009	3.286	2.968	1.22	0.852	2.699	2.515	2.419	2.339	1.9	1.286	4.253	4.109	4.585	4.552	4.067	3.486
J = 6																		
Winner	0.018	0.018	0.017	0.017	0.015	0.015	0.017	0.016	0.016	0.015	0.015	0.015	0.016	0.016	0.016	0.016	0.015	0.015
Loser	0.01	0.01	0.011	0.012	0.013	0.014	0.011	0.011	0.012	0.013	0.013	0.013	0.008	0.009	0.01	0.01	0.011	0.012
Hedge portfolio	0.009	0.007	0.006	0.005	0.002	0.001	0.006	0.005	0.004	0.003	0.002	0.001	0.009	0.007	0.006	0.005	0.004	0.003
t - ratios	4.182	4.232	4.227	3.639	1.332	0.973	2.913	2.958	2.25	1.83	1.742	1.181	4.456	4.03	4.134	3.669	3.394	2.869
J = 12																		
Winner	0.018	0.017	0.016	0.016	0.014	0.015	0.017	0.015	0.015	0.015	0.014	0.015	0.016	0.016	0.016	0.015	0.015	0.015
Loser	0.008	0.011	0.012	0.013	0.014	0.014	0.01	0.013	0.013	0.013	0.013	0.013	0.009	0.01	0.01	0.011	0.012	0.012
Hedge portfolio	0.01	0.006	0.005	0.003	8E-04	0.001	0.006	0.003	0.002	0.002	0.001	0.001	0.008	0.006	0.005	0.005	0.003	0.003
t - ratios	4.68	3.204	2.585	1.871	0.54	0.832	2.717	1.203	0.928	1.029	0.674	0.925	3.847	3.324	3.135	2.701	2.466	2.343

Table 4-3 (continued -1)

	Style portfolios based on PC						Style portfolios based on BM						Style portfolios based on DY					
	K = 3	K = 6	K = 9	K = 12	K = 24	K = 36	K = 3	K = 6	K = 9	K = 12	K = 24	K = 36	K = 3	K = 6	K = 9	K = 12	K = 24	K = 36
Panel B Hedge portfolio holds two style portfolios, skip 1 month																		
J = 3																		
Winner	0.015	0.0154	0.0151	0.0152	0.0139	0.0139	0.015	0.0147	0.0146	0.015	0.0144	0.0142	0.0141	0.0147	0.0143	0.0143	0.0142	0.014
Loser	0.0115	0.0112	0.0116	0.0123	0.0131	0.0134	0.0119	0.0116	0.0126	0.0127	0.0131	0.0135	0.0095	0.0098	0.0103	0.0104	0.0116	0.0121
Hedge portfoli	0.0035	0.0043	0.0035	0.0029	0.0009	0.0006	0.0031	0.0031	0.0021	0.0023	0.0013	0.0007	0.0046	0.0049	0.004	0.0039	0.0026	0.0019
t - ratios	1.8693	2.8415	2.8068	2.5571	0.8814	0.6743	1.4722	1.9172	1.4607	1.822	1.3794	0.8241	2.6267	3.5795	3.6048	3.8368	3.4487	3.0734
J = 12																		
Winner	0.0166	0.0159	0.0156	0.0152	0.0138	0.0142	0.0153	0.0145	0.0143	0.0141	0.0139	0.0141	0.0153	0.0157	0.0153	0.0151	0.0146	0.0144
Loser	0.0096	0.0116	0.0124	0.0128	0.0136	0.0134	0.0121	0.0137	0.0134	0.0131	0.0134	0.0132	0.0092	0.0103	0.0108	0.0111	0.0116	0.012
Hedge portfoli	0.0069	0.0043	0.0032	0.0024	0.0002	0.0008	0.0032	0.0008	0.0009	0.001	0.0005	0.0009	0.0061	0.0054	0.0045	0.004	0.003	0.0024
t - ratios	3.3131	2.1881	1.6953	1.2943	0.1499	0.5975	1.3012	0.3513	0.4043	0.5464	0.3243	0.6288	2.9669	2.8687	2.5309	2.3265	2.2166	2.1303

Table 4-3 (continued -2)

	Style portfolios based on PC						Style portfolios based on BM						Style portfolios based on DY					
	K = 3	K = 6	K = 9	K = 12	K = 24	K = 36	K = 3	K = 6	K = 9	K = 12	K = 24	K = 36	K = 3	K = 6	K = 9	K = 12	K = 24	K = 36
Panel C Hedge portfolio holds four style portfolios																		
J = 3																		
Winner	0.0166	0.0165	0.0162	0.0158	0.0146	0.0143	0.0165	0.0159	0.0157	0.0155	0.0146	0.0142	0.0154	0.0153	0.0152	0.015	0.0145	0.0142
Loser	0.0101	0.011	0.0112	0.0117	0.0127	0.0131	0.0103	0.011	0.0111	0.0116	0.0127	0.0131	0.0093	0.01	0.0101	0.0104	0.0116	0.0122
Hedge portfolio	0.0065	0.0055	0.005	0.0041	0.0019	0.0012	0.0062	0.0049	0.0046	0.0039	0.002	0.0011	0.0061	0.0053	0.0051	0.0045	0.003	0.002
t - ratios	3.8264	3.9944	4.3485	4.0253	2.3659	1.7925	3.5654	3.381	4.0197	3.7997	2.6491	1.6145	3.9432	4.0695	4.7077	4.4873	3.833	3.2147
J = 6																		
Winner	0.018	0.0177	0.0171	0.0166	0.0151	0.0149	0.0172	0.0165	0.0166	0.016	0.015	0.0144	0.0167	0.0164	0.0161	0.0158	0.0152	0.0148
Loser	0.0094	0.0101	0.0107	0.0113	0.0126	0.013	0.0097	0.0105	0.0111	0.0116	0.0127	0.013	0.009	0.0093	0.0099	0.0104	0.0115	0.0121
Hedge portfolio	0.0086	0.0076	0.0064	0.0053	0.0025	0.0018	0.0075	0.0061	0.0055	0.0043	0.0023	0.0014	0.0076	0.0071	0.0063	0.0054	0.0038	0.0027
t - ratios	4.8143	4.8925	4.6764	4.1764	2.3863	1.9051	3.9876	3.8793	3.9497	3.3651	2.3081	1.537	4.4596	4.7505	4.7786	4.4288	3.8288	3.385
J = 12																		
Winner	0.0172	0.0164	0.0159	0.0155	0.0145	0.0146	0.0178	0.0171	0.0164	0.0157	0.0144	0.0143	0.0164	0.016	0.0158	0.0154	0.0148	0.0147
Loser	0.0098	0.0114	0.0121	0.0125	0.0132	0.0133	0.0094	0.0109	0.0118	0.012	0.0128	0.0128	0.0089	0.0096	0.0103	0.0107	0.0118	0.0122
Hedge portfolio	0.0073	0.0049	0.0038	0.003	0.0013	0.0013	0.0084	0.0062	0.0046	0.0037	0.0016	0.0015	0.0075	0.0064	0.0055	0.0047	0.0031	0.0026
t - ratios	4.1374	2.9679	2.4005	2.0154	1.0361	1.1503	4.5644	3.685	2.9308	2.5378	1.2222	1.3243	4.3446	3.9757	3.6211	3.2687	2.5737	2.6666
Panel D Hedge portfolio holds four style portfolios, skip 1 month																		
J = 3																		
Winner	0.0159	0.016	0.0155	0.0153	0.0141	0.0139	0.0151	0.0153	0.015	0.0149	0.0143	0.0138	0.0142	0.0149	0.0146	0.0145	0.0141	0.0138
Loser	0.0111	0.0111	0.0114	0.0119	0.0127	0.013	0.0111	0.011	0.0113	0.0117	0.0126	0.013	0.01	0.0101	0.0104	0.0107	0.0117	0.0122
Hedge portfolio	0.0048	0.0049	0.0041	0.0034	0.0014	0.0009	0.004	0.0043	0.0037	0.0032	0.0016	0.0008	0.0042	0.0048	0.0041	0.0038	0.0025	0.0016
t - ratios	2.9101	3.7522	3.7521	3.3842	1.8284	1.4047	2.3028	3.1592	3.3279	3.1453	2.1896	1.2172	2.6576	3.7623	3.8644	3.7927	3.2091	2.7052
J = 12																		
Winner	0.0158	0.0154	0.0151	0.0148	0.0139	0.0141	0.0169	0.0161	0.0155	0.0148	0.0138	0.0138	0.0155	0.0154	0.0152	0.0149	0.0145	0.0144
Loser	0.0108	0.0122	0.0125	0.0127	0.0131	0.0132	0.0105	0.0115	0.012	0.0122	0.0128	0.0128	0.0093	0.0099	0.0105	0.0108	0.0118	0.0121
Hedge portfolio	0.005	0.0032	0.0027	0.0021	0.0008	0.001	0.0063	0.0047	0.0034	0.0026	0.001	0.0011	0.0062	0.0055	0.0046	0.0041	0.0027	0.0023
t - ratios	2.9013	1.9605	1.6778	1.4362	0.6053	0.8588	3.5338	2.7442	2.1394	1.7787	0.7794	0.9475	3.5513	3.4534	3.0485	2.8116	2.2387	2.4122

Table 4-4 Style momentum portfolios by quarter and year 1982-2004

At the beginning of each quarter (year), based on firm characteristic variable PC, BM and DY respectively, 9 style portfolios (P1-P9) are ranked by their returns over the previous quarter (year), and the most extreme winner or loser portfolios are identified. This table reports the corresponding compound returns of the winner and loser styles during 1980-2004. The 9 style portfolios are small-cap growth (SG), small-cap blend (SB), small-cap value (SV), mid-cap growth (MG), mid-cap blend (MB), mid-cap value (MV), large-cap growth (LG), large-cap blend (LB), large-cap value (LV).

	Past 3-, 12-month winner and loser	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
Panel A Style portfolios based on PC																								
Q1	Past 3-month winner	SB	MV	SV	SG	SV	SV	SV	MV	SB	MV	SB	SV	SV	SV	MV	SV	LV	MV	SG	MV	LV	SB	MV
	3-month winner return	14.69	22.07	28.5	19.4	30.26	37.8	15.95	23.13	4.02	34.2	4.25	37.08	16.6	3.42	10.65	10.79	20.69	19.38	25.72	5.51	15.11	0.11	11.27
	Past 3-month loser	LV	LG	LG	LB	LV	LB	SG	SG	SG	SG	SG	LG	LV	SG	LB	MG	SG	SG	LB	LG	LG	MG	LG
	3-month loser return	2.9	-2.72	10.16	-0.25	14.69	19.96	-0.58	11.05	-8.85	8.3	-9.52	-1.06	-6.37	-6.18	1.14	0.46	6.45	7.08	-7.51	-15.6	-5.63	-11.6	-4.7
	Past 12-month winner	SV	SV	SV	MV	SV	SV	SV	SV	LV	LB	MB	SV	SV	SV	SV	SB	LV	LB	SG	LV	LV	SV	SB
	12-month winner return	32.27	56.93	58.91	45.45	60.41	68.95	17.78	43.83	10.89	14.56	15.63	61.91	72.93	12.57	35.73	31.56	47.65	9.29	98.18	33.19	25.43	-6.78	107.1
	Past 12-month loser	MB	SG	MG	LG	MG	LB	LG	SG	SG	SG	SG	SG	LG	SG	LB	MG	SG	SG	LB	MG	MG	MG	LG
	12-month loser return	9.04	8.87	21.33	10.61	21.54	23.24	-14.8	13.5	-16.9	-19.1	-16.1	0.89	10.06	-18	12.62	2.84	4.01	-15.5	-0.37	-28.3	-22.5	-43.6	19.15
Q2	Past 3-month winner	LG	LV	LB	SG	SB	SB	SV	LB	LB	MB	SV	SV	SV	SV	SB	LV	MV	LV	LV	MV	SV	MV	SV
	3-month winner return	6.83	16.17	-4.5	3.29	14.48	27.58	17.74	6.01	8.48	2.31	21.01	18.51	2.98	11.14	12.03	7.57	5.15	19.17	17.89	13.2	2.7	32.92	11.18
	Past 3-month loser	SG	MB	SV	LG	LV	LG	LG	MG	SG	SG	LG	LB	MG	SG	LV	MB	LV	LG	MG	MG	LG	LG	SG
	3-month loser return	-3	6.87	-12.1	-7.76	-1.88	10.01	5.08	-0.79	-5.65	-8.21	1.74	0.02	-6.3	1.91	-0.55	-6.73	-4.16	2.32	-9.29	-7.86	-18.4	10.88	-2.38
	Past 12-month winner	SV	SV	SB	SV	SV	SV	SV	SV	LV	MV	SV	SV	SV	SV	SV	LV	MV	LV	SG	MV	SV	SV	SV
	12-month winner return	20.58	79.97	29.23	51.56	77.62	88.66	11.17	27.64	15.46	5.49	32.53	58.56	50.28	21.48	35.51	31.58	40.14	23.82	65.88	31.18	11.3	20.44	65.73
	Past 12-month loser	MB	SG	LG	LG	LV	LG	LG	MG	SG	SG	SG	MG	LG	SG	LB	MG	SG	MG	LB	LG	LG	MG	LG
	12-month loser return	0.61	21.9	2.45	6.95	25.78	35.04	-18.6	7.43	-23.2	-21.3	-5.1	3.78	2.75	-11.2	8.19	-7.97	11.28	-11.7	-3.32	-28	-28.3	-15.1	10.3

Table 4-4 (continued -1)

	Past 3-, 12-month winner and loser	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
Panel A Style portfolios based on PC (Continued)																								
Q3	Past 3-month winner	LG	SV	SV	SB	SG	SV	SV	LV	LV	MB	LV	SV	MV	LG	SB	LB	LB	SG	MG	LB	SV	SV	LB
	3-month winner return	25.51	2.21	14.14	11.29	1.07	14.53	3.72	7.76	-13.6	13.56	2.13	12.78	8.68	10.53	8.54	13.21	-8.7	11.82	6.74	-11.8	-11.9	25.9	4.63
	Past 3-month loser	SG	LG	LB	LV	LB	LV	SB	SG	MG	SG	MG	LG	SG	SB	MG	SB	MG	LB	LB	MG	MG	LB	MG
	3-month loser return	0.38	-5.57	5.72	2.91	-8.36	3.88	-2.68	-0.33	-22.7	6.7	-17.6	3.23	-3.04	1.22	-2.05	1.42	-28.7	-7.24	-3.84	-31	-30.2	3.36	-3.42
	Past 12-month winner	SV	SV	MV	SG	SV	SV	SV	LV	LV	MV	LB	SV	SV	SV	SB	LV	MV	LV	SG	MV	SV	SV	SV
	12-month winner return	64.78	52.83	41.46	48.81	58.14	123	0.68	34.89	-7.41	46.71	3.14	104.8	41.36	26.01	34.87	34.88	4.19	46.83	52.8	9.88	14.56	72.12	31.87
	Past 12-month loser	SG	LG	LG	LG	LV	LG	LG	SG	MG	SG	SG	LG	MG	SG	LB	MG	MG	LB	LB	MG	MG	LB	LG
	12-month loser return	23.25	3.57	17.58	4.68	18.92	52.81	-22.7	8	-36.2	1.35	-26.1	16.77	-1.54	-2.69	3	-4.55	-20	21.76	0.23	-52.9	-26.5	13.51	3.07
Q4	Past 3-month winner	MB	SB	MV	LB	LV	MV	LV	LV	LB	MB	LV	LV	LV	LV	LV	MV	LG	MG	LB	MG	LG	SB	MV
	3-month winner return	10.19	13.5	20.22	15.95	15.72	-22.9	1.88	5.61	8.89	-3.23	17.33	11.93	4.27	6.01	6.71	3.06	13.02	29.78	12.05	23.75	9	16.53	12.09
	Past 3-month loser	LG	LG	LG	SG	MG	SV	SB	MB	SB	LV	SG	MV	MV	MB	SG	LB	SB	LV	MG	LB	MB	MV	LG
	3-month loser return	-0.24	3.23	5.94	5.77	7.05	-28.9	-5.87	-11.2	-7.53	-13.4	0.09	2.1	-5.05	-1.3	-4.19	-2.97	-3.5	-1.24	-15.2	5.89	-1.67	6.25	2.82
	Past 12-month winner	SV	MV	MV	SV	SV	SV	SV	LV	LV	SV	LV	SV	SV	SV	SB	LV	LB	SB	LV	MV	SV	SB	MV
	12-month winner return	45.86	53.29	57.6	43.58	59.71	39.97	36.92	39.84	-5.46	41.94	25.34	103.3	26.92	32.33	32.42	29.36	16.14	79.26	22.84	16.54	2.15	86.98	38.59
	Past 12-month loser	SG	LG	LG	MG	MG	LG	SG	SG	MG	SG	SG	LG	MG	SB	LB	MG	SG	LB	LG	MG	MG	LG	LG
	12-month loser return	17.61	7.18	20.66	5.84	21.24	3.51	1.61	1.2	-33.7	0.45	-21.9	14.08	-7.47	3.72	7.32	-5.23	-16	17.46	-12.4	-31.3	-37.2	15.05	-1.58

Table 4-4 (continued -2)

	Past 3-, 12-month winner and loser	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
Panel B Style portfolios based on BM																								
Q1	Past 3-month winner	SG	MV	SV	SV	SB	SB	SV	LB	SV	MV	LG	SV	SG	LG	MV	SV	LG	LV	SG	MV	LB	LV	SG
	3-month winner return	19.72	25.94	30.55	16.99	27.21	35.27	11.83	18.13	-1.09	29.71	2.52	26.89	12.24	4.55	10.72	10.61	16.17	27.12	30.05	-1.49	11.93	-2.1	18.13
	Past 3-month loser	LG	LG	LB	LB	LV	LG	LG	SB	SG	SG	SG	LG	LG	SG	LG	LG	MB	SG	LB	MG	LV	SG	LG
	3-month loser return	3.05	-0.92	9.29	0.43	16.17	20.73	0.36	12.76	-8.63	12.41	-10.9	-0.28	-5.34	-5.81	4.15	2.45	7.7	-1.25	-4.68	-24.1	-20.8	-17.3	-1.19
	Past 12-month winner	LV	SB	MV	MV	MV	SV	SV	MV	LG	LB	LG	LV	SV	LV	MG	SV	LV	LV	SG	MV	MV	SV	MV
	12-month winner return	35.6	47.1	64.19	40.45	65.02	69.86	12.28	37.58	8.87	13.53	11.44	41.45	61.84	5.79	33.94	24.69	38.24	16.27	135.6	16.51	13.14	-12.9	112
	Past 12-month loser	LG	MG	LG	LB	LG	LG	LG	SG	SG	SG	SG	MB	LG	SG	LB	MG	MB	SG	LB	MG	SG	MG	LG
	12-month loser return	9.14	17.98	22.8	9.02	26.91	18.12	-14.5	15.58	-22.5	-19.2	-14.5	13.53	6.43	-20.3	19.31	7.84	-0.03	-17.3	5.79	-42.7	-39.2	-42	23.79
Q2	Past 3-month winner	LG	LV	LV	SG	SV	SB	SV	SV	LB	MG	SB	SV	SV	SB	SV	LV	SG	LV	MV	MV	SV	MV	SV
	3-month winner return	6.66	24.37	-0.53	1.62	15.23	26.36	14.56	5.41	8.18	3.02	13.14	18.04	2.1	9.18	10.83	8.32	3.18	24.35	9.92	11.31	-0.97	37.8	6.84
	Past 3-month loser	SG	SB	SV	LG	LG	LG	LV	MB	SG	MV	LB	LG	LV	MV	LV	MG	LV	LG	MG	SG	LV	LG	SG
	3-month loser return	-4.81	6.11	-9.93	-7.35	-1.73	8.8	5.7	-1.94	-10.1	-6.38	3.23	-0.52	-7.28	4.69	-2.88	-10.1	-0.07	2.25	-15.4	-12.1	-24.6	11.56	-11.8
	Past 12-month winner	MV	LV	MV	MV	SV	SB	SV	MV	LG	LB	SV	SV	SV	LV	MG	LV	LG	LV	SG	MV	MV	LV	SV
	12-month winner return	21.56	74.21	36.76	54	82.25	80.95	5.04	26.52	10.28	4.44	22.98	43.14	39.98	21.23	37.63	25.88	31.32	44.68	82.34	17.97	0.53	23.89	55.2
	Past 12-month loser	MG	MG	LG	LG	LG	LG	LB	SB	SG	SB	SG	MB	LG	SG	LV	MG	SG	SG	LB	MG	SG	SG	LG
	12-month loser return	1.32	27.9	2.4	11.86	34.61	30.77	-14.6	6.15	-31.1	-17.2	-2	12.73	0.92	-9.35	15.01	-11.6	7.57	-7.59	1.99	-40	-38	-14.5	15.04
Q3	Past 3-month winner	LG	LB	MG	MV	SG	SV	MV	LG	SG	SV	LG	SB	LV	MG	SG	LG	LB	MG	MG	LV	LV	SG	LV
	3-month winner return	22.53	4.23	12.04	17.15	3.02	13.67	3.82	9.28	-14.9	15.12	0.43	14.01	10	12.09	6.42	12.62	-11	12.35	8.26	-6.6	-12.5	29.88	6.47
	Past 3-month loser	SV	LG	LG	LB	LG	LB	MG	MB	MV	SG	MV	LG	SG	LV	MG	SG	MG	LB	LV	MG	MG	LG	SG
	3-month loser return	-2.12	-4.87	8.28	2.2	-9.58	3.3	-4.33	-2.47	-23.7	4.11	-20.5	3.26	-2.7	3.31	-5.12	-3.02	-26.8	-5.51	-3.39	-33.8	-27.2	2.87	-8.64
	Past 12-month winner	SG	LV	MV	MV	SV	SV	MV	LB	LV	LG	LG	MV	SV	LG	SG	LV	LV	LV	SG	MV	SV	MV	LB
	12-month winner return	60.31	58.28	49.94	61.08	54.56	112.8	0.7	32.68	-12	39.31	6.34	97.42	32.12	21.3	24.3	34.39	-0.38	64.35	84.72	-4.07	2.46	78.09	26.04
	Past 12-month loser	SV	LG	LG	LB	LG	LG	SG	MB	SG	SG	MV	LG	LG	SG	MB	MG	MB	LB	LV	MG	LV	LG	SG
	12-month loser return	14.19	7.61	16.56	9.19	14.4	54.89	-22.1	5.62	-40	6.2	-23.5	16.55	0.54	2.11	11.2	-3.25	-18	15.94	-1.16	-63.3	-37	10.13	-1.58
Q4	Past 3-month winner	SB	MV	MB	LB	SV	MV	MV	LV	LB	LG	MV	LB	LB	LV	LV	MV	LG	SG	LB	MG	LV	LV	MV
	3-month winner return	16.24	16	18.3	17.95	14.5	-20.9	1.38	4.52	9.42	-1.55	24.34	12.59	3.07	7.24	5.8	1.74	16.73	52.49	6.9	23.56	25.06	15.4	12.57
	Past 3-month loser	LG	LG	SG	MB	MG	SB	SG	SG	SG	LB	SB	MB	SG	MB	SB	SG	SB	MV	MG	LB	SB	SG	SG
	3-month loser return	0.85	3.25	4.26	6.29	2.97	-29.1	-8.71	-14.2	-6.1	-11.3	5.01	1.67	-6.47	-0.49	-4.02	-5.8	-1.43	4.05	-17.5	7.31	-2.09	3.4	3.19
	Past 12-month winner	SG	MV	MV	MV	SV	SB	MV	LG	LB	MG	LG	SV	SV	LG	MV	LV	LG	MG	MV	MV	SV	MV	SV
	12-month winner return	54.61	65.16	52.51	53.73	61.63	35.6	29.1	35.87	-7.1	30.52	22.88	84.04	16.86	23.84	20.61	25.61	16.45	118.5	17.79	5.05	-4.11	81.76	23.34
	Past 12-month loser	SV	LG	LB	MG	LG	LG	SG	MB	SG	SG	SG	LG	LG	MV	MB	MG	MV	LB	LG	SG	MG	LG	SG
	12-month loser return	9.87	10.18	18.64	9.3	14.77	2.9	-1.07	-2.15	-34.3	7.98	-10.3	12.11	-8.11	10.8	10.47	-6.1	-15.1	15.79	-13.5	-46.8	-39.7	15.76	-1.78

Table 4-4 (continued -3)

	Past 3-, 12-month winner and loser	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
Panel C Style portfolios based on DY																								
Q1	Past 3-month winner	MV	SB	SG	MB	SV	MB	MB	MV	SG	MV	LV	SV	SG	LB	LG	SB	SG	MB	MG	MV	LV	MV	MB
	3-month winner return	12.8	15.57	16.85	11.72	22.06	30.4	9.21	21.41	2.45	28.68	2.99	23.27	11.75	2.61	19.81	6.28	17.38	15.58	12.34	4.91	11.51	-2.98	10.63
	Past 3-month loser	LG	MG	LG	LG	LG	LG	LV	LG	SV	SG	SV	LG	LG	MV	LB	LG	SV	LG	MV	LG	LG	SG	LB
	3-month loser return	-4.69	7.19	-0.37	-34.6	7.72	12.69	3.1	10.45	-9.29	7.39	-6.4	-1.18	-15.7	-3.8	3.57	3.22	7.04	6.41	-6.47	-13.7	-5.88	-10.5	-1.48
	Past 12-month winner	MV	LB	LV	MB	SV	SV	SV	MV	LG	LV	LG	SV	SV	LB	LG	SG	LV	LV	SG	LV	LV	SV	SG
	12-month winner return	30.67	55.1	48.02	24.03	52.11	67.24	22.68	39.88	12.65	14.93	6.21	28.92	58.63	8.16	39.5	25.18	50.26	18.59	75.65	28.8	29.08	-9.05	93
	Past 12-month loser	LG	MG	MG	LG	LG	LG	LB	MG	MG	SG	MV	MB	LG	MB	SV	MB	SV	SG	LB	LG	MG	MG	LB
	12-month loser return	0.77	14	17.95	-20	7.17	10.32	-18	18.94	-16.9	-18.8	-13.2	11.15	-2.34	-7.34	17.69	6.36	8.1	-20.5	0.04	-23.3	-20.3	-37.8	22.82
Q2	Past 3-month winner	LG	LV	SB	SV	SV	SG	LV	LG	LB	LV	SV	SV	SG	SG	SG	LV	LG	MV	LV	MV	SV	MV	LV
	3-month winner return	4.09	18.11	1.94	2.81	15.23	33.47	18.79	15.55	6.13	6.18	12.71	15.67	2.05	8.77	11.71	14.35	12.12	17.4	16.11	15.46	5.7	38.75	7.17
	Past 3-month loser	MG	MB	MG	LG	LG	LB	LB	MB	SB	SV	LG	LB	LG	SV	LG	MV	SG	LG	MG	LG	LG	LB	MG
	3-month loser return	-1.7	4.37	-3.82	-8.1	-0.04	7.59	7.02	-0.57	-5.58	-6.18	-2.19	0.36	-6.33	3.44	2.81	-5.8	-2.42	-1.16	-6.33	-8.84	-18.4	12.41	-2.29
	Past 12-month winner	MV	LV	SV	SV	SV	SG	SV	LV	LB	LV	MB	SV	SV	LB	SG	LV	LG	LV	SG	MV	LV	SV	SB
	12-month winner return	16.28	71.5	33.56	25.61	70.49	89.89	4.75	27.86	6.22	19.98	13.36	32.3	36.76	18.52	36.49	28.19	38.43	38.06	51.49	30.2	14.71	13.6	45.45
	Past 12-month loser	LG	MG	LG	LG	LG	LG	LB	MG	SB	SV	LV	MB	LG	SV	LV	MV	SV	SG	LB	LG	MG	MG	LB
	12-month loser return	0.88	21.8	3.3	-23.6	16.58	25.41	-18.4	10.12	-21.6	-17.9	-8.98	8.68	-8.98	1.35	16.21	-4.75	13.63	-8.04	0.52	-27.5	-27.6	-12.2	15.62
Q3	Past 3-month winner	LB	SV	LG	SB	LV	SV	LV	LB	LV	SV	LG	SV	MV	MG	LB	LB	LV	SG	SB	LG	SB	SG	MV
	3-month winner return	17.01	7.56	18.35	10.89	7.09	23.02	2.11	4.26	-14.1	13.47	3.18	12.75	7.74	11.88	6.59	13.03	-4.66	8.11	5.09	-12.6	-9.36	18.71	4.92
	Past 3-month loser	SG	LB	SG	LB	LB	LB	MG	MG	MV	LG	MV	LG	LG	LV	MB	SV	MB	LB	LV	MG	MG	LB	LV
	3-month loser return	-2.73	0.51	2.27	-1.98	-8.13	2.25	-1.41	-1.46	-22.3	2.68	-20	2.28	-0.43	4.03	-4.39	3.91	-23.8	-5.09	-3.46	-28.9	-23.1	2.13	-0.47
	Past 12-month winner	LB	LV	LB	SV	SV	SV	LV	LG	LV	LV	LG	MV	SV	LB	SG	LV	LV	LV	SG	MV	LV	MV	SB
	12-month winner return	43.19	60.97	31.28	31.78	59.21	127.9	-7.14	30.24	-14.5	47.19	3.35	82.85	25.87	24.79	36.06	38.45	13.68	44.67	44.04	9.57	16.31	55.28	25.89
	Past 12-month loser	SG	MG	MG	LG	LG	LG	MG	MG	MG	SG	MV	LG	LG	SV	MB	MV	MB	LG	LB	MG	LG	LB	MG
	12-month loser return	6.63	22.73	9	-33.2	13.41	36.56	-21.7	10.06	-35.3	4.72	-30.4	16.7	-11.4	3.67	7.52	4.57	-14.2	14.33	4.11	-46.2	-28.2	9.5	7.74
Q4	Past 3-month winner	LB	SV	MG	LB	SG	LV	LV	LG	LG	SG	MV	LV	LG	SB	LV	SB	LG	SG	LB	LV	LG	SB	SB
	3-month winner return	18.38	9.96	8.22	15.81	17.39	-25.8	1.11	1.91	8.39	0.84	20.13	15.78	4.54	5.41	4.48	2.12	12.18	32	12.69	26.68	15.82	11.99	13.48
	Past 3-month loser	MG	MG	LV	MG	LG	MG	MG	SB	SV	LV	SG	MB	MV	MV	SV	LB	SG	LB	MG	LB	MB	MV	MG
	3-month loser return	6.21	-1.92	4.26	2.05	-2.7	-31.7	-5.13	-11.9	-7.82	-17.4	5.69	4.61	-5.1	-3.45	-0.89	-3.53	-5.94	0.41	-11.5	4.97	-2.58	2.78	4.1
	Past 12-month winner	LB	LV	LB	SV	SV	SV	LV	LG	LV	MB	LG	SV	SG	LB	SG	LV	LV	SG	LV	MV	SV	MV	MB
	12-month winner return	51.56	47.32	29.89	36.55	59.7	45.75	26.45	34.98	-8.74	25.32	18.5	75.56	14.12	25.12	31.48	33.72	24.23	76.91	36.62	21.76	2.24	60.99	27.82
	Past 12-month loser	SG	MG	MG	LG	LG	LB	MG	MB	SV	SB	SG	LG	LG	MV	MB	SG	SG	LB	LG	MG	MG	LB	MG
	12-month loser return	8.27	13.34	20.27	-35	5.46	-7.33	8.71	1.98	-35.3	10.71	-12.6	14.53	-17.8	5.55	8.69	5.53	-15	11.67	-10.7	-26.8	-36.2	17.01	4.41

To better understand the return patters of the P1-P9 style portfolios, Table 4-5 computes the fraction that a particular style is in long or short side for all monthly strategies that rank styles according to the prior 3- and 12-month returns. Separate statistics are reported for hedge portfolios that contain two or four extreme winner and loser styles. The distribution of winner and loser styles suggests that overall value styles dominate the winners and growth styles dominate the losers. Specifically, it is shown that in most cases investors tend to favour SV styles and dislike LG styles for PC- and BM-based categorisation. For DY-based style classification, it is found that LV is the in-favour investment style, and again LG is the out-of-favour style.

In summary, the empirical findings in this session would suggest that, consistent with the literature, overall value styles tend to be winner styles and growth styles tend to be loser styles. But once interacted with the size dimension, the winners and losers may change alone the size axis, suggesting that style momentum portfolios need active rebalancing. To illustrate this, Figure 4-4 depicts the stock migration rate (%) in winner and loser styles based on 12-month ranking period and the use of 2 extreme styles in hedge portfolios. The negative sign represents the short side (loser style). The migration rate represents the percentage of stocks that will be moved in and out the winner or loser styles based on new ranking. The number will be 100 in general should the winner and loser be changed completely, and it would be between 0-100 once the previous winner or loser continue to be the winner and loser but with some new stocks moved in or out. To complement Figure 4-4, Table 4-6 reports the average migration rate (%) of stocks between the same styles, i.e. the average percentage of stocks that are likely to be moved in or out for styles that are continue to be the winner or loser in the next period.

Figure 4-4 reveals that, even for 12-month ranking period, the winner and loser changes quite frequently at both long and short side, while for styles that are continue to be the winner or loser in the next period, on average there are about 5% of the stocks that will be reclassified and move in or out from where they used to be. It is suggested that such rebalance of style momentum portfolios would introduce non-trivial transaction costs. Arguably, rebalance is needed when (1) the winner and loser styles changed; (2) a stock moves in and out of the winner or loser styles and; (3) a stock demonstrates exceptional high cross-sectional volatility and thus style portfolio needs rebalancing. Obviously, the shorter the rank period is, the more rebalance may be needed, and therefore the more transaction cost occurred. Hence from a practical investment perspective, financial practitioners should assess whether style momentum is able to generate economically positive profit once transaction costs are considered. Chen and De Bondt (2004) propose that such strategy is most useful for asset allocation experts who direct fund flows or used to enhance passive investing such as indexation strategy.

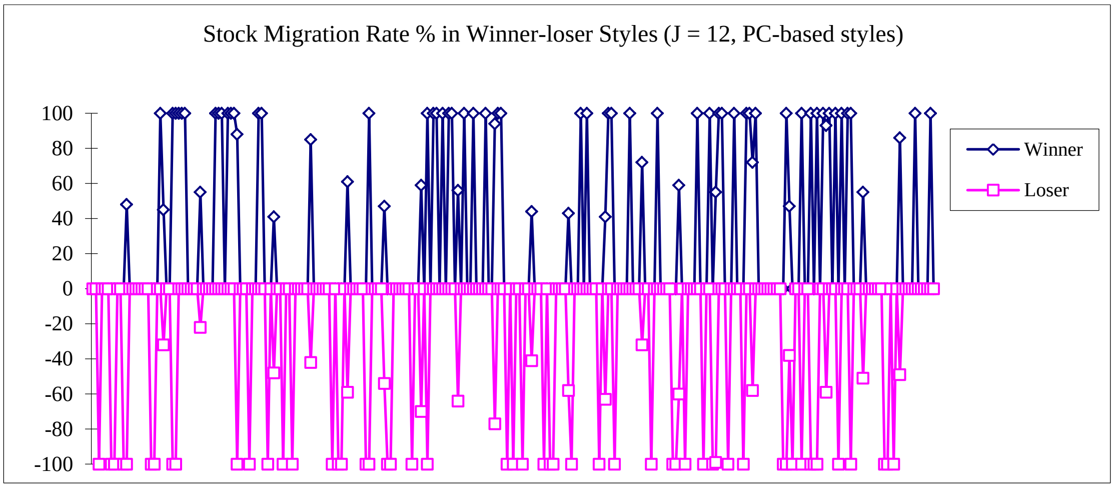
Table 4-5 The composition of style momentum portfolios

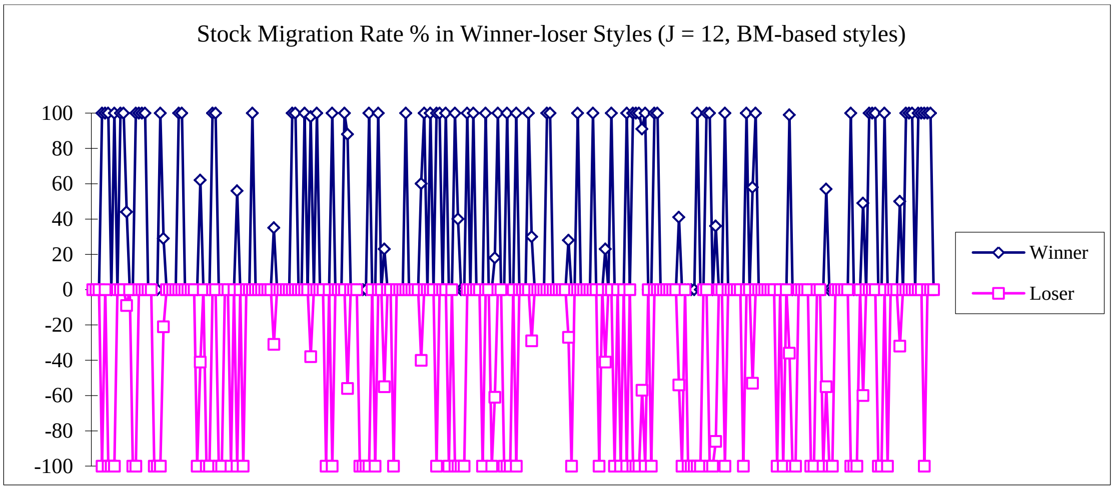
Every month between January 1982 and October 2003, based on firm characteristic variable PC, BM and DY respectively, 9 style portfolios (P1-P9) are ranked by their returns for the prior 3 or 12 months. The style momentum hedge portfolios are formed to buy winners (one or two style portfolios with the best past performance) and to sell losers (one or two style portfolios with the worst past performance). This table reports the percent of portfolio replications that either on long or short side.

		3-month rank periods				12-month rank periods			
Portfolios	definition	Buy one	Sell one	Buy two	Sell two	Buy one	Sell one	Buy twc	Sell two
Panel 1 Style momentum strategies based on PC									
P1	small_growth	6	23	10	36	5	28	8	46
P2	small_blend	10	6	22	13	7	2	26	7
P3	small_value	27	1	48	3	51	0	67	0
P4	middle_growth	2	18	5	47	0	26	3	68
P5	middle_blend	4	5	9	11	1	2	4	4
P6	middle_value	18	4	38	8	13	0	39	1
P7	large_growth	7	24	14	40	1	28	7	41
P8	large_blend	8	10	22	24	5	11	20	22
P9	large_value	20	10	31	18	18	4	27	9
Panel 2 Style momentum strategies based on BM									
P1	small_growth	10	24	17	38	7	27	13	42
P2	small_blend	8	6	18	18	4	3	13	9
P3	small_value	17	3	35	9	22	2	49	4
P4	middle_growth	4	14	13	30	4	14	11	42
P5	middle_blend	1	6	7	18	0	8	1	19
P6	middle_value	18	5	33	8	29	4	46	8
P7	large_growth	11	21	20	35	12	30	18	44
P8	large_blend	11	10	24	25	3	10	19	24
P9	large_value	19	11	34	18	18	3	29	8
Panel 3 Style momentum strategies based on DY									
P1	small_growth	11	10	19	21	12	11	16	24
P2	small_blend	8	4	20	14	3	1	19	4
P3	small_value	12	6	26	12	23	7	40	13
P4	middle_growth	5	18	11	34	2	24	11	42
P5	middle_blend	5	6	12	15	4	8	5	23
P6	middle_value	14	9	24	17	11	7	21	19
P7	large_growth	16	27	23	41	8	26	17	43
P8	large_blend	11	12	28	29	9	12	27	25
P9	large_value	19	7	37	16	28	3	42	8

Figure 4-4 Average stock migration rate % for winner and loser style

The figure below illustrates the percentage of stocks that will be moved in or out of winner and loser styles in next time period based on the current identification of winner and loser according to 12-month ranking period and the use of 2 extreme styles in hedge portfolios. The number will be 100 in general if the winner or loser is changed completely, and it would be between 0-100 once the previous winner or loser continues to be the winner and loser but with new stocks included or excluded.





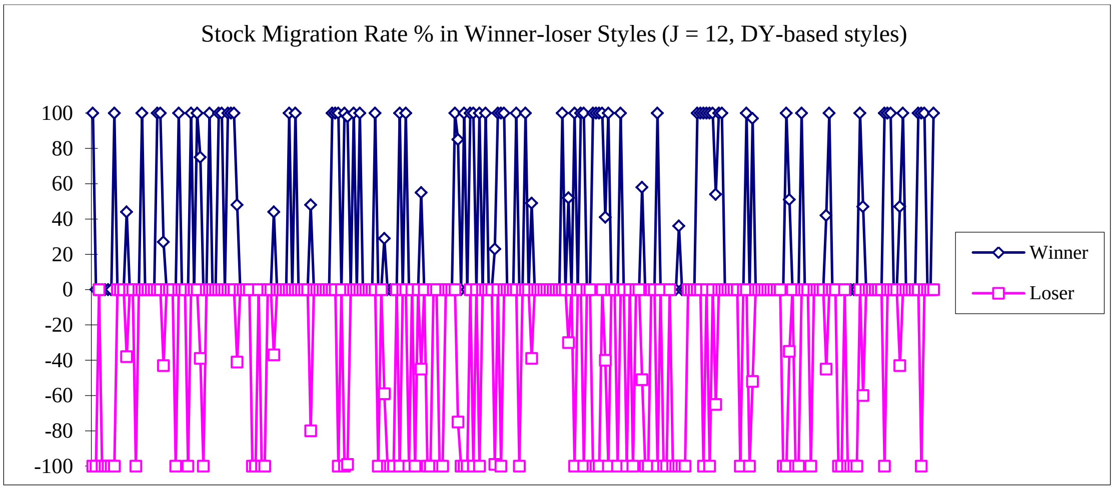


Table 4-6 Average migration rate (%) for stocks in consecutive extreme styles

This table reports the average migration rate (%) of stocks between the same winner or loser styles, i.e. the percentage of stocks that are likely to be moved in or out for styles that are continue to be the winner or loser in the next period.

		Based on 2 style portfolios		Based on 4 style portfolios	
Characteristics	Ranking period	Winner style	Loser style	Winner style	Loser style
	J = 3	4	3	3	4
PC	J = 6	5	4	6	4
	J = 12	5	4	4	4
	J = 3	3	2	3	3
BM	J = 6	4	3	5	4
	J = 12	4	4	5	3
	J = 3	3	5	3	6
DY	J = 6	3	5	4	5
	J = 12	4	4	5	4

4.6 Style, price and industry momentum

While section 5 has found the profitability of style momentum strategy in the U.K. stock market, one may well argue that such profits are simply the miracle of the price momentum of Jegadeesh and Titman (1993) or the industry momentum of Moskowitz and Grinblatt (1999) documented in the literature. This is because those stocks in current winner (loser) styles may also be categorised into the winner (loser) portfolios based on past individual stock returns, or winner (loser) industry portfolios. Therefore the style continuations may be simply due to a concentration of winner (loser) stocks within winner (loser) styles whose returns persist in the test periods. Grundy and Martin (2001) argue that price momentum strategy loads investors up on factors that perform well recently. Thus the return of price momentum captures the investors' sentiment about the firm's future perspective. Similarly, as Chen (2003) argues, industry momentum contains the changes of business sentiment about the industry's perspective. Hence it is important to disentangle style, price and industry effects.

Following Chen and De Bondt (2004), three methods are applied. First, the style momentum returns are calculated after adjusting price and industry momentum at the firm level. Next, a two-way independent sorting is implemented to investigate whether style momentum is independent from price and industry momentum. Finally, monthly cross-sectional regressions are tested by regressing expected returns for individual stocks on style momentum (SM), price momentum (PM) and industry momentum (IM) indicators to examine the explanatory ability of the three underlying momentum effects.

Every month, for each characteristic variable PC, BM and DY respectively, 9 style portfolios (P1-P9) are ranked according to their past 3- and 12-month returns starting from 1982 to 2003. Meanwhile, all stocks in P1-P9 styles are ranked into 9 quintiles according to (1) the past 3- or 12-month of the style portfolio returns to which they belong; (2) their own past 3- or 12-month total returns; and (3) the past 3- or 12-month industry portfolio returns to which they belong.[23]

Under this procedure, each stock will be properly plotted in a 3-D space with the information of style, price and industry momentum rankings. A pair of two ranking information will be examined and style momentum and price momentum are to buy the best quintile stocks and to sell the worst quintile stocks, while the industry momentum only buys and sells P1-P9 stocks that belong to the top and bottom of two industry portfolios whose ranking is based on all P1-P10 stocks in the universe.

Table 4-7 reports the value weighted average raw returns in the test periods up to 36 months as well as style, price or industry adjusted returns. The raw returns are adjusted on the individual stock level by deducting the contemporaneous value weighted returns of control portfolios. The control portfolios are either the industry momentum portfolios based on all stocks (P1-P10), or price momentum portfolios and style portfolios of based on stocks in P1-P9. Note that the style momentum returns reported in Table 4-7 are different from those in Table 4-3 because of the different weighting schemes used. The returns in Table 4-7 are based on value weighted scheme, and hence are smaller than those presented in Table 4-3 where equally-weighted scheme is used.

Table 4-7 suggests that it is difficult to disregard style momentum. Especially for stocks sorted on PC and DY and based on 12-month ranking and with holding period 6 and 9 months, the raw payoffs of style momentum have similar magnitude to PM- and IM-adjusted returns. It is also shown that SM, PM and IM are interacted. For example, once adjusting for PM effect, SM payoffs tend to decline. Similarly, PM effect tends to decrease when adjusting for IM or SM.

[23] The industry classification follows the Datastream variable INDC3. There are 14 industries identified altogether, i.e. BASIC,CYCGD, CYSER, GENIN, ITECH, NCYCG, NCYSR, OTHEQ, RESOR, SUSEQ, TOTLF, UNCLS, UQEQS and UTILS.

While IM also declines when adjusted for PM, it tends to increase the performance once SM is adjusted (except for IM-DY based on 3-month ranking). This would suggest a strong interaction between PM and IM effects, which is consistent with the literature. For example, prior studies such as Moskomitz and Grinblatt (1999) find that after controlling for industry effects price momentum disappears. Lee and Swaminathan (2001) show that adjusting for industries effects weakens the individual price momentum return from 12.5% to 10.1% per annum, and Grundy and Martin (2001) argue that industry momentums captures half of the size of price momentum effect. More recently, Lewellen (2002) and Chordia and Shivakumar (2002) also find individual momentum effect is still present after controlling for industry momentum.

Table 4-7 reveals some interesting findings. First, value weighted SM-BM returns are less persistent based on current sample data, and PM-DY demonstrates short term reversals (although not significant). Next, significance alone, the ranking of SM, PM and IM returns based on PC, BM and DY varies, suggesting that these firm attributes may capture different information affecting SM, PM and IM effects. For a (12, 12) strategy, it shows that IM-PC tends to have highest returns followed by PM-PC and SM-PC. In addition, IM-BM tends to have higher returns than SM-BM, and IM-DY tends to have highest returns followed by SM-DY, while PM-DY has the lowest performance. Overall, it should be safe to conclude that style momentum is a different phenomenon as compared to price and industry momentum.

It is necessary to further examine the interaction of style, price and industry momentum using an independent two-way sorting. Such two-way independent sorting avoids the problems criticised by Berk (2000) when distinguishing the explanatory power for future returns from two variables that are perceived to be correlated. Following Chen and De Bondt (2004), every month, for each variable BM, DY and PC, 9 style portfolios are first ranked either by 3- or 12-month past period returns. Style portfolios in the top three are labelled #1 (winners) while portfolios in the bottom three are labelled #3 (losers). Style portfolios in the middle range are labelled #2. Next, all stocks in P1-P9 styles are sorted into 3 quintiles according to their prior 3- or 12-month performance. The winner quintile is labelled #1 and the loser quintile is labelled #3 while the middle is labelled #2. Finally, 14 industry portfolios defined by the Datastream variable INDC3 are ranked by prior 3- or 12-month returns. Industry portfolios in the top 4 are labelled #1 (winners) while industries in the bottom 4 are labelled #3 (losers). Industry portfolios in between are labelled #2. Following These procedures, every stock in P1-P9 will be assigned to a 3 dimensional space containing the information of style, price and industry ranking.

Table 4-8 reports the equally weighted average monthly raw returns for the long, short and hedge momentum portfolio returns. Panel A is based on 3-month ranking and Panel B are the results for 12-month ranking period. Regardless which characteristics are used to define styles, it is demonstrated that once capitalising on the interaction with style effect, the price and industry momentum are significantly enhanced and the durations of return continuation are extended up to 2 years and possibly longer. It is evident that stocks in winner styles continue to outperform stocks in loser styles regardless whether they have been classified as price winner or losers, or whether they are in winner industries or loser industries. Moreover, the magnitude of return spreads for stocks in extreme styles but in the same times also classified into different price or industry performance categories are quantitatively similar. This indicates that style momentum plays more important role in affecting the structure of equity returns dynamics than price momentum or industry momentum does.

Table 4-7 Raw returns and style, price and industry adjusted returns

Every month, all stocks in P1-P9 styles based on variable X (X = PC, BM, DY) are ranked into 9 quintiles in ascending order according to (1) the past 3- or 12-month of the style portfolio returns to which they belong, (2) their own past 3- or 12-month total returns, and (3) the past 3- or 12-month industry portfolio returns to which they belong. Style momentum and price momentum are to buy the best quintile stocks (Q9) and sell the worst quintile stocks (Q1), while the industry momentum strategies only buy and sell P1-P9 stocks that belong to the top and bottom two industry portfolios whose ranking is based on all P1-P10 stocks. Value weighted average raw returns in the test periods as well as style-, price- or industry-adjusted returns are reported (K = 3, 6, 9, 12, 24 and 36 months). The raw returns are adjusted on the individual stock level by deducting the contemporaneous value weighted returns of control portfolios. The control portfolios are either the industry momentum portfolios based on all stocks (P1-P10), or the price momentum and style momentum portfolios based on P1-P9 stocks only.

	Rank periods = 3						Rank periods = 12					
	K = 3	K = 6	K = 9	K = 12	K = 24	K = 36	K = 3	K = 6	K = 9	K = 12	K = 24	K = 36
Panel A Style portfolios based on PC												
Style momentum	0.0020	0.0033	0.0034	0.0027	0.0017	0.0012	0.0080	0.0061	0.0045	0.0034	0.0017	0.0018
t - ratios	0.8602	1.9015	2.3680	2.1444	1.7617	1.4084	3.5539	3.0164	2.4171	1.8813	1.1241	1.3979
Price adjusted	0.0006	0.0025	0.0027	0.0019	0.0009	0.0004	0.0051	0.0031	0.0019	0.0012	0.0010	0.0014
t - ratios	0.2566	1.4622	1.9416	1.5315	1.0040	0.5403	2.4075	1.5900	1.0634	0.6657	0.6896	1.1192
Industry adjusted	0.0015	0.0028	0.0031	0.0024	0.0018	0.0014	0.0075	0.0053	0.0037	0.0024	0.0010	0.0011
t - ratios	0.6998	1.5871	2.0824	1.8084	1.9264	1.6672	3.4009	2.5713	1.9463	1.3349	0.6487	0.8143
Price momentum	0.0028	0.0051	0.0051	0.0063	0.0018	0.0001	0.0080	0.0066	0.0049	0.0023	-0.0029	-0.0040
t - ratios	0.7309	1.5855	1.7859	2.4655	1.0162	0.0589	1.7451	1.5496	1.2197	0.6033	-1.0134	-1.7814
Industry adjusted	-0.0004	0.0016	0.0015	0.0026	-0.0022	-0.0040	0.0051	0.0036	0.0020	-0.0007	-0.0065	-0.0081
t - ratios	-0.1003	0.4889	0.5252	1.0109	-1.2283	-2.8812	1.2677	0.8735	0.5160	-0.1960	-2.2655	-3.5929
Style adjusted	0.0003	0.0026	0.0029	0.0043	0.0003	-0.0013	0.0075	0.0060	0.0043	0.0017	-0.0035	-0.0045
t - ratios	0.0822	0.8070	1.0073	1.6790	0.1772	-0.9227	1.6651	1.4152	1.0686	0.4564	-1.2253	-2.0234
Industry momentum	0.0083	0.0060	0.0040	0.0031	0.0023	0.0011	0.0089	0.0060	0.0055	0.0039	0.0033	0.0018
t - ratios	1.4761	1.4330	1.0587	0.8634	0.8682	0.4989	1.4313	1.0838	1.0486	0.7772	0.8050	0.5547
Price adjusted	0.0073	0.0060	0.0037	0.0028	0.0017	0.0007	0.0092	0.0057	0.0051	0.0040	0.0064	0.0044
t - ratios	1.3015	1.4427	0.9815	0.7858	0.6525	0.3134	1.6161	1.0840	1.0112	0.8157	1.5570	1.3162
Style adjusted	0.0086	0.0066	0.0046	0.0035	0.0020	0.0007	0.0112	0.0088	0.0087	0.0074	0.0065	0.0045
t - ratios	1.4977	1.5416	1.1854	0.9636	0.7651	0.3184	1.8185	1.6072	1.6453	1.4910	1.5668	1.3367

Table 4-7 (continued -1)

	Rank periods = 3						Rank periods = 12					
	K = 3	K = 6	K = 9	K = 12	K = 24	K = 36	K = 3	K = 6	K = 9	K = 12	K = 24	K = 36
Panel B Style portfolios based on BM												
Style momentum	0.0032	0.0022	0.0023	0.0021	0.0010	0.0007	0.0039	0.0012	0.0010	0.0007	0.0007	0.0013
t - ratios	1.3090	1.1361	1.4841	1.6235	1.0312	0.7814	1.3468	0.5037	0.4338	0.3728	0.4194	0.8485
Price adjusted	0.0012	0.0010	0.0013	0.0014	0.0008	0.0007	0.0011	-0.0016	-0.0016	-0.0015	0.0002	0.0010
t - ratios	0.5208	0.5307	0.8656	1.0932	0.8013	0.7535	0.4591	-0.6882	-0.7228	-0.7367	0.1425	0.6567
Industry adjusted	0.0022	0.0010	0.0011	0.0009	-0.0002	-0.0005	0.0022	-0.0007	-0.0012	-0.0015	-0.0014	-0.0010
t - ratios	1.0071	0.5094	0.6823	0.6300	-0.2218	-0.5085	0.8698	-0.2994	-0.5454	-0.7384	-0.8143	-0.7052
Price momentum	0.0073	0.0094	0.0088	0.0093	0.0023	0.0002	0.0123	0.0100	0.0057	0.0026	-0.0030	-0.0045
t - ratios	1.7539	2.6387	2.7478	3.2130	1.1772	0.1641	2.3707	2.0836	1.2910	0.6241	-0.9670	-1.9314
Industry adjusted	0.0026	0.0044	0.0038	0.0042	-0.0031	-0.0050	0.0090	0.0064	0.0021	-0.0011	-0.0075	-0.0094
t - ratios	0.6670	1.2555	1.1666	1.4425	-1.5260	-3.2095	1.9187	1.3901	0.4990	-0.2744	-2.3976	-3.9319
Style adjusted	0.0056	0.0081	0.0077	0.0084	0.0015	-0.0005	0.0127	0.0108	0.0066	0.0035	-0.0023	-0.0038
t - ratios	1.3425	2.2541	2.3769	2.8562	0.7249	-0.3454	2.4535	2.2447	1.4867	0.8341	-0.7337	-1.5916
Industry momentum	0.0098	0.0085	0.0066	0.0053	0.0030	0.0016	0.0132	0.0091	0.0072	0.0049	0.0041	0.0023
t - ratios	1.7724	2.0510	1.7186	1.4665	1.1531	0.7314	2.1382	1.6821	1.4377	1.0559	1.1090	0.7731
Price adjusted	0.0076	0.0080	0.0061	0.0050	0.0026	0.0015	0.0128	0.0077	0.0060	0.0044	0.0072	0.0050
t - ratios	1.4039	1.9616	1.6068	1.4217	1.0158	0.6892	2.2594	1.4778	1.2509	0.9779	1.9329	1.6572
Style adjusted	0.0098	0.0081	0.0059	0.0046	0.0031	0.0016	0.0150	0.0112	0.0095	0.0079	0.0070	0.0047
t - ratios	1.7286	1.9084	1.5038	1.2786	1.2256	0.7684	2.4413	2.0646	1.8946	1.6953	1.8642	1.5410

Table 4-7 (continued -2)

	Rank periods = 3						Rank periods = 12					
	K = 3	K = 6	K = 9	K = 12	K = 24	K = 36	K = 3	K = 6	K = 9	K = 12	K = 24	K = 36
Panel C Style portfolios based on DY												
Style momentum	0.0026	0.0028	0.0022	0.0022	0.0020	0.0014	0.0052	0.0047	0.0044	0.0035	0.0026	0.0020
t - ratios	1.0333	1.4267	1.4362	1.5155	1.9519	1.8075	1.9169	1.9458	1.9617	1.6705	1.4797	1.3457
Price adjusted	0.0009	0.0021	0.0015	0.0014	0.0014	0.0009	0.0043	0.0034	0.0031	0.0022	0.0024	0.0019
t - ratios	0.3533	1.0587	0.9601	0.9603	1.4128	1.1610	1.6345	1.3947	1.3649	1.0388	1.3448	1.2495
Industry adjusted	0.0012	0.0013	0.0008	0.0007	0.0006	0.0000	0.0040	0.0034	0.0031	0.0022	0.0016	0.0011
t - ratios	0.5047	0.6209	0.4702	0.4695	0.5865	-0.0249	1.5870	1.4046	1.3998	1.0559	0.9126	0.7263
Price momentum	-0.0034	0.0011	0.0028	0.0036	0.0000	-0.0008	0.0016	0.0024	0.0003	-0.0021	-0.0051	-0.0060
t - ratios	-0.8061	0.3716	1.0460	1.4977	-0.0241	-0.6329	0.3441	0.5525	0.0749	-0.5117	-1.7688	-2.6877
Industry adjusted	-0.0063	-0.0019	-0.0003	0.0004	-0.0036	-0.0045	0.0012	0.0017	-0.0005	-0.0031	-0.0068	-0.0082
t - ratios	-1.6062	-0.6190	-0.1199	0.1768	-1.9992	-3.3635	0.2801	0.4091	-0.1177	-0.7901	-2.3629	-3.6298
Style adjusted	-0.0046	0.0004	0.0023	0.0033	0.0003	-0.0004	0.0021	0.0030	0.0009	-0.0017	-0.0045	-0.0056
t - ratios	-1.0885	0.1214	0.8582	1.3685	0.1722	-0.2700	0.4449	0.6903	0.2171	-0.4105	-1.5752	-2.4919
Industry momentum	0.0044	0.0030	0.0028	0.0023	0.0024	0.0016	0.0058	0.0050	0.0066	0.0061	0.0066	0.0041
t - ratios	0.7440	0.7047	0.7369	0.6582	0.9263	0.7113	0.9234	0.8947	1.2419	1.2304	1.6050	1.2033
Price adjusted	0.0039	0.0031	0.0024	0.0020	0.0019	0.0010	0.0052	0.0034	0.0052	0.0048	0.0073	0.0044
t - ratios	0.6694	0.7385	0.6496	0.5729	0.7312	0.4601	0.9057	0.6433	1.0289	0.9809	1.7875	1.2922
Style adjusted	0.0031	0.0017	0.0015	0.0011	0.0012	0.0006	0.0071	0.0059	0.0070	0.0060	0.0064	0.0039
t - ratios	0.5229	0.3960	0.3949	0.2972	0.4527	0.2853	1.1557	1.0650	1.3248	1.2154	1.5556	1.1711

Table 4-8 The returns of price and industry momentum portfolios that vary in style momentum

Every month, based on variable PC, BM and DY respectively, 9 style portfolios (P1-P9) are ranked based on their 3- or 12-month past returns. The top 3 style portfolios are labelled #1 (winners) and the bottom three style portfolios are labelled #3 (losers), styles in the middle range are labelled #2. Next, all P1-P9 stocks are sorted into 3 quintiles according to their prior 3- or 12-month performance. The winner quintile is labelled #1, the loser quintile is labelled #3 and the rest defined as #2. Finally, 14 industry portfolios defined by Datastream variable INDC3 are ranked by prior 3- or 12-month performance. The top 4 industry portfolios are labelled #1 (winners) while the bottom 4 industries are labelled #3 (losers). Industries in between are labelled #2. This table reports the monthly average raw returns based on such sorting.

	Portfolios based on PC						Portfolios based on BM						Portfolios based on DY					
	K = 3	K = 6	K = 9	K = 12	K = 24	K = 36	K = 3	K = 6	K = 9	K = 12	K = 24	K = 36	K = 3	K = 6	K = 9	K = 12	K = 24	K = 36
Panel A 3-month ramk periods																		
(P1,S1)	0.02	0.02	0.0191	0.0189	0.0163	0.0151	0.019	0.0183	0.018	0.0181	0.0158	0.0148	0.0174	0.0176	0.0173	0.0173	0.0156	0.0146
(P1,S3)	0.0114	0.0127	0.0126	0.0133	0.0126	0.0126	0.0129	0.0139	0.0133	0.0138	0.0125	0.0124	0.0126	0.0139	0.0135	0.014	0.0131	0.0132
(P1,S1)-(P1,S3)	0.0087	0.0073	0.0065	0.0057	0.0037	0.0025	0.0061	0.0044	0.0047	0.0043	0.0033	0.0025	0.0048	0.0037	0.0038	0.0033	0.0024	0.0014
t - ratios	5.9293	6.3172	7.04	6.9384	5.4134	4.2079	4.3457	3.9449	5.0633	4.9196	4.6805	4.0307	3.5425	3.2408	3.926	3.6507	3.4651	2.4224
(P2,S1)	0.019	0.0177	0.0171	0.0165	0.0155	0.015	0.0167	0.016	0.0159	0.0154	0.0149	0.0145	0.0155	0.0144	0.0144	0.0141	0.0138	0.0135
(P2,S3)	0.0087	0.0102	0.0108	0.0112	0.0118	0.0124	0.0095	0.0105	0.0106	0.0108	0.0117	0.0122	0.0087	0.0099	0.0102	0.0104	0.011	0.0115
(P2,S1)-(P2,S3)	0.0103	0.0075	0.0062	0.0053	0.0038	0.0026	0.0072	0.0055	0.0052	0.0046	0.0033	0.0024	0.0068	0.0046	0.0041	0.0037	0.0028	0.0019
t - ratios	7.8485	7.0843	6.8073	6.473	5.6198	4.2047	5.1272	4.7319	5.4077	5.2134	4.995	4.031	5.121	4.3484	4.5693	4.2356	4.1517	3.5953
(P3,S1)	0.0195	0.0173	0.0166	0.0154	0.0157	0.0158	0.0152	0.0134	0.0136	0.0129	0.0143	0.0147	0.0155	0.0141	0.0142	0.0139	0.0148	0.015
(P3,S3)	0.0077	0.0084	0.0091	0.0093	0.0115	0.0127	0.0059	0.0069	0.0078	0.0084	0.0115	0.0126	0.0078	0.0081	0.0087	0.009	0.0109	0.0121
(P3,S1)-(P3,S3)	0.0119	0.0089	0.0075	0.0061	0.0041	0.0032	0.0093	0.0065	0.0058	0.0045	0.0028	0.0021	0.0077	0.006	0.0055	0.0048	0.004	0.0029
t - ratios	7.1629	6.3612	6.2259	5.5666	4.8486	4.0158	5.5121	4.7629	5.0769	4.3866	3.7514	3.1974	4.5615	4.1888	4.4424	4.1786	4.5534	4.1356
(I1,S1)	0.023	0.0203	0.0188	0.0182	0.016	0.0155	0.019	0.0175	0.0173	0.0171	0.0153	0.0151	0.0175	0.0162	0.0154	0.0152	0.0144	0.0139
(I1,S3)	0.0139	0.0125	0.0121	0.0131	0.0128	0.0138	0.0139	0.0135	0.0124	0.0123	0.0126	0.0134	0.0121	0.0111	0.0109	0.0111	0.0117	0.0128
(I1,S1)-(P1,S3)	0.0091	0.0079	0.0067	0.0051	0.0033	0.0017	0.0052	0.004	0.0049	0.0049	0.0027	0.0017	0.0054	0.005	0.0045	0.0041	0.0027	0.0011
t - ratios	4.6795	4.9358	5.3238	4.385	3.7458	2.0945	2.4443	2.4007	3.8383	4.2221	3.4283	2.3772	2.6388	3.1346	3.3672	3.5547	3.3704	1.6927
(I2,S1)	0.0198	0.0196	0.0189	0.018	0.0164	0.0157	0.0166	0.0164	0.0162	0.0159	0.0154	0.0149	0.0153	0.0156	0.0155	0.0153	0.0148	0.0144
(I2,S3)	0.0102	0.0122	0.0124	0.0123	0.0123	0.0127	0.0086	0.0103	0.0103	0.0106	0.0117	0.0124	0.0101	0.0113	0.0116	0.0114	0.012	0.0127
(I2,S1)-(I2,S3)	0.0096	0.0074	0.0065	0.0057	0.0041	0.003	0.008	0.006	0.0059	0.0053	0.0036	0.0026	0.0052	0.0042	0.0039	0.0038	0.0028	0.0018
t - ratios	7.4974	6.9525	7.2601	7.0403	6.2643	4.826	5.6419	5.0578	6.0558	6.0331	5.5418	4.4056	3.7918	3.8944	4.2347	4.354	4.0687	3.2348
(I3,S1)	0.0181	0.0177	0.0174	0.016	0.015	0.0144	0.0143	0.0132	0.0139	0.0129	0.0131	0.0129	0.0157	0.0149	0.0144	0.0136	0.0138	0.0135
(I3,S3)	0.0051	0.0077	0.0088	0.0094	0.0108	0.0121	0.0037	0.0064	0.0075	0.0086	0.0103	0.0116	0.0054	0.0071	0.0073	0.0082	0.0099	0.0111
(I3,S1)-(I3,S3)	0.013	0.0099	0.0086	0.0066	0.0042	0.0023	0.0106	0.0068	0.0064	0.0043	0.0027	0.0013	0.0103	0.0078	0.0071	0.0053	0.0039	0.0025
t - ratios	5.2642	5.3127	5.1352	4.4475	3.6642	2.2904	5.0261	4.068	4.608	3.2841	2.8879	1.6424	4.3781	4.4939	4.6771	3.9422	3.8133	2.9262

Table 4-8 (continued)

	Portfolios based on PC						Portfolios based on BM						Portfolios based on DY					
	K = 3	K = 6	K = 9	K = 12	K = 24	K = 36	K = 3	K = 6	K = 9	K = 12	K = 24	K = 36	K = 3	K = 6	K = 9	K = 12	K = 24	K = 36
Panel B 12-month ramk periods																		
(P1,S1)	0.0238	0.0222	0.0205	0.0191	0.016	0.015	0.0231	0.021	0.0195	0.018	0.0152	0.0143	0.0208	0.0192	0.0182	0.0171	0.0149	0.0141
(P1,S3)	0.0142	0.0136	0.0129	0.0127	0.0116	0.0113	0.0168	0.0155	0.0143	0.0133	0.011	0.0108	0.0172	0.0161	0.015	0.014	0.0125	0.0123
(P1,S1)-(P1,S3)	0.0097	0.0086	0.0076	0.0064	0.0043	0.0037	0.0063	0.0055	0.0052	0.0047	0.0042	0.0035	0.0036	0.0031	0.0031	0.0031	0.0024	0.0018
t - ratios	6.2219	5.8113	5.5051	4.9882	3.804	3.7295	4.2574	4.1014	4.1082	3.8596	3.6865	3.4785	2.4055	2.2672	2.4588	2.5433	2.2461	1.9884
(P2,S1)	0.0183	0.0176	0.0169	0.0167	0.0161	0.0158	0.0164	0.0153	0.0148	0.0145	0.0143	0.0146	0.0153	0.0146	0.0143	0.0142	0.0141	0.0142
(P2,S3)	0.0076	0.0086	0.0094	0.01	0.0106	0.0113	0.0073	0.0084	0.0089	0.0094	0.0109	0.0117	0.009	0.0095	0.0099	0.0103	0.0109	0.0114
(P2,S1)-(P2,S3)	0.0108	0.0091	0.0075	0.0068	0.0054	0.0045	0.009	0.007	0.0059	0.0051	0.0034	0.0029	0.0062	0.0051	0.0044	0.0039	0.0032	0.0027
t - ratios	6.9734	6.3647	5.6403	5.2631	4.9138	4.4665	5.6997	4.8766	4.3	3.951	2.8497	2.8208	4.1777	3.7293	3.4312	3.1299	3.0084	3.1024
(P3,S1)	0.0179	0.0169	0.0169	0.0168	0.0173	0.0172	0.0141	0.014	0.0143	0.0143	0.0157	0.0161	0.0134	0.0132	0.0141	0.0147	0.0157	0.0158
(P3,S3)	0.0055	0.0074	0.0088	0.0098	0.012	0.0128	0.0047	0.0067	0.0086	0.0099	0.0126	0.0131	0.0059	0.0071	0.0085	0.0093	0.0114	0.0123
(P3,S1)-(P3,S3)	0.0125	0.0095	0.0081	0.007	0.0053	0.0044	0.0094	0.0073	0.0057	0.0043	0.0031	0.0031	0.0075	0.0061	0.0056	0.0054	0.0043	0.0035
t - ratios	6.5305	5.486	4.9587	4.5044	4.1595	3.8944	4.8666	4.0499	3.3411	2.7237	2.2235	2.6111	3.6785	3.2172	3.2751	3.3698	3.5178	3.47
(I1,S1)	0.0222	0.0198	0.0183	0.0175	0.0162	0.0155	0.022	0.0189	0.0176	0.0166	0.0156	0.0154	0.0179	0.0161	0.0156	0.0154	0.0144	0.0139
(I1,S3)	0.0131	0.0117	0.0111	0.0111	0.0114	0.0113	0.0122	0.0106	0.0103	0.0105	0.0119	0.0118	0.0115	0.0104	0.0101	0.0103	0.0114	0.0116
(I1,S1)-(P1,S3)	0.0091	0.0081	0.0071	0.0065	0.0048	0.0042	0.0098	0.0084	0.0073	0.0061	0.0037	0.0036	0.0063	0.0057	0.0055	0.0051	0.003	0.0023
t - ratios	4.3644	4.6263	4.5597	4.3477	3.4354	3.3424	4.9472	4.9363	4.429	3.8306	2.3986	2.5929	3.2061	3.4231	3.687	3.6547	2.5168	2.2505
(I2,S1)	0.0218	0.0211	0.0202	0.0193	0.0173	0.0166	0.0182	0.018	0.0173	0.0166	0.0153	0.0152	0.0169	0.0165	0.0163	0.016	0.0153	0.0149
(I2,S3)	0.0096	0.0111	0.0118	0.0119	0.012	0.0125	0.0089	0.0102	0.011	0.0113	0.0117	0.0125	0.011	0.012	0.0123	0.0121	0.0123	0.0127
(I2,S1)-(I2,S3)	0.0122	0.01	0.0084	0.0074	0.0053	0.0041	0.0092	0.0078	0.0063	0.0053	0.0036	0.0027	0.006	0.0045	0.004	0.004	0.003	0.0022
t - ratios	8.4294	7.258	6.2734	5.8565	5.1213	4.5506	5.9822	5.4593	4.6382	4.1939	3.3404	2.928	3.9759	3.1715	2.9869	3.096	2.8402	2.4701
(I3,S1)	0.0193	0.018	0.0178	0.0176	0.017	0.0156	0.0153	0.0143	0.0144	0.0141	0.0145	0.0137	0.0138	0.0133	0.0134	0.0133	0.0131	0.0131
(I3,S3)	0.0065	0.0086	0.01	0.011	0.0116	0.0115	0.0081	0.0104	0.0116	0.0123	0.0123	0.0125	0.0083	0.0079	0.0087	0.0095	0.0106	0.0113
(I3,S1)-(I3,S3)	0.0127	0.0093	0.0078	0.0065	0.0054	0.0041	0.0072	0.004	0.0028	0.0019	0.0023	0.0012	0.0055	0.0055	0.0047	0.0038	0.0026	0.0018
t - ratios	4.4167	3.7534	3.4452	3.0941	3.2466	2.8167	2.5789	1.7521	1.3661	0.9745	1.4004	0.8536	2.246	2.5436	2.2892	2.0098	1.6318	1.3927

To disentangle style, price and industry momentum effects, Table 4-9 applies Fama-MacBeth (1973) cross-sectional multivariate regressions. Specifically, each month all stocks in P1-P9 style portfolios are first assigned into 9 deciles in ascending order according to their returns over the previous 3, 6, and 12 months. Hence loser stocks are in decile 1 and winner stocks are in decile 9. The price momentum indicator (PM) is simply the decile number to which P1-P9 stocks belong (i.e. 1, 2 ,..., 9). Further, 14 industry portfolios defined by Datastream INDC3 are ranked based on the prior 3-, 6-, and 12-month industry returns. The industry with the lowest rank receives a score of 1 and that with the highest rank receives a score of 14. Thus every P1-P9 stock receives the score of the industry (IM) ranking to which it belongs. Finally, style momentum indicator (SM) is computed by ranking all 9 style portfolios based on their 3-, 6-, and 12-month returns. Again the loser style has a score of 1 and the winner style is assigned a score of 9. Thus every P1-P9 stock receives the score of the style portfolio to which it belongs. Under this procedure, every single stock in the style portfolios will have 3 parameters containing the price, industry and momentum ranking information. Cross-sectional regressions of raw buy-and-hold test period returns for individual stocks with 3-, 6- 12-, and 24-months holding periods on the SM, PM and IM indicators are fitted. Table 4-9 reports the time-series average estimated regression coefficients for styles based on different firm characteristics and test periods.

The results in Table 4-9 would suggest that, together with PM and IM, SM is a determinant that affects the equity return dynamics. The explanatory power of SM extends to at least 12 months and possibly longer. Similar to SM, the IM factor also has the ability in explaining stock returns. This is not the case for IM factor which shows the short-term explanatory ability only. It is estimated that the annual return differential between a stock that is from in-favour style and another from the out-of-favour style based on 3-month ranking would be 1.28%*(8) = 10.5% for PC-based style classification, and the spreads would be 7.9% and 5.8% for BM- and DY-based styles, respectively. The return spreads are equivalent in magnitude for stocks based on PM ranking but not for IM ranking. The explanatory power of SM generally increases for future stock returns longer than 12 months, and decrease for PM. Hence SM tends to have longer-lasting effects than PM does, which is consistent with Chen (2003). However, the tests based on U.K. sample suggest that the explanatory power of IM to individual stock returns is less significant, in particular when sorting is based on relatively long period and for longer stock return predictions.

As a summary, the empirical findings in this session suggest that style momentum is distinct from the price and industry momentum documented in the literature. The test results above confirm the style-based positive feedback trading story of Barberis and Shleifer (2003) that style effects should persist even after controlling for stock-level continuations. Further, since information of style cycles is useful in predicting future individual stock returns, the results are also consistent with Berk *et al.* (1999) that firms of similar characteristics will have similar systematic risks and tend to be at the similar stage of investment style, and hence characteristic-based style portfolios could price stock returns. Overall, it is evident that equity style cycles do exist in the U.K stock market, and the evolution of equity style cycles conveys useful information and therefore plays an important role in the return generating process.

Table 4-9 Momentum effects and the cross-sectional stock returns

Every month, all stocks in P1-P9 portfolios are assigned into 9 deciles in ascending order based on their previous 3-, 6-, and 12-month returns. Loser stocks are in decile 1 and winner stocks are in decile 9. A stock's price momentum indicator (PM) is simply the decile number to which the stock belongs (i.e. 1, 2,..., 9). Further, 14 industry portfolios defined by Datastream INDC3 are ranked based on the prior 3-, 6-, and 12-month industry returns. The industry with the lowest rank receives a score of 1 and that with the highest rank receives a score of 14. Thus every stock receives the score of the industry (IM) ranking value to which it belongs. Finally, style momentum indicator (SM) is computed by ranking 9 style portfolios based on their 3-, 6-, and 12-month returns. Again the loser style has a score of 1 and the winner style is assigned a score of 9, and every stock receives the SM score of the style portfolio to which it belongs. Under this procedure, every stock in the style portfolios P1-P9 will have 3 parameters containing the price, industry and momentum ranking information. Cross-sectional regressions of raw buy-and-hold test period returns for individual stocks with 3-, 6- and 12-months holding periods on the SM, PM and IM indicators are tested. Following Fama-MacBeth (1973), this table reports the time-series average estimated regression coefficients for styles based on different firm characteristics and test periods. The t ratios in brackets are calculated based on the Newey-West (1987) heteroscedasticity and autocorrelation consistent standard errors with lags equal to K, the testing periods. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

	3-month rank period			6-month rank period			12-month rank period		
	SM	PM	IM	SM	PM	IM	SM	PM	IM
Panel A Style portfolios based on APC									
3-M test returns	0.0048	0.0010	0.0014	0.0055	0.0027	0.0011	0.0054	0.0034	0.0009
t-ratios	(7.35)***	(1.31)	(2.86)***	(8.48)***	(2.98)***	(2.10)*	(7.81)***	(3.42)***	(1.36)
6-M test returns	0.0077	0.0042	0.0015	0.0095	0.0059	0.0010	0.0092	0.0057	0.0005
t-ratios	(7.08)***	(3.35)***	(1.80)*	(6.60)***	(3.75)***	(1.12)	(5.15)***	(3.15)***	(0.50)
12-M test returns	0.0128	0.0102	0.0016	0.0159	0.0112	0.0007	0.0163	0.0055	-0.0005
t-ratios	(5.16)***	(4.78)***	(1.28)	(4.33)***	(3.97)***	0.51)	(3.75)***	(1.53)	(-0.27)
24-M test returns	0.0210	0.0080	0.0008	0.0285	0.0063	0.0022	0.0305	-0.0034	0.0020
t-ratios	(3.59)***	(2.41)**	(0.32)	(3.61)***	(1.45)	(0.61)	(2.92)***	(-0.67)	(0.50)
Panel B Style portfolios based on BM									
3-M test returns	0.0037	0.0029	0.0019	0.0039	0.0048	0.0016	0.0038	0.0055	0.0013
t-ratios	(5.00)***	(3.29)***	(2.94)***	(4.48)***	(4.83)***	(2.52)**	(4.75)***	(5.24)***	(1.50)
6-M test returns	0.0056	0.0067	0.0024	0.0063	0.0087	0.0018	0.0060	0.0088	0.0008
t-ratios	(4.32)***	(4.74)***	(2.29)**	(4.34)***	(5.05)***	(1.88)*	(3.14)***	(4.29)***	(0.65)
12-M test returns	0.0099	0.0128	0.0022	0.0106	0.0142	0.0015	0.0096	0.0080	0.0000
t-ratios	(3.72)***	(4.95)***	(1.69)*	(2.74)***	(4.08)***	(0.92)	(1.98)**	(1.92)*	(0.00)
24-M test returns	0.0155	0.0107	0.0024	0.0185	0.0105	0.0042	0.0194	0.0003	0.0036
t-ratios	(2.24)**	(2.67)***	(0.81)	(1.89)*	(2.12)**	(0.84)	(1.55)	(0.05)	(0.76)
Panel C Style portfolios based on DY									
3-M test returns	0.0028	0.0025	0.0008	0.0026	0.0045	0.0006	0.0025	0.0052	0.0007
t-ratios	(3.83)***	(3.25)***	(1.67)*	(3.89)***	(5.21)***	(1.33)	(3.28)***	(5.37)***	(1.09)
6-M test returns	0.0044	0.0085	0.0004	0.0044	0.0085	0.0004	0.0040	0.0086	0.0001
t-ratios	(3.14)***	(5.82)***	(0.46)	(3.14)***	(5.82)***	(0.46)	(2.31)**	(4.71)***	(0.05)
12-M test returns	0.0072	0.0123	0.0006	0.0068	0.0139	-0.0007	0.0072	0.0091	-0.0014
t-ratios	(2.41)**	(6.23)***	(0.55)	(1.77)*	(5.01)***	(-0.42)	(1.66)*	(2.53)**	(-0.61)
24-M test returns	0.0109	0.0121	0.0012	0.0109	0.0121	0.0012	0.0116	0.0031	0.0010
t-ratios	(1.10)	(2.63)***	(0.29)	(1.10)	(2.63)***	(0.29)	(1.02)	(0.69)	(0.19)

4.7 The risk exposures of style momentum strategies

Previous sections in this Chapter finds that style momentum is a phenomenon that is different from price and industry momentum, and the information of style cycles has predictive ability in future stock returns. It is noteworthy however that the predictive power of prior in-favour or out-of-favour investment styles may be confounded with the well recognised book-to-market and size effect in the context of Fama and French (1996) three-factor model. For this reason, it is necessary to investigate whether style momentum portfolios contain additional information to predict future stock returns once the size and BM factors are controlled. To verify whether style momentum effect is due to covariation with such common risk factors, this section employs the Fama and French (1993) three-factor model to evaluate the payoffs of style momentum investing. The use of Fama and French three-factor model as a risk-based tool for performance evaluation is justified by its superiority over single factor models such as CAPM. In addition, studies such as Liew and Vassalou (2000) argue that SMB and HML contain the business cycle information like future GDP growth.

For each firm characteristics PC, MV and DY, the already familiar 9 style portfolios are ranked by their prior 3- or 12-month returns and hedge portfolios are formed to buy the past winner style and to sell the past loser style. The winner, loser and the hedge portfolio are held for 3 or 12 months when the strategy is repeated. Thus the test periods and the rank periods are non-overlapping. Starting from 1982:01-2003:12, the equally weighted average hedge portfolio returns during the test periods in excess of the 1-month Treasury bill rate are regressed on the contemporaneous monthly returns of Fama and French three factors. The Datastream UK index return is used as a proxy for market return.

Table 4-10 summarises the results. The three-factor model explains some of the variations in equity style momentum returns defined by characteristics variables BM and DY, but not for styles classified by PC. The Fama-French alphas of PC-based style momentum is 0.0084 and 0.0072 for ranking periods of 3- and 12-month respectively, both are significant at 1% level. However, when measured against the Fama-French three-factor model, the style-level mispricing for portfolios based on characteristics BM and DY is not significant. It is shown that the Fama-French alphas are 0.0025, 0.0017 for BM portfolios and 0.0015 and -0.0012 for DY portfolios based on 3- and 12-month ranking, respectively. Thus BM- and DY-based style momentum strategies do not generate abnormal returns at all.

There are also strong size-effects found in momentum returns because all loadings for the SMB factors are significantly positive, while the HML loadings vary. Specifically, the HML loading for PC-based hedge portfolio is positive and statistically significant, indicating that the loser style contains more value stocks than the winner style in short term. This is also evidenced by the positive but insignificant (significant) HML loading for winner (loser) style. In contrast, when the style ranking period is based on 12-month, both winner and loser styles as well as the momentum hedge portfolios contain positive and significant HML loadings, suggesting that over longer periods, value stocks outperform growth stocks defined PC. Similar results for HML factors can be found for DY-based style momentum returns but BM-based results seem to be slightly different. Even based on longer ranking period of 12-month, the HML loading for BM-based hedge portfolio is significantly negative (at 10% level), implying that growth stocks tend to outperform value stocks based on BM sorting. The negative sign of HML loadings suggests that controlling for the value and growth exposures can actually improve style momentum returns. It is also noted that the alphas of winner styles are positive and those of loser styles are negative. This may suggest that style investors are more apt to move money in a style that has shown persistent good performance than moving out money from a style that is found to perform poorly.

While PC-based momentum seems to be able to generate abnormal returns, such risk-adjusted returns are less likely caused by the differences in market risk of winner and loser styles. This is because regardless which style variables are tested, in most cases winner styles tend to have smaller betas than the losers. Jegadeesh and Titman (1993) also show that differences in market risk of long short side of the hedge portfolios do not cause price momentum profits. The style momentum portfolios are generally market neutral, only DY-based portfolio of 3-month ranking has significant negative beta.

As a final step, Table 4-11 examines the risk-return characteristics of style momentum strategies based on different subsamples. Because of the time-varying nature of style performance, a number of prior studies have related the momentum returns with the stage of business cycles. For example, Chordia and Shivakumar (2003) find that during economic recessions there is no price momentum effect. Table 4-11 subdivides the whole sample period into 4 sub-periods, i.e. 1982-1986, 1987-1993, 1994-1999 and 2000-2004. It is shown that style momentum strategies perform better after year 1999 when the technology-media-telecoms (TMT) bubbles collapsed. This result is consistent with the empirical findings regarding the value and growth stock performance during 1990s and after 2000. Given that SV style generally beat LG style as suggested in Table 4-2, it is not surprisingly to find that the average raw monthly style momentum payoffs are much higher during year 2000-2004 than those in other periods. However, characteristics PC-based style momentum strategy for 3-month ranking periods seems does not work for periods 1982-1993, while BM-based strategy does not work in period 1994-1999, so it is with DY-based style momentum performance.

Table 4-10 the risk of style momentum returns

For each firm characteristics PC, MV and DY, 9 style portfolios are ranked by their prior 3- or 12-month returns. The hedge portfolios are formed to buy the past winner style and to sell the past loser style. The winner and loser style portfolios as well as the hedge portfolio are held for 3 or 12 months when the strategy is repeated. Thus, the test periods and the rank periods are non-overlapping. Starting from January 1982 to December 2004, the equally weighted average hedge portfolio returns during the test periods in excess of the 1-month Treasury bill rate are regressed on the contemporaneous monthly returns of Fama and French (1996) three factors. The Datastream UK country index is used as proxy for market index. The t-ratios are reported in brackets, and *, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Intercept	R_M - R_f	SMB	HML	R^2
Panel A Style portfolio based on PC					
		J = 3, K = 3			
Winner style	0.0079	0.9955	0.7711	0.0057	0.7731
t-ratio	(5.023)***	(28.338)***	(15.807)***	(0.094)	
Loser style	-0.0069	1.0218	0.5856	0.3664	0.6973
t-ratio	(-3.761)***	(24.879)***	(10.268)***	(5.161)***	
Hedge portfolio	0.0084	-0.0233	0.1985	-0.3443	0.0977
t-ratio	(3.545)***	(-0.442)	(2.711)***	(-3.778)***	
		J = 12, K = 12			
Winner style	0.0071	1.0468	0.8135	0.4613	0.7629
t-ratio	(4.346)***	(28.663)***	(16.042)***	(7.307)***	
Loser style	-0.0066	1.0430	0.6378	0.1617	0.6853
t-ratio	(-3.354)***	(23.748)***	(10.458)***	(2.131)**	
Hedge portfolio	0.0072	0.0068	0.1887	0.3159	0.0594
t-ratio	(3.132)***	(0.132)	(2.628)***	(3.535)***	
Panel B Style portfolio based on BM					
		J = 3, K = 3			
Winner style	0.0045	1.0344	0.9870	-0.0251	0.7350
t-ratio	(2.371)**	(24.357)***	(16.737)***	(-0.342)	
Loser style	-0.0044	1.0417	0.7321	0.3182	0.6752
t-ratio	(-2.2052)**	(23.208)***	(11.747)***	(4.102)***	
Hedge portfolio	0.0025	-0.0043	0.2678	-0.3270	0.0919
t-ratio	(0.922)	(-0.072)	(3.197)***	(-3.137)***	
		J = 12, K = 12			
Winner style	0.0024	1.0650	0.9495	0.0567	0.7866
t-ratio	(1.482)	(28.899)***	(18.556)***	(0.891)	
Loser style	-0.0057	1.0301	0.7077	0.2310	0.7149
t-ratio	(-3.144)***	(25.393)***	(12.564)***	(3.295)***	
Hedge portfolio	0.0017	0.0379	0.2547	-0.1579	0.0632
t-ratio	(0.698)	(0.693)	(3.358)***	(-1.672)*	
Panel C Style portfolio based on DY					
		J = 3, K = 3			
Winner style	0.0033	0.9277	0.7436	0.2752	0.7284
t-ratio	(2.063)**	(25.869)***	(14.934)***	(4.439)***	
Loser style	-0.0046	1.0149	0.5862	0.3613	0.7397
t-ratio	(-2.825)**	(27.616)***	(11.487)***	(5.688)***	
Hedge portfolio	0.0015	-0.0843	0.1704	-0.0698	0.0491
t-ratio	(0.676)	(-1.687)*	(2.456)**	(-0.808)	
		J = 12, K = 12			
Winner style	0.0016	0.9392	0.8281	0.3888	0.7446
t-ratio	(1.036)	(26.667)***	(16.932)***	(6.387)***	
Loser style	-0.0036	0.9900	0.6723	0.2523	0.7396
t-ratio	(-2.211)*	(27.127)***	(13.266)***	(3.999)***	
Hedge portfolio	-0.0012	-0.0479	0.1687	0.1529	0.0448
t-ratio	(-0.565)	(-1.007)	(2.556)**	(1.861)*	

Table 4-11 Style momentum returns in selected time periods

9 style portfolios are ranked by their prior 3- or 12-month returns. The style momentum hedge portfolios are formed to buy the winner style and to short the loser style. The hedge portfolio is held for K = 3, 6, 9, or 12 months and monthly equally weighted average test period returns are reported. Panel A studies three subperiods. Panel B studies different market conditions according to the return spreads between the best and worst styles in rank periods. A high cross-sectional dispersion in style performance is defined by the top 20% of the style return spreads, with medium dispersion being the middle 60% and low dispersion being the bottom 20%. Panel C studies the style momentum performance under bull, normal and bear market conditions defined by the ranking period returns on the Datastream UK country index. The bull market is defined as the 20% of the best market performance; the normal market is the middle 60% and bear market is the 20% with the worst performance periods. The test periods are 3 and 12 months starting from January 1982 to December 2004.

	3-month rank periods				12-month rank periods			
	K = 3	K = 6	K = 9	K = 12	K = 3	K = 6	K = 9	K = 12
Panel A Style portfolios based on PC								
	1982-1986							
Winner	0.0261	0.0254	0.0253	0.0258	0.0316	0.0305	0.0300	0.0292
Loser	0.0230	0.0239	0.0233	0.0228	0.0188	0.0197	0.0206	0.0214
Winner - Loser	0.0031	0.0016	0.0020	0.0030	0.0127	0.0107	0.0094	0.0078
t - ratios	1.0003	0.7346	1.1034	1.5673	3.5709	3.4878	3.1077	2.6076
	1987-1993							
Winner	0.0131	0.0136	0.0137	0.0135	0.0159	0.0151	0.0149	0.0139
Loser	0.0128	0.0120	0.0106	0.0112	0.0085	0.0099	0.0105	0.0109
Winner - Loser	0.0003	0.0016	0.0031	0.0024	0.0073	0.0052	0.0044	0.0030
t - ratios	0.0994	0.7052	1.4951	1.2326	2.2070	1.6378	1.4776	1.0206
	1994-1999							
Winner	0.0161	0.0144	0.0139	0.0134	0.0134	0.0124	0.0117	0.0116
Loser	0.0102	0.0107	0.0105	0.0114	0.0067	0.0097	0.0108	0.0115
Winner - Loser	0.0059	0.0037	0.0034	0.0020	0.0066	0.0026	0.0009	0.0001
t - ratios	2.0401	1.8026	2.1413	1.2563	2.1652	0.8481	0.3200	0.0456
	2000-2004							
Winner	0.0101	0.0120	0.0108	0.0110	0.0123	0.0106	0.0101	0.0099
Loser	-0.0013	-0.0013	0.0016	0.0039	-0.0020	0.0030	0.0050	0.0069
Winner - Loser	0.0114	0.0133	0.0092	0.0070	0.0142	0.0076	0.0051	0.0031
t - ratios	1.7743	2.4503	2.0522	1.8946	2.1036	1.2375	0.8939	0.5562
	After high cross-sectional dispersion							
Winner	0.0126	0.0120	0.0151	0.0171	0.0111	0.0112	0.0147	0.0168
Loser	-0.0012	0.0061	0.0114	0.0139	-0.0018	0.0071	0.0119	0.0139
Winner - Loser	0.0137	0.0059	0.0037	0.0033	0.0129	0.0041	0.0028	0.0030
t - ratios	3.1912	2.2320	2.0553	2.2795	2.9157	1.3044	1.1009	1.3457
	After medium cross-sectional dispersion							
Winner	0.0148	0.0164	0.0160	0.0153	0.0171	0.0171	0.0167	0.0155
Loser	0.0130	0.0119	0.0119	0.0114	0.0096	0.0111	0.0121	0.0117
Winner - Loser	0.0018	0.0045	0.0041	0.0039	0.0075	0.0061	0.0046	0.0039
t - ratios	1.0512	3.1459	3.4423	3.5457	3.8262	3.3524	2.6500	2.2296
	After low cross-sectional dispersion							
Winner	0.0155	0.0168	0.0146	0.0132	0.0197	0.0183	0.0161	0.0134
Loser	0.0151	0.0133	0.0099	0.0089	0.0103	0.0119	0.0097	0.0090
Winner - Loser	0.0005	0.0035	0.0047	0.0043	0.0094	0.0063	0.0064	0.0044
t - ratios	0.2175	2.4609	3.7448	3.3175	3.4396	3.0396	3.3374	2.2094

Table 4-11 (continued -1)

	3-month rank periods				12-month rank periods			
	K = 3	K = 6	K = 9	K = 12	K = 3	K = 6	K = 9	K = 12
Panel A Style portfolios based on PC								
	After bull markets							
Winner	0.017	0.0159	0.0166	0.0164	0.021	0.0173	0.017	0.0163
Loser	0.0164	0.013	0.0134	0.0135	0.0131	0.0121	0.0136	0.0139
Winner - Loser	0.0006	0.003	0.0032	0.0029	0.0079	0.0052	0.0033	0.0024
t - ratios	0.2094	1.6091	2.419	2.4975	2.5207	2.3692	1.7398	1.3493
	After normal markets							
Winner	0.017	0.0165	0.0156	0.0156	0.0186	0.0171	0.0163	0.0158
Loser	0.012	0.0119	0.0114	0.0122	0.0094	0.0109	0.0116	0.0125
Winner - Loser	0.005	0.0046	0.0043	0.0034	0.0092	0.0062	0.0047	0.0033
t - ratios	2.6759	2.9949	3.2855	2.9676	4.4044	3.3023	2.585	1.8706
	After bear markets							
Winner	0.0074	0.0153	0.0158	0.0155	0.006	0.015	0.0162	0.0154
Loser	0.0034	0.0115	0.0118	0.0118	-0.0012	0.0102	0.0119	0.0121
Winner - Loser	0.004	0.0038	0.0039	0.0036	0.0072	0.0048	0.0044	0.0033
t - ratios	1.128	1.649	2.4499	2.7473	1.9932	1.7501	1.9202	1.608
Panel B Style portfolios based on BM								
	1982-1986							
Winner	0.0277	0.0265	0.0264	0.0277	0.0302	0.0306	0.0303	0.0295
Loser	0.0245	0.0228	0.0226	0.022	0.0204	0.0209	0.0202	0.0197
Winner - Loser	0.0032	0.0037	0.0038	0.0057	0.0098	0.0097	0.0102	0.0098
t - ratios	1.0694	1.427	1.5199	2.3104	2.8298	2.8591	3.1546	3.1708
	1987-1993							
Winner	0.0159	0.0147	0.0149	0.0143	0.0149	0.0142	0.0137	0.0134
Loser	0.0102	0.0089	0.0089	0.0098	0.0089	0.0084	0.0083	0.0086
Winner - Loser	0.0057	0.0058	0.006	0.0046	0.006	0.0059	0.0054	0.0048
t - ratios	1.8685	2.3019	2.6978	2.218	1.6602	1.7635	1.7287	1.5935
	1994-1999							
Winner	0.0138	0.0121	0.0127	0.0132	0.0122	0.011	0.0109	0.0108
Loser	0.0099	0.0123	0.0136	0.0136	0.012	0.0168	0.0172	0.0164
Winner - Loser	0.0039	-0.0003	-0.0009	-0.0004	0.0003	-0.0058	-0.0063	-0.0056
t - ratios	1.1421	-0.1076	-0.3605	-0.1665	0.0717	-1.2366	-1.3338	-1.5863
	2000-2004							
Winner	0.0124	0.0103	0.009	0.0081	0.0102	0.0071	0.0066	0.0063
Loser	0.0022	0.0027	0.0048	0.0066	-0.0001	0.0059	0.0079	0.0073
Winner - Loser	0.0102	0.0076	0.0042	0.0015	0.0103	0.0013	-0.0013	-0.001
t - ratios	1.4433	1.3738	1.0698	0.4673	1.3803	0.2085	-0.2458	-0.2068
	After high cross-sectional dispersion							
Winner	0.012	0.0123	0.0142	0.0141	0.0161	0.0119	0.0127	0.012
Loser	0.005	0.0109	0.0139	0.0136	0.0071	0.0094	0.0111	0.0087
Winner - Loser	0.007	0.0014	0.0003	0.0005	0.009	0.0025	0.0016	0.0032
t - ratios	1.3724	0.4712	0.1441	0.3038	1.4277	0.4803	0.371	0.9936
	After medium cross-sectional dispersion							
Winner	0.0158	0.0158	0.0153	0.0153	0.0204	0.0178	0.0162	0.0158
Loser	0.0125	0.0111	0.0118	0.0123	0.0139	0.0139	0.0133	0.0131
Winner - Loser	0.0033	0.0047	0.0035	0.003	0.0065	0.0039	0.0029	0.0027
t - ratios	1.805	2.9331	2.5172	2.4566	2.85	1.7166	1.3437	1.4867
	After low cross-sectional dispersion							
Winner	0.0108	0.0163	0.017	0.018	0.0101	0.0124	0.0128	0.0132
Loser	0.0075	0.0129	0.0118	0.0124	0.0064	0.012	0.0133	0.0141
Winner - Loser	0.0033	0.0034	0.0051	0.0056	0.0037	0.0004	-0.0005	-0.0009
t - ratios	1.4476	1.9254	3.4489	4.3302	1.4643	0.1999	-0.2636	-0.5379

Table 4-11 (continued -2)

	3-month rank periods				12-month rank periods			
	K = 3	K = 6	K = 9	K = 12	K = 3	K = 6	K = 9	K = 12
Panel B Style portfolios based on BM								
	After bull markets							
Winner	0.0207	0.0161	0.0167	0.0165	0.0193	0.0159	0.0158	0.0151
Loser	0.0161	0.0123	0.0137	0.0137	0.0139	0.0136	0.0151	0.014
Winner - Loser	0.0046	0.0038	0.003	0.0028	0.0054	0.0022	0.0007	0.001
t - ratios	1.3153	1.8893	2.0367	2.2275	1.4326	0.9129	0.3085	0.5422
	After normal markets							
Winner	0.0179	0.0162	0.0155	0.0156	0.0169	0.0158	0.015	0.0147
Loser	0.0128	0.0124	0.0122	0.0127	0.0118	0.0137	0.0131	0.0128
Winner - Loser	0.0052	0.0038	0.0033	0.0029	0.0051	0.0022	0.0019	0.0019
t - ratios	2.4704	2.304	2.4193	2.3388	2.19	0.9873	0.9276	1.0287
	After bear markets							
Winner	0.0085	0.0154	0.0159	0.0156	0.0066	0.0144	0.0155	0.015
Loser	0.0013	0.0111	0.0134	0.0131	0.001	0.0133	0.0147	0.0132
Winner - Loser	0.0073	0.0042	0.0025	0.0025	0.0056	0.0011	0.0007	0.0018
t - ratios	2.0611	1.8495	1.5207	1.7728	1.4488	0.3604	0.2816	0.8746
Panel C Style portfolios based on DY								
	1982-1986							
Winner	0.0246	0.0236	0.0237	0.0234	0.0258	0.026	0.0263	0.0258
Loser	0.0137	0.0158	0.0167	0.0166	0.0145	0.0148	0.015	0.0155
Winner - Loser	0.0109	0.0078	0.007	0.0067	0.0113	0.0112	0.0113	0.0104
t - ratios	4.7661	3.5284	3.7473	4.37	3.7849	3.8478	4.225	4.1639
	1987-1993							
Winner	0.0141	0.0134	0.0139	0.0138	0.0148	0.0165	0.0165	0.0162
Loser	0.0098	0.0101	0.0098	0.0105	0.0079	0.0083	0.0086	0.0091
Winner - Loser	0.0043	0.0032	0.0041	0.0034	0.0069	0.0082	0.0079	0.0072
t - ratios	1.4513	1.3083	2.0443	1.7023	1.9288	2.3177	2.2645	2.082
	1994-1999							
Winner	0.0126	0.012	0.0125	0.0121	0.0123	0.0113	0.0106	0.0101
Loser	0.0093	0.0107	0.0094	0.01	0.0093	0.0112	0.0117	0.0122
Winner - Loser	0.0034	0.0013	0.0031	0.0021	0.0031	0.0001	-0.0012	-0.0021
t - ratios	1.2316	0.7773	2.2932	1.6339	0.9498	0.0213	-0.3932	-0.7586
	2000-2004							
Winner	0.0142	0.0148	0.0117	0.0117	0.0133	0.0111	0.0109	0.0103
Loser	0.0013	0.0021	0.0039	0.0042	0.0026	0.0052	0.0068	0.0074
Winner - Loser	0.0129	0.0127	0.0078	0.0076	0.0107	0.0059	0.0041	0.0029
t - ratios	2.3685	2.833	2.1053	2.441	1.7913	1.1353	0.9264	0.6934
	After high cross-sectional dispersion							
Winner	0.0148	0.014	0.0149	0.0142	0.0204	0.019	0.0168	0.0172
Loser	0.0021	0.0064	0.0094	0.0096	0.0021	0.0044	0.0046	0.0082
Winner - Loser	0.0127	0.0076	0.0055	0.0046	0.0183	0.0146	0.0122	0.009
t - ratios	3.2859	3.1094	3.245	3.3143	3.88	3.7715	3.8962	3.0707
	After medium cross-sectional dispersion							
Winner	0.0162	0.0158	0.0152	0.015	0.0163	0.0169	0.0158	0.0154
Loser	0.0109	0.0101	0.0099	0.0103	0.0083	0.0107	0.0103	0.0109
Winner - Loser	0.0054	0.0056	0.0053	0.0047	0.008	0.0061	0.0055	0.0045
t - ratios	3.1053	3.9748	4.5849	4.5522	3.5726	3.1134	3.0936	2.7008
	After low cross-sectional dispersion							
Winner	0.0141	0.0161	0.015	0.0146	0.0071	0.0095	0.013	0.0142
Loser	0.0116	0.0129	0.0099	0.0095	0.0015	0.0063	0.0088	0.0106
Winner - Loser	0.0025	0.0032	0.0052	0.0051	0.0056	0.0031	0.0042	0.0036
t - ratios	1.4829	2.3991	4.5599	4.6564	2.303	1.4596	2.1946	2.1575

Table 4-11 (continued -3)

	3-month rank periods				12-month rank periods			
	K = 3	K = 6	K = 9	K = 12	K = 3	K = 6	K = 9	K = 12
Panel C Style portfolios based on DY								
	After bull markets							
Winner	0.017	0.0156	0.0161	0.0157	0.0197	0.0168	0.0166	0.0161
Loser	0.0129	0.0103	0.0114	0.0114	0.0122	0.0105	0.0122	0.0123
Winner - Loser	0.0041	0.0053	0.0046	0.0043	0.0075	0.0064	0.0044	0.0039
t - ratios	1.5357	3.1298	3.8316	4.1529	2.3664	2.8795	2.393	2.2573
	After normal markets							
Winner	0.0168	0.0161	0.0152	0.015	0.0167	0.0167	0.0159	0.0154
Loser	0.0098	0.0104	0.0099	0.0103	0.0099	0.0104	0.0104	0.0109
Winner - Loser	0.007	0.0057	0.0053	0.0047	0.0068	0.0063	0.0054	0.0045
t - ratios	4.0646	4.1303	4.5849	4.5522	3.4364	3.3465	3.1348	2.7008
	After bear markets							
Winner	0.0077	0.0141	0.0152	0.0147	0.0063	0.014	0.0156	0.0153
Loser	0.0011	0.0087	0.0097	0.0097	-0.0006	0.0082	0.0099	0.0102
Winner - Loser	0.0066	0.0054	0.0055	0.005	0.0069	0.0058	0.0057	0.0051
t - ratios	2.0817	2.6495	3.9337	4.2939	2.0836	2.2844	2.7577	2.6638

Table 4-11 also compares the performance of style continuation during different market conditions. Prior studies such as Cooper *et al.* (2004) argue that momentum profits depend on the state of the market. Price momentum is much stronger in the up-market than that in down markets. The return decomposition introduced in section 2 suggests that momentum returns can be potentially driven by the dispersion in unconditional expected returns as Conrad and Kaul (1998) argue. Pesaran and Timmermann (1995) also suggest that the predictability of stock returns is low during calm market conditions. For this reason, the profitability of style momentum strategy may depend on the relative force of past momentum. It can also be hypothesised that if winner style is risky than loser style, it should perform poorly (better) in bad (good) market states. Hence, the whole sample period is now subdivided into different periods with low, medium and high cross-sectional style volatilities. A high cross-sectional dispersion in style return is defined by the top 20% of the style spreads, with medium dispersion being the middle 60% and low dispersion being the bottom 20%. The style momentum performance under bull, normal and bear market conditions is defined by the volatility on the Datastream UK country index in the ranking period.

Namely, the bull market is defined as the 20% of the best market performance; the normal market condition is the middle 60% and the bear market is the 20% with the worst performance periods. Table 4-11 would suggest that style momentum strategies tend to perform very well shortly after the portfolio formation in bull market. However, for longer holding periods the evidence is mixed.

4.8 Summary and conclusions

Motivated by the time-varying nature of relative style performance and the potential benefit of tactical style rotation in the stock market, Chapter 4 explores a dynamic trading strategy to select stocks based on its in-favour or out-of-favour style category. In doing so, a set of firm characteristic variables PC, BM and DY is used to categorise different stock groups. The use of such firm characteristics is justified partly by prior studies such as Fama and French (1993, 1996), Kothari and Shanken (1997), and Chan *et al.* (1998) who suggest that these variables are important fundamentals relating to the variations in expected stock returns. It is argued that as assets perform differently during various stages of a market cycle, style momentum strategies to buy asset groups that perform well and to sell asset classes that do poorly in the past could generate positive returns up to 12 months and possibly longer. Given the perceived interaction amongst style momentum and the price and industry momentum effects, three methods are analysed to disentangle style, price and industry momentums. The procedure includes doing the price and industry effect adjustment on the individual level, the independent two-way sorting and the application of Fama-MacBeth (1973) cross-sectional regressions. The empirical results in this study shows that consistent with the literature, style momentum in the U.K. market is a distinct phenomenon from price and industry momentum effects documented in the literature. The information of whether stocks are in current in-favour or out-of-favour styles conveys unique predictive ability about future returns.

The profit of style momentum based on firm characteristics seems to pose challenge to financial theories based on rational agents and frictionless markets. Prior studies provide mixed evidence for risk-based models in explaining asset-level momentum. For example, Jegadeesh and Titman (1993) show that differences in market risk of long short side of the hedge portfolios do not cause momentum profits. Fama and French (1996) fail to price momentum returns using their unconditional three factor model (1993). Jegadeesh and Titman (2001) find that risk-adjustment tends to increase rather than decrease the momentum profits. Other studies such as Conrad and Kaul (1998), Johnson (2002) and Lewellen (2002) contend that momentum effect relates to the cross-sectional and time-series variations in risks. Motivated by the lack of straightforward risk-based explanation for the momentum profits on individual stock level, recently, an increasing number of studies focus on the role investors' behaviour plays in affecting asset pricing. Studies such as Daniel *et al.* (1998), Barberis et al. (1998), Hong and Stein (1999, 2000), Lee and Swaminathan (2000) are only a few examples. These studies suggest that the profit of asset-level momentum arise form a delayed overreaction to news.

The existence of style momentum strategy may be explained by the findings of Berk *et al.* (1999) on the rational basis or the behavioural model of Barberis and Shleifer (2003). Berk *et al.* (1999) argue that firms with same characteristics are affected by the same state variables relating to the systematic risks and expected returns. The payoffs of momentum strategies are compensation for systematic risks that changes in predictive ways over the periods comparable to the average life of firm's investment project. Barberis and Shleifer (2003) propose that in an economy with two heterogeneous investor groups, i.e. switchers and fundamental traders, style-based noisy traders allocate their money on the style level based on relative style performance, causing some styles becoming popular and others, often regarded as the "twin style", being disliked. The arbitrageurs (fundamental traders) ensure that the irrational style-based investors do not push asset prices too far away from its fundamental values. The model of Barberis and Shleifer (2003) predicts that style momentum strategies are as profitable as asset-level momentum. Empirical studies such as Lewellen (2002), Chen (2003), Chen and De Bondt (2004) all provide evidence which are consistent with the prediction of Barberis and Shleifer (2003).

While this Chapter find significant raw style momentum payoffs, the risk-adjusted performance evolution based on the Fama-French three-factor model suggests that such strategy should be implemented with caution. When measured against the Fama and French three-factor model, the style-level misspricing is insignificant for BM- and DY-based style sorting. However, stocks classified by characteristics PC still remain significant misspricing. This suggests that the information content of characteristics PC, BM and DY may differ. On the other hand, due to its regular rebalancing nature, equity style momentum strategy could introduce non-trivial transaction cost. Hence financial practitioner should assess whether style momentum can generate positive returns after accounting for the transaction cost. Arguably, style momentum strategy is best implemented to enhance passive investing such as indexation strategy. The relative fixed composition nature of market index results in constant overall style exposures which is inefficient under the changing market environment. Style momentum strategies based on ETF (Exchange Traded Funds) of style benchmarks can be used to enhance index returns. Since the style momentum hedge portfolios are generally market neutral thus are free of market risk. Given that the transaction cost for ETFs is low and its liquidity is high, arguably the long-short style momentum hedge portfolio can be designed to overlay with the underlying index to eliminate its least attractive style exposures. Hence index hedging based solely on the equity style momentum would be possible and be an interesting subject to explore.

Chapter 5

Optimal Multi-Style Investing Parameterising on Business Cycle Predictors

5.1 Introduction

There is substantial evidence in empirical finance suggesting that the distributions of stock returns are time-varying and predictable using business cycle variables. Prior studies such as Fama and French (1996) show that company characteristics of size (firm capitalisation), book to market ratios and lagged past performance are related to the variations on expected stock returns of both time-series and cross-sectional level. The expected stock returns are also related to the variance and covariance structure with other stocks (e.g. Chan *et al.* (1998)). These findings yield fresh insights into portfolio management in the investment practice. A number of recent studies have addressed the issue of portfolio choice problem when incorporating the stock predictability to capture the changing investment opportunities and enhance portfolio returns. For example, Kandel and Stambaugh (1996) show that from an *ex ante* perspective variables predicting the distributions of moments of stock returns have significant impact on a myopic portfolio setting. Brennan and Schwartz (1996), Brennan *et al.* (1997) and Barberis (2000) numerically study the impact of myopic versus dynamic portfolio choice problem. Ferson and Siege (2001) derive the optimal portfolio weights for mean-variance investors assuming that the moments of stock returns are known functions of state variables. More recently, Avramov and Chordia (2006a, 2006b) find that a real-time optimising investor benefits from incorporating business cycle information to the asset allocation between stocks and cash or investment strategies of 'fund of mutual funds'. These studies, amongst others, develop a general framework to study dynamic portfolio choice implications of return predictability and provide further evidence on the value of active portfolio management over the business cycles.

While previous studies have made contributions to our understanding regarding the impact of predictability of the first and second moments of stock returns on the portfolio selection process, their empirical approaches generally arise one or two of the issues:

First, on the one hand, the analysis of portfolio choice with the time-varying investment opportunity set has generally focused primarily on the well-diversified market portfolio (or all stocks in the investment universe) plus cash and bonds. Such arrangement is not designed to help investors who hold multiple equity asset classes like 'fund of funds' asset managers. In today's investment industry, institutional investors such as mutual funds and pension funds are generally structured around different asset classes to follow some predefined investment styles (e.g. Brown and Goetzmann (1997), Fung and Hsieh (1997), Chan *et al.* (2002)). This is even predominant in the hedge fund industry where mangers generally have expertise in and focus solely on some specific asset classes. Hence investors of 'fund of funds' equivalently exposes themselves to specific asset class within the market segments. Meanwhile, large institutional investors such as pension and endowment funds generally delegate their investment to different managers who are specialised in a single asset class. Sharpe (1981) argues that such 'centralised decision' may be motivated by the desire to exploit managers' specialisation or to diversity among managers. Barry and Starks (1984) also contend that risk-sharing may be a motivation to hire multi-managers. Given these situations, it is reasonable to assume that in addition to cash and bonds, investors would hold multiple equity asset classes instead of accessing to only one domestic equity portfolio (i.e. market index). Arguably, investing in a market index or all the stocks in the market is neither attractive nor technically applicable simply because such strategy cannot satisfy investors' different return-risk preferences.

On the other hand, when considering business cycle predictability in the asset allocation process, focusing on market portfolio alone may hamper our understanding of the underlying mechanism as how the economic exogenous forces affect equity returns in a changing environment. For example, the divergent returns between value and growth stocks are well recognised but the underlying driving forces for such return differentials are not fully explained yet. Campbell and Vuolteenaho (2004) recently study the risk characteristics of the two styles and find that growth stocks have larger conditional correlation of returns with variables that proxy for time variation in aggregate stock market discount. In contrast, value stocks have higher conditional correlation of returns with changes in aggregate stock market cash flows news. Indeed, from the perspective of a long-horizon risk-averse investor who holds the market portfolio, value stocks are riskier than growth stocks because aggregate cash flow shocks tend to be permanent while aggregate discount rate shocks appear to be transitory. Similarly, small and large stocks also demonstrate different risk-return characteristics during different phase of business cycles (*c.f.* Chan and Chen 1991). Obviously investing in a market index is by definition not optimal because of the different risk-return characteristics for value-growth and small-large stocks within the index constitution. Such different return-risk profiles of different styles would induce hedging demand as suggested by Merton (1973) for multi-period style investors. Lynch (2001) also argues that such hedging demand can affect not just the weights allocated to equities but the composition of equity portfolio as well. Hence optimal portfolio selection problem is perhaps best framed in the context of multi styles allocation because multi-asset investors require style timing when the return distribution or the covariance structure of different equity classes changes corresponding to change of economic states.

Second, although academic researchers have developed a variety of theoretical solutions to solve the theoretical optimal portfolio choice problem based on return predictability, most techniques are out of reach for ordinary market practitioners and hence are not practically useful for real-world investment. Investment optimisation has always been a challenging job since most often the close-form solutions are not available. Over the years the Markowitz (1952) mean-variance framework is the workhorse of portfolio optimisation in the investment industry. As Brandt and Santa-Clara (2006) states that prior studies incorporating the predictability of asset returns generally solve the optimal portfolio choice problem by first solving optimal portfolio of Arrow-Debreu securities that pays state prices, and then replicate the optimal portfolio by dynamically trading basis assets. Some papers also first specify the conditional moments with state variables and then apply the traditional Markowitz approach to characterise the portfolio choice. These methodologies could raise a number of concerns. For this approach to work, the rigid assumption that market is complete must be satisfied so Arrow-Debreu securities can exist, or ad hoc distributional assumptions must be applied between moments of returns and state variables to guarantee the positive definiteness of the variance-covariance matrix. There is a major problem of being not parsimonious – there are a large number of moments (e.g. parameters of expected returns and covariance) to be estimated. Such 'curse of dimensionality' could inevitably cause notoriously noisy and unstable test results (*c.f.* Michaud (1989)). Since a portfolio manager's livelihood depends largely on the outcome of the investment decisions, the traditional two-step econometric approaches for optimal portfolio choice offers little help if there is any in the real-world investment management practice.

Because of the difficulty in modelling conditional distributions of stock returns, academia has been exploring different approaches to simply the investment process. Recently Brandt (1999) develops a framework to directly estimate the optimal portfolio weights based on the state variables. This approach is intuitively appealing since it bypasses the auxiliary yet difficult procedure of estimating the joint conditional distributions of stock returns. Ait- Sahalia and Brandt (2001) argue that the predictability of the first (expected returns) and second moments (covariance) of stock returns is difficult to be translated into portfolio selection advice because the two moments may be predicted by different variables. In addition, a variable may be both significant for predicting the variations of expected return and variance but such variations offset hence it is essentially useless for determining optimal portfolio weights. Indeed, the investor's ultimate interest is to obtain optimal portfolio weights while the moments of returns serve as inputs to the underlying problem and are therefore endogenous to investor's preference. Interestingly, within this framework, Brandt and Santa-Clara (2006) propose a method to solve a dynamic portfolio selection problem for a mean-variance investor who optimises the expected end-of-period wealth. By introducing managed and timing portfolios in the asset space, they provide an approximation to the problem that is easy to apply by investors in the traditional static Markowitz paradigm.

5.2 Motivation and research questions

Chapter 5 is motivated by the identified gap in the literature regarding the optimal multi-asset investing (style timing) over business cycles. First, as mentioned previously, while the extant literature provides perspective on the benefits of considering business cycle predictors on the asset allocation process, in most previous studies the investable equity instrument is designed as market portfolio only, which is not realistic. To offer a fresh insight, this chapter contributes to the extant literature by allowing the investors to have access to different market segments of equity stocks and invest different equity style portfolios with no restrictions of long or short. Such investors can be regarded as hypothesised "fund of hedge funds" investors.

Second, existing literature on the portfolio choice implications of business cycle effect often focus more on the time-varying nature of return distributions driven by different business cycle predictors. However the role such predictors play on determining optimal multi style allocation is less directly explored. The transmission mechanism of business cycle volatility to asset return dynamics and consequently the optimal style allocation is not extensively studied. If a multi-style investor believes that business cycle variables predict the conditional distributions of equity style returns, the moments of style returns to be predicted are endogenous to the investor's preference due to model specification. Hence, in order to capture the changing investment opportunities related to the business cycle fluctuation, the investor should focus primarily on identifying how the same exogenous state variable directly predicts her ultimate style investing choices (i.e. optimal style timing weights).

Based on the methodology of Brandt and Santa-Clara (2006), Chapter 5 contributes to the literature by applying an optimisation framework to test several equity style investing strategies based on business cycle information and examine their *ex ante* in-sample and *ex post* out-of-sample performance in the U.K. stock market. The aim of this chapter is to give multi-style investors an intuitive manner to understand their asset allocation process of incorporating business cycle predictability. This chapter will answer some key questions such as if business cycle predictor variable *X* increases, should the investor move to or move away from *Y* style? Formally, the major objective of this chapter is to investigate:

- Can a mean-variance multi-style investor benefit from using business cycle information to optimally implement multi-style investing strategies according to the time-varying investment opportunity set?

- If business cycle predictors affect the distribution of equity style returns, how such economic exogenous forces could affect the investor's style choices in the context of style level asset allocation? Specifically, which economic variable or a set of such variables should be tracked when investors implementing equity investing based on market segments?
- How investor's style investing policy differs when following the traditional two-step Markowitz approach and with that directly predicts optimal style allocation weights based on the state variables as suggested by Brandt and Santa-Clara (2006)?

5.3 Testable Hypothesis

Based on the research questions, there are some hypotheses that can be examined:

- If business cycle information affects style allocation process, multi-style investing on the basis of- business cycle predictors (i.e. conditional on the state variables) should yield better performance, both in-sample and out-of-sample, as compared to the same strategies disregarding business cycle information (unconditional investing). Such multi-style trading strategy should also outperform single-fixed passive style investing due to its nature of active style timing as suggested by business cycle predictors to capture changing investment opportunities;
- The optimal style allocation weights conditional on business cycle information should exhibit dynamic and large variations in style tilts. Predictability should induce investors to aggressively take extreme positions on specific styles because they can reduce the exposures in bad times given their prior beliefs

regarding the conditional distributions of style returns predicted by state variables;

- Business cycle variables should exert different influence on different equity styles in the allocation process. For example, if one variable could positively predict the optimal weight of one specific style (e.g. value stocks), it should also negatively predict the optimal weight of its counterpart style (e.g. growth stocks);
- The optimal style tilts suggested by following the traditional two-step econometric approach and that of Brandt and Santa-Clara (2006) should exhibit significant difference. Since Brandt and Santa-Clara (2006) directly predicts the optimal style weights with business cycle predictors, it can arguably capture higher moments beyond the first and second moments of stock returns that affect asset allocation decision and therefore could yield more extreme weights but better in- and out-of-sample performance.

5.4 Methodology and econometric framework

Suppose that at each date t there are N equity styles in the financial market. Each style i has an *excess return* of $r_{i,t+1}$ from time t to $t+1$, and r_{t+1} is the vector of excess returns for all N styles. The dynamics of r_{t+1} is associated with a vector of state variables z_t that is observable at time t. Consider an investor who implements a multi-style timing strategy. The investor's problem is to choose the optimal style weights $w_t = (w_{1,t}, w_{2,t}, \cdots, w_{N,t})$ to maximise a utility function of the trade-off between the expected style investing performance and the underlying investing risk. Formally, this unconstrained single-period optimal style selection problem can be conventionally described as (*c.f.* Brandt and Santa-Clara (2006)):

$$\max \; E_t[U(W_{t+1}) \mid z_t] \tag{1}$$

The solution to (1), called the *style timing policy*, maps the preference parameter set ϕ that is *ex-ante*, the state vector z_t and the parameters of the data generating process θ to the optimal style weights w_t:

$$w_t^* = w(\phi, z_t, \theta) \tag{2}$$

Parameter θ can be estimated from a given sample research data set $r_T = \{r_{t+1}\}_{t=0}^{T}$, and typically it is unbiased or at least assume consistent estimates $\hat{\theta}$ can be obtained. Thus the *estimates* of the optimal style weights are:

$$\hat{w}_t^* = w(\phi, z_t, \hat{\theta}) \tag{3}$$

If $\hat{\theta}$ is consistent, according to the central limit theorem the asymptotic distribution is $\sqrt{T}(\hat{\theta}-\theta) \overset{T\to\infty}{\sim} N[0, Var(\theta)]$. Suppose that the mapping function (2) is well specified with θ, the asymptotic distribution of estimator w_t is[24]

$$\sqrt{T}(\hat{w}_t^* - w_t^*) \overset{T\to\infty}{\sim} N[0, Var(\theta)(\frac{\partial w}{\partial \theta})^2] \tag{3}$$

The relation between the style timing policy and the moments of style excess return data given observable state vector z_t depends on the

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[24] From the first two terms of Taylor series, the estimator w_t is

$$\hat{w}_t^* = w(\phi, z_t, \hat{\theta}) \approx w(\phi, z_t, \theta) + \frac{\partial w(\phi, z_t, \theta)}{\partial \theta} \bullet (\hat{\theta} - \theta)$$

Using vector notation for the gradient:

$$\hat{w}_t^* \approx w_t^* + \nabla w_t^{*T} \bullet (\hat{\theta} - \theta)$$

The variance of estimator w_t is approximately

$$Var(\hat{w}_t^*) \approx Var[w_t^* + \nabla w_t^{*T} \bullet (\hat{\theta} - \theta)] = \nabla w_t^{*T} \bullet Var(\theta) \bullet \nabla w_t^*$$

Hence the asymptotic distribution of estimator w_t is

$$\sqrt{T}(\hat{w}_t^* - w_t^*) \overset{T\to\infty}{\sim} N[0, Var(\theta)(\frac{\partial w}{\partial \theta})^2]$$

specification of the objective utility function in (1). Consider a typical investor with standard mean-variance preference:

$$\max\ E_t[W_{t+1} - \frac{b_t}{2} W_{t+1}^2 \mid z_t] \tag{4}$$

Where b_t >0, and b_t is small enough to ensure that the marginal utility of wealth remains positive. Assume that the state vector observed at time t is $z_t = (z_t^1, z_t^2, z_t^3, z_t^4) = (div_t, spread_t, yld_t, term_t)$[25]. Let $r_{p,t+1}$ be the *excess returns* of investor's style timing portfolio from time t to t+1. After simple manipulation, (4) can be rewritten as:

$$\max E_t[r_{p,t+1} - \frac{\gamma}{2}(r_{p,t+1})^2 \mid z_t] \tag{5}$$

Where γ is a positive constant, representing the degree of absolute risk aversion. Now problem (5) is:

$$\max_{w_t} E_t[w_t^T r_{t+1} - \frac{\gamma}{2} w_t^T r_{t+1} r_{t+1}^T w_t \mid z_t] \tag{6}$$

In the unrealistic case when excess returns are *iid* and optimal style weights are constant over time (i.e. $w_t = w$), the conditional expectation of (6) can be replaced by unconditional expectation. Using Lagrange method, it is easy to show that the investor's optimal style timing policy is

$$w^* = \frac{1}{\gamma} Var(r_{p,t+1} \mid z_t)^{-1} \bullet E(r_{p,t+1} \mid z_t) \tag{7}$$

[25] Alternatively we can assume *Z* is Fama-French factors (SMB and HML) and/or momentum factor Carhart (1997). These state variables are available for investors in the lagged values. The use of the 4 macroeconomic variables used in this chapter are default risk premium (*def*), dividend yield (*div*), the term spread (*term*) and short-term interest rate (*yld*), they are also used in chapter 3.

Given sample research data $r_T = \{r_{t+1}\}_{t=0}^{T}$, the moments in (7) can be estimated using sample analogues.

While not so straightforward, the analytical expression of (7) suggests a link between predictability of state variables and style timing policy. Theoretically, if state vector z_t captures the first and second moments of style returns, one can identify which state variable is important in the style timing policy by first modelling the conditional means, variance and covariance of style returns as a function of z_t and then derive the optimal style weights as a function of state variables (e.g. Ferson and Siegel, 2001). This approach suffers from the difficulty in modelling the conditional covariance with state variables. It is also not parsimonies because there are too many parameters to be estimated.

Brandt and Clara (2006) present an interesting methodology that focuses directly on the portfolio weights, rather on the underlying styles' conditional return distributions. They argue that this approach is an approximation of the traditional solution provided by Ferson and Siegel (2001). In this framework, the optimal portfolio weights are a linear function of the observed state variables, i.e. $w_t = \theta z_t$. Thus the optimization problem (6) becomes

$$\max_{\theta} E_t[(\theta z_t)^T r_{t+1} - \frac{\gamma}{2}(\theta z_t)^T r_{t+1} r_{t+1}^T (\theta z_t)] \tag{8}$$

Doing some simple algebra manipulation, it yields:

$$(\theta z_t)^T r_{t+1} = z_t{}^T \theta^T r_{t+1} = vec(\theta)^T (z_t \otimes r_{t+1}) \tag{9}$$

Where $vec(\theta)$ is a vector that stacks all the columns in θ, and $\otimes$ is the Kronecker product of two matrices. Now let $\tilde{w} = vec(\theta)$ and $\tilde{r}_{t+1} = z_t \otimes r_{t+1}$, problem (8) becomes

$$\max_{\tilde{w}} E_t[\tilde{w}^T \tilde{r}_{t+1} - \frac{\gamma}{2} \tilde{w}^T \tilde{r}_{t+1} \tilde{r}_{t+1}^T \tilde{w}] \quad (10)$$

Since style weight matrix $\tilde{w}$ maximises the conditional expected utility at all time t, it should also maximises the unconditional utility, hence the optimization problem is

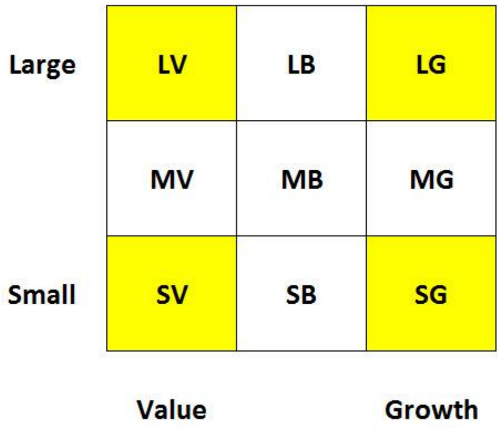
$$\max_{\tilde{w}} E[\tilde{w}^T \tilde{r}_{t+1} - \frac{\gamma}{2} \tilde{w}^T \tilde{r}_{t+1} \tilde{r}_{t+1}^T \tilde{w}] \quad (11)$$

Correspondingly, this is to find the optimal *unconditional portfolio weights of $\tilde{w}$ for the expanded risky asset set of $N \times K$ (i.e. number of styles $\times$ number of state variables) with returns of $\tilde{r}_{t+1}$*. Therefore, following (7), the practical solution to the investor's problem is

$$\tilde{w} = \frac{1}{\gamma} Var(\tilde{r}_{t+1})^{-1} \bullet E(\tilde{r}_{t+1}) \quad (12)$$

Based on the solution (12), the investor can retrieve the weight investing in each of the styles by adding the corresponding products of $\tilde{w}$ and z_t.

Now consider an economy with 4 investable equity styles, S1, S2, S3 and S4, corresponding to Small-Value (SV), Small-Growth (SG), Large-Value (LV) and Large-Growth (LG) stock groups, respectively. While one can always use 9 styles to fill the entire equity universe, it is more efficient to choose only 4 highlighted styles to capture the interaction of two basic style dimensions that have shown to have wider return spreads in Chapter 3. The selection of these 4 styles is also justified by recent empirical findings. For example, Horowitz *et al.* (2000a) find that the observed size premium is not linear across all stocks but is concentrated only in smaller firms. Likewise, Fama and French (2008) observe that the size premium is the strongest among U.S. tiny stock groups based on data from 1963-2005. Fama and French (2012) also find that both value premiums and momentum effect differ across size dimension, specifically, value premiums and momentum returns decrease from smaller to large stocks.



These 4 styles (s_1, s_2, s_3, s_4) act as basis assets and are obtained by sorting stocks according to company characteristics of PC, BM and DY, respectively. This process is consistent with previous Chapter 3 and 4 in the research. Consider the time series of 60 months historical observations of excess returns for these 4 styles:

$$\begin{pmatrix} r_1^{s_1} & r_1^{s_2} & r_1^{s_3} & r_1^{s_4} \\ r_2^{s_1} & r_2^{s_2} & r_2^{s_3} & r_2^{s_4} \\ r_3^{s_1} & r_3^{s_2} & r_3^{s_3} & r_3^{s_4} \\ \vdots & \vdots & \vdots & \vdots \\ r_{60}^{s_1} & r_{60}^{s_2} & r_{60}^{s_3} & r_{60}^{s_4} \end{pmatrix} \tag{13}$$

Equation (7) directly gives the Markowitz solution of optimal static weights for these 4 styles, namely $w = (w_1, w_2, w_3, w_4)$. This solution takes into account the sample covariance matrix of style excess returns and the vector of sample mean excess returns.

Suppose now the conditional distribution of style excess returns is affected by the business cycle effect, and the investor can observe a set of economic variables that relate to the business cycle. The state variables are $z_t = (z_t^1, z_t^2, z_t^3, z_t^4) = (div_t, spread_t, yld_t, term_t)$. It should be noted that these variables are only known at the beginning of each return period hence are one month lagged behind. The matrix of the time series of state variables is:

$$\begin{pmatrix} z_0^1 & z_0^2 & z_0^3 & z_0^4 \\ z_1^1 & z_1^2 & z_1^3 & z_1^4 \\ z_2^1 & z_2^2 & z_2^3 & z_2^4 \\ \vdots & \vdots & \vdots & \vdots \\ z_{59}^1 & z_{59}^2 & z_{59}^3 & z_{59}^4 \end{pmatrix} \tag{14}$$

In the spirit of Brandt and Clara (2006) approach, the basis style assets return matrix (13) can be expanded in the following manner:

$$\begin{pmatrix} r_1^{s_1} & r_1^{s_2} & r_1^{s_3} & r_1^{s_4} & r_1^{s_1}z_0^1 & r_1^{s_1}z_0^2 & r_1^{s_1}z_0^3 & r_1^{s_1}z_0^4 & r_1^{s_2}z_0^1 & r_1^{s_2}z_0^2 & r_1^{s_2}z_0^3 & r_1^{s_2}z_0^4 & r_1^{s_3}z_0^1 & r_1^{s_3}z_0^2 & r_1^{s_3}z_0^3 & r_1^{s_3}z_0^4 & r_1^{s_4}z_0^1 & r_1^{s_4}z_0^2 & r_1^{s_4}z_0^3 & r_1^{s_4}z_0^4 \\ r_2^{s_1} & r_2^{s_2} & r_2^{s_3} & r_2^{s_4} & r_2^{s_1}z_1^1 & r_2^{s_1}z_1^2 & r_2^{s_1}z_1^3 & r_2^{s_1}z_1^4 & r_2^{s_2}z_1^1 & r_2^{s_2}z_1^2 & r_2^{s_2}z_1^3 & r_2^{s_2}z_1^4 & r_2^{s_3}z_1^1 & r_2^{s_3}z_1^2 & r_2^{s_3}z_1^3 & r_2^{s_3}z_1^4 & r_2^{s_4}z_1^1 & r_2^{s_4}z_1^2 & r_2^{s_4}z_1^3 & r_2^{s_4}z_1^4 \\ r_3^{s_1} & r_3^{s_2} & r_3^{s_3} & r_3^{s_4} & r_3^{s_1}z_2^1 & r_3^{s_1}z_2^2 & r_3^{s_1}z_2^3 & r_3^{s_1}z_2^4 & r_3^{s_2}z_2^1 & r_3^{s_2}z_2^2 & r_3^{s_2}z_2^3 & r_3^{s_2}z_2^4 & r_3^{s_3}z_2^1 & r_3^{s_3}z_2^2 & r_3^{s_3}z_2^3 & r_3^{s_3}z_2^4 & r_3^{s_4}z_2^1 & r_3^{s_4}z_2^2 & r_3^{s_4}z_2^3 & r_3^{s_4}z_2^4 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ r_{60}^{s_1} & r_{60}^{s_2} & r_{60}^{s_3} & r_{60}^{s_4} & r_{60}^{s_1}z_{59}^1 & r_{60}^{s_1}z_{59}^2 & r_{60}^{s_1}z_{59}^3 & r_{60}^{s_1}z_{59}^4 & r_{60}^{s_2}z_{59}^1 & r_{60}^{s_2}z_{59}^2 & r_{60}^{s_2}z_{59}^3 & r_{60}^{s_2}z_{59}^4 & r_{60}^{s_3}z_{59}^1 & r_{60}^{s_3}z_{59}^2 & r_{60}^{s_3}z_{59}^3 & r_{60}^{s_3}z_{59}^4 & r_{60}^{s_4}z_{59}^1 & r_{60}^{s_4}z_{59}^2 & r_{60}^{s_4}z_{59}^3 & r_{60}^{s_4}z_{59}^4 \end{pmatrix}$$

(15)

The optimal static portfolio of this expanded set of assets can be computed by equation (12) using sample analogues. The static solution is $\tilde{w} = (\tilde{w}_1, \tilde{w}_2, \tilde{w}_3, \cdots, \tilde{w}_{20})$, corresponding to each of the 4 basis styles and 16 managed portfolios in matrix (15). Based on these results, the optimal weights invested in the 4 styles are:

$$\begin{pmatrix} w_t^{s_1} \\ w_t^{s_2} \\ w_t^{s_3} \\ w_t^{s_4} \end{pmatrix} = \begin{pmatrix} \tilde{w}_1 + \tilde{w}_5 z_t^1 + \tilde{w}_6 z_t^2 + \tilde{w}_7 z_t^3 + \tilde{w}_8 z_t^4 \\ \tilde{w}_2 + \tilde{w}_9 z_t^1 + \tilde{w}_{10} z_t^2 + \tilde{w}_{11} z_t^3 + \tilde{w}_{12} z_t^4 \\ \tilde{w}_3 + \tilde{w}_{13} z_t^1 + \tilde{w}_{14} z_t^2 + \tilde{w}_{15} z_t^3 + \tilde{w}_{16} z_t^4 \\ \tilde{w}_4 + \tilde{w}_{17} z_t^1 + \tilde{w}_{18} z_t^2 + \tilde{w}_{19} z_t^3 + \tilde{w}_{20} z_t^4 \end{pmatrix} \tag{16}$$

If excess returns are based on risk-free asset, the portion invested in the risk-free asset is $1 - \sum_{i=1}^{4} w_t^{s_i}$.

5.5 Data, style definition and test results

5.5.1 Data

From Jan 1980 to Dec 2004, at the end of each June/December, all U.K. stocks are divided into 2 parts based on previous 6-month firm characteristic value X (to be consistent with previous two chapters, here X is APC, BM, DY, respectively)[26]. Only stocks with positive X values and denominated by local currency (£) are included in the study. Stocks denominated by foreign currencies are excluded since their returns are also affected by foreign exchange rate fluctuations. Following the literature, stocks that belong to the financial sectors are also excluded because their firm characteristics (e.g. APC, BM, DY) do not have the same meanings as that of non-financial stocks. To avoid the sample selection bias, all delisted stocks are retrieved and added back to the sample during the time that they are still "alive". If a firm is delisted, the proceeds from the sale of this stock are invested equally in other firms in the style that it belongs to. After cleaning the data, at the end of each June/December, qualified stocks are ranked independently in ascending order by X and market value (MV). All sorted stocks are further allocated to 3 equal-sized MV and 3 equal-sized X groups, resulting 9 (interaction) style portfolios. After styles are defined at the end of each June/December, the style category of a stock belonging to will be maintained fixed for the next 6 months, regardless whether the underlying stock's characteristic value X is changed or not.

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[26] Chapter 3 shows that based on the role of the *predicted risk premias* from the state variables z_t and the *pricing errors* in the observed style premiums, it is suggested that the size premium and value premiums on stocks based on characteristics of APC and BM are likely related to the *unpredicted component* of the vector z_t, while value premium based on DY seems to represent compensation for bearing business cycle risk. Such relative style returns are mainly driven by the *predicted component* from the state vector. In this conditional style timing policy problem that is linear on z_t, style portfolios based on company characteristics of APC and BM are still included to study because z_t may be significant predictor of the optimal style weights although it may fail to predict the style return moments.

Based on this procedure, monthly style return series are generated. 9 equity styles are prepared here (i.e. SV, SB, SG, MV, MB, MG, LV, LB and LG), both with value weighted and equally-weighted time-series returns from Jan 1981-Dec 2004.

Table 5-1 reports the summary statistics of the returns of simple style investing strategies during the sample period (Jan 1981 – Dec 2004). It also reports the descriptive statistics of the 4 business cycle related variables used in this chapter. To be consistent with Chapter 3, the 4 macroeconomic variables used are default risk premium (*def*), dividend yield (*div*), the term spread (*term*) and short-term interest rate (*yld*). *def* is the yield spread between the lower- to higher- bond and is measured as the yield on corporate bonds less the yield on long-term U.K. government bonds. *div* is the dividend yield on the overall market index as proxied by the Datastream U.K. market index. *term* is the difference between the 20-year gilt and 3-month Treasury bill yields and the short-term interest rate *yld* is proxied by the 3-month Treasury bill yield. It is generally believed that these variables convey information about the macroeconomy and business cycle conditions and therefore affects the inter-temporal behaviour of equity style returns.

Table 5-1 shows that during the sample period raw monthly returns derived from simple style investing strategies are both positive and significant based on standard t test (sample size 288). Regardless which firm characteristic variables to define the value style dimension, each month on average equally-weighted value investing outperform growth investing by 1.48%, 0.94% and 0.77% based on APC, BM and DY sorting, while value-weighted style return differentials would be 1.40%, 0.77% and 0.73%, respectively. Likewise, each month on average an equally-weighted portfolio with small stocks and positive APC, BM and DY values could beat the counterpart portfolios with large stocks only by 0.78%, 0.36% and 0.50%, respectively. Such return differentials are generally significant in a t-statistics sense.

Since both value and small styles could beat their growth and large counterparts, arguably a style investing with stocks that capture the interaction of value and size effects could generate even better results. Indeed, as Table 5-1 suggests, investing equally on the small value (SV) stocks earns average monthly returns of 2.79% if sorted by APC (2.10% and 2.00% based on BM and DY, respectively). The same strategy with large growth (LG) stocks yields monthly average returns of 0.99% by APC sorting (0.77% and 0.84% based on BM and DY, respectively). Similar results obtained for value weighted scheme. When comparing the return differentials (spreads) between SV and LG stock groups to those with broad small-large and value-growth stocks, regardless how returns are calculated, it shows that the style return spread between SV and LG stocks is the largest, indicating that they do capture the principle investment characteristics of value and size styles and hence represent better risk-return structure. This justifies the selection of 4 styles (i.e. LV, LG, SV, SG) rather than the all 9 style portfolios in the style allocation process discussed later in this Chapter.

Table 5-1 Descriptive statistics of the performance of simple style investing strategies

From Jan 1980 to Dec 2004, at the end of each June/December, all U.K. stocks (excluding financial sectors, dead/delisted stocks retrieved and dealt with properly) are sorted according to previous 6-month firm characteristic values of APC, BM and DY (only stocks with positive research values are studied). All sorted stocks are further sorted according to the market capitalisations, resulting 9 (intersection) style portfolios. Based on the sorting simple style investing returns are calculated. All returns are denominated by £, equally-weighted (EW) and value weighted (VW) schemes are reported.

	APC			BM			DY		
	Mean	Std	t-ratios	Mean	Std	t-ratios	Mean	Std	t-ratios
Research variables									
rf_rate	0.0073	0.0006	209.995	0.0073	0.0006	209.995	0.0073	0.0006	209.995
return_m	0.0122	0.0471	4.408	0.0122	0.0471	4.408	0.0122	0.0471	4.408
def	0.0119	0.0055	36.580	0.0119	0.0055	36.580	0.0119	0.0055	36.580
yld	0.0001	0.0127	0.110	0.0001	0.0127	0.110	0.0001	0.0127	0.110
div	0.0405	0.0095	72.375	0.0405	0.0095	72.375	0.0405	0.0095	72.375
term	0.0007	0.0183	0.608	0.0007	0.0183	0.608	0.0007	0.0183	0.608
Style returns									
Small Growth (vw)	0.0148	0.0586	4.289	0.0116	0.0628	3.137	0.0155	0.0521	5.035
Small Blend (vw)	0.0211	0.0588	6.106	0.0142	0.0539	4.470	0.0175	0.0492	6.037
Small Value (vw)	0.0304	0.0669	7.715	0.0195	0.0527	6.268	0.0226	0.0703	5.460
Middle Growth (vw)	0.0098	0.0585	2.857	0.0100	0.0641	2.640	0.0095	0.0511	3.146
Middle Blend (vw)	0.0147	0.0505	4.935	0.0132	0.0542	4.145	0.0133	0.0457	4.954
Middle Value (vw)	0.0263	0.0815	5.473	0.0187	0.0548	5.802	0.0164	0.0517	5.405
Large Growth (vw)	0.0082	0.0501	2.782	0.0086	0.0487	3.008	0.0077	0.0482	2.710
Large Blend (vw)	0.0126	0.0482	4.426	0.0127	0.0496	4.355	0.0119	0.0433	4.656
Large Value (vw)	0.0180	0.0577	5.305	0.0151	0.0573	4.468	0.0156	0.0468	5.641
Value (vw)	0.0249	0.0587	7.204	0.0178	0.0492	6.124	0.0182	0.0469	6.585
Growth (vw)	0.0110	0.0496	3.747	0.0101	0.0530	3.224	0.0109	0.0430	4.290
Small (vw)	0.0221	0.0543	6.909	0.0151	0.0529	4.843	0.0185	0.0469	6.702
Large (vw)	0.0129	0.0478	4.595	0.0121	0.0476	4.330	0.0117	0.0412	4.824
Small Growth (ew)	0.0163	0.0553	5.004	0.0128	0.0605	3.578	0.0133	0.0460	4.901
Small Blend (ew)	0.0231	0.0699	5.621	0.0150	0.0531	4.790	0.0194	0.0701	4.701
Small Value (ew)	0.0279	0.0503	9.409	0.0210	0.0506	7.046	0.0200	0.0496	6.840
Middle Growth (ew)	0.0092	0.0560	2.799	0.0088	0.0614	2.419	0.0077	0.0494	2.639
Middle Blend (ew)	0.0147	0.0497	5.007	0.0122	0.0537	3.844	0.0123	0.0452	4.612
Middle Value (ew)	0.0314	0.1459	3.649	0.0183	0.0540	5.764	0.0161	0.0516	5.314
Large Growth (ew)	0.0099	0.0621	2.704	0.0077	0.0560	2.320	0.0084	0.0497	2.875
Large Blend (ew)	0.0136	0.0513	4.502	0.0124	0.0550	3.835	0.0130	0.0486	4.544
Large Value (ew)	0.0205	0.0702	4.949	0.0179	0.0560	5.425	0.0163	0.0504	5.499
Value (ew)	0.0266	0.0723	6.239	0.0191	0.0505	6.413	0.0175	0.0472	6.298
Growth (ew)	0.0118	0.0528	3.800	0.0097	0.0561	2.943	0.0098	0.0448	3.707
Small (ew)	0.0224	0.0512	7.435	0.0163	0.0519	5.318	0.0176	0.0476	6.266
Large (ew)	0.0147	0.0550	4.519	0.0127	0.0533	4.031	0.0126	0.0475	4.503
Style spreads (SV: Small Value, LG: Large Growth)									
Small - Large (vw)	0.0092	0.0415	3.754	0.0029	0.0405	1.234	0.0068	0.0415	2.791
Value - Growth (vw)	0.0140	0.0375	6.320	0.0077	0.0286	4.557	0.0073	0.0318	3.919
SV - LG (vw)	0.0222	0.0600	6.277	0.0108	0.0457	4.026	0.0149	0.0698	3.631
Small - Large (ew)	0.0078	0.0351	3.767	0.0036	0.0340	1.788	0.0050	0.0362	2.328
Value - Growth (ew)	0.0148	0.0543	4.613	0.0094	0.0294	5.401	0.0077	0.0255	5.137
SV - LG (ew)	0.0180	0.0442	6.902	0.0133	0.0380	5.968	0.0116	0.0405	4.852

5.5.2 Style definition and investor type

The underlying investment opportunity set is investor specific because different investors have different preferences. Assume a hypothesised multi-style investor has access to the following equity style portfolios in the market:

1. Small and large stocks (2 styles)
2. Value and growth stocks (2 styles)
3. Small Value (SV), Small Growth (SG), Large Value (LV) and Large Growth (LG) (4 styles)
4. Small Value (SV), Small Blend (SB), Small Growth (SG), Middle Value (MV), Middle Blend (MB), Middle Growth (MG), Large Value (LV), Large Blend (LB) and Large Growth (LG) (9 styles)

The assumption of these investment instruments are reasonable in today's financial market, in particular given the rapid development of Exchange Traded Funds (ETF) that track a specific market or market segments. For example, Vanguard follows a nine-box style box to form US stock ETF funds with holdings distributed by primary investment styles like growth, value, or blend and market segment (large-, mid-, and small-cap companies). The value-growth and small-large of (1) and (2) are typical two dimensions of equity style definition, while (3) and (4) offer more options based on the interactions of size and value-growth definition and hence represent specific risk-return structure.

Assume that the investors are mean-variance optimisers in traditional Markowitz paradigm with degree of risk aversion γ of 5. Assume that these investors can be broadly divided into two types:

1. *Sceptics* – these investors disregard business cycle effect in their asset allocation process and hence implement the unconditional optimal style investing;
2. *Doctrinaires* – these investors trust that business cycle condition could affect their asset allocation decision, and therefore apply

conditional optimal style investing incorporating the business cycle information;

The *Doctrinaires* can also be subdivided into those who follow the traditional two-step approach and those apply Brandt and Santa-Clara (2006) when timing their investings. At this stage it is assumed the *Doctrinaires* are Brandt and Santa-Clara (2006) followers.

Consider monthly and quarterly return frequencies[27]. The optimal multi-style investing (i.e. 'portfolio of style portfolios') are first derived using the initial 120 (60) monthly (quarterly) returns, then using the 121 (61) observations, and so on, ..., and are finally rebalanced using the T-1 observations, where T = 288 (T = 96) denoting the sample size based on monthly (quarterly) returns. The expected one-period-ahead excess investing returns are obtained from multiplying the optimal style weights of period *t-1* by period *t* realised style excess returns[28]. The time-series of this recursive scheme are recorded and analysed.

5.5.3 Test results and discussion

There are many test results based on various controlling parameters. The motivation to use different control variables is to obtain a general insight of the findings for the research questions. The definition of equity styles is sometimes ambiguous in the literature. For example, value stocks can be defined as those with low price to cash-flow ratios, or high book-to-market ratios or stocks with high dividend yields. This Chapter use firm characteristics of APC, BM and DY to form portfolios on the value-growth dimension. Arguably, using different variables to

[27] The sample data length (288 months returns or 96 quarterly returns) does not allow the test of annual returns using 4 or 9 styles due to loss of degree of freedom. The minimum number of observations to test the 9 styles investing under Brandt and Santa-Clara (2006) approach is 46.
[28] Two excess returns are used in the study, one is based on risk-free rate and the other is based on market index (not reported here). The optimal style investing based on excess returns on market index captures the gain from beating an index with low tracking error, and is equivalent to an "active indexation" strategy with optimal weights interpreted as "active weights".

sort stocks into value-growth styles can help generalise the findings. Table 5-2 below lists the control variables used in the study.

Table 5-2 Parameters used to control the test

Parameters description	Explanation	# of parameters
How style portfolios are formed?	based on company characteristics of APC, BM or DY	3
How many style portfolios are used in the allocation process?	There are 5 scenarios in total	5
How excess returns are defined?	with risk free rate or a market index	2
How portfolio returns are calculated?	Value weighted or equally weighted schemes	2
How in-sample size is defined?	Using fixed length rolling window or the incremental sample size that increase 1 in every subsequent period	2
Which investing (allocation) mode?	Unconditional allocation only or conditional allocation based on business cycle observable predictors	2
How long is the out-sample style investing holding period?	Optimal style investing will be evaluated for 1, 3, 6 and 12 months (1, 2, 4 and 8 quarters) based on the previous in-sample optimal style weights and average monthly returns obtained	4
Investor's risk aversion degree?	assume 5, can changed	1

Basically, the test results largely confirm the hypothesis proposed above. As an example and for concise purpose, the test results based on style portfolios sorted on stock characteristics APC only is reported below. Results can be quantitatively different with BM and DY sorted style portfolios nevertheless they all qualitatively support the same conclusion.

Table 5-3 provides estimates of single-period optimal style investing. Panel A is for monthly return frequency and Panel B for quarterly frequency. Each panel reports the time-series average weights for different styles. R(tangent) refers the average expected monthly returns of the tangency style investing portfolios and R(predicted) refers the average monthly-equivalent one-period ahead optimal style investing returns according to the optimal style investing weights (namely style investing policy). The sample is from January 1981 to December 2004 (288 months or 96 quarters). The first 120 months (60 quarters) is used to estimate the initial optimal weights of the style investing policy and then form out-of-sample monthly (quarterly) "portfolio of style portfolios" using those weights in the next period. Every subsequent period the style timing policy is re-estimated by enlarging the sample. The t-ratios for unconditional optimal style weights and for the business cycle variables of conditional investing are obtained based on Britten-Jones (1999) approach, and the corresponding standard errors are retrieved from these t-ratios. Note the t-ratios reported in this table are calculated from the time-series average coefficients and the time-series average standard errors. The * refers that it is significant for at least 10% level.

Table 5-3 Single-Period Optimal Style Investing (Portfolio are based on stocks sorted on firm characteristic APC)

Small-Large styles, Panel A: Monthly														
	Unconditional						Conditional							
	VW			EW			VW				EW			
Variable	weight	std	t	weight	std	t	weight	coeff	std	t	weight	coeff	std	t
SMALL	1227	0.346	3.55*	1689	0.427	3.96*	2.481	6.903	2.920	2.36*	3.456	9.377	3.346	2.80*
s_def								-0.160	1003	-0.16		-0.475	1096	-0.434
s_yld								0.626	0.389	1609		0.455	0.507	0.898
s_div								-1124	0.458	-2.45*		-1487	0.534	-2.78*
s_ter								0.622	0.275	2.27*		0.622	0.325	192*
LARGE	-0.506	0.408	-1240	-0.795	0.422	-188*	-0.423	-4.668	3.216	-1452	-1578	-7.231	3.108	-2.33*
l_def								-0.629	1015	-0.62		-0.236	1133	-0.208
l_yld								-1125	0.386	-2.92*		-0.811	0.393	-2.06*
l_div								1190	0.556	2.14*		1526	0.502	3.04*
l_ter								-0.178	0.284	-0.628		-0.148	0.318	-0.467
Total Weigh	0.721			0.894			2.058				1878			
R(tangent)	0.016	0.002	9.62*	0.020	0.002	12.22*		0.037	0.023	166*		0.043	0.018	2.42*
R(predicted)	0.012	0.044	0.261	0.017	0.048	0.360		0.039	0.122	0.320		0.047	0.122	0.385
Small-Large styles, Panel B: Quarterly														
SMALL	0.784	0.275	2.85*	1138	0.353	3.22*	1513	3.388	2.181	1554	2.087	5.338	2.571	2.08*
s_def								-0.137	0.805	-0.170		0.056	0.915	0.062
s_yld								0.740	0.402	184*		0.740	0.528	1400
s_div								-0.506	0.353	-1435		-0.961	0.450	-2.14*
s_ter								0.584	0.244	2.39*		0.448	0.273	165*
LARGE	-0.256	0.427	-0.601	-0.637	0.448	-1421	0.785	-0.827	3.106	-0.266	-0.930	-5.172	3.007	-172*
l_def								-0.476	1244	-0.382		-0.655	1210	-0.541
l_yld								-1650	0.538	-3.06*		-1317	0.551	-2.39*
l_div								0.493	0.591	0.835		1351	0.573	2.36*
l_ter								-0.058	0.316	-0.183		-0.042	0.317	-0.131
Total Weigh	0.527			0.500			2.297				1157			
R(tangent)	0.011	0.002	6.23*	0.014	0.001	9.53*		0.029	0.031	0.937		0.026	0.020	1341
R(predicted)	0.008	0.038	0.210	0.011	0.039	0.273		0.025	0.128	0.195		0.028	0.115	0.242

Value-Growth styles, Panel A: Monthly														
	Unconditional						Conditional							
	VW			EW			VW				EW			
Variable	weight	std	t	weight	std	t	weight	coeff	std	t	weight	coeff	std	t
VALUE	1753	0.354	4.95*	0.796	0.231	3.44*	9.934	20.946	4.144	5.05*	10.676	23.324	4.907	4.75*
v_def								-0.762	1205	-0.632		-0.145	1448	-0.100
v_yld								-1186	0.447	-2.65*		-1212	0.424	-2.86*
v_div								-2.757	0.708	-3.89*		-3.355	0.806	-4.16*
v_ter								-0.551	0.447	-1231		-0.650	0.492	-1322
GROWTH	-1410	0.468	-3.01*	-0.433	0.373	-1161	-8.078	-18.455	4.465	-4.13*	-8.886	-21552	5.364	-4.02*
g_def								0.039	1134	0.035		-0.515	1399	-0.368
g_yld								0.671	0.529	1269		0.730	0.498	1464
g_div								2.636	0.776	3.40*		3.367	0.901	3.74*
g_ter								1175	0.506	2.32*		1348	0.569	2.37*
Total Weigh	0.344			0.364			1856				1790			
R(tangent)	0.027	0.002	11.77*	0.014	0.001	10.18*		0.153	0.067	2.28*		0.175	0.069	2.529
R(predicted)	0.022	0.040	0.543	0.011	0.019	0.589		0.108	0.215	0.504		0.122	0.229	0.535
Value-Growth styles, Panel B: Quarterly														
VALUE	2.258	0.382	5.90*	1164	0.262	4.45*	7.340	8.113	3.617	2.24*	9.139	12.376	4.524	2.74*
v_def								1569	1547	1014		1087	1791	0.607
v_yld								-1134	0.540	-2.10*		-1209	0.567	-2.13*
v_div								-0.924	0.642	-1439		-1625	0.735	-2.21*
v_ter								0.187	0.443	0.421		0.098	0.403	0.243
GROWTH	-1917	0.509	-3.76*	-0.628	0.347	-181*	-6.195	-6.857	4.840	-1417	-8.767	-13.725	5.824	-2.36*
g_def								-3.304	2.158	-1531		-2.633	2.310	-1140
g_yld								0.923	0.657	1405		1242	0.672	185*
g_div								1272	0.910	1398		2.493	0.896	2.78*
g_ter								0.304	0.555	0.548		0.591	0.525	1124
Total Weigh	0.340			0.536			1145				0.372			
R(tangent)	0.032	0.011	3.09*	0.020	0.002	10.04*		0.100	0.090	1106		0.122	0.138	0.880
R(predicted)	0.023	0.087	0.262	0.015	0.038	0.406		0.065	0.262	0.249		0.073	0.400	0.184

Table 5-3 (continued -1)

SG, SV, LG and LV styles, Panel A: Monthly														
	Unconditional						Conditional							
	VW			EW			VW				EW			
Variable	weight	std	t	weight	std	t	weight	coeff	std	t	weight	coeff	std	t
SG	-0.487	0.387	-1258	-0.820	0.422	-194*	-3.774	-9.830	4.505	-2.18*	-6.376	-8.038	4.277	-188*
sg_def								0.209	1257	0.166		-0.257	1312	-0.196
sg_yld								1411	0.676	2.086*		0.369	0.707	0.522
sg_div								1370	0.765	179*		1302	0.665	196*
sg_ter								0.464	0.446	1040		0.291	0.439	0.663
SV	1261	0.302	4.18*	3.098	0.493	6.29*	7.422	16.022	4.129	3.880	7.946	17.526	4.530	3.87*
sv_def								-0.780	1033	-0.755		-0.999	1086	-0.920
sv_yld								-0.610	0.438	-1392		-0.002	0.720	-0.003
sv_div								-2.314	0.707	-3.27*		-2.586	0.849	-3.04*
sv_ter								0.097	0.375	0.259		0.196	0.402	0.489
LG	-0.583	0.447	-1305	-1240	0.383	-3.24*	-2.788	-4.371	4.144	-1055	-2.184	-6.473	5.042	-1284
lg_def								-0.651	1024	-0.635		-1045	1238	-0.844
lg_yld								-0.689	0.566	-1217		-0.189	0.622	-0.304
lg_div								0.854	0.744	1148		1202	0.809	1486
lg_ter								0.100	0.400	0.250		0.287	0.558	0.515
LV	0.225	0.396	0.567	-0.003	0.280	-0.011	0.975	-0.112	3.758	-0.030	1502	-1740	4.948	-0.352
lv_def								0.409	1133	0.361		1468	1758	0.835
lv_yld								-0.470	0.464	-1012		-0.559	0.482	-1160
lv_div								0.169	0.667	0.253		0.311	0.860	0.362
lv_ter								-0.194	0.388	-0.499		-0.175	0.503	-0.347
Total Weight	0.416			1035			1836				0.889			
R(tangent)	0.028	0.003	9.85*	0.051	0.008	6.13*		0.147	0.043	3.41*		0.120	0.033	3.61*
R(predicted)	0.024	0.039	0.600	0.057	0.077	0.738		0.120	0.199	0.604		0.123	0.190	0.649

SG, SV, LG and LV styles, Panel B: Quarterly														
	Unconditional						Conditional							
	VW			EW			VW				EW			
Variable	weight	std	t	weight	std	t	weight	coeff	std	t	weight	coeff	std	t
SG	-1996	0.611	-3.27*	-0.791	0.498	-1588	-6.424	-4.922	9.083	-0.542	-4.749	-7.520	7.480	-1005
sg_def								1508	2.351	0.641		-1695	2.049	-0.827
sg_yld								1719	1453	1183		1856	1372	1353
sg_div								-0.384	1646	-0.234		1482	1220	1215
sg_ter								0.462	0.852	0.542		0.014	0.724	0.020
SV	2.334	0.469	4.97*	2.046	0.430	4.75*	8.078	15.172	7.583	2.00*	5.717	9.176	6.455	1421
sv_def								-3.194	2.288	-1396		-0.115	1856	-0.062
sv_yld								-0.698	1148	-0.608		-0.098	1032	-0.095
sv_div								-1217	1234	-0.986		-1052	1209	-0.870
sv_ter								-0.077	0.705	-0.109		0.265	0.565	0.469
LG	-0.505	0.536	-0.941	-1056	0.390	-2.71*	-0.185	2.333	8.620	0.271	-1096	2.976	10.273	0.290
lg_def								-6.935	2.793	-2.48*		-3.500	2.553	-1371
lg_yld								-0.840	1251	-0.671		-1390	1156	-1202
lg_div								0.952	1379	0.690		-0.099	1587	-0.062
lg_ter								-0.451	0.864	-0.523		-0.152	0.970	-0.156
LV	-0.125	0.573	-0.217	0.262	0.360	0.726	-0.253	-10.132	9.253	-1095	0.283	-6.406	8.783	-0.729
lv_def								7.414	3.079	2.41*		3.563	3.474	1026
lv_yld								-0.886	1334	-0.665		-0.658	0.753	-0.874
lv_div								0.509	1502	0.339		0.592	1460	0.405
lv_ter								0.505	0.925	0.546		0.290	0.863	0.336
Total Weight	-0.291			0.460			1216				0.154			
R(tangent)	0.041	0.011	3.69*	0.035	0.009	4.02*		0.137	0.053	2.56*		0.073	0.024	3.10*
R(predicted)	0.033	0.074	0.446	0.038	0.069	0.543		0.113	0.290	0.390		0.080	0.239	0.333

Table 5-3 (continued -2)

SG, SB, SV, MG, MB, MV, LG, LB and LV Styles, Panel A: Monthly														
	Unconditional						Conditional							
	VW			EW			VW				EW			
Variable	weight	std	t	weight	std	t	weight	coeff	std	t	weight	coeff	std	t
SG	-0.301	0.449	-0.671	0.038	0.567	0.068	-4.041	-5.489	7.598	-0.722	-4.589	-3.118	7.514	-0.415
sg_def								-0.390	1853	-0.211		-0.286	2.275	-0.126
sg_yld								1252	1387	0.903		1735	1282	1354
sg_div								0.904	1262	0.717		0.328	1.182	0.278
sg_ter								-0.253	0.680	-0.373		-0.436	0.737	-0.592
SB	0.838	0.395	2.12*	0.983	0.553	178*	2.075	4.345	8.846	0.491	1285	-3.316	11.12	-0.298
sb_def								-1524	2.459	-0.620		-1400	2.962	-0.473
sb_yld								-1686	1389	-1213		-1993	1818	-1096
sb_div								-0.420	1371	-0.307		1503	1800	0.835
sb_ter								1454	1057	1375		1921	1347	1426
SV	1.141	0.349	3.27*	6.650	0.814	8.17*	12.026	26.599	7.908	3.36*	11.290	17.854	10.330	173*
sv_def								-1356	2.425	-0.559		-1928	2.383	-0.809
sv_yld								-0.409	0.855	-0.478		-0.117	1487	-0.079
sv_div								-3.964	1236	-3.21*		-1087	1900	-0.572
sv_ter								-0.493	0.872	-0.566		-0.527	0.971	-0.543
MG	-1461	0.679	-2.15*	-5.172	1275	-4.06*	-13.39	-18.04	7.317	-2.47*	-6.753	-47.51	15.564	-3.05*
mg_def								-1029	2.537	-0.405		-0.905	3.815	-0.237
mg_yld								1603	1394	1.149		-0.111	2.127	-0.052
mg_div								2.615	1243	2.10*		8.141	3.116	2.61*
mg_ter								0.734	0.992	0.740		1.131	1298	0.872
MB	-0.081	0.908	-0.089	-3.081	1560	-198*	5.829	2.212	12.459	0.178	-1206	37.197	18.076	2.06*
mb_def								2.755	2.920	0.944		0.604	3.758	0.161
mb_yld								-0.656	2.310	-0.284		-1834	2.906	-0.631
mb_div								-1242	2.351	-0.528		-8.413	3.736	-2.25*
mb_ter								0.242	1341	0.181		0.959	1519	0.631
MV	0.331	0.237	1396	0.096	0.122	0.786	0.688	-1253	8.268	-0.152	1451	4.582	10.553	0.434
mv_def								0.819	2.717	0.302		2.138	2.771	0.772
mv_yld								-0.617	0.933	-0.661		0.936	1002	0.934
mv_div								0.503	1563	0.322		-1356	1996	-0.679
mv_ter								-0.555	0.887	-0.626		-1342	1008	-1331
LG	-1246	0.744	-168*	-2.086	1047	-199*	0.900	-3.020	9.436	-0.320	-1680	15.312	13.085	1170
lg_def								-1045	2.112	-0.495		0.991	2.910	0.340
lg_yld								0.430	1374	0.31		0.023	1632	0.014
lg_div								0.744	1845	0.403		-4.102	2.444	-168*
lg_ter								-0.258	0.854	-0.302		0.643	1298	0.495
LB	1297	0.876	1481	3.139	1.135	2.77*	-5.135	-6.345	10.985	-0.578	-1879	-29.38	15.879	-185*
lb_def								1786	2.678	0.667		3.953	3.438	1150
lb_yld								-0.484	1759	-0.275		0.972	2.502	0.388
lb_div								1.166	2.241	0.520		5.938	3.218	185*
lb_ter								0.426	1067	0.400		0.137	1471	0.093
LV	-0.038	0.466	-0.082	0.228	0.363	0.627	3.529	3.488	6.373	0.547	1968	8.420	9.218	0.913
lv_def								-0.228	1693	-0.134		-3.632	3.352	-1084
lv_yld								-0.177	0.879	-0.201		-0.790	1.161	-0.681
lv_div								-0.500	1245	-0.401		-0.457	1744	-0.262
lv_ter								-0.463	0.694	-0.667		-1325	1011	-1311
Total Weight	0.481			0.796			2.362				2.477			
R(tangent)	0.046	0.004	10.24*	0.144	0.026	5.46*		0.299	0.083	3.61*		0.315	0.087	3.63*
R(predicted)	0.030	0.059	0.506	0.119	0.188	0.634		0.193	0.325	0.594		0.267	0.409	0.653

Table 5-3 (continued -3)

SG, SB, SV, MG, MB, MV, LG, LB and LV Styles, Panel B: Quarterly														
	Unconditional						Conditional							
	VW			EW			VW				EW			
Variable	weight	std	t	weight	std	t	weight	coeff	std	t	weight	coeff	std	t
SG	-1754	0.807	-2.17*	-0.697	0.759	-0.919	-19.324	-36.987	42.183	-0.877	-4.897	13.221	32.631	0.405
sg_def								1397	7.972	0.175		-13.520	8.079	-167*
sg_yld								9.753	10.148	0.961		7.969	5.177	1539
sg_div								5.476	9.334	0.587		-0.669	5.918	-0.113
sg_ter								-3.791	2.834	-1338		-1887	2.553	-0.739
SB	0.426	0.406	1050	0.623	0.658	0.947	2.504	0.839	41567	0.020	6.144	3.404	48.367	0.070
sb_def								-17.973	15.648	-1149		-8.115	14.634	-0.554
sb_yld								-3.235	6.274	-0.516		-2.455	6.568	-0.374
sb_div								3.402	6.402	0.531		1851	8.354	0.222
sb_ter								0.389	4.464	0.087		0.845	4.376	0.193
SV	1986	0.668	2.97*	4.697	0.752	6.24*	41139	109.006	39.247	2.777	13.513	9.628	31685	0.304
sv_def								-5.715	17.393	-0.329		-6.724	13.613	-0.494
sv_yld								-5.959	8.062	-0.739		-2.570	4.547	-0.565
sv_div								-16.782	6.672	-2.515		3.184	5.913	0.538
sv_ter								-3.321	4.201	-0.791		-1215	3.013	-0.403
MG	-1747	0.886	-197*	-4.039	1385	-2.92*	-17.358	-2.129	35.127	-0.061	-25.185	-37.303	47.213	-0.790
mg_def								12.237	10.746	1139		6.110	11.116	0.550
mg_yld								-0.447	8.515	-0.053		-3.353	8.875	-0.378
mg_div								-6.906	6.293	-1097		2.293	11591	0.198
mg_ter								3.272	4.132	0.792		0.733	4.352	0.168
MB	0.453	0.945	0.479	-2.489	1703	-1462	5.559	35.206	57.077	0.617	19.014	54.667	56.467	0.968
mb_def								-17.561	16.144	-1088		-3.701	20.369	-0.182
mb_yld								-5.902	9.682	-0.610		-3.448	11322	-0.305
mb_div								-4.017	9.741	-0.412		-11.114	11444	-0.971
mb_ter								-2.893	5.904	-0.490		0.799	4.991	0.160
MV	0.494	0.427	1159	0.068	0.184	0.368	-14.005	-63.423	31940	-199*	-10.819	-33.804	29.718	-1137
mv_def								18.604	9.897	188*		25.593	11555	2.21*
mv_yld								0.935	5.944	0.157		3.819	5.154	0.741
mv_div								8.658	6.543	1323		0.174	6.045	0.029
mv_ter								5.500	3.806	1445		2.871	2.726	1053
LG	-0.748	0.812	-0.921	-1163	1295	-0.899	37.112	131979	36.857	3.58*	22.977	83.515	55.807	1496
lg_def								-27.474	12.287	-2.24*		-12.687	13.101	-0.968
lg_yld								-12.934	7.372	-175*		-4.520	8.321	-0.543
lg_div								-20.359	6.742	-3.02*		-14.741	12.334	-1195
lg_ter								-5.307	3.868	-1372		-6.000	4.784	-1254
LB	0.785	1007	0.779	1875	1513	1239	-45.477	-194.992	50.638	-3.85*	-24.844	-92.170	65.523	-1407
lb_def								3.179	13.892	0.229		-5.958	19.865	-0.300
lb_yld								9.784	9.598	1019		5.721	11320	0.505
lb_div								42.580	10.238	4.16*		21805	14.598	1494
lb_ter								6.499	5.097	1275		4.775	5.610	0.851
LV	0.032	0.718	0.044	1104	0.591	187*	12.941	8.126	29.603	0.275	11032	18.829	29.733	0.633
lv_def								20.952	16.514	1269		7.509	14.196	0.529
lv_yld								8.445	7.880	1072		-2.153	4.961	-0.434
lv_div								-5.343	6.585	-0.811		-4.168	5.046	-0.826
lv_ter								-0.967	3.664	-0.264		-0.876	3.580	-0.245
Total Weight	-0.073			-0.021			3.092				6.934			
R(tangent)	0.053	0.033	1616	0.096	0.066	1462		0.429	0.200	2.14*		0.231	0.241	0.956
R(predicted)	0.024	0.161	0.146	0.059	0.266	0.220		0.177	1381	0.128		0.191	0.926	0.207

Table 5-3 first suggests that investors using value-weighted portfolio strategies would generally give up a large fraction of wealth to have access to large stocks. A style portfolio with fund equally distributed to all constituent stocks tends to outperform that based on market capitalisation to allocate funds (i.e. value-weighted scheme). This is because small stocks tend to outperform large stocks in the long run.

While equally-weighted investing generally yield higher volatility, their out-of-sample Sharp Ratios are also generally higher than value-weighted schemes. Consistent with the literature about the divergent returns of value-growth stocks and small-large stocks, regardless of return horizons, all types of investors are shown to significantly long value stocks and small stocks, and also tend to significantly short growth stocks or large stocks. In more detailed market segments, it can be seen that investors tend to long SV, LB, LV and short SG, MG and LG, and the long positions on SV stocks are overwhelmingly significant on both monthly and quarterly horizons.

The unconditional style investing and the conditional style investing using business cycle information are very much different. First, investors who disregard the business cycle predictability are relatively conservative with respect to their overall net equity exposures. While these *Skeptics* also overweight some specific styles both at long and short directions, they eventually all end up with allocating part of their wealth to cash. In sharp contrast, investors who have strong prior beliefs about the business cycle information are very aggressive in equity investing and therefore generally end up with large long exposures to equities that must be leveraged by borrowing.

Comparing the holdings of corresponding styles for both types of investors, it is evident that the return predictability from business cycle information tends to induce the *Doctrinaires* to consistently pursue extreme positions on value (small) stocks and/or growth (large) stocks than the *Skeptics do*. For example, in the case of two styles of small and large stocks based on monthly returns, the *Skeptics* would long 122.7% (168.9%) of their wealth on small stocks financed by shorting 50.6% (79.5%) of the value on large stocks, ending with 72.1% (89.4%) of the initial wealth that allocated to long equity styles and the remaining 27.9% (10.6%) allocated to cash on value-weighted (equally-weighted) portfolio scheme. The *Doctrinaires*, in contrast, would tilt 248.1% (345.6%) of the initial wealth to long small stocks and short

42.3% (157.8%) value of large stocks, yielding net borrowing of 105.8% (87.8%) amount of the initial wealth for value-weighted (equally-weighted) investing. Similar finding holds for quarterly horizons and for other styles. The fundamental reason for such extreme tilt is because the *Doctrinaires* believe the return spreads of these twin-styles can be estimated using business cycle predictors and therefore the exposure can be reduced at bad times when expected returns are low or volatility is high.

The conditional investing is quite sensitive to the state variables and these variables affect the optimal style investing in quite a different mechanism. Consider the basic style box, along the small and large dimension, regardless whether it is based on monthly or quarterly horizon, the short-term interest rate (*yld*) and the term spread (*term*) tend to induce investors to tilt to small stocks and tilt away from large stocks, both in a very important manner. On the contrary, market dividend yield (*div*) significantly leads investors to tilt away from small stocks to large stocks relative to their early holdings.

Along value and growth axis, variable *yld, div* and *term* all significantly or importantly suggest investors moving away from value stocks and tilt to growth stocks on the monthly rebalancing. For the quarterly frequency, the variable *term* becomes less informative while variable *yld* or *div* still functions the same as it does in monthly frequency case, and the default spread (*def*) appears to lead investors to tilt to value stocks despite that it appears to be less informative for the entire style space on monthly rebalancing frequency.

If considering style interactions and thus more detailed equity market segments, it can be seen that importantly *yld* and *div* tend to lead investors to tilt to small growth stocks (SG) and tilt away from small value stocks (SV) for both monthly and quarterly horizons. In addition, variable *term* appears to suggest investors moving away from large value (LV) stocks on monthly horizon or large growth (LG) stocks on quarterly rebalancing periods.

In summary, business cycle predictive variables of *yld*, *div*, *term* and *def* tend to exert significant or important impact on investors' optimal style investing policy. To be significant in predicting optimal style allocation weight in the mean-variance framework, a state variable should ideally either predict the expected style returns or the variance of style returns. Ait-Sahalia and Brandt (2001) study the moments of the market index of S&P 500 and find that *def* is positively related to the variance-covariance of monthly returns and positively but not significantly related to the expected returns. They argue that *div* is positively related to the expected stock returns by the definition of the present value formula, and the variable *term* is the most important and should be positively related with expected returns and negatively related with return variance. Given the fact that the research data of Ait-Sahalia and Brandt (2001) is based on the U.S. markets and the nature that business cycle variables are country specific, the results in table 5-3 are overall consistent with the existing literature. It is also noted that the coefficients of significant state variables generally have opposite signs for counterpart style allocations, suggesting that such variables indeed exert different impact on optimal style investing policies.

Business cycle predictability could benefit investors' dynamic style investing. Smart investors capitalising on the conditional business cycle information consistently beat those disregarding business cycle conditions, both in-sample and out-of-sample. For example, on the monthly return frequency, the average optimal monthly returns of conditional investing is 14.7%, 4% and 3.4% as compared to 2.8%, 2.2% and 1.4% of unconditional investing based on style variables of APC, BM and DY, respectively (BM and DY returns are not shown in the table and are available on request). Except for style portfolios based on BM, the corresponding one-month out-of-sample performance is

9.9% and 1.9% as compared to 2.3% and 1.0% based on APC and DY, respectively. Similar findings are shown for quarterly basis (and this time BM also outperforms in one-quarter-ahead period). It should note that the in-sample expected excess returns of optimal tangent style investing portfolio are generally significant, while out-sample average returns are not. Indeed, such predictability-based style investing typically have high volatility, nevertheless such strategy provides investors with different return-risk trade off.

Figure 5-1 displays the time-series optimal style weights of conditional and unconditional investing using equally-weighted monthly and quarterly returns (results for the value-weighted schemes are qualitatively the same). Evidently, optimal style investing policies of the two types of investors are fundamentally different. The *Doctrinaires*' conditional investing policy is more dynamic giving its timing nature suggested by different economic states. Style allocations across different horizons tend to demonstrate similar characteristics, suggesting that in principle business cycle variables predict optimal style allocation in a consistent manner for different rebalancing periods. However, conditional style investing based on different return frequencies can be different due to drastic changes in the conditional volatilities and correlations of different asset classes across horizons. Overall, by focusing directly on the optimal style weights as suggested by Brandt and Santa-Clara (2006), the *Doctrinaires* are able to capture the entire distributions of style returns as opposed to the expected returns only, and hence should obtain better style investing policies.

Figure 5-1 Style portfolio weights of conditional and unconditional policies

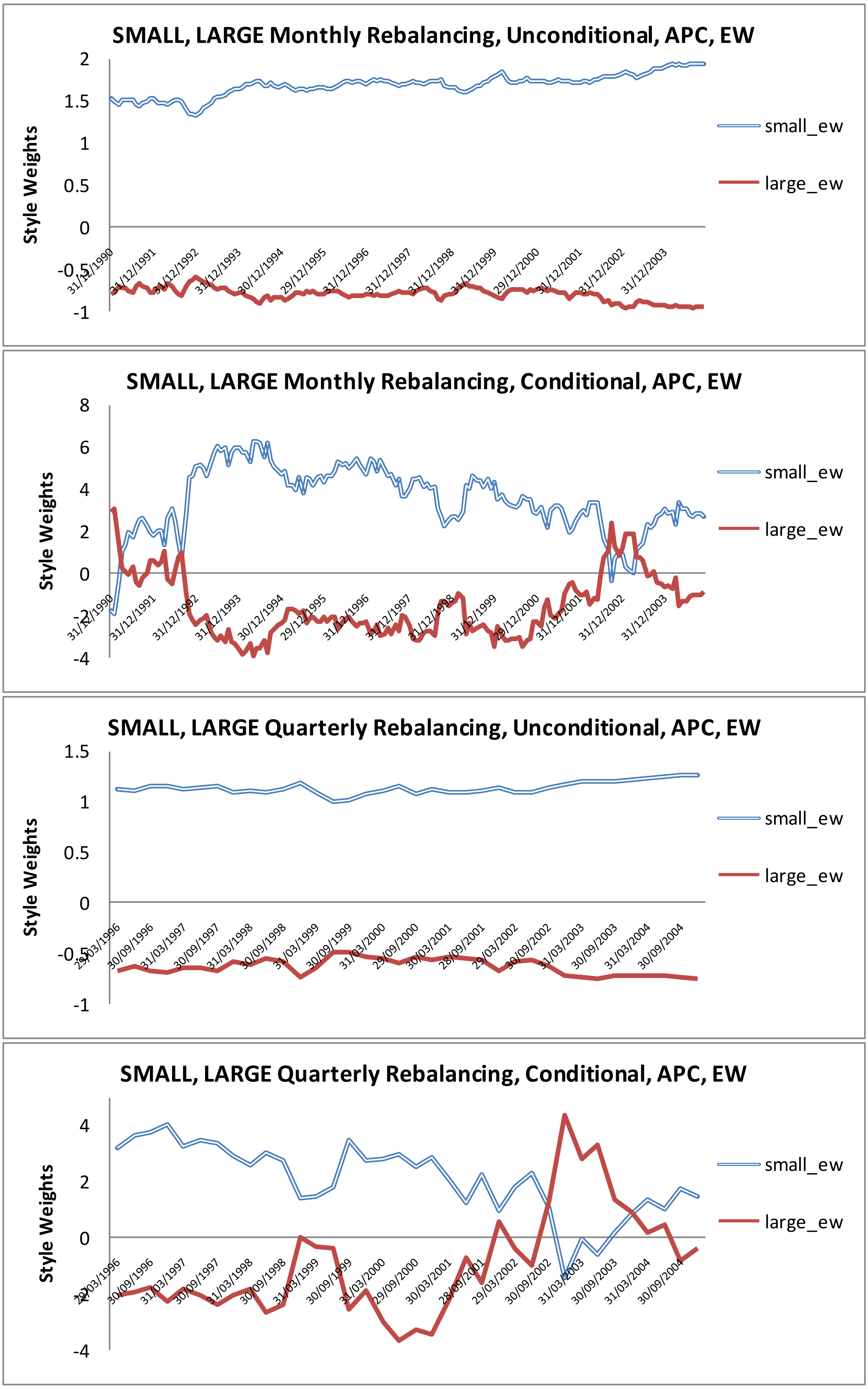
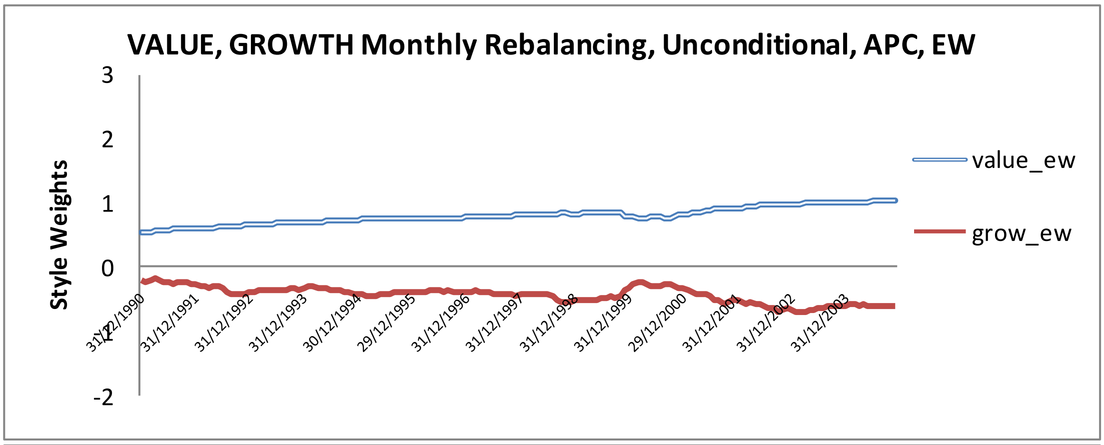
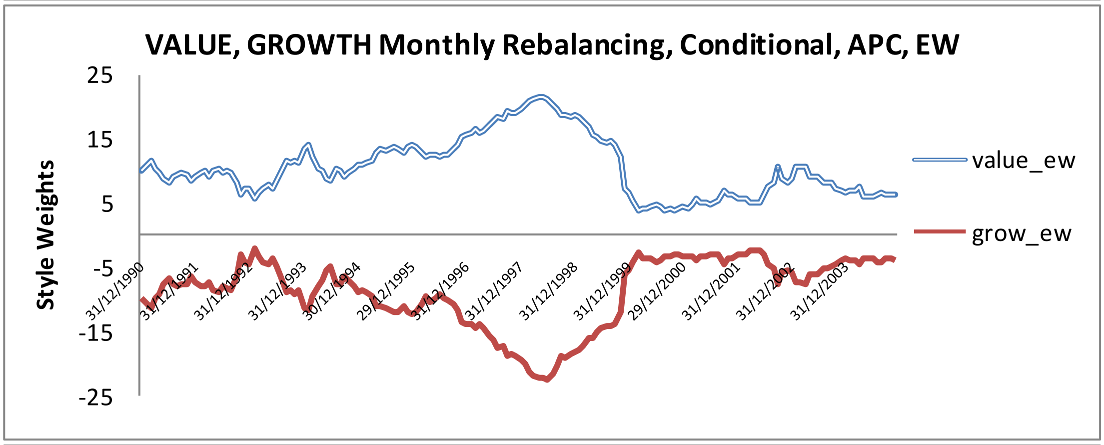
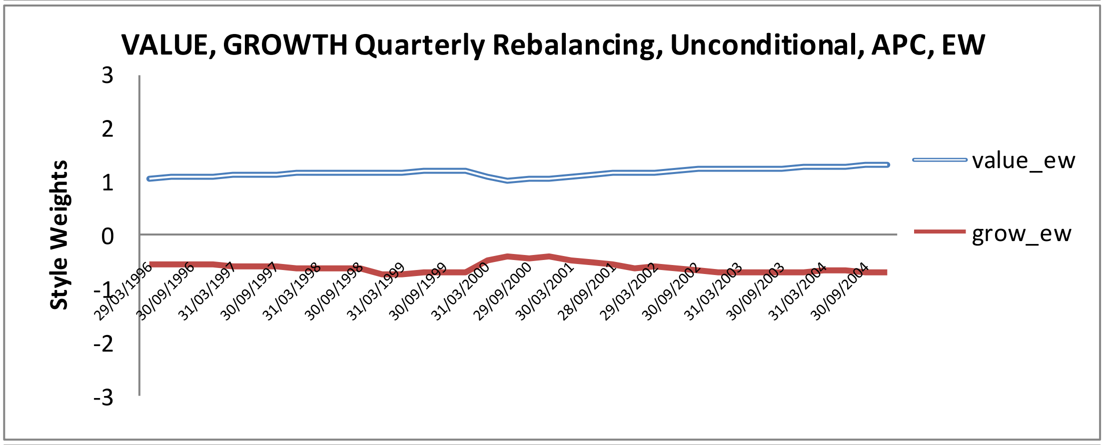


Figure 5-1 (continued -1)







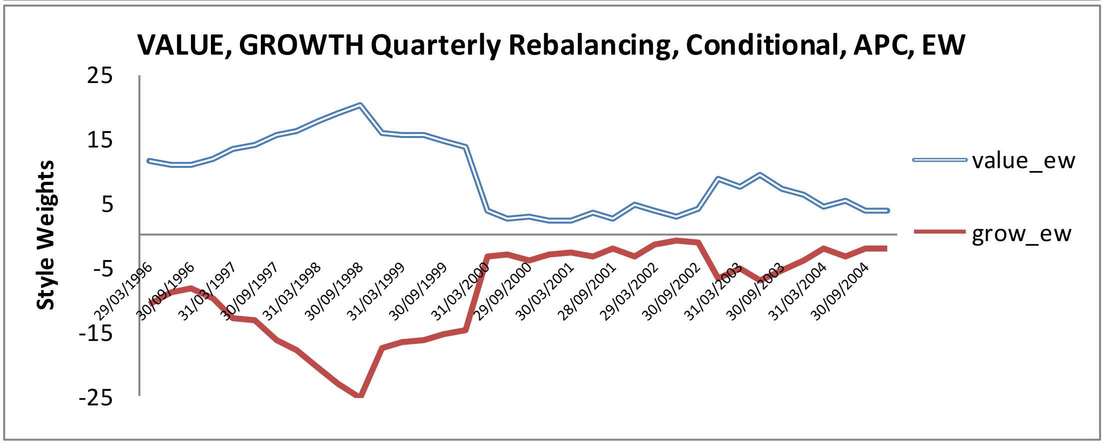
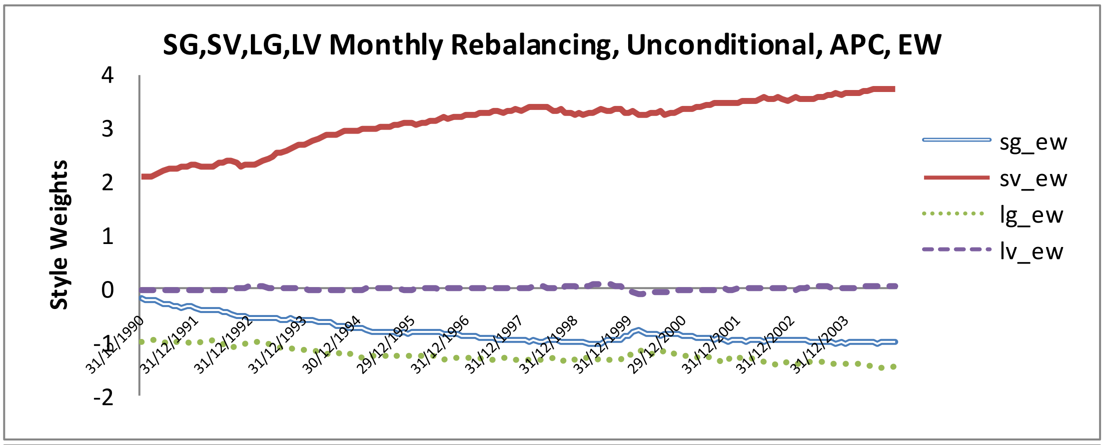
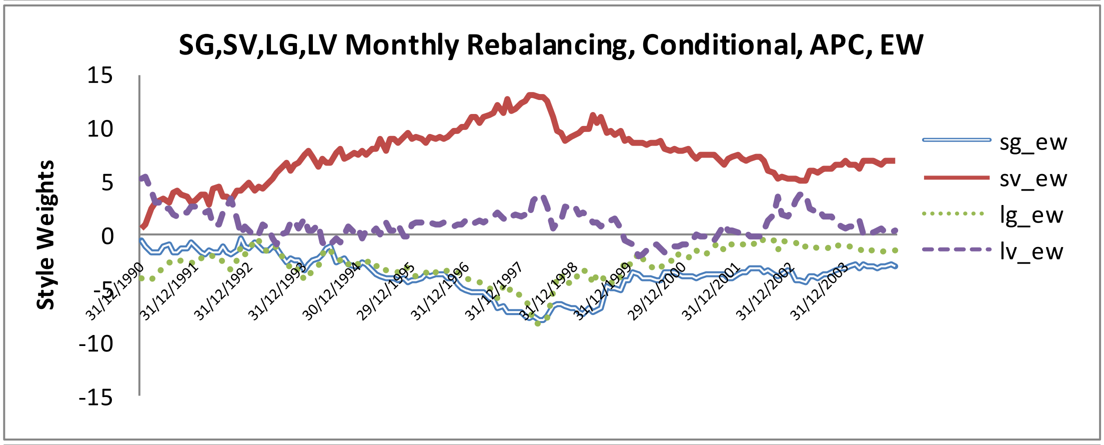
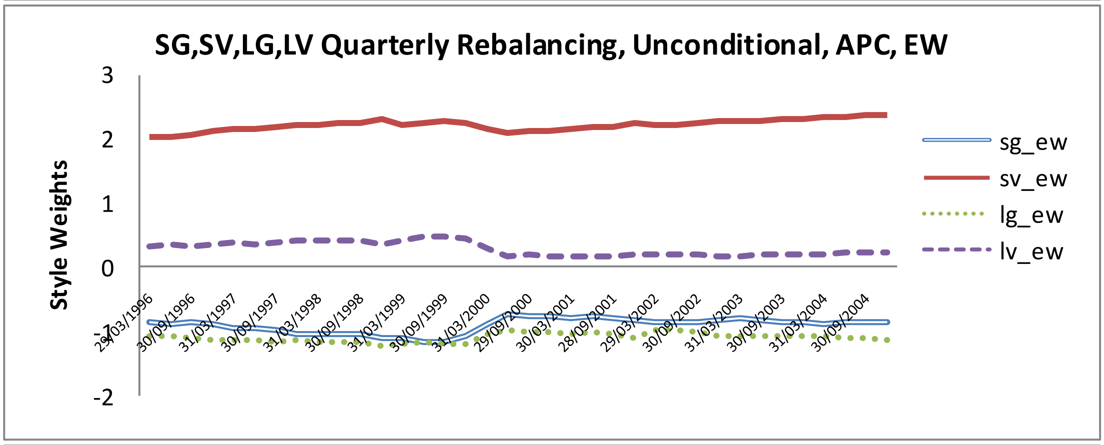


Figure 5-1 (continued -2)







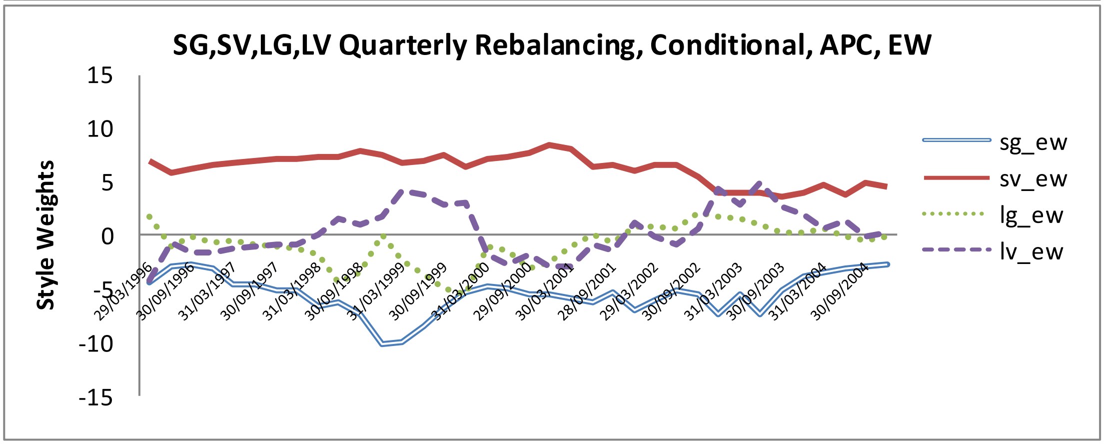
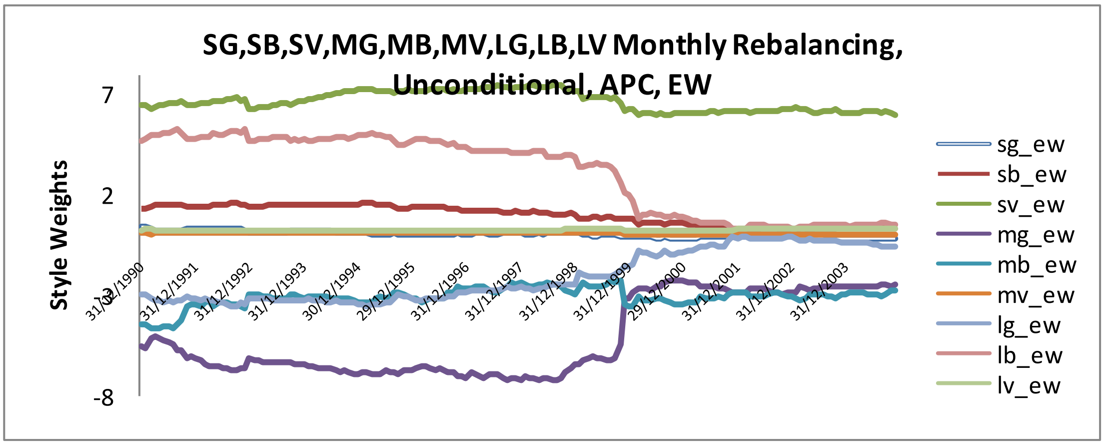
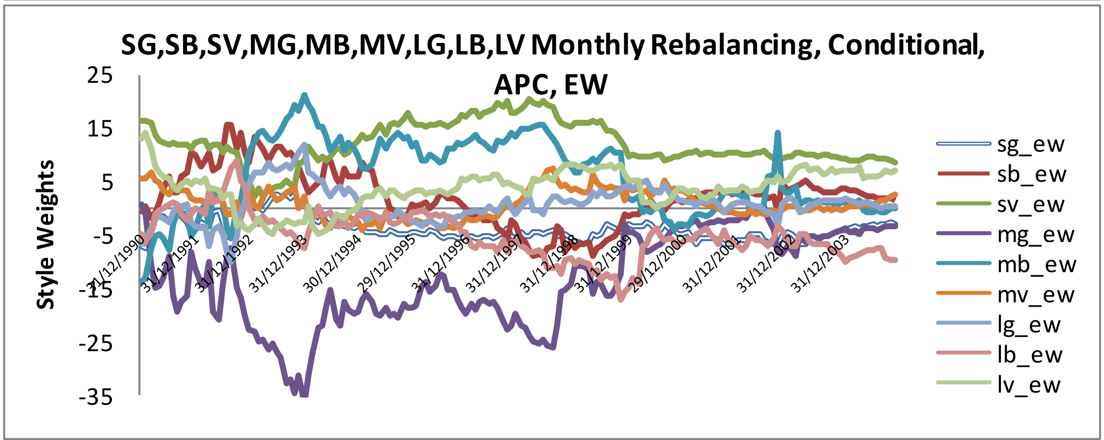
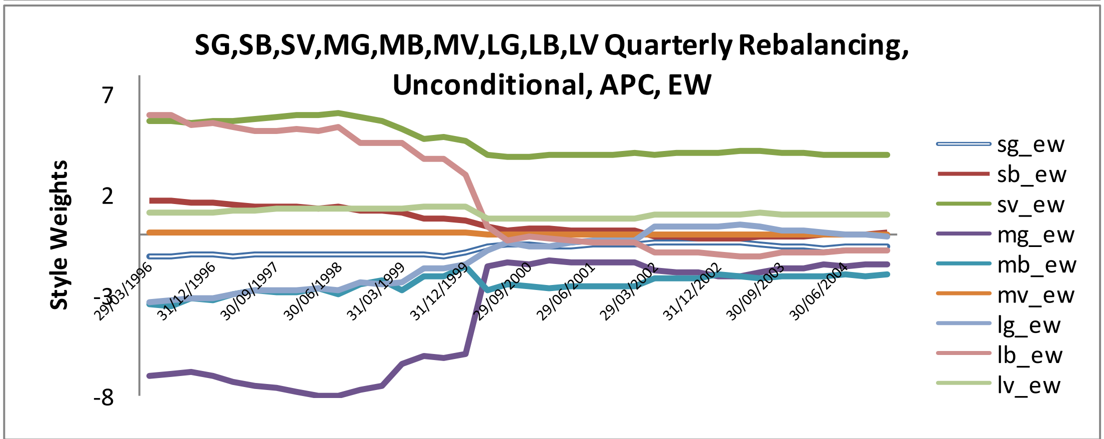
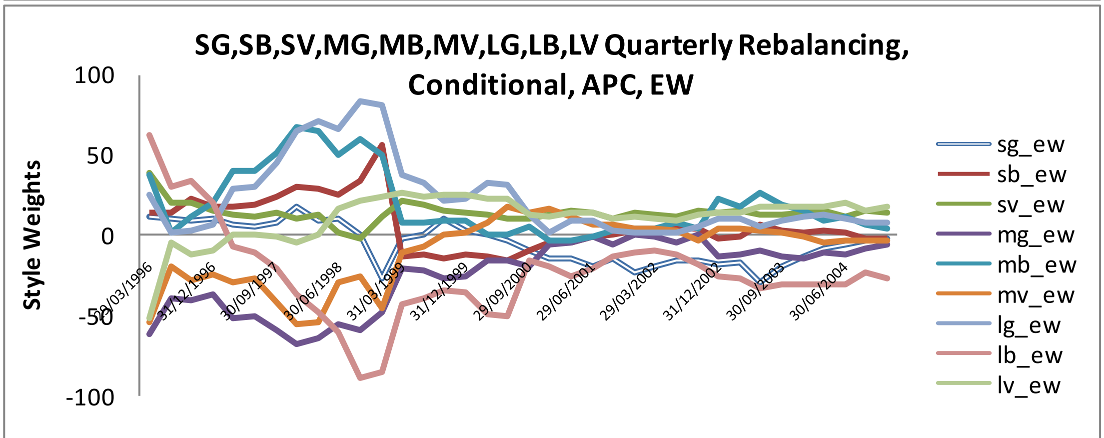


Figure 5-1 (continued -3)









To deepen the understanding of Brandt and Santa-Clara (2006), it is useful to compare the conditional style policies to a more traditional approach that first modelling the conditional style portfolio returns and then choose the optimal style investing weights. Specifically, unlike the previous method that uses the sample moment as expected style returns, this time the expected style returns are estimated using regressions based on the set of business cycle predictors (one-period-ahead forecasts of returns), while the variance-covariance matrix is formed *unconditionally* (using sample analogue). In this way, the optimal style investing only takes into account the predictability of the state variables to style returns but simply ignores their impact on variance-covariance structure of different styles. Table 5-4 compares the results of the two approaches.

Table 5-4 Traditional versus Conditional Style Investing on State variables

This table compares the style investing that uses business cycle information to predict the first moment of style returns to that directly predicts optimal style timing policy with same predictors. The conditional expected returns are obtained from an in-sample regression of returns on the predictors and the statistic Markowitz solution is applied to these conditional expected returns together with the unconditional variance-covariance matrix from sample analogue. Panel A displays the estimated regressions of style portfolio returns on the conditioning business cycle variables at both monthly and quarterly frequency. Panel B summarizes the two investing policies, reporting the time-series average of the weights on style portfolios and the in-sample and on-period-ahead-out-of-sample returns (monthly equivalent).

SMALL, LARGE Styles, Panel A: Regression Estimates (Portfolios are based on APC)												
Style/State	Monthly (VW)			Monthly (EW)			Quarterly (VW)			Quarterly (EW)		
variables	Coefficients	std	t	Coefficients	std	t	Coefficients	std	t	Coefficients	std	t
Small_constan	-0.0422	0.0366	-115	-0.0008	0.0316	-0.03	-0.1012	0.0725	-140	-0.0749	0.0728	-103
s_def	-16798	0.8183	-2.05*	-12556	0.7097	-177*	-3.5660	2.0701	-172*	-3.3098	2.0744	-160
s_yld	0.7624	0.5251	145	0.2611	0.4549	0.57	0.3627	13327	0.27	-0.0075	13363	-0.01
s_div	19204	0.7534	2.55*	0.8929	0.6517	137	4.4015	16166	2.72*	3.7660	16223	2.32*
s_ter	0.4000	0.2826	142	0.4259	0.2449	174*	11967	0.6843	175*	12005	0.6856	175*
R-square	0.0835			0.0649			0.1550			0.1362		
Large_constan	-0.0164	0.0253	-0.65	-0.0218	0.0275	-0.79	-0.0365	0.0496	-0.74	-0.0581	0.0546	-106
s_def	-11442	0.5718	-2.00*	-11696	0.6229	-188*	-18338	14173	-129	-2.0584	15607	-132
s_yld	-0.9757	0.3656	-2.67*	-0.8966	0.3978	-2.25*	-19734	0.9114	-2.17*	-17463	10032	-174*
s_div	0.8409	0.5223	161	0.9877	0.5677	174*	19004	11062	172*	2.4964	12170	2.05*
s_ter	0.0913	0.1971	0.46	0.1513	0.2147	0.70	0.3916	0.4685	0.84	0.5208	0.5160	101
R-square	0.0809			0.0743			0.1406			0.1406		

SMALL, LARGE Styles, Panel B: Style timing policies (Portfolios are based on APC)								
	Monthly (VW)		Monthly (EW)		Quarterly (VW)		Quarterly (EW)	
	Traditional	Conditional	Traditional	Conditional	Traditional	Conditional	Traditional	Conditional
SMALL	0.2920	2.4811	3.3563	3.4559	-0.2150	15128	0.9036	2.0873
LARGE	0.1931	-0.4234	-18898	-15783	0.7367	0.7845	-0.7343	-0.9305
WT_all	0.4851	2.0577	14665	18776	0.5217	2.2973	0.1693	11568
R(tangent)	0.0283	0.0375	0.1084	0.0426	0.0212	0.0292	0.0199	0.0262
R(predicted)	0.0164	0.0392	0.0812	0.0468	0.0045	0.0249	0.0112	0.0278

VALUE, GROWTH Styles, Panel A: Regression Estimates (Portfolios are based on APC)												
Style/State	Monthly (VW)			Monthly (EW)			Quarterly (VW)			Quarterly (EW)		
variables	Coefficients	std	t	Coefficients	std	t	Coefficients	std	t	Coefficients	std	t
Value_constan	-0.0443	0.0317	-139	-0.0510	0.0362	-141	-0.1133	0.0634	-179*	-0.1202	0.0673	-179*
v_def	-12061	0.7119	-169*	-11941	0.8105	-147	-2.9933	18136	-165*	-3.1593	19225	-164*
v_yld	0.3199	0.4564	0.70	0.5284	0.5201	102	0.2319	11668	0.20	0.5719	12373	0.46
v_div	17159	0.6541	2.62*	18645	0.7463	2.50*	4.6732	14147	3.30*	4.9075	15004	3.27*
v_ter	0.2486	0.2458	101	0.2700	0.2800	0.96	11726	0.5996	196*	13020	0.6356	2.05*
R-square	0.0630			0.0580			0.1911			0.1923		
Growth_consta	-0.0073	0.0248	-0.30	-0.0076	0.0251	-0.30	-0.0401	0.0555	-0.72	-0.0478	0.0586	-0.82
v_def	-0.9617	0.5621	-171*	-0.9510	0.5700	-167*	-2.2210	16019	-139	-2.2267	16892	-132
v_yld	-0.4309	0.3591	-120	-0.4215	0.3639	-116	-11361	10269	-111	-11537	10830	-107
v_div	0.5881	0.5121	115	0.6046	0.5185	117	19101	12405	154	2.1224	13092	162
v_ter	0.2529	0.1938	131	0.2735	0.1964	139	0.8574	0.5300	162	0.8917	0.5588	160
R-square	0.0472			0.0479			0.1147			0.1132		

VALUE, GROWTH Styles, Panel B: Style timing policies (Portfolios are based on APC)								
	Monthly (VW)		Monthly (EW)		Quarterly (VW)		Quarterly (EW)	
	Traditional	Conditional	Traditional	Conditional	Traditional	Conditional	Traditional	Conditional
VALUE	0.1442	9.9340	-0.1355	10.6761	0.2770	7.3396	0.0923	9.1390
GROWTH	0.3380	-8.0781	0.6525	-8.8858	-0.0605	-6.1947	0.0792	-8.7674
WT_all	0.4822	18558	0.5171	17902	0.2165	11449	0.1715	0.3717
R(tangent)	0.0124	0.1526	0.0132	0.1749	0.0143	0.0998	0.0122	0.1216
R(predicted)	0.0039	0.1081	0.0009	0.1222	0.0060	0.0653	0.0050	0.0735

SG,SV,LG,LV Style, Panel A: Regression Estimates												
Style/State	Monthly (VW)			Monthly (EW)			Quarterly (VW)			Quarterly (EW)		
variables	Coefficients	std	t	Coefficients	std	t	Coefficients	std	t	Coefficients	std	t
SG_constant	-0.0145	0.0301	-0.48	-0.0072	0.0295	-0.24	-0.0696	0.0953	-0.73	-0.0499	0.0944	-0.53
sg_def	-0.0099	0.0068	-1.46	-0.0097	0.0067	-1.46	-0.0269	0.0214	-1.25	-0.0279	0.0212	-1.32
sg_yld	0.0008	0.0044	0.19	0.0008	0.0043	0.20	0.0037	0.0145	0.25	0.0029	0.0143	0.21
sg_div	0.0080	0.0062	1.29	0.0065	0.0061	1.07	0.0294	0.0195	1.50	0.0260	0.0193	1.34
sg_ter	0.0032	0.0023	1.36	0.0033	0.0023	1.43	0.0118	0.0074	1.59	0.0118	0.0073	1.61
R-square	0.0388			0.0378			0.1137			0.1109		
SV_constant	-0.0422	0.0366	-1.15	-0.0008	0.0316	-0.03	-0.1712	0.1178	-1.45	-0.0439	0.1109	-0.40
sv_def	-0.0168	0.0082	-2.05*	-0.0126	0.0071	-1.77*	-0.0435	0.0262	-1.66*	-0.0328	0.0247	-1.33
sv_yld	0.0076	0.0053	1.45	0.0026	0.0045	0.57	0.0096	0.0178	0.54	-0.0044	0.0168	-0.26
sv_div	0.0192	0.0075	2.55*	0.0089	0.0065	1.37	0.0679	0.0241	2.82*	0.0368	0.0227	1.62
sv_ter	0.0040	0.0028	1.42	0.0043	0.0024	1.74*	0.0169	0.0091	1.86*	0.0168	0.0085	1.96*
R-square	0.0835			0.0649			0.2146			0.1634		
LG_constant	-0.0164	0.0253	-0.65	-0.0218	0.0275	-0.79	-0.0559	0.0755	-0.74	-0.0767	0.0870	-0.88
lg_def	-0.0114	0.0057	-2.00*	-0.0117	0.0062	-1.88*	-0.0245	0.0168	-1.45	-0.0270	0.0194	-1.39
lg_yld	-0.0098	0.0037	-2.67*	-0.0090	0.0040	-2.25*	-0.0219	0.0114	-1.92*	-0.0203	0.0132	-1.54
lg_div	0.0084	0.0052	1.61	0.0099	0.0057	1.74*	0.0230	0.0154	1.49	0.0291	0.0178	1.63
lg_ter	0.0009	0.0020	0.46	0.0015	0.0021	0.70	0.0047	0.0058	0.80	0.0066	0.0067	0.98
R-square	0.0809			0.0743			0.1639			0.1547		
LV_constant	-0.0195	0.0300	-0.65	-0.0366	0.0343	-1.07	-0.0445	0.0822	-0.54	-0.0960	0.0942	-1.02
lv_def	-0.0071	0.0068	-1.05	-0.0086	0.0077	-1.12	-0.0147	0.0184	-0.80	-0.0211	0.0210	-1.01
lv_yld	-0.0061	0.0043	-1.41	-0.0037	0.0049	-0.75	-0.0124	0.0125	-0.99	-0.0064	0.0143	-0.45
lv_div	0.0091	0.0062	1.48	0.0135	0.0071	1.90*	0.0217	0.0168	1.29	0.0355	0.0193	1.85*
lv_ter	0.0009	0.0023	0.39	0.0013	0.0027	0.47	0.0054	0.0064	0.85	0.0062	0.0073	0.85
R-square	0.0351			0.0374			0.0842			0.1043		

SG,SV,LG,LV Style, Panel B: Style timing policies								
	Monthly (VW)		Monthly (EW)		Quarterly (VW)		Quarterly (EW)	
	Traditional	Conditional	Traditional	Conditional	Traditional	Conditional	Traditional	Conditional
SG	-0.2129	-5.3705	-1.4313	-3.7736	-0.9285	-6.4238	-1.3255	-4.7492
SV	0.2733	7.4083	4.8202	7.4225	0.8269	8.0775	3.4011	5.7169
LG	0.0276	-1.3242	-1.4170	-2.7879	-0.1803	-0.1845	-1.3638	-1.0962
LV	0.4031	0.9132	-0.7339	0.9753	0.4928	-0.2527	-0.4401	0.2829
WT_all	0.4912	1.6268	1.2380	1.8363	0.2108	1.2165	0.2717	0.1544
R(tangent)	0.0377	0.1472	0.1410	0.1196	0.0383	0.1560	0.1009	0.0788
R(predicted)	0.0048	0.0989	0.0782	0.1196	0.0020	0.1059	0.0504	0.0884

SG,SB,SV,MG,MB,MV,LG,LB,LV Style, Panel A: Regression Estimates												
Style/State	Monthly (VW)			Monthly (EW)			Quarterly (VW)			Quarterly (EW)		
variables	Coefficients	std	t	Coefficients	std	t	Coefficients	std	t	Coefficients	std	t
SG_constant	-0.0145	0.0301	-0.48	-0.0072	0.0295	-0.24	-0.0707	0.0692	-1.02	-0.0583	0.0683	-0.85
sg_def	-0.9949	0.6811	-1.46	-0.9731	0.6664	-1.46	-2.4426	1.9839	-1.23	-2.4979	1.9535	-1.28
sg_yld	0.0825	0.4357	0.19	0.0832	0.4263	0.20	0.3960	1.2753	0.31	0.3451	1.2568	0.27
sg_div	0.8021	0.6219	1.29	0.6543	0.6088	1.07	2.8196	1.5439	1.83*	2.6166	1.5233	1.72*
sg_ter	0.3201	0.2349	1.36	0.3285	0.2298	1.43	1.0203	0.6560	1.56	1.0056	0.6459	1.56
R-square	0.0388			0.0378			0.0945			0.0924		
SB_constant	-0.0097	0.0313	-0.31	-0.0203	0.0353	-0.58	-0.0743	0.0878	-0.85	-0.1026	0.0968	-1.06
sb_def	-1.3572	0.7043	-1.93	-1.4638	0.7905	-1.85*	-4.1241	2.4997	-1.65*	-4.5814	2.7513	-1.67*
sb_yld	-0.0888	0.4512	-0.20	-0.0458	0.5072	-0.09	-0.3351	1.6116	-0.21	-0.1634	1.7752	-0.09
sb_div	0.9582	0.6459	1.48	1.2523	0.7275	1.72*	3.9214	1.9564	2.00*	4.7812	2.1571	2.22*
sb_ter	0.3530	0.2431	1.45	0.3667	0.2730	1.34	1.0466	0.8261	1.27	1.1128	0.9092	1.22
R-square	0.0529			0.0531			0.1062			0.1124		
SV_constant	-0.0422	0.0366	-1.15	-0.0008	0.0316	-0.03	-0.1455	0.0831	-1.75*	-0.0571	0.0787	-0.73
sv_def	-1.6798	0.8183	-2.05*	-1.2556	0.7097	-1.77*	-3.9201	2.3656	-1.66*	-2.7322	2.2368	-1.22
sv_yld	0.7624	0.5251	1.45	0.2611	0.4549	0.57	0.7066	1.5247	0.46	-0.3804	1.4419	-0.26
sv_div	1.9204	0.7534	2.55*	0.8929	0.6517	1.37	6.1113	1.8526	3.30*	3.7204	1.7530	2.12*
sv_ter	0.4000	0.2826	1.42	0.4259	0.2449	1.74*	1.5483	0.7818	1.98*	1.5010	0.7392	2.03*
R-square	0.0835			0.0649			0.1913			0.1434		
MG_constant	0.0089	0.0275	0.32	0.0061	0.0268	0.23	-0.0033	0.0632	-0.05	-0.0157	0.0639	-0.25
mg_def	-0.7459	0.6294	-1.19	-0.7109	0.6130	-1.16	-1.5323	1.8377	-0.83	-1.3314	1.8546	-0.72
mg_yld	-0.4001	0.4010	-1.00	-0.4520	0.3904	-1.16	-1.6315	1.1744	-1.39	-1.7886	1.1859	-1.51
mg_div	0.1206	0.5695	0.21	0.1712	0.5545	0.31	0.7660	1.4140	0.54	0.9802	1.4292	0.69
mg_ter	0.3475	0.2167	1.60	0.3408	0.2111	1.61	1.1493	0.6084	1.89*	1.1022	0.6139	1.80*
R-square	0.0322			0.0344			0.0969			0.0965		
MB_constant	0.0139	0.0260	0.54	0.0154	0.0257	0.60	-0.0032	0.0611	-0.05	-0.0033	0.0613	-0.05
mb_def	-0.4952	0.5883	-0.84	-0.5416	0.5827	-0.93	-1.0209	1.7474	-0.58	-1.0496	1.7526	-0.60
mb_yld	-0.6657	0.3761	-1.77*	-0.6439	0.3724	-1.73*	-1.9887	1.1237	-1.77*	-1.9718	1.1270	-1.75*
mb_div	0.0784	0.5368	0.15	0.0559	0.5315	0.11	0.9830	1.3638	0.72	0.9914	1.3678	0.72
mb_ter	0.2898	0.2028	1.43	0.3029	0.2008	1.51	0.8206	0.5777	1.42	0.8734	0.5794	1.51
R-square	0.0332			0.0347			0.0865			0.0892		
MV_constant	-0.0710	0.0461	-1.54	-0.1156	0.0661	-1.75*	-0.1582	0.0811	-1.95*	-0.2304	0.1090	-2.11*
mv_def	-1.2253	1.0286	-1.19	-1.4627	1.4695	-1.00	-3.3697	2.3135	-1.46	-4.4748	3.1017	-1.44
mv_yld	0.8093	0.6606	1.23	1.6972	0.9450	1.80*	1.0958	1.4904	0.74	2.8598	2.0004	1.43
mv_div	2.3132	0.9487	2.44*	3.3541	1.3594	2.47*	5.8296	1.8088	3.22*	7.8555	2.4296	3.23*
mv_ter	0.2557	0.3554	0.72	0.2589	0.5082	0.51	1.4648	0.7647	1.92*	1.8276	1.0250	1.78*
R-square	0.0489			0.0508			0.1782			0.1809		

SG,SB,SV,MG,MB,MV,LG,LB,LV Style, Panel A: Regression Estimates (continued)												
Style/State	Monthly (VW)			Monthly (EW)			Quarterly (VW)			Quarterly (EW)		
variables	Coefficients	std	t	Coefficients	std	t	Coefficients	std	t	Coefficients	std	t
LG_constant	-0.0164	0.0253	-0.65	-0.0218	0.0275	-0.79	-0.0475	0.0536	-0.89	-0.0699	0.0620	-1.13
lg_def	-1.1442	0.5718	-2.00*	-1.1696	0.6229	-1.88*	-2.6824	1.5343	-1.75*	-2.8415	1.7773	-1.60
lg_yld	-0.9757	0.3656	-2.67*	-0.8966	0.3978	-2.25*	-2.1640	0.9862	-2.19*	-2.0184	1.1410	-1.77*
lg_div	0.8409	0.5223	1.61	0.9877	0.5677	1.74*	2.1777	1.1959	1.82*	2.7826	1.3831	2.01*
lg_ter	0.0913	0.1971	0.46	0.1513	0.2147	0.70	0.4129	0.5073	0.81	0.5732	0.5878	0.98
R-square	0.0809			0.0743			0.1613			0.1493		
LB_constant	-0.0101	0.0247	-0.41	-0.0079	0.0252	-0.31	-0.0311	0.0495	-0.63	-0.0327	0.0517	-0.63
lb_def	-0.5186	0.5580	-0.93	-0.5112	0.5718	-0.89	-1.2042	1.4138	-0.85	-1.0872	1.4815	-0.73
lb_yld	-1.1349	0.3567	-3.18*	-1.0891	0.3654	-2.98*	-2.4477	0.9086	-2.69*	-2.3919	0.9516	-2.51*
lb_div	0.6143	0.5095	1.21	0.5705	0.5215	1.09	1.5779	1.1030	1.43	1.5970	1.1541	1.38
lb_ter	0.1034	0.1923	0.54	0.1632	0.1970	0.83	0.2297	0.4674	0.49	0.3860	0.4899	0.79
R-square	0.0764			0.0700			0.1471			0.1372		
LV_constant	-0.0195	0.0300	-0.65	-0.0366	0.0343	-1.07	-0.0279	0.0590	-0.47	-0.0674	0.0670	-1.01
lv_def	-0.7125	0.6778	-1.05	-0.8636	0.7722	-1.12	-1.5819	1.6913	-0.94	-2.2004	1.9171	-1.15
lv_yld	-0.6112	0.4336	-1.41	-0.3729	0.4948	-0.75	-1.3466	1.0874	-1.24	-0.8952	1.2337	-0.73
lv_div	0.9137	0.6194	1.48	1.3460	0.7082	1.90*	1.8652	1.3172	1.42	3.0028	1.4952	2.01*
lv_ter	0.0900	0.2338	0.39	0.1251	0.2666	0.47	0.5241	0.5592	0.94	0.5971	0.6338	0.94
R-square	0.0351			0.0374			0.0785			0.0946		

SG,SB,SV,MG,MB,MV,LG,LB,LV Style, Panel B: Style timing policies								
	Monthly (VW)		Monthly (EW)		Quarterly (VW)		Quarterly (EW)	
	Traditional	Conditional	Traditional	Conditional	Traditional	Conditional	Traditional	Conditional
SG	-0.6705	-3.8158	-0.5661	-4.0412	-2.4551	-19.3237	-1.7297	-4.8969
SB	0.4223	2.1778	0.2137	2.0748	0.1181	2.5039	0.3618	6.1437
SV	0.2077	11.0021	7.8083	12.0257	1.4032	41.1388	5.0697	13.5127
MG	-0.7743	-8.6825	-5.4121	-13.3943	0.8767	-17.3578	-2.4498	-25.1850
MB	2.3410	0.4506	-1.6559	5.8286	1.6932	5.5595	-1.5898	19.0139
MV	-0.4610	1.0788	-0.2809	0.6883	-0.9046	-14.0054	-0.3706	-10.8189
LG	-0.9765	-0.6942	-1.5809	0.8999	-1.1323	37.1120	-1.6432	22.9774
LB	0.6764	-0.4955	3.3140	-5.1346	0.0431	-45.4766	1.7036	-24.8440
LV	0.0526	1.3403	-0.6040	3.5294	0.1499	12.9415	0.2737	11.0315
WT_all	0.8178	2.3616	1.2361	2.4766	-0.2077	3.0920	-0.3744	6.9344
R(tangent)	0.0854	0.2985	0.2477	0.3145	0.0649	0.4290	0.1281	0.2306
R(predicted)	0.0286	0.1929	0.1486	0.2673	0.0178	0.1767	0.0601	0.1912

The results in Panel A of Table 5-4 demonstrate the predictability of business cycle variables to the conditional stock returns. First, the signs of the coefficients are highly consistent for both monthly and quarterly horizons. It is noted that the regression coefficients for variables *div* and *term* are all positive and often significant. It is suggested that movements in the *div* series are related to long-term business conditions and hence they capture predictable components of equity style returns. Ait-Sahalia and Brandt (2001) argue that *div* should forecast returns on the basis of the present value formula (since *div* does not appear to predict dividend growth). Fama and French (1989) find that the slope of the yield curve moves in tandem with the business cycle. They show that the variable term spread (*term*) tends to decrease near peaks of business cycle and increases when the economy troughs. Since the expected stock returns are low when the economy peaks and high when the economy troughs, the variable *term* positively predict expected returns. Ait-Sahalia and Brandt (2001) also find *term* is positively related with expected returns.

Second, the average coefficient of variable default spread (*def*) is negative and often significant. This is a bit intriguing as Ait-Sahalia and Brandt (2001) find that *def* is positively but not significantly related to the expected returns. Fama and French (1989) document that *def* tracks time variations in expected stock returns that appear to be persistent beyond the short-term business cycle fluctuations. The negative coefficients of *def* would arguably suggest that equity styles are unable to track the long-run trends in the business cycle. Third, the impact of *yld* on the expected returns is often positive but less significant for small and value styles, and is negative but more significant for large and growth stocks. This is consistent with Fama and Schwert (1977) and Fama (1981) who document that the short interest rate is negatively related to future market returns (since market index mainly constitute large stocks on both value and growth dimensions, and momentum is most pronounced in small-growth and small-value styles). Table 5-4 also suggests that returns are more predictable with long horizons than at short horizons as the average R^2 increases with return horizons. This is because the time series of business cycle variables demonstrate slow mean-reverting properties.

Although business cycle information predicts the first moment of conditional style returns, evidently, ignoring the predictability on the variance-covariance structure of style returns could result in less better style investing performance as opposed to the conditional investing strategies parameterising on variables that arguably capture the time variation in all moments of style returns. In almost all cases the conditional style investing predominantly beat the traditional investing approach, particularly in out-of-sample periods. For example, optimal style investing based on small-large (value-growth) with monthly rebalancing yields 2.83% (1.24%) in-sample returns and 1.64% (0.39%) one-period-ahead monthly returns based on value-weighted return calculations. In contrast, the returns for optimal conditional investing is 3.75% (15.26%) and 3.92% (10.81%) for in-samples and out-of-samples, respectively. The advantage of conditional investing is also seen on the quarterly horizons.

But where does the outperformance of conditional style investing come from? To understand the mechanism as how business cycle information affecting the style allocation process with different firm characteristics, Table 5-5 compares average time-series coefficients of the state variables for the conditional style investing policy described in Table 5-2 and the coefficients from the regressions of expected style returns reported in Table 5-4 (* refers that the coefficient is significant for at least 10% level).

Table 5-5 Average coefficients of business cycle predictors in conditional expected return regressions and conditional style allocations

Allocation Type		BS Variables	Monthly Horizon SMALL	LARGE	VALUE	GROWTH	Quarterly Horizon SMALL	LARGE	VALUE	GROWTH
VW	Regression	*def*	-1.344*	-0.792*	-1.206*	-0.962*	-3.566*	-1.834	-2.993*	-2.221
		yld	0.252	-0.907*	0.320	-0.431	0.363	-1.973*	0.232	-1.136
		div	1.227*	0.790	1.716*	0.588	4.401*	1.900*	4.673*	1.910
		term	0.358	0.095	0.249	0.253	1.197*	0.392	1.173*	0.857
	Conditional	*def*	-0.160	-0.629	-0.762	0.039	-0.137	-0.476	1.569	-3.304
		yld	0.626	-1.125*	-1.186*	0.671	0.740*	-1.650*	-1.134*	0.923
		div	-1.124*	1.190*	-2.757*	2.636*	-0.506	0.493	-0.924	1.272
		term	0.622*	-0.178	-0.551	1.175*	0.584*	-0.058	0.187	0.304
EW	Regression	*def*	-1.231*	-0.848*	-1.194	-0.951*	-3.310	-2.058	-3.159*	-2.227
		yld	0.099	-0.786*	0.528	-0.422	-0.007	-1.746*	0.572	-1.154
		div	0.933	0.968*	1.864*	0.605	3.766*	2.496*	4.908*	2.122
		term	0.374*	0.147	0.270	0.273	1.201*	0.521	1.302*	0.892
	Conditional	*def*	-0.475	-0.236	-0.145	-0.515	0.056	-0.655	1.087	-2.633
		yld	0.455	-0.811*	-1.212*	0.730	0.740	-1.317	-1.209*	1.242*
		div	-1.487*	1.526*	-3.355*	3.367*	-0.961*	1.351*	-1.625*	2.493*
		term	0.622*	-0.148	-0.650	1.348*	0.448*	-0.042	0.098	0.591

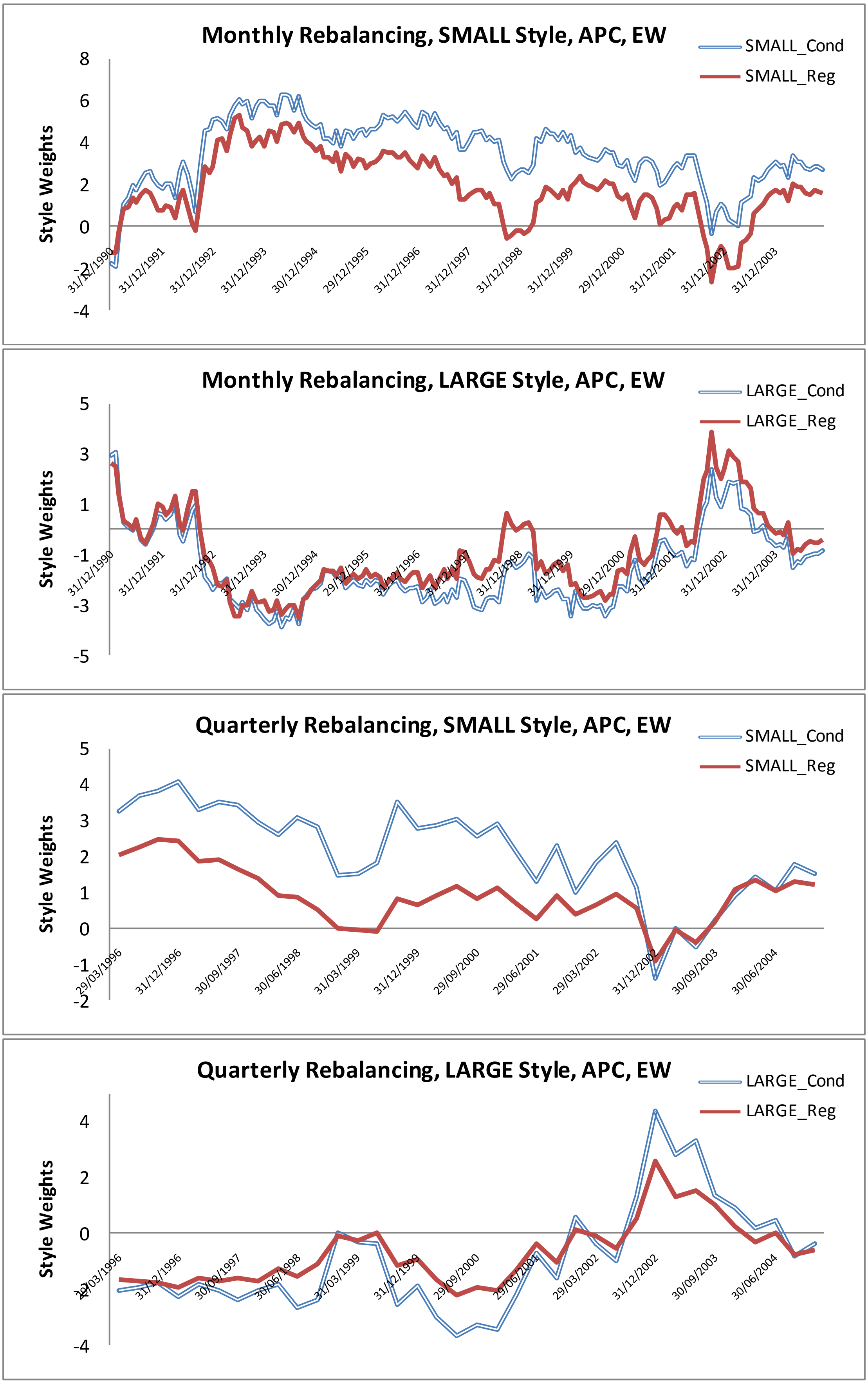
It is evident that the mechanism business cycle variables predict expected style returns and in turn the optimal style allocation policy is substantially different. First, while the role default spread (*def*) plays is similar in both expected returns and style allocation context, it is no longer significant in the style investing decision-making despite of its significance in the expected style return distributions. In addition, although the lower expected returns for small cap stocks and higher expected returns for large cap stocks are suggested by the regression, *yld* predicts that a positive shock to this variable would induces investors to overweight small stocks and underweight large stocks. However, a positive shock to *yld* would lead investors to tilt to growth stocks, which matches their higher expected returns signalled by changes of *yld*. Similarly, the dividend yield (*div*) statistically predicts the style allocation along both size and value dimensions. Although *div* has more significant (positive) impact on returns for small cap stocks (value stocks) than for large cap stocks (growth stocks), it induces investors to overweight large stocks or growth stocks and underweight small cap stocks or value stocks when experiencing positive shocks.

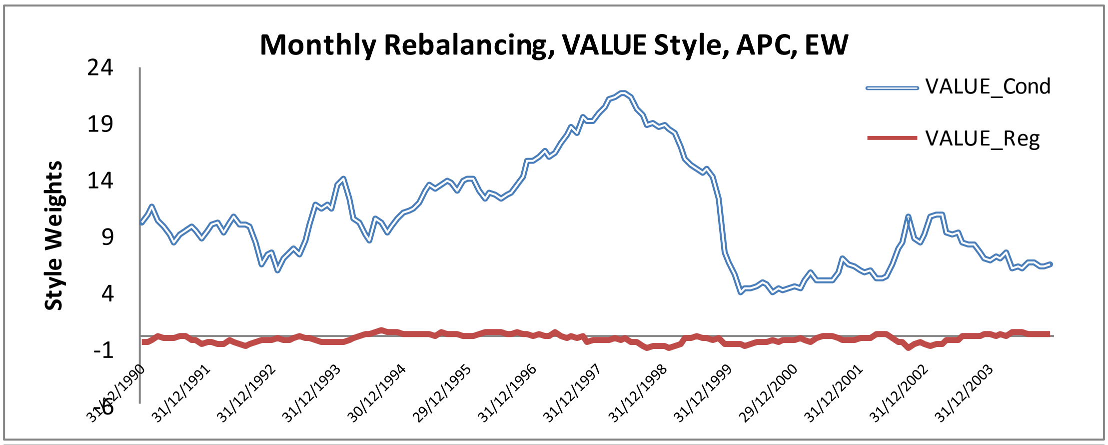
The term spread (*term*) also exerts significant impact on the style allocation process. The regression coefficients of *term* are all positive, and in the style allocation context it has significant positive tilt for small stocks at both monthly and quarterly horizons, and significant positive sign for growth stocks on monthly frequency. This suggests that a positive shock to variable *term* would encourage investors to overweight small cap stocks or growth stocks. Fama and French (1989) point out that term spread tracks the short term fluctuations of business cycle and its value to signal expected returns are high during recessions and low during expansions. It is argued that positive shocks to *term* happen at bad times while the negative shocks happen at good times. Hence investors are induced to hold more small stocks or growth stocks when economic situations are bad. This conclusion seems intuitively contradicts to the results documented by Chan and Chen (1991) for small size stocks but is consistent with Petkova and Zhang (2004). Chan and Chen (1991) argue that small firms tend to be marginal firms that have generally lost market value due to poor performance. Such firms have high financial leverage and cash flow problems and hence are difficult to survive to bad times. In light of this argument, it is reasonable to assume that investors would underweight small cap stocks when economy is in recession. On the other hand, Petkova and Zhang (2004) argue that value stocks are riskier than growth stocks in bad times and less riskier during good times, suggesting that investors should tilt to growth stocks and tilt away from value stocks when economy is in turmoil.

As a summary, business cycle variables exert different mechanisms to the conditional style return distributions and the style investing implementations. Variables such as *def*, *yld*, *div* and *term* convey useful information about the current and future directions in the broad economy and business cycle environment assumed to determine the inter-temporal behaviour of equity style dynamics. As Petkova (2006) points out, these variables model the two aspects of the time-varying investment opportunity, the yield curve and the distribution of stock returns. Investment strategies incorporating such business cycle predictors typically yield better performance relative to strategies disregarding the stock return predictability. Traditional portfolio selection generally first specifies a model for the moments of stock returns and then implementing the optimal allocation using plugged estimates that is based on partial information for expected returns forecasting. In contrast, investing strategies directly parameterising on the business cycle variables can arguably capture the time variations of all the moments of asset returns and therefore generate higher returns. Such outperformance is arguably driven by the different mechanisms that business cycle information affects in the investment process. Namely, shocks to the variables are found to be transmitted very differently in asset pricing and asset allocation process. It is found that apart from their predictability on return distributions, variables such as *yld*, *div* and *term* exert significant impact on style allocation on both size and value dimensions. Interestingly, the optimal asset allocation policy derived by such variables often contradicts to empirical asset pricing predictions. The optimal style investing strategies significantly tilt to holding small-cap and growth stocks during economic bad times despite small stocks may have financial difficulties in recessions and lower expected returns results from positive shocks to the variables. These results are consistent with Avramov and Chordia (2006) who also find that their outperforming strategies in NYSE-AMEX stocks hold small cap, growth and momentum stocks. Since mean-variance optimal investing uses asset returns and volatility as inputs, it is suggested that style volatility, not the expected style returns, plays a key role in the optimal style investing framework.

To get a more clear perspective as how information of style volatility affects the allocation process, Figure 5-2 shows the time-series of style allocation weights based on these two approaches. Indeed, conditional investing capitalising on the information of the business cycle exhibits significant difference and tends to bet more extreme positions on both long and short directions. Such investing tends to long more for the long side and short more for the short side as compared to the traditional optimal investing. Investors following the conditional investing (the *Doctrinaires*) directly predict their optimal style investing weights with business cycle predictors and hence benefiting from capturing more information beyond the first and second moments of stock returns that affect asset allocation decision, and therefore yield more extreme tilts but better in- and out-of-sample performance.

Figure 5-2 The time-series of style weights based on traditional and unconditional (regression-based) style investing

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19
14
9
4
-1
-6
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VALUE_Reg
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31/12/1991
31/12/1992
31/12/1993
30/12/1994
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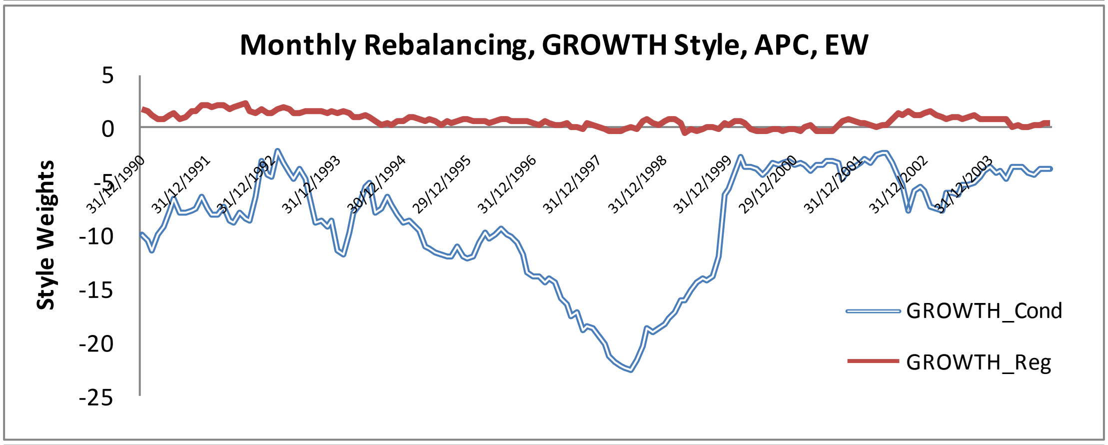
31/12/2003


Monthly Rebalancing, GROWTH Style, APC, EW
Style Weights
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0
-5
-10
-15
-20
-25
GROWTH_Cond
GROWTH_Reg
31/12/1990
31/12/1991
31/12/1992
31/12/1993
30/12/1994
29/12/1995
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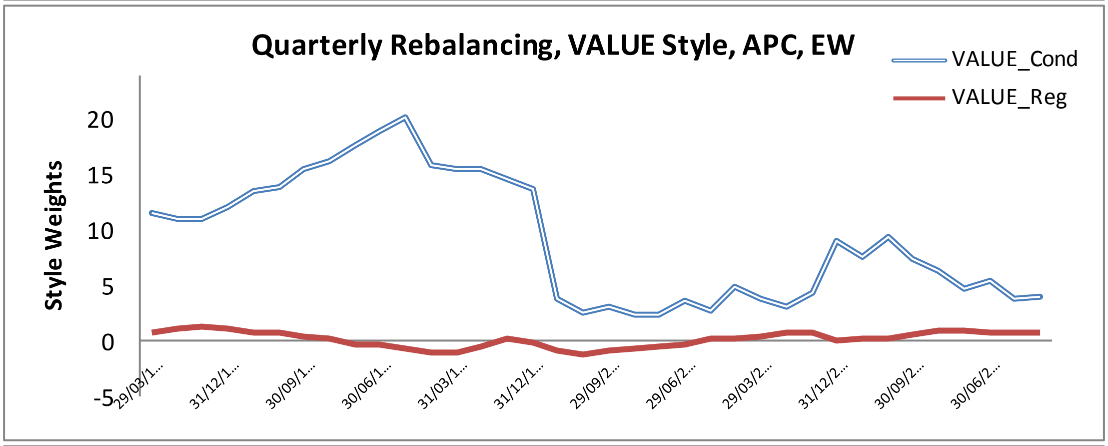
31/12/2002
31/12/2003


Quarterly Rebalancing, VALUE Style, APC, EW
Style Weights
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15
10
5
0
-5
VALUE_Cond
VALUE_Reg
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30/09/1...
30/06/1...
31/03/1...
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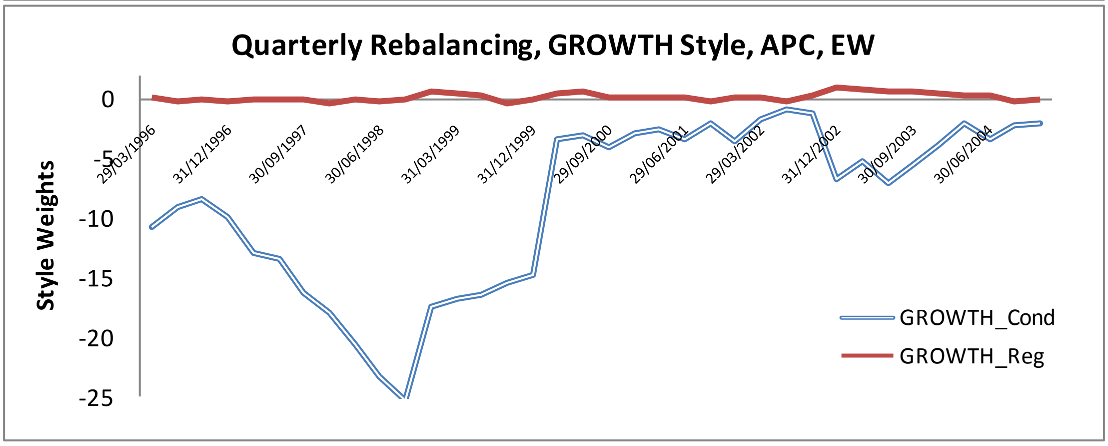
30/09/2...
30/06/2...


Quarterly Rebalancing, GROWTH Style, APC, EW
Style Weights
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-5
-10
-15
-20
-25
GROWTH_Cond
GROWTH_Reg
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31/12/1996
30/09/1997
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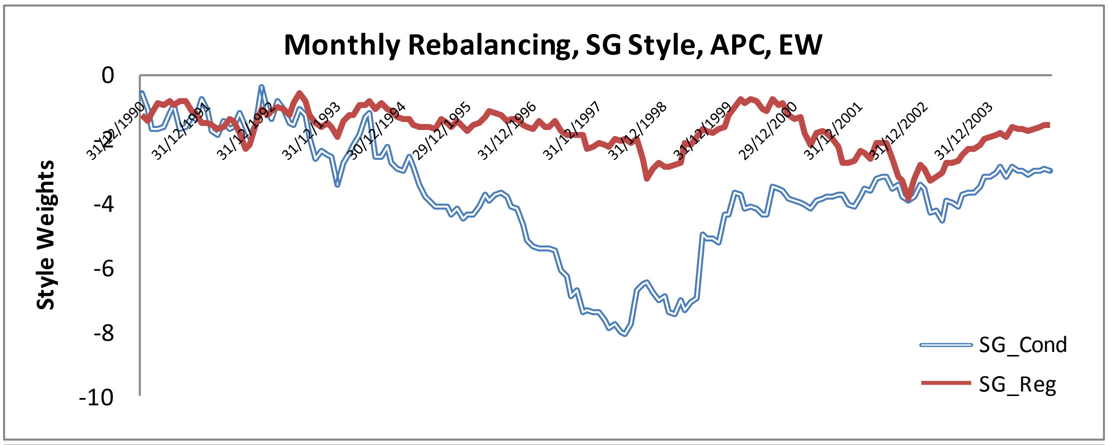
30/09/2003
30/06/2004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Style Weights
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31/12/1996
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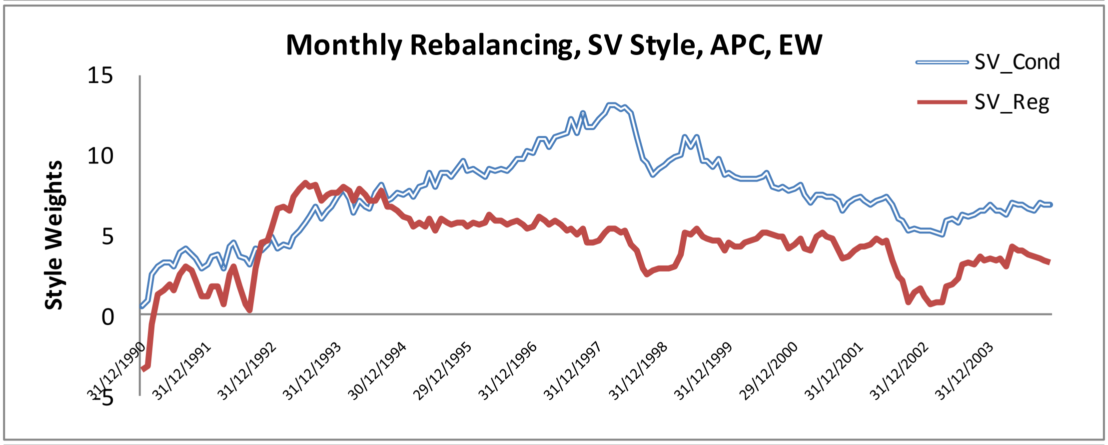
31/12/2003
SG_Cond
SG_Reg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Style Weights
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10
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31/12/1991
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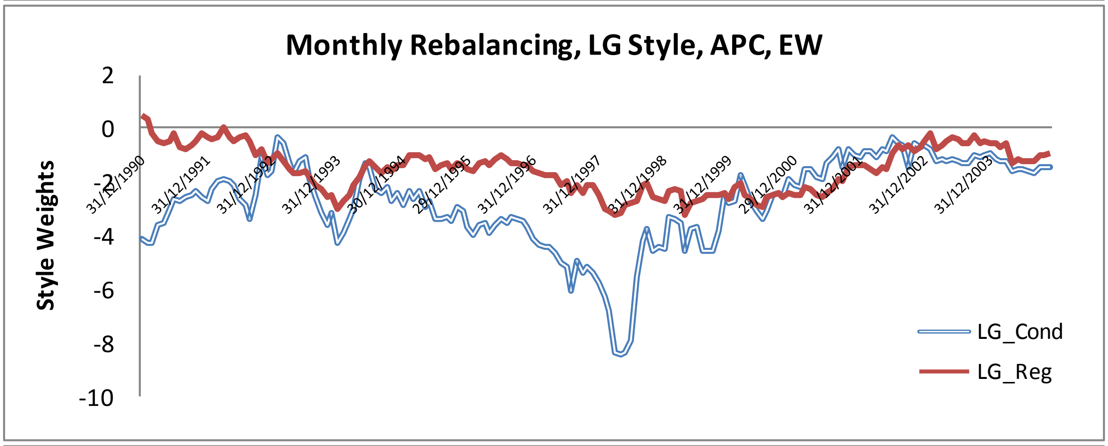
31/12/2003
SV_Cond
SV_Reg


Monthly Rebalancing, LG Style, APC, EW
Style Weights
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-2
-4
-6
-8
-10
31/12/1990
31/12/1991
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31/12/1993
30/12/1994
29/12/1995
31/12/1996
31/12/1997
31/12/1998
31/12/1999
29/12/2000
31/12/2001
31/12/2002
31/12/2003
LG_Cond
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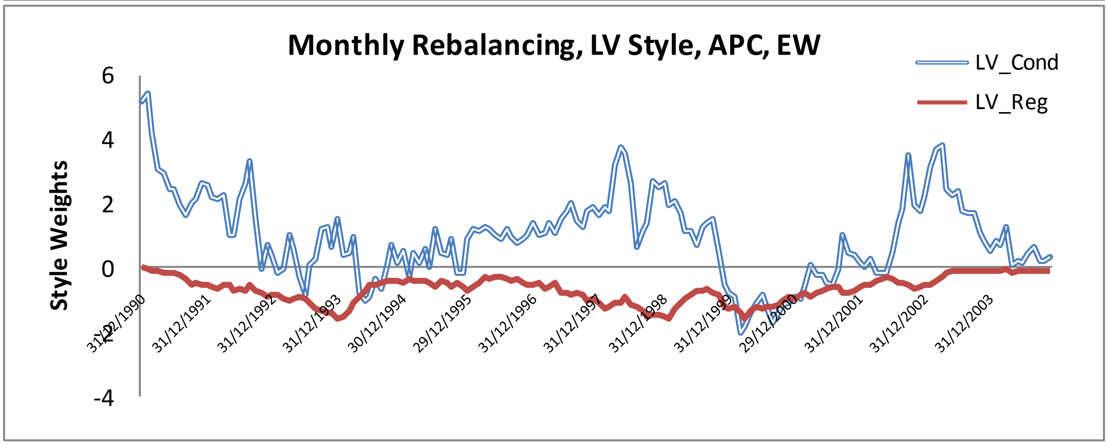
Monthly Rebalancing, LV Style, APC, EW
Style Weights
6
4
2
0
-2
-4
31/12/1990
31/12/1991
31/12/1992
31/12/1993
30/12/1994
29/12/1995
31/12/1996
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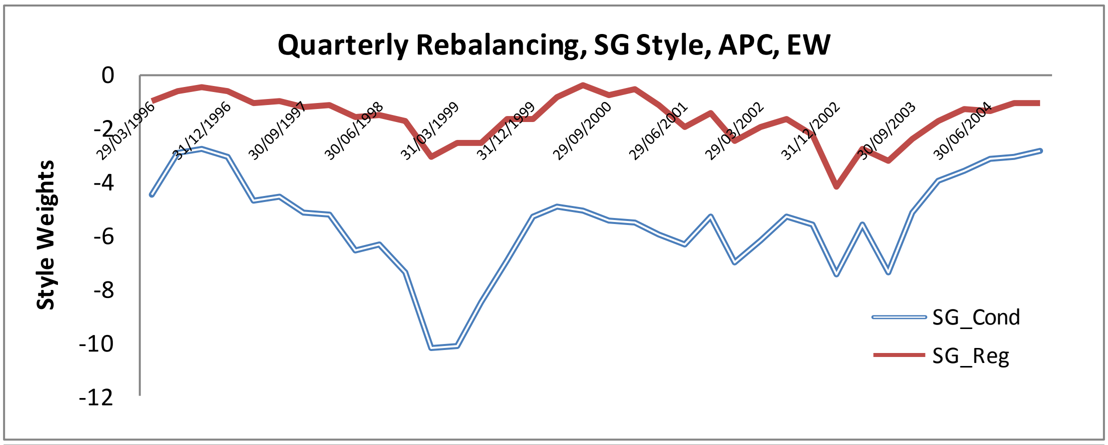
31/12/2003
LV_Cond
LV_Reg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Style Weights
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-6
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30/06/1998
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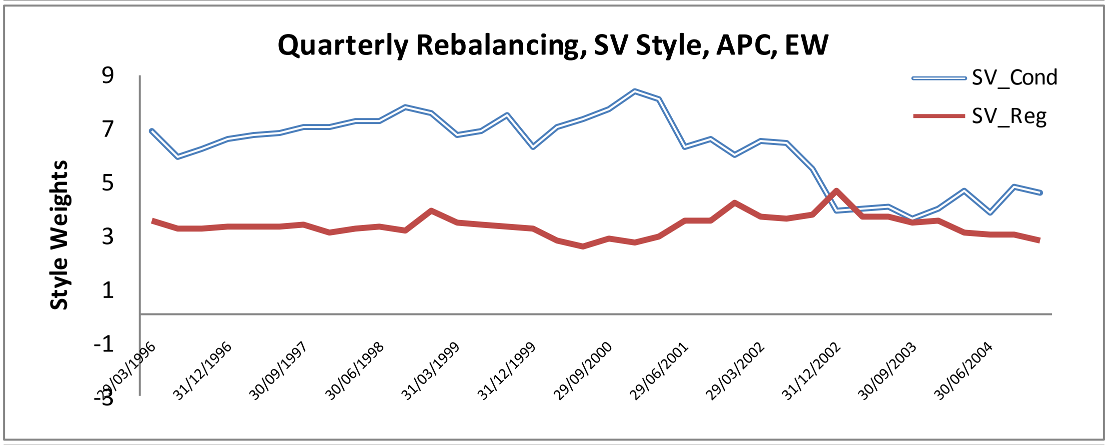
30/06/2004
SG_Cond
SG_Reg


Quarterly Rebalancing, SV Style, APC, EW
Style Weights
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5
3
1
-1
-3
29/03/1996
31/12/1996
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30/06/1998
31/03/1999
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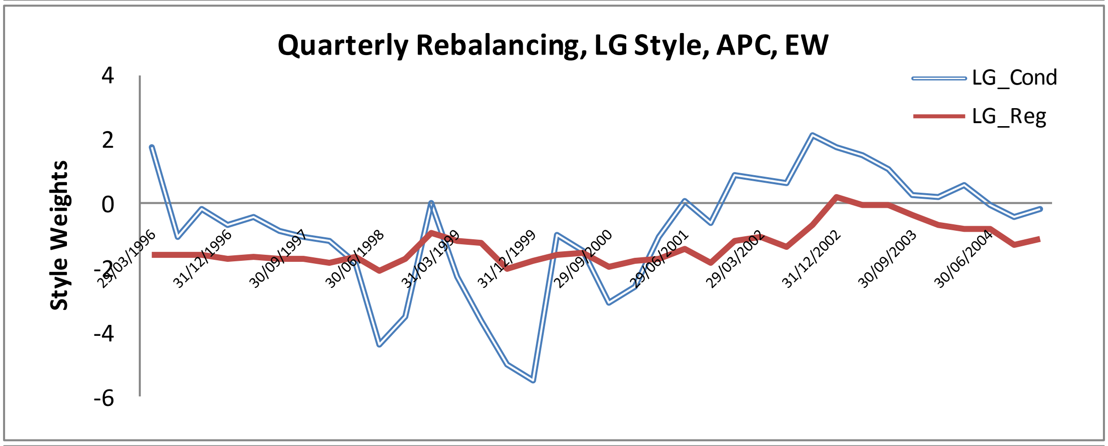
30/06/2004
SV_Cond
SV_Reg


Quarterly Rebalancing, LG Style, APC, EW
Style Weights
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-6
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LG_Cond
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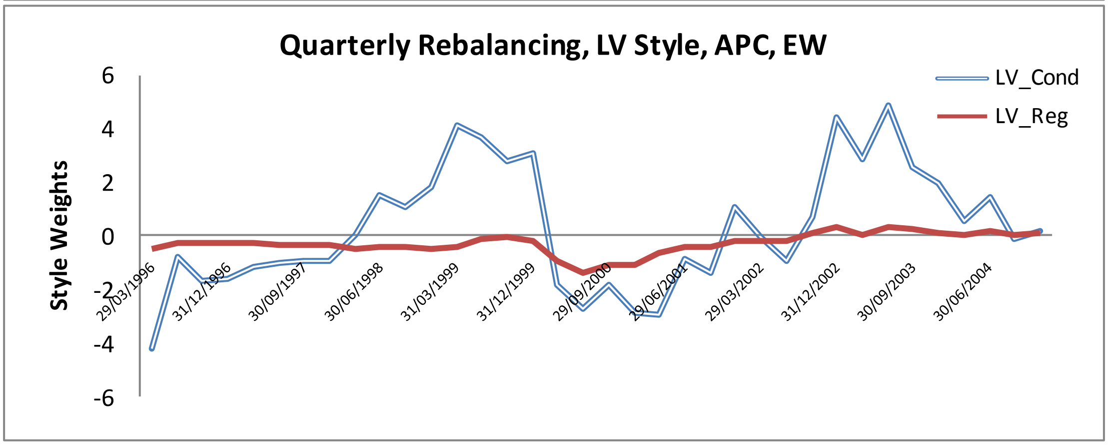
Quarterly Rebalancing, LV Style, APC, EW
Style Weights
6
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30/06/2004
LV_Cond
LV_Reg

5.6 Summary and conclusions

Extant literature documents the benefits of incorporating business cycle effects on investor's asset allocation process. However, the transmission mechanism of such business cycle volatility to portfolio selection is not extensively studied. Meanwhile, prior studies generally unrealistically focus on all the stocks in the market. When dealing with optimal portfolio selection problem, prior studies take the tradition approach of Markowitz (1952) and focus more on the time-varying nature of return distributions driven by different business cycle predictors. However, the role such predictive variables play on determining optimal portfolio allocation is less directly explored.

Chapter 5 contributes to the literature by allowing the hypothesised investors to have access to different market segments and implement different equity style investing without the restriction of long or short. Such investors can be regarded as hypothesised "fund of hedge funds" investors. It is understandable that investors care more about how the economic exogenous forces directly determine the ultimate investing choices (i.e. optimal style timing weights). Following the methodology proposed by Brandt and Santa-Clara (2006), this chapter implement an optimisation framework to investigate several equity style investing strategies based on business cycle information and examine their *ex ante* in-sample and *ex post* out-sample performance. By answering questions like if business cycle predictor variable x increases, should the investor move to/away from y style, this chapter gives multi-style investors an intuitive manner to understand their asset allocation process when incorporating business cycle predictability.

The empirical results in this chapter first suggest that regardless of return horizons, investors tend to significantly long value stocks or small stocks, and short growth stocks or large stocks in their optimal style allocation process. The U.K. market data shows that investors tend to buy small value, large blend and large value stocks in the long position, and short sell small growth, middle growth and large growth stocks. In particular the small value stocks are overwhelmingly to be held as it best captures the interaction of size and value effects.

It is found that the conditional style investing incorporating business cycle information and the unconditional style investing disregarding business cycle effect is much different. Specifically, sceptical investors who disregard business cycle predictability are conservative regarding their overall net equity exposures relative to the Doctrinaires who have strong prior beliefs about the business cycle information. The latter tend to be aggressive and generally end up with extreme positions to some styles and often financed by leverage. One reason for such extreme tilt is because the Doctrinaires believe the return differential of these styles can be estimated using business cycle predictors thus the exposure can be reduced at bad times when expected returns are low or volatility is high.

This chapter shows that business cycle variables affect the conditional style returns and the optimal style investing in quite a different way:

First, default spread (*def)* plays is similar role in both expected returns and style allocation, however its significance declines in the style investing process despite of its significant role in the expected return distributions. In addition, it is predicted that a positive shock to the short-term interest rate (*yld)* would induces investors to overweight small stocks and underweight large stocks despite the lower expected returns for small stocks and higher expected returns for large stocks are estimated. In addition, a positive shock to *yld* would lead investors to tilt to growth stocks, which matches their higher expected returns signalled by changes of *yld*.

Second, the dividend yield (*div*) predicts the style allocation along both size and value dimensions. Although *div* has more significant (positive) impact on returns for small cap stocks (value stocks) than for large cap stocks (growth stocks), a positive shock to this variable would induce investors to overweight large stocks (growth stocks) and underweight small stocks (value stocks). The term spread (*term*) also exerts significant impact on the style allocation process. Generally a positive shock to *term* would induce investors to overweight small cap stocks or growth stocks.

Overall, it is concluded that business cycle predictability benefits investors' dynamic optimal style investing. Variables such as *yld*, *term*, *div* and *def* exert a strong influence on the shape or location of investor's optimal style investing frontier. Smart investors who can capitalise on the conditional business cycle information consistently beat those disregarding business cycle influence, both in-sample and out-of-sample.

Chapter 6

Summary, conclusions, implementations and recommendations for future research

6.1 Summary of the research

Human beings are capable of classifying objects into categories to simplify the decision-making process. The idea of categorisation is also pervasive in today's financial market. Investors generally classify all the assets in the market into several groups like equity, cash, real estate etc. Within each asset class they also define some subgroups that share properties similar to the major asset class but are unique along specific dimension. For example, stocks can be subdivided according to market values as small-caps and large-caps. In addition, they can also be classified as value stocks and growth stocks based on some valuation multipliers. According to the relative returns, stocks can be labelled as 'winners' or 'losers'. In the investment world, 'style' refers to such systematic classification of investing assets by market segments. The definition of style is not fixed, due to market innovation or academic research findings, new styles may evolve and old styles may die off as time goes by. Equity style investing is an investment strategy based on stock classifications. In today's investment industry, style investing is well recognised and has gained growing popularity.

The concept of equity style and style investing offers an example of the exchange of ideas between academic research and investing practice. Style investing changes the way academics and practitioners think about investment. Recent empirical studies suggest that Institutional investors like fiduciaries of pension and endowment funds follow specific investment styles (Brown and Goetzmann (1997), Fung and Hsieh (1997), Chan *et al.* (2002)). For these institutional investors, the control of investment style has become a critical aspect of investment monitoring and decision-making process. Despite the obvious simplicity of following style investing in the asset allocation process, money manager's incentive for equity style investing also stems from capitalising on the relative performance across equity styles.

Financial markets have long observed the style return differentials together with the tremendous swings of equity style dynamics. Overall, empirical findings have shown that over the long term small-cap investing and value investing have been more advantageous in most equity markets around the world, but there are periods where small-large returns and value-growth returns reverses dramatically. The dynamics of equity style returns have introduced the new risk-return structure for active portfolio management. But to capitalise on the style effect, money managers would need to not only be able to identify the underlying drivers that determine the relative style performance, but also to capture the mechanisms through which those underlying driving forces work. Most importantly, active managers must be able to capture the dynamic properties of those driving forces to forecast the future style trends in order to optimise their investment process.

Over the years, although the benefits of style investing have been well recognised, the academic view of the cause for such benefits is very much debatable. There is still no general consensus as why some asset classes earn better returns than others do in the same period. Style investing is based on asset classification, sensible categorisation of assets should be arguably based on characteristics that relate to the asset's cross-sectional expected returns. Under efficient market hypothesis that stock price contains all relevant information, style investing should not be more profitable than any portfolios containing randomly selected subset of stocks. Moreover, single style investing would not be mean-variance efficient as investors do not diversify across styles. Hence equity style investing might be fundamentally risky, and the findings of style premium would suggest that either the markets are inefficient or the traditional asset pricing models are misspecified. Rationalist like Fama and French (1992, 1996) argue that market values and book-to-market ratios (BM) are proxies for risk factors, thus the outperformance of small-cap and value investing is compensation for risk. Daniel and Titman (1997), however, disregard such risk-based interpretation. They argue that firm characteristics do not relate to the covariance structure of stock returns. On the other hand, behaviourists such as Lakonishok *et al.* (1994) propose that value premium is driven by irrational investors' overreaction. Namely, investors mistakenly extrapolate past growth rate too far into future but subsequently experience disappointing financial results for the underlying stocks. Meanwhile, a growing number of studies suggest that a variety of business cycle variables contain information useful in explaining the expected stock returns. Therefore it is argued that the observed relative style return should be related with the fundamental characteristics and the shocks from the macro economy.

This PhD research is motived by several gaps identified in the existing literature. First, while academic study finds the relationship between stock returns, firm characteristics and the business cycle fluctuations, the relative importance of such driving sources is not extensively studied. The first part of this research fills the gap in the literature by explicitly examining how firm-specific characteristics and the business cycle conditions function separately to affect the stock performance based on the size and value-growth categorisations. Specifically, it aims to address a key question: what is the dominant driver that affects the relative style performance, the firm characteristics or the business cycle risk? To achieve that, a set of equity characteristics such as price to cash-flow (PC), dividend yield (DY), market-to-book values (MTBV) and market values (MV) are used to classify stocks into different size, value and growth categorisations and simple style investing strategies are tested. In response to the recent popularity of linking macroeconomic effects with the cross-sectional variations on average stock returns, following the framework of Chordia and

Shivakumar (2002), Chapter 3 examines the relative importance of common risk factors and the firm-specific information in determining stock returns across styles by focusing on the role of the predicted risk premias and the pricing errors in the observed style premiums.

Second, this research is also motivated by the benefits of active portfolio management based on the relative style returns within equity style cycles. The divergence of style returns evolve all the time with cyclical nature. Over the time there are styles moving in and out of favour by investors according to their relative past performance driven by changes of investment opportunity set. There is no single style or a mix of styles that can dominate under all economy regimes. If equity style cycles do exist and are of long duration, the reward to take investment strategy by identifying the turning point of the leading styles and to opportunistically transition portfolio holding to next prevailing market segments should be massive. Motivated by that, Chapter 4 investigates a dynamic tactical trading strategy by applying a binomial approach to focus on the shifting between pairs of equity styles such as value versus growth or small versus large styles. Each time investors extrapolate the relative performance of different asset classes based on their past performance and bet 100% of investing on the 'winner' style financed by shorting the 'loser' style. Previous research documented the value of such price-driven strategies like the momentum of Jegadeesh and Titman (1993) and the contrarian of De Bondt and Thaler (1985). However, momentum strategies along the style level have not been well studied, in particular in the U.K. stock market. Chapter 4 contributes to the extant literature by providing valuable empirical evidence in the U.K. stock market to compare with other studies in different economic and institutional environments. The research in this Chapter answers 2 key questions of whether investors can profit from the information of equity style cycles and whether the return dynamics of equity style momentum is distinct from price and industry momentum effects.

Chapter 5 of this PhD thesis is motivated by the apparent gap in the literature about the optimal multi-asset investing over the business cycles. Substantial evidence suggests that the distributions of stock returns contains time-varying predictable component in the business cycles. The benefit of considering business cycle predictors on asset allocations on the stock level is well studied. However, the portfolio choice implications of business cycle effect in prior studies often focus on the time-varying nature of return distributions driven by business cycle predictors, but the role such economic variables play in affecting optimal multi-style level allocation is less directly explored. Motivated by this gap, Chapter 5 implements an optimisation framework to test several equity style investing based on business cycle information and examine the *ex-ante* in-sample and *ex post* out-of-sample performance. By answering questions such as which economic variable or a set of variables should be tracked when implementing optimal style and how to adjust the exposures to specific market segments given shocks to such underlying variables, Chapter 5 gives multi-style investors like 'fund of hedge funds' managers an intuitive advice to optimise their asset allocations when incorporating business cycle predictability.

6.2 Conclusions

This PhD research has yielded several meaningful conclusions. First, consistent with the literature, significant size and value premiums are found in the U.K. stock market over the period of 1980:01-2004:12, justifying the applicability of simple equity style investing strategies. The outperformance of investing small-cap and value stocks are more pronounced during recessionary periods. It is again found that the underlying driving forces determining the dynamics of relative style performance are indeed much controversial. Overall, the divergent returns of small-cap versus large-cap stocks and the value versus growth stocks as characterised by PC and MTBV are mainly driven by the cross-sectional pricing errors in the context of a multifactor business cycle model. This would suggest that the outperformance of small stocks and the better returns of investing in value stocks with low PC or MTBV (i.e. high BM) may be caused by investors' irrational trading behaviour to such stock groups that result from cognitive biases like underreaction to firm-specific news. In contrast, the outperformance of value stocks with high dividend yield (DY) is likely to be attributed to cross-sectional difference in *conditionally expected returns* predicted by business cycle model. Therefore it represents the compensation for bearing business cycle risk. It is also concluded that although on the individual stock level the relative returns of value stocks based on PC and MTBV sorting are not likely driven by the business cycle risks, on the portfolio level the business cycle model could still partly capture the time-series expected value premiums. Hence equity valuation multipliers such as PC, DY and MTBV contain time-varying predictable component in the expected returns, which is consistent with findings of empirical studies focusing on time-series relations among expected returns, risk and equity characteristics (e.g. Fama and French (1993, 1996), Kothari and Shanken (1997), and Chan *et al.* (1998), among others).

The profit of style momentum strategy would suggest the existence of U.K. equity style cycles. Since styles perform differently during various stages of a market cycle, investing strategies to buy stocks in current in-favour styles could continue to outperform those in current out-of-favour styles for a period up to 12 months or possibly longer. Such payoffs generally increase with longer ranking periods and decrease with longer test periods. Consistent with the literature, it is found that style momentum effect has strong independent explanatory power for the future individual stock's expected returns, and style momentum is distinct from price momentum of Jegadeesh and Titman (1993) and industry momentum of Moskowitz and Grinblatt (1999) documented in the literature.

The empirical findings in Chapter 5 concludes that on a strategic perspective investors tend to significantly hold value stocks or small-cap stocks, and short sell growth stocks or large-cap stocks in their optimal style allocation process. It is much different for style investing incorporating or disregarding business cycle effects. Disregarding the business cycle predictability would usually introduce a strategy that is relatively conservative regarding the overall net equity exposures as compared to those that incorporate strong prior beliefs about the business cycle conditions. Style investing incorporating business cycle predictability generally result in more extreme weights to some styles at both long and short sides, possibly because investors believe that because of predictability such extreme exposures can be eventually reduced at bad times when the investment opportunity set changes. It is also suggested in Chapter 5 that business cycle predictors affect the conditional equity style returns and the optimal style investing in a different mechanism. Indeed, economic pervasive variables such as *yld*, *term*, *div* and *def* exert a strong influence on the shape or location of the optimal style investing frontier. Style investing capitalising on the conditional business cycle information consistently beat that disregarding such business cycle influence, both in-sample and out-of-sample.

6.3 The practical implementations

The empirical findings in Chapter 3, 4 and 5 would have practical implementations in the investment practice. First, the findings in chapter 3 provide practical guidance for active portfolio management. Portfolio managers who pursue style investing by allocating their funds to characteristic-sorted asset groups must first understand the different risk-related mechanism behind the observed divergent style returns. For example, if the return differentials are driven by bearing macroeconomic risks, active style management should aim to incorporate the business cycle effect. Conversely, if risks outside the business cycles drive the mispricing are the major driving forces of the relative style returns, style timing should focus on identifying the underlying stock groups related to investors' trading behaviour.

The profitability of style momentum documented in Chapter 4 would suggest how investors could manage their portfolio's style exposure efficiently. Namely, style exposures can be bought and sold and the investing portfolios can be constructed with desired style exposures, both positive and negative according to the style performance relates to market cycles. This technique can be easily implemented to help passive investors enhance the returns. Passive investors normally invest on an index fund. Index fund is a mutual fund or exchange traded fund (ETF) with a clearly predefined set of constituents that are constant regardless of market conditions. Passive investors do not expect to beat the overall market but rather pursue average market returns. Such strategy may be supported by efficient market hypothesis but clearly lacks efficiency. The divergent style returns under different market regimes indicates that equity style exposures can be used to hedge the inefficiency of an index fund by eliminating its least attractive portion. Extant literature regarding index hedging focuses primarily on the application of derivatives such as options and futures. The results in Chapter 4 provide a plausible method of adaptively constructing long short market neutral style portfolios to hedge the deficiency of an index fund under different state of the economy.

The research findings in Chapter 5 offer a simple yet intuitive way for mean-variance investors to optimise their style allocations. First, investors like 'fund of funds' managers are advised to incorporate business cycle information when implementing active style investing. Using macro information to assist in style selection has always been a hot topic in the quant circles in the investment community. There is certain evidence to suggest that different style factors are more or less relevant during different states of the macroeconomy conditions.

Hence conditional multi-style investing strategies following business cycle information generally outperform the unconditional strategies. Second, mean-variance multi-style investors could follow simplified optimisation approaches such as Brandt and Santa-Clara (2006) to parameterising directly on business cycle predictors when applying optimal style allocation. Namely, investors could follow a dynamic approach that is 'macro driven' to timing their style investing. By doing this a set of business cycle related economic variables should be tracked which forms the 'tradable environment states'. With the popularity of Exchange Traded Funds (ETF) and its flexibility and low trading expenses and high liquidity in leading financial markets, a combination of such optimal hybrid strategy should arguably help investors to squeeze more juice from the investing returns.

6.4 Recommendations for areas of future research

Despite enormous effort has been devoted to this PhD research, due to data availability and the time constraints, the author has identified several directions where further research is needed. The areas of recommended further research include the following:

First, it should make sense to extend the sample to the latest available data to test whether the basic findings are still hold. The sample data used in this research is till the end of 2004. Over the past 8 years global financial markets have undergone some fundamental changes. As major financial markets collapsed during 2007-2008 due to credit crunch, several most influential large investment firms have had their share prices plummet as a result of such subprime bust[29]. While this

[29] For example, Lehman Brothers reported a loss over $2.8 billion for the second quarter of 2008. Its stock price had fallen over 62% till 24 June 2008. The global financial service firm eventually has to declare bankruptcy, which was the largest bankruptcy in U.S. history. Other firms like Merrill Lynch reported an $8.6 billion net loss on 17 January 2008, while on 15 January 2008 Citigroup reported a fourth quarter net loss of $9.83 billion, including $18.1 billion in pre-tax write downs on its subprime investment. Similarly, UBS shut down one of its hedge funds in 2007 due to loss of $123 million assets and also reported a $4.4 billion loss on fixed-income securities for the third quarter 2007.

research does not contain stocks in the financial service industry, the collective market behaviour of these global key players arguably would inevitably cause excess volatility of other assets in the stock market and therefore affecting the asset pricing dynamics. By extending the research sample to contain the most recent credit crunch period, one is able to test the sensitivity of the findings and more reliable test results should be yielded. While this research is mainly based on the U.K stock market, it is also interesting to cover other developed markets that have different institutional environment[30].

Second, the style investing strategies discussed in this thesis often contains the structure of short selling. In market practice this process involves using of borrowed shares that are often from brokerage firms or institutional investors based on collateral. Short selling introduces costs. D'Avolio (2002) shows that the value-weighted cost to borrow stocks is 0.25% annually. In addition to the short selling cost, there exists general transaction cost in the market trading activity. Chan and Lakonishok (1997) argue that in the NYSE market the average round-trip transaction cost for small-cap and large-cap stocks are 3.31% and 0.90%, respectively. It is argued that academics generally underestimate the impact of such transaction cost in the empirical research (*c.f.* Sadka (2004), Lesmond et al. (2004), Hanna and Ready (2005)). Indeed, momentum effects are more pronounced in small size stocks with wider bid-ask spread, and such strategy requires frequent rebalancing that results in high turnover. This would suggest that it is important to incorporate the impact of various trading cost in the style investing strategies. Hence it makes sense to explore if the empirical findings still hold once possible trading costs are adjusted.

Third, the optimal style portfolio allocation examined in Chapter 5 is based on the assumption that investors face a single-period case to maximise their mean-variance objective. However the optimal choice

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[30] Recent study of Chao *et al.* (2012) examines the equity style momentum strategies in major international markets. However, their work mainly focuses on the testing part, rather to explore the underlying reason for the profitability of such strategies.

based on multi-period is not covered yet. Indeed, instead of the single period case investors may also wish to maximise their utility following a multi-period investment scenario. It makes sense to conduct the study of such multi-period optimal style allocation problem and also compare the results with that derived from the single-period case.

Fourth, Chapter 5 uses the risk-adjusted returns in the study. It will be very interesting to conduct a similar research based on the excess returns to the market index. The optimal style investing based on such excess returns captures the gain from beating an index with low tracking errors and is therefore equivalent to an 'active indexation' strategy, and the optimal weights can be interpreted as 'active weights'. Since market index also exposes to the business cycle effect, it is interesting to compare if the underlying optimal style policy would change given the two research schemes. Additionally, in response to the concerns that Markowitz optimal framework often yields extreme long-short weights (*c.f.* Best and Graner (1991)) due to the imprecise estimation of stock return moments, it makes sense to follow the use of shrinkage to improve estimates of means (*c.f.* Jagannathan and Ma (2003)).

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