ESSAYS ON INVESTMENT

by

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DECLARATION

I certify that this work has not been accepted in substance for any degree, and is not concurrently being submitted for any degree other than that of Doctor of Philosophy (PhD) being studied at the University of Greenwich. I also declare that this work is the result of my own investigations except where otherwise identified by references and that I have not plagiarised another's work.

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ABSTRACT

This research provides three self-contained empirical studies in investment management. The first essay performs a comparative analysis of the asymmetries in size, value, and momentum premiums and their macroeconomic determinants over the UK economic cycles, using Markov switching approach. We find clear evidence of cyclical variations in the three premiums, most notable in the size premium. Macroeconomic variables prompting such cyclicality the most are variables that proxy credit market conditions, namely the interest rates, term structure and credit spread. We find that forecasts based on our model have considerable economic significance for investors, particularly for trading strategies involving small-cap stocks.

The second essay contributes to the style timing literature by quantifying survival time of style portfolio momentum and implement style timing strategies based on the mean survival time. We find that empirical survival times differ from those implied by theoretical models (Random Walk and ARMA (1, 1)) - suggesting the profitability of momentum trading. We illustrate this by forming long-only, short-only and long-short trading strategies that exploit positive and negative momentum and their average survival time. Our trading strategies show that utilising momentum mean survival time yields considerably higher Sharpe ratios than the naive buy-and-hold at a feasible level of transaction costs. This finding is most pronounced among the long/short strategies.

The third essay contributes to the scarce literature of sector rotation by studying the risk-adjusted performance of sector portfolios with Fama-French three-factor (3FM) and five-factor models (5FM). We argue that if either of the models generates true alpha then we can incorporate investment strategies to generate higher returns. Although our empirical findings assert the theoretical argument that 5FM explains cross section of expected sector returns in greater accuracy, it is not found to be significantly different from 3FM while trading with Fama-French sector portfolios. However, while trading with readily investable sector ETFs, 5FM found to outperform 3FM which justifies our argument that Fama-French 5FM provides truer alpha than 3FM that can be exploited by sector rotation strategies.

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CHAPTER ONE: INTRODUCTION

1.1 Introduction

This research contributes to the literature of portfolio management over three self-contained essays. In chapter three (Essay One)[1], we investigate the asymmetries of size, value and momentum premiums over the economic cycles and their macroeconomic determinants. We implement dynamic regime-based methods (Markov Switching Model) to identify the possible nonlinear phenomena of UK style factors. In chapter four (Essay Two) we investigate the momentum (survival time) of style portfolios. Chapter five (Essay Three) studies the risk-adjusted performance of sector/ industry portfolios with Fama-French three-factor and five-factor models; and formulates sector rotation strategies of sector portfolios based on the rolling alphas of Fama-French models (three-factor and/or five factor).

'Style investment' is a portfolio allocation strategy where portfolio managers select stocks based on different categories rather than individual stocks (Barberis and Shleifer, 2003). There are also some other characteristics that portfolio managers use to categorise asset classes as a basis of style, simply because securities with these characteristics perform historically better among others. Frank Russell Company (a Global Asset Management firm) categorises assets into four broad styles: Value, Growth, Market Oriented and Small Capitalisation. Value and Growth stocks are classified by the ratios of specific stock fundamentals of the corresponding firms. For example, firms with the higher book-to-market ratio, i.e. lower market price relative to fundamentals are classified as value stocks. On the contrary, firms with lower book-to-market ratio, i.e. higher market price relative to fundamentals are classified as growth stocks. Whereas, firms with small (large) market capitalisation are classified as small (large) capitalisation stocks. In particular, size and value investment strategies drew their attention from the early 80s (see for instance

[1] A Version of essay one is published in Applied Economics, Available at: http://www.tandfonline.com/doi/full/10.1080/00036846.2016.1200184.

Stattman, 1980; Banz, 1981; Reinganum, 1981; Roll, 1981; Rosenberg et al., 1985, etc.). The seminal Fama and French (1992) paper exposes academics and practitioners to factors explaining the cross-section of expected stock returns other than market beta. Their findings suggest that beta doesn't explain the return, i.e. portfolios with high-beta stocks don't have higher returns than portfolios with low-beta stocks. Moreover, size (market equity) and value (book-to-market equity) do provide significant characterisations of the cross-section of average stock returns. Fama and French (1993) identified value premium and size premium in their proposed three-factor model (extension of Capital Asset Pricing Model [CAPM]). In the Fama-French three-factor model value premium or HML (High-minus-Low) is the spread in returns between the value and growth stocks which meant to mimic risk factor in returns related to the value of the firm. And the size premium or SMB (Small-minus-Big) is the spread in returns between the small and large capitalisation firms which meant to mimic risk factor in returns related to size.

Another investment strategy which is widely documented by academics and active research area is the momentum investing. Momentum investors aim to capitalise on the continuance of existing market trend. They believe that an increase in the security price will be followed by an additional gain and a decrease in the security price will be followed by an additional loss. Momentum investors take long positions on the upward trending securities and short sale the downward trending securities. Their concept is that once the trend has established then it is more likely move in the same direction than the reverse direction. After the documentation of momentum investment by Jegadeesh and Titman (1993), Carhart (1997) further includes a momentum factor (WML : Winner-minus-Loser or UMD: Up-minus-Down) with the Fama-French three-factor model, known as Carhart's four-factor model, to capture the pattern of cross-sectional return.

Since Fama and French (1993) and Carhart (1997) related small cap, value and momentum premiums to excess returns, a vast body of literature studies the determinants of those premiums. While, for instance, DeBondt and Thaler (1985) and Daniel, Hirshleifer and Subrahmanyam (1998) argue that the value premium arises due to the overreaction of investors, a number of academic studies point that the value and size premiums are proxies for some non-diversifiable risks not captured by the standard CAPM model, such as risks resulting from variations in macroeconomic factors (see Perez-Quiros and Timmermann, 2000; Liew and Vassalou, 2000; Kelly, 2003; Vassalou, 2003; Petkova, 2006; Black and McMillan, 2005; Zhang et al., 2009; Gulen, Xing and Zhang, 2011; Kim et al., 2014). We also contribute to this literature by extending the study in the UK market. The first essay (chapter three) of this study, however, scrutinises the relative difference in change between size, value and momentum premiums over business cycles impacted by the variation in their responsiveness to macroeconomic variables during different economic phases. In addition, to the best of our knowledge, this is the first study that examines how all three equity premiums are impacted by macroeconomic factors during the recent financial crisis in the UK.

The concept of style investment strategy is that fundamentally unrelated securities will move together simply because they have been grouped into the same asset class. Since style investors allocate funds at the level of a style, they generate coordinated demand shocks across all assets in the style, leading to co-movement in prices even if there is none in fundamentals (Barberis and Shleifer, 2003). For this co-movement (i.e. momentum) in prices style momentum evolves. Style momentum refers to the momentum of style portfolios, i.e. to a portfolio of asset or security that share similar characteristics. Since Jegadeesh and Titman (1993) reported momentum profits in the equity market, momentum has been extended to different asset classes, portfolios, and international equity markets. The Economic significance of style momentum is that an investor can achieve extra return by selling (buying) those portfolios whose past performance were better (worse) than other style portfolios in a case when style momentum exists. The discovery of style momentum (or portfolio momentum) led to the formulation of two alternative theories of momentum, i.e. the excess comovement theory of Lewellen (2002) and the style investing theory of Barberis and Shleifer (2003). Whereas earlier behavioural theories (e.g. DeBondt and Thaler, 1985; Daniel et al., 1998; Hong and Stein, 1999, etc.) identified investors' underreaction as the source of momentum profits, new theories identified the tendency of fundamentally unrelated firms to co-move and investors' tendency to classify assets as the source of momentum (Kim et al., 2014).

Moreover, market timing literature, pioneered by Treynor and Mazuy (1966) and Henriksson and Merton (1981), investigate whether investments on size, book-to-market can be timed (Copeland and Copeland, 1999; Kao and Shumaker, 1999; Levis and Liodakis, 1999; Chen and De Bondt, 2004; Desrosiers et al., 2004; Knewtson et al., 2010; Bird and Casavecchia, 2011; Gallagher et al., 2015; Miller et al., 2015). Heart of market timing and/or momentum trading depends on identifying the trends early and react quickly; hence academics and as well as the financial institutions spend a considerable amount of time into this phenomenon. We contribute to the literature of style timing [chapter four (Essay Two)] in twofold: firstly, we extend the literature of style momentum of the portfolios that are used to construct style factors; secondly we incorporate survival based econometrical model in the style timing literature that identifies style portfolio momentums and derive switching strategies to exploit the momentums.

On the other hand, it is widely documented that understanding the risk and return profiles of style investment is an important challenge in modern financial economics. Capital Asset Pricing Model (CAPM) by Sharpe (1964) and Lintner (1965) has long been served as the backbone of academic finance in this regard. However, the pre-eminence of CAPM has been challenged by academics as well as practitioners because of empirical deficiencies and observed unexplainable anomalies. Due to the inadequacy of CAPM, the academic literature has experienced continuing search for a model explaining the cross-section of expected stock returns. CAPM has then extended to ICAPM (Intertemporal CAPM), CCAPM (Consumption CAPM) etc. Market capitalisation and related financial ratios have been a challenge to CAPM because of their ability to predict the cross section of returns. Fama and French (1993)'s proposal of including two additional factors (explanatory variables) to CAPM has the argument that size and book-to-market do explain the cross-section of expected return better than CAPM. Several recent studies use the Fama-French three-factor model (hereafter Fama-French 3FM) as an empirical asset pricing model. However, the model left unexplained for some anomalies, such as the positive relationship with momentum returns, negative relationship with financial distress, net stock issues, asset growth etc., and the hunt to include additional factors remained. Carhart (1997) got into this hunt and advocate to add one additional factor (momentum factor or UMD) to the Fama-French 3FM. The proposed 4 factor model of Carhart (1997) (hereafter Carhart 4FM) is also widely acknowledged by the academics, however also been criticised because it goes against the conventional contrarian investment strategies. Although, Fama-French 3FM was a significant improvement over the CAPM because it is adjusted for outperformance tendency, but academics questioned about its ability to explain some anomalies as well as the cross-sectional variation in expected returns particularly related to profitability and investment. Motivated by this evidence, Fama and French (2015) proposed five-factor model which added two additional factors, profitability and investment, in addition to their previous three-factor model. They argue that three-factor model was an inadequate model for expected returns because it overlooks the variation in average returns related to profitability and investment.

In the presence of several asset pricing models, academics, as well as practitioners, remain puzzled to pick one appropriate model for their portfolio management. In the case of performance measure of portfolios based on particular asset pricing model, risk-adjusted performance measure (alpha) is widely accepted by the academics as well as practitioners. If the corresponding asset pricing model completely captures the expected returns, the Alpha (intercept) of an asset pricing model is expected to be indistinguishable from zero while regressing asset's excess returns on the model's factor returns. A non-zero alpha can then be attributed to the abnormal performance of the portfolio or to the amount of return that cannot be captured by the model used. The search for non-zero alpha or measuring the portfolio performance in the literature is extensive, till today. Early studies of performance evaluation use Jensen's alpha (Alpha of CAPM) as a measure of risk-adjusted performance (e.g. Jensen, 1968; John and Donald, 1974; Lehman and Modest, 1987; Ippolito, 1989; Grinblatt and Titman, 1994; Kao et al., 1998; etc.). Researchers use multifactor models for performance measurement after the multifactor models evolved (e.g. Cai et al., 1997; Daniel et al., 1997; Kothari and Warner, 2001; Otten and Bams, 2002; Otten and Bams, 2004; Kacperczyk et al., 2005; Cuthbertson et al., 2008; Cremers et al., 2012; Angelidis et al., 2013; Vidal-garcía, 2013; etc.). However, the debate of finding a model that explains the cross-section of expected stock returns still remains.

If an asset pricing model can be found that generates true alpha i.e. explains the cross-section of expected stock returns in greater accuracy, then it can be used to rotate funds among different portfolios (rotation strategies) to gain higher returns. In the group rotation step of asset allocation process, funds are apportioned to groups of securities. In this step, managers attempt to identify economic sectors and industries that stand to gain or lose relative to the overall market. In the security selection/analysis step, investors or fund managers choose combinations of securities from each of several stocks or bonds groups. However, the literature of sector/industry return predictability is surprisingly scarce with respect to the importance of sector/industry analysis in the investment process. One of the earlier studies that focused on industry rotation strategies is done by Sorensen and Burke (1986). They argue that, while individual industry rankings varied considerably, industry-specific stock price movements tend to persist for at least two quarters. A naive strategy based on rotating portfolio holdings in each quarter among the three, five or ten best-performing industry groups generates superior returns. Grauer, Hakansson and Shen (1990) also show that active industry rotation strategies of the multiperiod model show better performance to the value-weighted industry indexes. Other studies that perform sector/industry rotation strategies includes Moskowitz and Grinblatt (1999); Baca, Garbe and Weiss (2000); Pan, Liano and Huang (2004); Conover et al. (2005); Sassetti and Tani (2006); Conover et al. (2008); Shynkevich (2013); Dou et al. (2014).

The intuition of sector rotations strategies is that companies in the same sector or industry would exhibit higher pairwise return-correlations from the companies of the different industry. Firms within the same industry that operate under the same regulatory environment are likely to react similarly to technological innovations, and also exhibit similar sensitivity to macroeconomic shocks and/or government policy. Because of highly correlated returns on the stocks of the same industry and integrated financial markets, it would be sensible to look for any added benefit for sector asset allocation, more specifically by performing sector rotation which is relatively less explored area of asset allocation. In the third essay, together with the performance evaluation of sector portfolios by using Fama-French asset pricing models (3FM and 5FM), we contribute to the scarce literature of sector rotation strategies. This is also the first study that compares the newly evolved Fama-French Five-Factor Model (5FM) with their previous Three-Factor Model (3FM) as a benchmark model of performance evaluation; in the sector/ industry perspective. We perform sector rotation by following the study of Sassetti and Tani (2006), who claim that a sector rotations based on the Alpha indicator appear to be more regular and stable.

The remainder of this introductory chapter formulates the research objectives, assesses the significance of this study and finally outlines the structure of the thesis.

1.1 Research Objectives

This study is based on the asset pricing models of Fama-French. The main focus is to exploit the scopes to 'beat the market'. To identify scopes and strategies to 'beat the market', we study asymmetries of size, value and momentum premiums over the economic cycles and their macroeconomic determinants in the third chapter. In the fourth chapter, we study style timing strategy of different size and value portfolios. In the chapter five we study the sector rotation strategies. To present the study in a meaningful and convenient manner, three self-contained essays are included in the thesis, forming chapter 3, 4 and 5. The research objectives of each essay are presented in this section.

1.1.1 Objectives of Chapter Three (Essay One)

It is widely documented that understanding the risk and return profiles of style investment is an important challenge in modern financial economics. One substantial section of the literature focuses on the existence of the size, value, and momentum premiums. Though the size, value and momentum premiums have drawn attention from a wide range of academics and practitioners, the existing literature mainly examines how the potential state variables explain the equity returns. This has led to a lack of literature examining style investment during different phases of the economic cycle.

The overall objectives of essay one (Chapter three) are to examine the asymmetries of size, value and momentum premiums over the economic cycles and their macroeconomic determinants. The specific objectives can be outlined as follows:

First, in the UK market, the style factors are relatively less explored compared to the US market. This provides scope to study the relationship of size, value, and momentum premiums with the macroeconomic variables during different phases of the economic cycles in the UK market.

Second, analyse the economic nature of style factors and examine the effect in portfolio management.

Third, implement dynamic regime-based methods to identify the possible nonlinear phenomena of UK style factors.

Fourth objective concerns appropriate risk-adjusted trading techniques to gain excess returns. We, therefore, aim to identify trading strategies to exploit the asymmetries of size, value and momentum premiums over the economic cycles.

1.1.2 Objectives of Chapter Four (Essay Two)

While regular price momentum is already a well-documented characteristic of the financial market, style momentum (momentum among style portfolios) can be considered as a new empirical study defying the theory of efficient market. Chapter four (Essay Two) investigate the timing strategies of style portfolios based on the style momentum. The objectives of chapter four (Essay Two) are in twofold: first, extend the literature of style momentum by studying the momentum of portfolios that are used to construct style factors; second, incorporate survival based econometrical model in the style timing literature that identifies potential momentum of style portfolios. The specific objectives are:

First, investigate the momentum of style factors, namely Small Size & Low BTM (SL), Small Size & Medium BTM (SM), Small Size & High BTM (SH), Big Size & Low BTM (BL), Big Size & Medium BTM (BM), and Big Size & High BTM (BH) Portfolios.

Second, incorporate survival based econometrical model in the style timing literature that identifies and quantifies momentum of style portfolios.

Third, once we identify the survival curve of style portfolios, it can be explored whether this survival can be economically significant or not. Hence our third objective is to identify trading strategies to exploit the momentum of style portfolios.

Fourth, it is documented that momentum can be affected by different economic conditions. We, therefore, aim to test whether this survival of momentum differ across business cycles.

The fifth objective of this chapter is to examine whether the survival of momentum is associated with macroeconomic variables. To do so, we use macroeconomic variables that are found to be significant in chapter three (Essay One), that is the variables that describe credit market conditions: Interest rates, Term spread and Credit spread.

1.1.3 Objectives of Chapter Five (Essay Three)

The lack of literature of sector/industry return predictability is surprising with respect to the importance of sector/industry analysis in the investment process. The main objective of chapter five (Essay Three) is to contribute to the scarce literature of sector/sector rotation. Moreover, the recent five-factor model of Fama-French raises the question whether the five-factor model provides better descriptions of average returns than the Fama-French three-factor model. Therefore the academics, as well as practitioners, will be puzzled to pick an appropriate model in their study. Hence, the objectives of chapter four (Essay Two) are in twofold: first, investigate the risk-adjusted performance of sector portfolios in terms of Fama-French three-factor and five-factor models; second, formulate sector rotation strategies of sector/industry portfolios based on the rolling alphas of Fama-French models (three-factor and/or five factor).

The specific objectives are:

First, compare Fama-French three-factor model (3FM) and five-factor model (5FM) as a benchmark model of (portfolio) performance evaluation.

Second, most of the literature in performance measurement studies the performance of different variety of funds (mainly mutual funds). Hence, our second objective is to contribute to the performance measurement literature by studying the performance of sector/industry portfolios.

Third, if the factor models of Fama-French (whether three-factor and/or five-factor model) generate true alpha (intercept) then we can incorporate investment strategies (in this chapter sector rotation strategies) to ‘beat the market’. The third objective of this chapter is to explore such sector rotation strategies.

1.2 Significance of the Research

Based on the research objectives we perform empirical studies based on the most recent data. Our contributions to the existing literature of investment management are methodological as well as theoretical.

The research significance and main contributions to the existing literature of each of the three self-contained essays are presented separately here.

1.2.1 Contributions of Chapter Three

- Chapter three scrutinises the *relative difference in change* between size, value and momentum premiums over business cycles impacted by the variation in their responsiveness to macroeconomic variables during different economic phases.
- First comprehensive study in the UK contexts to measure the effect of a set of relevant macroeconomic variables on style premiums.
- Only study that includes all three premiums and compare their responsiveness over business cycles.
- Uses most recent data that includes recent financial crisis.

1.2.2 Contributions of Chapter Four

- Chapter four contributes to the literature of style momentum by studying momentum of style portfolios that are used to construct style factors.
- This is the first study of style timing in the UK context that studies style portfolios.
- This study uses most recent data that includes recent financial crisis.
- This is the first study that incorporates survival based econometrical model in the style timing literature that identifies potential momentum of style portfolios.
- This study assesses whether the survival of momentum of style portfolios differ across business cycles or not.
- This study also investigates whether the survival of momentum is associated with macroeconomic variables, mainly the variables that describe credit market conditions.

1.2.3 Contributions of Chapter Five

- In chapter 5, together with the (portfolio) performance evaluation by factor models (3FM and 5FM); we contribute to the scarce literature of sector rotation strategies.
- This is also the first study that compares the portfolio performance by using newly evolved Fama-French Five-Factor Model (5FM) with their previous Three-Factor Model (3FM), as benchmarks, in the industry/sector perspective.
- Sassetti and Tani (2006), claim that a sector rotation based on the Alpha indicator appear more regular and stable. We test their claim by studying the performance of sector/industry portfolios based on rolling alpha. This study is first of a kind in sector rotation literature that uses rolling alpha to perform the rotation.
- This study uses most recent data that includes recent financial crisis.

1.3 Organisation of the Thesis

In the second chapter, we summarised the literature based on our research objectives. The rest of the thesis divided into three self-contained essays that attempt to model and exploit, from traders' perspectives, Fama-French factor model(s). The introduction of each essay contains theoretical framework and background of the corresponding study. Each essay has also the methodology section that formulates the methodological framework of the corresponding study.

Chapter 3 (Essay One) investigates the asymmetries of size, value and momentum premiums over the economic cycles and their macroeconomic determinants. We implement dynamic regime-based methods (Markov Switching Model) to identify the possible nonlinear phenomena of UK style factors. In Chapter 4 (Essay Two) we investigate the momentum of style factors, namely Small Size & Low BTM (SL), Small Size & Medium BTM (SM), Small Size & High BTM (SH), Big Size & Low BTM (BL), Big Size & Medium BTM (BM), and Big Size & High BTM (BH) Portfolios. We incorporate survival based econometrical model (Kaplan-Meier (KM) estimator) in the style timing literature that identifies momentum of style portfolios. Chapter 5 (Essay Three) structured in twofold: firstly, we compare Fama-French three-factor and newly evolved five-factor model as a benchmark model of performance evaluation; secondly we formulate sector rotation strategies of sector/industry portfolios based on the rolling alphas of Fama-French models (three-factor and/or five-factor).

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

Let us now review the literature that motivated and helped to define the research objectives of this thesis. Section 2.2, 2.3 and 2.4 of this chapter reviews the main literature associated with essay one, two and three respectively.

2.2 The Literature on Size, Value and Momentum Premiums

Size, value and momentum effects gain importance because of the popularity of Fama-French three-factor model (Fama and French, 1993) and Carhart four-factor model (Carhart, 1997). SMB (reflecting size effect), HML (reflecting book-to-market effect) and UMD (reflecting momentum effect) factors are by construction proxies the size, value, and momentum premiums respectively. Although the economic sources of these premiums are debatable, the understanding of the possible sources of size, value and momentum effects might be handy to distinguish the information content of Fama-French three-factor and Carhart four-factor model; and vice-versa.

The market performance of size (small capitalisation), value (high book-to-market) and winner firms, since the seminal paper of Fama and French (1992); Jegadeesh and Titman (1993), is still a debatable issue. A vast amount of literature looks for the empirical evidence and the nature of size, value and momentum (winner minus loser) anomalies. Size anomaly explains that small (large) firms generate higher (lower) average return than what the CAPM (Capital Asset Pricing Model) predicts. Similarly, book-to-market anomaly explains that firms with high book-to-market (value firms) generate higher (lower) average return than the predicted return of CAPM. Moreover, momentum anomaly explains the higher (lower) average return of prior winners (losers) comparing to the predicted CAPM returns.

The literature on size, value and momentum premiums in the US market is extensive. Based on our research objectives our literature mainly focuses UK studies. However, the next section reviews some mainstream literature in the US market. Afterwards, in section 2.2.2, we review the literature of size, value and momentum premiums in the UK market.

2.2.1 Size, Value and Momentum Premiums in the US

The literature on market anomalies predominantly focuses on the US market. The study of size anomaly can be traced back to early 80s when Banz (1981) documents that average returns of small stocks are too high given their beta estimates compare to the lower average returns of large stocks. Banz examines all common stocks listed on the New York Stock Exchange over the period 1926 to 1975 and finds that stocks in the quintile portfolio with the smallest market capitalization earn a risk-adjusted return that is 0.40% per month higher than the remaining firms. Reinganum (1981) investigates the size effect in a sample of 566 NYSE and AMEX firms over the period 1963–1977. He finds that the smallest size decile outperforms the largest by 1.77% per month. During same year Roll (1981) also studies the small firm effect in the US market. He finds that small firm effects arise because of the improperly measured riskiness of firms. By studying NYSE firms over the period 1962 to 1978, Basu (1983) also confirms that small NYSE firms earn significantly higher returns than stocks of large NYSE firms. Keim (1983) uses a broader sample of NYSE and AMEX firms over the period 1963–1979 and confirms the outperformance of size premium by at least 2.5% per month.

By investigating NYSE firms over the period 1958 to 1977, Chan, Chen and Hsieh (1985) argue that small firms are more exposed to production risk and changes in the risk premium. Chan and Chen (1991) examine the characteristics of different size firms with the same economic news. They prove that, characteristics of a firm rather than size matters for the size premium. For each year from 1961 to 1985, they group firms that have been on the NYSE for the previous 5 years into five size quintiles based on their market capitalization as of December of the previous year. They find that smallest quintile outperform others. On the contrary, Bhardwaj and Brooks (1993) study the size effect of NYSE and AMEX stocks in bull and bear markets during 1926 to 1988 and claim that small firms underperform large firms. However, they argue that small firm returns were substantially larger between 1971 and 1980 than between 1981 and 1990.

Kim and Burnie (2002) investigate whether the firm size effect is driven by economic cycles. They hypothesise that, if small firms have large abnormal returns, they should have earned these returns in the expansion phase of the economic cycle rather than in the contraction phase. By using COMPUSTAT data from January 1976 to December 1995, they confirm the hypothesis that the small firm effect occurs in the expansion phase of the economic cycle. Switzer (2010) extends the study of Kim and Burnie (2002) to the US and Canadian market. He examines whether or not small firm anomalies are due to the business cycles or default risk or interest rate risk or inflation risk. His empirical study over the period 1926 to 2010 shows the abnormal positive performance of US small caps in the recent (post-2001) period as well as for the long horizon is attributable to the small-cap growth stocks.

Stattman (1980); and Rosenberg, Reid and Lanstein (1985) observe value effect on the US market during the early 80s. They observe that average returns on US stocks are positively related to firm's book-to-market ratio. The seminal paper of Fama and French (1992) attracted vast bulk of research on the size and value premiums. By using the US stock market from 1963-1990 to study the impact of market beta in the Sharpe-Lintner-Black model of average return and risk, Fama and French (1992) evaluate the impact of size, leverage and book-to-market equity in the cross-section of average returns. They argue that beta doesn’t explain the return, i.e. portfolios with high-beta stocks don’t have higher returns than portfolios of low-beta stocks. Moreover, size (ME) and the value (book-to-market) do provide significant characterisation of the cross-section of average stock returns. Later in 1993, Fama and French (1993) demonstrate that risk factors constructed on the basis of book-to-market and market capitalisation are incrementally important beyond a market factor in explaining the time series of US portfolio returns.

Avramov and Chordia (2006) develop a framework for single securities to justify asset pricing model explanation of value, size and momentum premiums of NYSE, AMEX and NASDAQ listed companies over the period of July 1964-December 2001. They looked for whether factor loadings vary with firm-specific market capitalisation, book-to-market as well as business cycles. They find that the betas on the excess market return and the size premium increase during the recession- confirming time variation. They also document that, prior returns are positively related to excess returns- confirming momentum premium. Gulen, Xing, and Zhang (2011) show that expected value premium of the US market shows an upward spike during recessions, which follows a gradual declining in the subsequent expansions.

Many empirical studies, i.e. Lakonishok, Shleifer and Vishny (1994) and La Porta et al. (1997), show the outperformance of value stocks with respect to growth stocks for the US stock market. Lakonishok, Shleifer and Vishny (1994) document the outperformance of value investing on NYSE and AMEX stocks sorted by different valuation descriptors. They report that value portfolios sorted by book-to-market ratios outperform the growth counterparts by 10.5% annually over the five years after formation. Moreover, the average size-adjusted value investing return is 3.5%, indicating a 7.8% spread relative to the growth strategy. Vassalou and Xing (2004) find outperformance of size and value premiums in the US market over the period 1963 to 1999. They report that the size effect is very strong with an average return difference between small and big firms of 3.82% percent per month. They also document prominent value effect in the two quintiles with the highest default risk. Other studies like Fama and French (1995); Daniel and Titman (1997); Dhatt, Kim and Mukherji (1999); Guidolin and Timmermann (2008); and Israel and Moskowitz (2013), etc., also provide similar evidence of the outperformance of small and value stocks in the U.S markets.

Jegadeesh and Titman (1993) are the first to document price momentum profits. By using CRSP daily data over the period 1965 to 1989 they document that strategies which buy past winner stocks and sell past loser stocks generate significant positive returns over 3- to 12-month holding periods. More specifically, they find that momentum portfolios produce significant 1.3% abnormal profits per month over the sample period. Jegadeesh and Titman (2001) further confirm the profits of momentum strategies, of about 1% per month, continue through the 1990s suggesting that their initial results were not due to data mining.

After the seminal study of Jegadeesh and Titman (1993), a large body of empirical literature documents the outperformance of past winners over past losers. Chan, Jegadeesh and Lakonishok (1996) report comparable profits for momentum strategies based on all stocks listed on NYSE, AMEX and NASDAQ over the period from January 1977 to January 1993. Grinblatt, Titman and Wermers (1995) investigate momentum strategies of 277 US mutual funds over the sample period December 1974 to December 1984. They report that funds that invested on momentum realised significant outperformance over other funds. Moreover, 77% of the funds engage in momentum trading in their sample. Carhart (1997) investigate mutual funds data from January 1962 to December 1993 and illustrate that 1-year momentum effect explains the performance persistence of mutual funds, but that individual funds following momentum strategies do not exhibit superior performance. He reports that momentum strategies are not exploitable after transaction cost. However, the study of Korajczyk and Sadka (2004) claims that trading on past winners remain profitable even after transaction cost.

Grundy and Martin (2001) documents that momentum strategies based on winner or loser firms on stock-specific return components are more profitable than those based on total returns. By using the common stocks listed on the NYSE, AMEX, and NASDAQ from January 1960 to December 2004, Liu and Zhang (2008) conclude that winners have temporarily higher future average growth rates than losers and that the duration of the expected-growth spread roughly matches that of momentum profits.

Chen and DeBondt (2004) provide evidence of style momentum over the period 1976 to 2000 in S&P500. They find that past winner (currently in favour) stocks outperform past losers (currently out-of-favour) for up to 1 year and possibly longer. However, Cooper, Jr and Hameed (2004) argue that momentum profits depend critically on the state of the market. By using NYSE and AMEX stocks over the period January 1926 to December 1995 they find that the mean monthly momentum profit following positive market returns is 0.93%, whereas this profit is -0.37% following negative market returns.

The outperformances of size, value and momentum premiums are not only confined to the US market. Several studies also report the outperformance of style premium in international markets (e.g. Fama and French, 2012; Black, 2002; Rouwenhorst, 1998; Switzer 2012; Liew and Vassalou, 2000, etc.).

Although, most of the studies of size, value and momentum anomalies are based on the US market, there are relatively few studies of this type based on UK market. We intend to contribute to the literature by extending the study in the UK market. Based on our research objectives our literature will focus on the studies of the UK market. The next section, hence, will review the empirical literature of size, value and momentum premiums in the UK market.

2.2.2 Size, Value and Momentum Premiums in the UK

The empirical study of size effect in the UK market can be traced back to Levis (1985). He investigates the relationship between average return and firm size for UK companies over the period 1958 to 1982. He finds that the smallest size decile of firms significantly outperforms the largest size decile by 6·5% per year. However, this size effect is found to be the unstable over time in his empirical study. Beenstock and Chan (1986) also study the average market return and firm size in the UK market. They measure firm size in terms of market valuations of the corresponding firm. Using the UK market data over the period 1962 to 1981, however, they do not find any correlation between firm size and average market returns.

To investigate whether the size and value effect can be extended to the UK market, Chan and Chui (1996) use Fama and MacBeth (1973) methodology in the UK market data (both annually and monthly) over the period of 1971-1990. Their study, consistent with Fama and French (1992), reveals that beta has very little role in explaining the cross-sectional return in the UK market. In the univariate regression for monthly data, they find a significant positive relationship between the book-to-market ratio (value effect) and risk premium against stock returns. In multivariate regression, this also remains significant along with the market value of the firm's equity. However, in contrast to Fama and French (1992), they find insignificant effect of size variable (proxied by annual logarithm of the market value of the firm's equity) on average return. Similar methodology is also used in the study of Miles and Timmermann (1996) who examine the variation in expected monthly stock returns for the cross-section of 457 non-financial UK firms over the period 1979-1991. They find that book-to-market ratio is highly significant and has a positive effect on expected stock return. However, size effect is found to be insignificant, similar to Chan and

Chui (1996), in explaining the cross-sectional variations in expected returns, whether regress alone or with other firms' factors. Brouwer, Put and Veld (1997) expand the study in the European context by studying the performance of value strategies in France, Germany, Netherland and the United Kingdom markets. Their sample period covers both high and low economic regimes over the period June 1982 to June 1993. They also adopt both Univariate and Multivariate regression technique (Fama and MacBeth (1973) methodology) to find out the significant value strategies. Their empirical results indicate that market value of firm’s equity has a significant negative relationship with stock returns. However, the book-to-market ratio is found to be positive but insignificant both in univariate and multivariate regression. The positive relationship (however significant) between average return and book-to-market equity is also documented in the study of Strong and Xu (1997). More specifically, they document that higher book-to-market equity generates 1.19% higher return per month (15.25% per year) than lowest book-to-market equity.

The cross-sectional study of Leledakis and Davidson (2001) also find the significant positive relationship of the book-to-market ratio (BV/MV) and significant negative relationship market value of equity (MVE) with average market returns respectively. In their study, they use portfolio grouping and cross-sectional regression to study the UK stock market data of 1420 firms over the period of July 1980 to June 1996. Their study finds the significant explanatory power of sales-to-price ratio (P/S) beyond the contribution of book-to-market ratio (BV/MV) and market value of equity (MVE).

Gregory, Harris and Michou (2001) shed further light on the profitability of value strategies in the UK market. Their sample covers 350 companies of London stock exchange over the period January 1975 to December 1998. Their study supports the evidence that value stocks generate higher return in the UK. Michou, Mouselli and Stark (2007) estimate the size and value premiums using nine different methods of constructing SMB and HML by using the UK market data over the period July 1980 to April 2003. They hypothesise that if size and value premiums capture risk factors there would be positive significant mean returns. Their empirical study suggests a positive value premium in all nine estimation methods (however only three methods are found to be significant). Size premium, in their study, is found to be positive and significant in five estimation methods out of nine, however, the negative size premiums are not found to be statistically significant.

The outperformance of value stocks is also documented in the study of Levis and Liodakis (2001). Their empirical study in London Stock Exchange, over the period of July 1968 to June 1997, finds the outperformance (11.6% in the year immediately after formation) of the high book-to-market portfolio over the low book-to-market portfolio. The outperformance of value stocks continues in the following 5 years, although the spread between high and book-to-market stocks declines and no longer remains statistically significant.

Dimson and Marsh (2001) construct new set of indexes of the UK market that cover equities, high capitalisation, low capitalisation, micro capitalisation, Government bonds (high maturities and mid maturities), index linked bonds and treasury bills for the period of 1955 to 1999. Over the sample period, they find the outperformance of small-cap and micro-cap stocks over high cap stocks. However, they also find that small firm premium went into reverse soon after the detection of size effect. They argue that this recent underperformance and the earlier overperformance of small-cap stocks may largely be attributed to the fundamental performance of underlying small firms, i.e. the firms' initial income, dividend growth and price-dividend ratio.

The existence of value effect, together with size effect, also looked at by Hussain, Toms and Diacon (2002) in the UK market over the period 1974 to 1998. Their empirical study shows that value stocks tend to have higher returns than growth stocks over their sample period. They find monotonic pattern in book-to-market sorted portfolio suggesting a systematic relationship between value and stock market return. Nonetheless, stocks with high book-to-market, high E/P, high C/P or low sales growth tend to load positively (positive slope) on value premium (HML) as they are relatively distressed firms. Whereas, stocks with low book-to-market, low E/P, low C/P or, high sales growth tend to load negatively (negative slope) on value premium. Their study also shows the outperformance of smallest size portfolio over the biggest size portfolio. However, they don't find any monotonic pattern in monthly mean access returns in size sorted portfolio; suggesting a less systematic relationship between size and stock return that is reported by Fama and French (1993). In the contrary, the study of Hwang and Lu (2007) in the UK market (cross-sectional stock return) over the period January 1987 to December 2004 do not find the support for outperformance of value and small size stocks. Their results show that large firms outperform small firms, whereas firms with low book-to-market outperform firms with high book-to-market during the sample period.

On the other hand, Liu, Strong and Xu (1999); Hon and Tonks (2003); and Li et al. (2008) study the profitability of momentum strategy in the UK market. The study of Liu, Strong and Xu (1999) covers 4128 stocks over the period January 1977 to June 1998 of London Stock price database. They adopt the trading strategy of Jegadeesh and Titman (1993) where the stocks are grouped into ranked decile portfolios according to non-overlapping prior return periods of different durations up to a year, and these equally weighted portfolio returns are then observed individually over the succeeding holding periods. Their study confirms the momentum effect in UK stock market. They also confirm that momentum profit does not abolish after controlling risk (beta), size, price (market value), book-to-market ratio or cash earnings-to-price ratio separately.

The profitability of momentum trading strategies is also examined by Hon and Tonks (2003) for all the listed companies in UK stock market over the period January 1955 to December 1996. After examining the profits generated by extreme decile portfolios formed on historical returns, the study finds that momentum premium (WML) is positive and significant over almost all investment horizons up to 24 months of portfolio formation. There is also evidence of momentum effect in the short horizon to the medium horizon where investors take long position in winner portfolio and sell loser portfolio. They further tested the momentum strategy by splitting the sample into two subsamples: 1955-1976 and 1977-1996. They find little evidence in favour of momentum strategy for an earlier period but find evidence of profitability of momentum strategy for latter period. They argue that the positive momentum premium in the entire sample period, hence, due to the high profitability of momentum strategy in the latter period. This may indicate that the positive serial correlation in the stock prices of the UK market is not a general feature of the whole period but is only confined to subsamples. They argue that the less volatile period of pre-1976 exhibits random walk characteristics of the UK stock market and hence might explain the findings of their study.

Li et al. (2008) use the dividend adjusted monthly stock prices over the period February 1975 to December 2001 to examine the profitability of momentum strategy in the UK. Their findings suggest that winner stocks systematically outperform loser stocks at 1% level of significance. They also argue that, although systematic risk explains most of the overperformance of winner stocks, it fails to explain the underperformance of the loser stocks.

By using the mean group estimator approach over the period July 1971 to June 1997 in 541 stocks, Bagella, Becchetti and Carpentieri (2000) look for the sources of value and size effect in the UK market. They find the persistence of size and value effects of UK stock market even when risk adjusted. They document that small firms are significantly exposed to size specific risk factors but less exposed to non-diversifiable systematic risk than large firms; whereas book-to-market portfolios are significantly exposed to three distinct risks: non-diversifiable systematic risk, size specific risk and book-to-market specific risk.

The sources of value and size effect in the UK context is also documented in the study of Levis and Liodakis (2001); and Hung, Shackleton and Xu (2004). Four different time series model: namely Fama & MacBeth CAPM, ex-post conditional beta & return relationship, higher co-moment models, and Fama-French model are used by Hung, Shackleton and Xu (2004) to compare their ability to explain the profits due to beta, size and value strategies. Their study analyses the CAPM, higher co-moment and factor models in the UK context by using the data of London Stock Price Database (LSPD) over the period January 1975 to December 2000. Their empirical results find significant betas for all the four models they have used. However, higher co-moment term (co-skewness and co-kurtosis) does not increase the explanatory power of the model as the slope coefficient (estimated) is not found to be significant in their study. Nonetheless, the coefficients of both size premium (SMB) and value premium (HML) found to be positive and significant for higher co-moment model and Fama-French factor model. These findings support the high significance of Fama-French factors in explaining the cross-section of stock returns in the UK market. Moreover, when the up and down markets are separated and allocate negative realised risk premium to the down market; the size effect is found to be affected differently to up and down markets (different slope coefficient). More precisely, the size effect seems to be evident by its anomalous higher returns for small-cap stocks in the down markets. However, no evidence is found for the asymmetrical behaviour of value premium over up and down market as the study finds the systematic behaviour of value strategy over the up and down market.

The economic significance of size and value stocks, based on style rotation strategies, is analysed by Levis and Liodakis (1999) over the period 1968 to 1997. Based on small/large-cap and value/growth segments in the United Kingdom they find that, on average annual return, small-cap stock outperform large-cap stocks by 83 basis points; whereas value stocks outperform growth stocks by 1160 basis points. They also find that value portfolios have higher dividend and cash flow yield but lower price earning ratio compare to growth portfolios. Whereas, size portfolios do not indicate any clear difference on any of the above measures. The study of Levis and Liodakis (2001) also documents the economic significance of value strategies. Their empirical study finds that long position in value stocks would have earned a cumulative return of 211.9% compared to 118.4% for growth stocks for an investment horizon of 5 years.

Dimson, Nagel and Quigley (2003) analyse the historical performance of value versus growth stock of UK stock market over the period 1955 to 2000. The portfolios in their study are formed by sorting independently on book-to-market ratio and market capitalisation. They show the evidence that value and size premiums are independent of each other where size premium is relatively more volatile than value premium until 1970’s. Furthermore, the long-term value premium is notably higher than long-term size premium. Their results also illustrate higher standard deviation of SMB relative to HML; meaning that value premium is relatively more stable and persistent compared to size premium.

The recent study of Gregory, Tharyan and Christidis (2013) constructs and tests the Fama-French and Carhart models in the UK context over the period October 1980 to December 2010. They find a positive size effect, although insignificant, in the UK. Whereas, the value and momentum premiums are found to be positive and significant at 10% and 5% level of significance respectively in their study. Momentum premium is also found to be higher than size and value premium in the UK market.

2.2.3 Possible Explanation of Value, Size and Momentum Premiums

There are two different schools of thoughts regarding the existence of style premium (size, value, and momentum premiums). One school of thoughts (Fama and French, 1993; Fama and French, 1995; Fama and French, 2006; Liew and Vassalou, 2000; Copeland and Copeland, 1999; Vassalou, 2003, etc.) argue that firm characteristics proxy the risk factor and the premium is the compensation of taking higher risk. Other school of thoughts (Lakonishok et al., 1994; Haugen and Baker, 1996; Daniel and Titman, 1997, etc.) argue that the source of style premium is the market inefficiencies. Meaning that, the style premium arises from the over-estimation by putting excessive weight on the past history. Psychologically, individuals who make unconventional decisions (e.g. buying unknown firms) that turn out badly have more regret than if the decisions were conventional (e.g. buying blue chip stocks). DeBondt and Thaler (1987) argue that avoidance of such regret is consistent with the size and value premium. High book-to-market (value firms) are likely to have depressed stock price and hence are out of favour. Similarly, small firms are less known and likely to be in financially precarious position. Investing in high book-to-market and small firms are courageous and less conventional, which increases require rate of return. Bodie, Kane and Marcus (2011) claim that mental accounting can also add to this regret avoidance effect. Investors become more risk averse concerning stocks with poor performance and discount their cash flows at a higher rate when they focus on the gains or losses of individual stocks, rather than on broad portfolios. This mental accounting, hence, creates risk premium. This explanation of mental accounting can also explain the momentum in stock prices. Since investors become more risk tolerant if they are currently in winning position (view investments as largely funded out of a "capital gains account"), they discount future cash flows at a lower rate and hence push up the price further.

Chandra and Reinstein (2011) explained two possible reasons for stock mispricing: post-earnings announcement drift and accrual anomaly. According to the drift theory, stock prices continue to drift in the direction of the initial price response for at least 120 trading days after the earnings announcement. Whereas, according to the accrual theory, the market fails to appreciate the accrual[2] component of earnings which is less persistent than the cash flow component of earnings. Hence market over-reacts to the earnings of a firm that include a huge amount of accrual component. When the market realises the earnings of the firm is not sustainable then in the following period the over-reaction is subsequently reversed. Identification of less consistent accruals decreases earnings persistently and leads to significant mispricing of the stocks. However, the findings of Aretz, Bartram and Pope (2010) suggest that style premiums (SMB, HML and UMD) are related to fundamentally different macroeconomic risk exposures. They conclude that, if the value of investor's liability depends on the macroeconomic factors, style investing can have an impact on hedging against or exacerbating such risks. The two different school of thoughts can be generalised by risk-based and mispricing-based explanation of style premium that is explored in this study.

2.2.3.1 Possible Explanation of Size Premium

Economic reasons of the risk and return characteristics of small firms are argued by Chan and Chen (1991). They prove that, characteristics of a firm rather than size matters for the size premium. They found a large proportion of marginal firms which have relatively lower production efficiency and higher financial leverage in the portfolio of small firms, and hence argue that small firms tend to have the characteristics of marginal firms. They argue that since marginal firms lost their market value because of poor performance, have higher financial leverage and cash flow problems; their price tends to be more sensible to economic states.

Characteristics based explanation of size premium is also given in the study of Daniel and Titman (1997); and Avramov and Chordia (2006). Avramov and Chordia (2006) assess the empirical performance of conditional asset pricing models in a framework where factor loadings may vary with firm-specific market capitalisation and book-to-market ratio as well as with business cycle-related variables. They argue that time-varying beta version of Fama-French model captures risk impact of the size of the

[2] Accruals are the expenses or assets that are recognised in the balance sheet before it is paid. Accruals are the adjustments for the revenues that have been earned but are not yet recorded in the accounts, and the expenses that have been incurred but are not yet recorded in the accounts.

firms in the expected returns. Hahn and Lee (2006) also support the characteristics based explanation of size premium. Their argument is that, since size premium is formed of portfolio returns sorted on firm characteristics, the covariance pattern may not necessarily imply that this size factor proxies for risk. Nonetheless, the persistence size characteristics of securities, in the study of Liew and Vassalou (2000), also supports the hypothesis of a risk-based explanation for the returns of size premium.

Arbel and Strebel (1983); and Beard and Sias (1997) interpret size premium as neglected firm effect. Since small firms tend to be neglected by large institutional investors, less information about smaller firms is available. Moreover, smaller firms are less monitored and carry greater likelihood that managers and insiders might exploit shareholders, Beard and Sias (1997). Small firms become "generic" stocks because of this information deficiency and greater uncertainty about firms' value. Therefore investors demand higher return to buy those "generic" stocks. The neglected firm effect is also supported by Merton (1987) who show that neglected firms might command higher equilibrium returns to compensate the risk associated with the limited information. In this sense, the size premium is not strictly market inefficiency but is a type of risk premium.

The empirical study of Bagella, Becchetti and Carpentieri (2000) suggests the persistence of size effects of the UK stock market even when risk adjusted. They find that small firms are significantly exposed to size specific risk factors but less exposed to non-diversifiable systematic risk than large firms. In contrast, Arshanapalli, Fabozzi and Nelson (2006) argue that small-cap firms are exposed to non-diversifiable risk factors (e.g. economic conditions). They find that small firms behave more like risk factors as they perform poorer during down market, recession and restrictive monetary policy.

Campbel and Vuolteenaho (2004) argue that the risk of long-term stock investment is not determined by overall market beta but by its cash flow beta (bad beta) with the secondary influence of discount rate beta (good beta). They suggest that a rational investor demands greater return of higher risk by bearing bad betas. Their empirical findings suggest the size premium in the stock market as the small-cap stocks have considerable higher cash flow betas (bad betas) than large-cap stocks.

Mispricing-based explanation of size premium is also supported by some academics. The argument of mispricing-based explanation is that size anomaly is a statistical artefact of improperly measured risk and arises due to the infrequent trading of small stocks, (Roll, 1981). Merton (1987) argues that stocks of less renowned firms with smaller investors base have superior expected return.

Daniel, Hirshleifer and Subrahmanyam (1998) argue that investors are overconfident and overreact to their private information. If the investors are biased by their self-attribution as well, they will react asymmetrically to confirming versus disconfirming pieces of the subsequent (public) information (news). More specifically, investors characterise successes to their own skill more than they should and characterise failures to external noises more than they should. This behaviour further increases the overconfidence to the confirming news. The increased overconfidence pushes the initial overreaction and generates higher return.

Information asymmetries of firms are also argued by Zhang (2006) and assert that firm's size is more like a proxy for information uncertainty, i.e., smaller firms provide poorer information to investors. The poor information about the firm's volatile fundamentals hence leads to the irrational pricing of stocks. van Dijk (2011) supports the information asymmetries and argues that the size anomalies can be due to the incomplete information of small firms.

2.2.3.2 Possible Explanation of Value Premium

The risk-based explanation of value premium ascertains that value stocks outperform growth stocks because they are fundamentally riskier in some respect. Book-to-market value and earnings yields are in fact proxies for the sensitivity of certain risk factors associated with, e.g. financial distress (Gregory, Harris and Michou, 2001). The model of Berk, Green and Naik (1999) predicts that firms' fundamentals, such as book-to-market and size (market capitalisation), proxy investment related changes in risk. They argue that firms' book-to-market ratio convey information about its changing risk and that its scale summarises the importance of its growth options relative to its assets in place. Therefore, firms decrease their systematic risk when they invest because the systematic risk of a funded investment project is lower than that of the firm's combined portfolio of assets in place and unexercised real options, ceteris paribus. Because corporate systematic risk is lower, subsequent expected returns are also smaller. Hence, investment dynamics can create an empirically positive (negative) association between book-to-market value (market value) and stock returns.

In the explanation of risk-based paradigm of value premium Zhang (2005) argue that, according to the conventional wisdom, growth option pivots upon future economic conditions. Since growth opportunities are usually the source of high betas, growth option is always riskier than assets-in-place.

The link between expected value premium and the macroeconomic variables provide support for the risk-based explanation of the value premium, (Chen et al. 2008). Their study finds a positive relationship between default spread and the expected value premium (HML) and a negative relationship between growth rate of real investment (well known pro-cyclical variable) and the expected value premium (HML). Similar argument of risk-based explanation can also be found in the studies of Maio and Santa-Clara (2011); Aretz et al. (2010); Akbas et al. (2010); Petkova (2006); Kelly (2003); Black and McMillan (2002); Liew and Vassalou (2000), etc.

Three different sources of systematic risk have been identified by Maio and Santa-Clara (2011) that might explain the value anomalies. The first source of systematic risk other than market factor arises for the time-varying betas. The second source of systematic risk arises for the reinvestment risk because the stocks are highly correlated with future investment opportunities and should earn higher risk premium as they don't have hedge for reinvestment risk. Whereas, the final (third) source of risk arises for a common macroeconomic variable, interest rates; meaning that time-varying market risk premium in the current and future period is driven by interest rate risk. Together with systematic risk, Bagella, Becchetti and Carpentieri (2000) find the significant exposure of book-to-market portfolios to size specific risk and book-to-market specific risk. In their study, the value effects of UK stock market are found to be persistence even when risk adjusted. Campbel and Vuolteenaho (2004) investigate systematic risk in terms of beta. They claim that cash-flow beta (bad beta) and discount rate beta (good beta) can capture the systematic risk associated with the stocks. The argument is that a rational investor demands greater return of higher risk by bearing 'bad' cash flow beta. Their empirical findings suggest the outperformance of value premium in the stock market as the value stocks have substantial higher cash flow betas (bad betas) than growth stocks.

The study of Hahn and Lee (2006) also support risk-based explanation of book-to-market effects. Their argument is that, since value premium (HML) is formed of portfolio returns sorted on firm characteristics, the covariance pattern may not necessarily imply that this book-to-market factors proxies for risk. The higher return of value stocks is compensation of higher risks that are not captured by the market betas. Higher loading of value stocks on term spread is the compensation of higher risk exposure to changing credit market conditions.

An alternative interpretation, however, is that value stocks outperform growth stocks because they are mispriced by the investors, i.e. investors erroneously extrapolate past performance, (Gregory, Harris and Michou, 2001). Value strategies have higher returns because they are contrarian to naive strategies followed by other investors, (Lakonishok, Shleifer and Vishny, 1994). They argue that investors extrapolate past earnings growth too far into the future by assuming that low earnings growth of value firms and the high earnings growth of glamour (growth) firms will persist for a long time before reverting to their normal level after the book-to-market portfolio formation. Glamour stocks get overpriced because some investors tend to get overly excited about the past performance of glamour stocks. Similarly, they overreact to value stocks badly and these stocks become out-of-favour. Because naive investors inappropriately underpriced (overpriced) value stocks (growth stocks) and under-invest (overinvest); upon the correction of these pricing errors, value stocks tend to outperform market, (DeBondt and Thaler, 1985; Lakonishok, Shleifer and Vishny, 1994; Haugen, 1994).

In the risk-based explanation of value premium, investors require higher rate of return to possess risky firms (i.e. firms with high book-to-market) and are priced lower, vice versa. Because valuation ratios help to identify variation in expected returns, with higher book-to-markets indicating higher required rates, value firms generate higher average returns than growth firms. Novy-Marx (2013) argues that this risk-based explanation also works in behavioural explanation of value premium, i.e. if variation in expected returns is driven by behavioural forces. If high book-to-market (low book-to-market) is underpriced (overpriced) than buying value stocks and selling growth stocks represents a simple but effective method for exploiting mispricing in the cross section. Black and McMillan (2006) argue that investors sell overvalued stocks and buy undervalued stocks in the logic that 'current loser' will outperform 'current winner'. This suggests that investors overreact to news and hence put excessive weight on recent performance and news. These investors are based on non-fundaments and are trend-chasing. If investors over-react to the news and recent performance, after a negative economic shock the market become more optimistic and hence reduces the risk premium, and accordingly required rate of return decreases as the current prices of stocks increases. According to this theory, since growth stock was the last year's winner, this transmission mechanism would have amplified effect on growth stocks and hence lowers the return below value stocks.

The behavioural explanation of Haugen (1997) ascertains that investors overreact to recent news, both good and bad. Thus, firms with recent negative abnormal profits (value stocks) tend to become underpriced at the present, and firms with recent positive abnormal profits (growth stocks) tend to become over- priced at the present. He also argues that, stocks with undiscovered abnormal profit, i.e. growth stocks, selling at reasonable prices (growth at a reasonable price) can be expected to outperform. Ahmed and Nanda (2001) find that stocks with growth at a reasonable price, defined as stocks of firms with high earnings growth but with reasonable price-to-earnings ratios, outperform other classes of stocks.

La Porta et al. (1997) analyse the past and expected future growth rates of value and glamour stocks. They define glamour stocks as stocks that had a high growth in the past and high expected future growth and define value stocks that had a low growth in the past and low expected future growth. They argue that investors fail to impose mean reversion on growth forecasts and hence value anomaly arises. To find out whether the investors make systematic errors in pricing the stocks, they examine the market's reaction to earnings. This test can be seen as a direct test of expectational error hypothesis. Since the higher returns of value strategies persist for at least 5 years, long period of positive earnings surprises for value stocks and a long period of negative earnings surprises for growth stocks are expected. Their empirical findings suggest that outperformance of value stocks arise from the expectational errors about the future earnings. They also find that the post-formation earnings announcement returns are considerably higher for value stocks comparing to glamour stocks.

Gregory, Harris and Michou (2003) assert that value and growth portfolios cannot be explained by their loadings when they are formed on the basis of past sales growth and current book-to-market ratio. They question whether the return of value investing strategy is due to the fundamental risk of the firms or investors misprice the value of the firms. However, they conclude that value stocks are not fundamentally riskier as their findings do not provide the evidence that the value strategy does worse in adverse economic states. Indeed, the opposite is found to be true, supporting the mispricing theory rather than rational risk-based theory.

Athanassakos (2006) puts further lights on the value premium and how the value premium is driven by doing an out-of-sample experiment of Canadian stock market. He argues that value investors look for undesirability that includes bankrupted firms or firms affected by severe financial distress, firms suffer from overcapacity, an unexpected increase in import, and the threat of legislative or regulatory penalty. He argues for the combination of risk and mispricing-based explanation of value premium. The logic is that undesirability because of financial distress indicates higher risk, however, it also indicates the less aspiration of holding stocks by institutional investors and hence possible mispricing. His empirical findings reject the risk-based explanation of value premium (consistent with Lettau and Wachter (2007)) and accept the mispricing explanation of value premium. He concludes that, risk-adjusted returns of value stocks are higher than growth stock not because the value stocks are riskier according to traditional measures (potentially beta) but because the investors make systematic errors by paying too much for winners (potentially glamour stocks) and too little for losers (potentially boring companies, poor performing, unknown and unloved companies).

2.2.3.3 Possible Explanation of Momentum Premium

Rational risk-based explanation of momentum premium is the compensation of bearing risk because winner stocks are riskier than loser stocks (e.g., Conrad and Kaul, 1998; Berk et al., 1999; Liu and Zhang, 2008). Li et al. (2008) hypothesise that momentum premiums are the compensation of time-varying unsystematic risk. They find that the volatility of winner stocks are more sensitive to recent news and less persistent comparing to loser stocks. However, the volatility of loser stocks is found to be more sensitive to distant news and more persistent comparing to winner stocks. They conclude that both winner and loser stocks response asymmetrically to good news and bad news; and the conditional risk premium can explain the profitability of momentum premium. However, Maio and Santa-Clara (2011) argues for systematic risk (time-varying betas, reinvestment risk, macroeconomic variable) that might explain the momentum anomaly. Alternatively, the model of Johnson (2002) explains that dividend growth rate risk is proportionate to expected growth rates. If this risk carries a positive price, then expected returns covary positively with past growth rates.

The explanation of Ang, Chen and Xing (2001), on the other hand, is that momentum profits arise not due to the variation in regular risk but for the downside risk which seems to have more explanatory power regarding momentum profits. They find that momentum portfolios of past winner stocks have a greater exposure to downside risk, measured by higher correlations conditional on downside moves of the market, than momentum portfolios of past loser stocks. Hence, they conclude that momentum profits are a compensation for this higher downside risk. While Ang, Chen and Xing (2001), focus on the impact of market downturns, several other studies examine the impact of the macroeconomic variables on the momentum profit. Chordia and Shivakumar (2002) document that momentum profit is linked to common factors in the macro economy. Furthermore, momentum profit is driven by the strategy which ranks stocks on the basis of the returns predicted from the lagged macroeconomic variables. The authors conclude that the momentum profit is linked to common factors in the macro economy. Griffin, Ji and Martin (2003) extend the work of Chordia and Shivakumar (2002) to the international context. However, they do not find any evidence that lagged macroeconomic variables can explain momentum.

Momentum anomaly in the study of Chordia and Shivakumar (2002) is so far defied risk-based explanations. The behavioural theories of momentum premium suggest that investors' psychological biases in the reaction to information may be causing systematic underreaction, resulting continuation of short-term returns. However, the persistence of momentum returns long after the anomaly has been widely disseminated suggests that behavioural theories may not provide the full picture.

On the contrary, DeBondt and Thaler (1985) argue that investors overreact to unexpected and dramatic news events. Investors tend to overweight recent information and underweight prior (or base rate) data. Consistent with their overreaction hypothesis, they find that past losers outperform past winners even though past winners are significantly riskier. They also find the asymmetric overreaction effect; that is the overreaction is larger for losers than for winners. Daniel, Hirshleifer and Subrahmanyam (1998) also develop a plausible model based on a similar psychological argument which includes investors' overreaction and self-attribution bias. They argue that investors are overconfident and overreact to their private information. If the investors are biased by their self-attribution as well, they will react asymmetrically to confirming versus disconfirming pieces of the subsequent (public) information (news). More specifically, investors characterise successes to their own skill more than they should and characterise failures to external noises more than they should. This behaviour further increases the overconfidence to the confirming news. The increased overconfidence pushes the initial overreaction and generates return momentum.

The theory of Daniel, Hirshleifer and Subrahmanyam (1998), according to Cooper, Jr and Hameed (2004), can be extended to predict differences in momentum profits across different states of the market. The argument is that aggregate overconfidence should be greater following market gains. Since investors, on average, hold long positions in the equity market, increases in market prices will tend to be attributed excessively to investors' skill and generate greater aggregate overconfidence. If overconfidence is, in fact, higher following market gains, then the overreactions will be stronger following these up markets and therefore generate greater momentum in the short run.

Nevertheless, investors irrationality based explanation of momentum premium is loser-centred. Wang and Xu (2010) argue that investors react differently to negative information during different phases of economic cycles. Investors overreact to negative aspects associated with loser stocks during down market and hence over-sold them whereas, investors underreact to negative aspects during upmarket and hence over-bought the prior loser stocks. They conclude that momentum premium cannot be fully explained by the risk-based theory, but can be explained by irrationality based theory.

Lo and MacKinlay (1990) demonstrate that autocorrelation in returns, cross-serial correlation (lead-lag relations among stocks), or cross-sectional dispersion in unconditional means can create momentum in stock returns. Intuitively a stock that outperformed other stocks in the past might continue to do so for three reasons: firstly, the stock return is positively autocorrelated, so its own past return predicts high future returns; secondly, the stock return is negatively correlated with the lagged returns on other stocks, so their poor performance predicts high future returns; and thirdly, the stock simply has a high unconditional mean relative to other stocks. Lewellen (2002) argues that autocorrelation patterns in stock returns are empirically inconsistent with portfolio specific underreaction. He reports negative auto-correlation and cross-serial correlation in style portfolios and argues that stronger cross-serial correlation between style portfolios rather than auto-correlation generates momentum profits.

The behavioural model of Hong and Stein (1999) comes up with two types of investors, namely 'news watchers' and ‘momentum traders’, with different information sets but acting rationally with their information. The momentum traders invest in simple trading strategies, conditioning their demand for the price continuation of stocks. Whereas, the news watchers base their value of the firm on the fundamental news that is available to them at a certain point in time. Subsequent positive serial correlation in returns attracts the attention of the momentum traders whose trading activity results in an eventual overreaction to news. Their model also implies positive serial correlations on investment styles in the short run and negative serial correlations in the long run, generating long-run mean reversion. Parts of this model are empirically validated in Lewellen (2002), who finds similar correlation patterns.

The strong contribution of Liu, Strong and Xu (1999) in the literature of momentum investing is the detailed study of the potential sources of momentum profits. They consider several possible risk explanation for momentum profits by controlling risk (beta), size, price (market value), book-to-market ratio or cash earnings-to-price ratio using the Fama-French three-factor model. Their empirical study shows that neither systematic risk nor total risk can explain the momentum profits on the UK. Momentum profit is also not likely to be because of high book-to-market effect and also there is not a strong support for the cash flow or price explanation. Moreover, they reject the likelihood of data-snooping as the momentum profits are consistent across different stock markets. The findings of Liu, Strong and Xu (1999) support the behavioural theories to explain momentum profits as a result of systematic departures from the investor rationality model.

Moreover, the empirical findings of Scheurle and Spremann (2010) do not provide support that the outperformance of momentum strategies are compensation of risks associated to difference phases of economic cycles. They find that in lag 1 and lag 3 months after economic peaks the momentum returns are higher. During that time the investors are enthusiastic about the economy and stock market returns and the naive investors who buy recent winner stocks might be attracted. They conclude that if momentum returns are real than behavioural explanation might hold.

Ovtchinnikov and McConnell (2009) argue that firm’s investment opportunities are reflected in its stock price and the positive relationship between stock price and investment is the by-product of their positive relationship with investment opportunities. This argument is consistent with the logic that firms with higher (lower) growth opportunities have higher (lower) price. Hence past winners would invest more than past loser because they have better investment opportunities. Moreover, Maio and Santa-Clara (2011) argue that stocks (winner firms) that are highly correlated with future investment opportunities should earn higher risk premium as they don’t have hedge for reinvestment risk.

On the other hand, equity issuance channel of Baker, Stein and Wurger (2003) imply that past winners would invest more than past losers as they can issue more overpriced shares to finance their investments that would not otherwise be undertaken. This is consistent with the rationale of higher (lower) stock prices of firms with higher (lower) growth opportunities. As investors welcome the new efficient investments, past winners might be further mispriced, and the return continuation might be sustained. An alternative view is provided by Polk and Sapienza (2009) who argue that if past winners and past losers are mispriced due to investors misjudging their investments, past winners might continue to invest to maintain their upward price movement, hence the return continuation persists.

2.2.4 Cyclical Asymmetries in the Expected Style Premiums

During the uncertain states of the economy, the investors are more likely to react to the news, (Chung, Hung and Yeh, 2012). In the uncertain period the expected future volatility and required return of stocks are expected to rise, and hence driving the stock prices down. The investors' sentiment to the news might create asymmetries in the stock market return across different economic regimes. "For example, suppose that the current economy is in the recession state and π_t, the conditional probability that the economy is staying in the expansion state, is assumed to be 0.1 in reflecting the idea that investors believe times are bad. Bullish sentiment may give rise to an increase in the stock price. This increase can be regarded as a positive price shock and drive up π_t close to 0.5, the point of maximum uncertainty about the economy. Hence, the overpricing caused by bullish sentiment may be offset by the stock price drop due to the increased uncertainty. In contrast, when the economy is in the expansion state, π_t is assumed to be 0.9 because investors believe times are good. The increase in stock prices caused by bullish sentiment is seen as a positive price shock and then πt approaches one, the point without uncertainty. This decreased uncertainty may further increase stock prices. The overpricing caused by bullish sentiment is strengthened by the decreased uncertainty." Chung et al. (2012). Cooper, Jr and Hameed (2004) document that, asymmetries are conditional on the state of the market and hence complement the evidence of asymmetries in factor sensitivities, volatility, correlations, and expected returns. They argue that asset pricing models, both rational and behavioural, need to incorporate (or predict) such asymmetries.

An influential amount of empirical studies investigates the relation of value, size and momentum premiums with macroeconomic factors as well as different states of the economy. It is natural to suppose value, size and winner stocks would more sensible to recessions than other stocks. And hence value, size and momentum premiums will emerge accordingly. This section reviews the existing literature and the possible sources of cyclical asymmetries in style premiums.

2.2.4.1 Cyclical Asymmetries in the Size Premium

A variety of sources can cause asymmetries in small and large firms and accordingly expected return over different phases of the business cycle. The sources of finance for small and large firms are different and have very different degrees of access to the finance. Hence small and large firms are supposed to be affected differently by credit market constraints. Since the credit market constraints are time varying, the small firms should be affected adversely by worsening credit market conditions during the economic downturn, (Perez-Quiros and Timmermann, 2000). On the other hand, Chan and Chen (1991) examine the characteristics of different size firms with the same economic news. They prove that, characteristics of a firm rather than size matters for the size premium. They find a large proportion of marginal firms (have relatively lower production efficiency and higher financial leverage) in the portfolio of small firms, and hence small firms tend to have the characteristics of marginal firms. They argue that since marginal firms have lost market value because of the poor performance, have higher financial leverage and cash flow problems; their price tends to be more sensible to the economic states. Kim and Burnie (2002) assess the hypothesis of Chan and Chen (1991), i.e. whether small firms generate large abnormal profit in the economic expansion. Their empirical findings confirm the small firm effect in the economic expansion. They document that during economic expansion small firms generate large abnormal profit. The rationale is that small firms have low productivity and high financial leverage. That’s why in good economic conditions small firms grow faster than large firms; whereas in the worst economic condition the performances of small firms are poor. Based on this economic rationale this study assumes that there is no significant firm size effect in economic contraction.

The study of Kim and Burnie (2002) asserts the differential small and large firms’ return as the state of business cycles. They postulate the underperformance of small firms during economic downturns for the relatively less productive performance and high financial leverage over economic contractions. Following this study (Switzer, 2010) provides evidence of small firm anomalies in US and Canadian stock market and examines that, whether or not this anomaly is due to the business cycles, default risk, interest rate risk or inflation risk. His empirical findings of the US market show that even the coefficients of term structure and inflation are positive, they are not significant. But default risk is significant for small firm premium or size premium. On the contrary, the effect of recession found to be significant only for two cases (1937-1938 and 1969-1970).

Scheurle and Spremann (2010) argue that negative returns of size premium (SMB) near peaks highlight the poor returns of small-cap firms during upper economic turning points. Nevertheless, the positive returns of size premium near troughs highlight the superior performance of small-cap firms during lower economic activity. Therefore, size premium probably reflects macroeconomic risks that are associated with economic cycles. They find that because of the level of diversification with respect to imperfectly correlated business activities small-cap firms show higher return whereas large-cap firms show moderate return during an improving economy. Moreover, during contraction period the credit market conditions are tighter and hence smaller companies who are more dependable to loans face difficulties.

A positive relationship would exist between GDP growth and SMB (size premium) if the high return in SMB is associated with future good states of the economy, (Liew and Vassalou, 2000). That means that small capitalisation firms are better able to prosper than big capitalisation firms during the period of high economic growth. Their empirical findings provide the evidence of a positive relationship between GDP growth and size premium. On the other hand, investors would rather hold stocks whose returns are relatively high when they presume about the future bad economic conditions. Therefore they would hold big capitalisation firms with good growth opportunities and low debt ratios. Avramov and Chordia (2006) find the significant variation in the factor loading of size premium which is related to economic states. Using the dummy variable approach to define business cycles, they find a significant correlation between factor loading of size premium and recession; suggesting that risk of holding small-cap stocks, accordingly size premium (SMB), increase during recessions. However, Arshanapalli, D'Ouville and Nelson (2004) find only marginal evidence of the size stock and recession relations in their study of the time-varying structure of size premium during the downturn.

Whereas, Gala (2005) look for the explanation of size effects from investors' perspective. He argues that investment irreversibility plays a vital role in explaining the size effects in stock returns and their relation to risk and firms' fundamentals. During bad times the cost of capital adjustment and investment irreversibility deprive small firms' flexibility in cutting capital, causing the small firms riskier than large.

2.2.4.2 Cyclical Asymmetries in the Value Premium

To explain the sources of time variations in expected value premium investment based asset pricing theories can provide some clues. Gulen, Xing, and Zhang (2011) argue that due to a variety of sources value firms are not flexible as growth firms in mitigating recessionary shocks, these firms are riskier than growth firms in recession. Therefore, since during recession the risk of value firms are higher the investors expect higher returns for holding value stocks than holding growth stocks.

Three distinct sources: costly reversibility, operating leverage and financial leverage can raise the relative inflexibility of value firms. Costly reversibility means the higher cost of firms' to scrap down the scale of productive assets than expand. The value firms want to disinvest more in the economic downturn because the assets of value firms are less profitable than growth firms; whereas this disinvesting is less important for growth firms, Gulen, Xing, and Zhang (2011). Since disinvesting is restricted by costly reversibility, the fundamentals of value firms are affected more severely than the fundamentals of growth firms in the economic downturn when the credit market conditions are bad.

Operating leverage is also a source of time variation of expected value premium. When the demand of the product of a firm decreases stock prices of the corresponding firm also decreases. This decrease is in-line with book values and average values of the corresponding firm, i.e. stocks fall relative to book values and revenue falls relative to average values. Since, stock prices and revenues of value firms fall more relative to book values and average level, respectively, the value firms ought to have higher operating leverage than growth firms. Moreover, fixed costs of firms do not decrease proportionally with revenues in the economic downturn; and hence the earnings (revenue minus fixed and variable costs) will decrease more than proportionally relative to revenues. This operating leverage mechanism will have adverse effects on value firms by the negative aggregate shocks during the economic downturn. Gulen, Xing, and Zhang (2011) show that since value firms are not flexible as growth firms in mitigating recessionary shocks, these firms are riskier than growth firms in recession. Moreover, the fundamentals of value firms are affected more severely than the fundamentals of growth firms in economic recessions. They concluded that expected value premium shows an upward spike during recessions, which follows a gradual declining in the subsequent expansions. Operational leverage of value premium is also acknowledged in the study of Zhang (2005). He argues that firms find it hard to scale down the unproductive capital during the economic downturn. Moreover, in comparing to growth firms, value firms have more assets in place and they are riskier during the economic downturn when the price of risk is high.

Scheurle and Spremann (2010) argue that value firms have higher book value than their market value and hence need for reorganisation. Managements need to take steps to avoid bankruptcy and to increase market value. Value firms are in a vulnerable situation during reorganisation project as the project locks resources and management focuses on the company rather than the economic condition. Since reorganisation project may fail during worsen economic conditions, value stocks react well in advance to an upcoming recession and hence exhibits asymmetric behaviour during different phases of economy cycles.

Financial leverage might affect risk and expected return in two possible channels, Livdan, Sapriza, and Zhang (2009). The first channel based on the standard leverage hypothesis. According to this hypothesis, higher financial leverage indicates the proportion of risk that the shareholders bear and hence demand higher risk premium. The second mechanism is the inflexibility of underlying asset risk that increases with leverage. Since firms with higher leverage are burdened with more debt and pay more interests, these firms are likely to face binding collateral constraints. These firms are also less flexible to use investment to smooth dividends and hence riskier. The value firms are characterised with higher leverage and investors require higher expected returns to hold higher levered stocks during the economic downturn when the value firms are more exposed to the financial constraints.

In a different perspective Gala (2005) argues that the riskiness of firms can be derived from their ability to provide consumption insurance. However, this ability depends on the way the firms assure smooth dividend during the economic shocks which in turn depends on the cost of capital adjustment and irreversibility of firms' investment. During recessions value firms face high capital adjustment costs and investment irreversibility- causing them riskier than growth firms. On the other hand, during good times ability of providing smooth dividend is more or less same for value and growth firms because they are less likely to face investment irreversibility constraint.

The time varying liquidity risk also plays an important role in explaining the asymmetries of value premium during different economic conditions. Akbas et al. (2010) argue that during bad time value stocks have higher liquidity betas than in good time, while the growth stocks experience the opposite. Because of this fact value stocks have higher market risk during bad times than growth stocks. Moreover, because investors want to be in the safe side during bad times they may want to liquidate value stocks more aggressively than growth stocks. This increased selling pressure can make the value stocks more sensitive to liquidity risk during bad economic conditions.

Liew and Vassalou (2000) argue that, if the high return in HML is associated with the future good economic state a positive relationship would exist between GDP growth and HML - meaning that high book-to-market firms (value firms) are better able to prosper than low book-to-market firms during the period of high economic growth. Their empirical findings provide the evidence of a positive relationship. On the other hand, investors would rather hold stocks whose returns are relatively high when they presume about the future bad economic conditions. Hence they would hold low book-to-market firms (growth firms) with good growth opportunities and low debt ratios. Black and McMillan (2005) seek the evidence of whether or not the value premium arises from the inherent risk of value stock, and thus whether such risk is due to changes in macroeconomic conditions. The empirical results support the asymmetric behaviour of returns over macroeconomic factors. Portfolio returns respond more to the changes in interest rates and money supply over the recessionary period than the expansionary period. However, their study provides evidence that stock prices exhibit random walk behaviour in the expansionary period (i.e. the parameters are insignificant).

In contract, consistent with the findings of Athanassakos (2006), Kwag and Lee (2006) find the outperformance of value stocks over growth stocks regardless of economic conditions; i.e. both in economic expansion and contraction.

2.2.4.3 Cyclical Asymmetries in the Momentum Premium

Log price-dividend ratio is a convex function of expected growth, (Johnson, 2002). Because of this convexity, during the high expected growth the log price-dividend ratios or stock returns tend to be more sensitive to changes in expected growth. If GDP growth or Industrial Production growth is a factor that summarises the firm-level changes in expected growth, then loadings of GDP growth or Industrial production growth should be high among stocks with high expected growth and low among stocks with low expected growth. Consistent with this argument, Liu and Zhang (2008) find that winners (stocks with high expected growth) have higher short-term average future growth rates than losers. Griffin, Ji and Martin (2003) examine whether the macroeconomic risk can explain the momentum premium. They argue that, if momentum return relates to economic distress risk then negative momentum would be expected when the distress risk is realised; that is during low or negative GDP growth. However, their results suggest a positive momentum return both in the economic downturn (negative GDP growth) and upturn (positive GDP growth).

Chordia and Shivakumar (2002) examine the time-varying expected returns of momentum premium. They show that momentum premium is positive during expansionary periods when the marginal utility of returns is likely to be lower and is negative during economic recessions. This evidence suggests the time-varying expected return of momentum premium. Scheurle and Spremann (2010) find positive expected momentum return in most of the observed phases of economic cycles. However, from time to time expected momentum returns indicate opposite signs comparing to aggregate market. During peak when the broad market goes down momentum returns are significantly positive, whereas during trough when the excess market returns are significantly positive momentum returns are significantly negative.

They argue that these asymmetries might be attributable to cross-sectional differences in risk that is in expected returns.

With the use of dividend adjusted monthly UK stock prices, Li et al. (2008) find that profitability of momentum strategy is the compensation of time-varying unsystematic risk. They further added that winner stocks are affected by time-varying unsystematic risk more than loser stocks and hence explain the outperformance of winner stocks. They find that the volatility of winner stocks are more sensitive to recent news but less persistent comparing to loser stocks. However, the volatility of loser stocks is found to be more sensitive to distant news and more persistent comparing to winner stocks. They conclude that both the asymmetric response of losers stocks to good news and bad news, and the conditional risk premium can explain the profitability of momentum premium.

However, Avramov and Chordia (2006) argue for the asset pricing misspecification. They develop a framework for single securities to justify asset pricing model explanation of value, size and momentum premiums of NYSE, AMEX and NASDAQ listed companies over the period of July 1964-December 2001. They looked for whether factor loadings vary with firm-specific market capitalisation, book-to-market as well as business cycles. They find that past returns can significantly predict future returns and exhibit about 1% abnormal returns of momentum investment strategies. They also conclude that momentum profits are consistent with asset pricing misspecification that varies with business cycles. Their results point out systematic rather than idiosyncratic sources of momentum premium.

On the other hand, in a behavioural perception Wang and Xu (2010) argue that investors fear to hold prior loser stocks, particularly the stocks with low credit rating or high information uncertainty, in down market when the volatility is high. Since investors oversell prior losers to avoid uncertainty or the risk of default during down market, the consequent price reversal of prior loser gives rise of low momentum payoffs. However, in upmarket investors are overconfident and overlook the negative aspects of prior loser stocks to some extent. Investors are keener to buy cheap stocks e.g. prior loser stocks that have higher information uncertainty or higher default risk, generating high momentum returns. The over-reaction of investors during down market generates higher return of prior loser stocks because those stocks are oversold that time. However, the under-reaction of investors during upmarket generates lower return of prior loser stocks because those stocks are overbought that time.

2.2.5 Style Premiums and Macroeconomic Variables

According to the theory of finance, the asset prices are determined by the expected future cash flow changes and the corresponding discount rate. Hence the observed return differences of different firms should be characterised by the reactions of corresponding firms to their cash flow and discount rates. However, the future cash flow and discount rates vary according to the economic conditions. Moreover, the firms' behavioural differences to economic conditions are likely to be because of the variations of underlying fundamentals of different types of firms, (Michou, Mouselli and Stark, 2007).

Chan and Chen (1991) argued that small firms lost market values because of poor performance and are more likely to have high financial leverage and cash flow problems. Small firms are marginal in the sense that their stock prices tend to be more sensitive to the changes of economic conditions and are less likely to survive adverse economic states. “For example, in a competitive economy with continuing technological changes, firms that become relatively inefficient or have higher costs will decrease in relative size. While a more efficiently run firm may do well and even prosper if the aggregate economy is growing slowly, a less efficiently run firm may not survive a low growth rate for very long. Furthermore, firms that suffer from past misfortunes tend to be smaller in size. If they do not change their capital structure accordingly, they have higher financial leverage. In addition, if information is imperfect in the capital market, poor past performance and high current financial leverage may restrict the firms' accessibility to external financing, especially during tight credit periods. Consequently, the same piece of economic news affects the return of a portfolio of small firms, which tends to contain a higher proportion of these marginal firms, more than it affects the return of a portfolio of large firms” (Chan and Chen, 1991). Hence, marginal firms react differently from healthier firms to the same piece of macroeconomic news.

SMB, HML and UMD are risk factors as well as proxies the size, value and momentum premiums respectively. An influential amount of studies looks for the relationships between size, value, and momentum factors and macroeconomic variables to understand the economic sources behind those premia. The following section will review the existing literature that explains and find the possible link of style factors with macroeconomic variables: GDP growth, inflation, interest rates, term spread, credit spread and money supply.

2.2.5.1 Size Premium and Macroeconomic Variables

Small firms with little collateral seem to be affected strongly by credit market conditions, (Perez-Quiros and Timmermann, 2000). They document that, small firms are strongly affected by the worsening credit market conditions, hence macroeconomic variables that measure credit market conditions, e.g. interest rates, money supply, and default spread, has a significant effect on size premium. However, these variables produce higher degree of variation during the recession as the credit market become tighter during the recession.

Bagella, Becchetti and Carpentieri (2000) analyse the determinants cross-sectional stock returns of London Stock Exchange over the period July 1971 to June 1997. They look for the sensitivity of size strategy with GDP growth. They find the low covariance (-0.13) of small size firms with GDP compared to large firms (1.38). These findings suggest that the small firms (size premium) are less exposed to non-diversifiable systematic risk than large firms. Liew and Vassalou (2000), also test for the possible relationship of future GDP growth with size premium. Using univariate and bivariate regression in ten countries they find that, size premium contain significant information about future GDP growth. They document these findings during both good and bad states of business cycles in ten sample countries. Consistent with Liew and Vassalou (2000) and Vassalou (2003); Gregory, Harris and Michou (2003) find positive correlation of future GDP growth with both value and size premium. They also find a positive relation between size premium and Treasury bill rate, but the relation is negative with lagged yield and again positive with term structure. Vassalou (2003) shows that news related GDP growth is an important factor in explaining the size portfolios. Her empirical findings confirm the earlier findings of Liew and Vassalou (2000) that size premium is correlated with nominal

GDP growth. The findings of Kelly (2003) also confirm that size premium is correlated with shocks in real GDP growth.

Kelly (2003) investigates the relationship of size premium (SMB) with real economic growth and unexpected inflation in 18 countries. He finds a positive and significant relationship between GDP growth and SMB. He also finds that SMB is negatively correlated with unexpected inflation at five (ten) percent level of significance in five (five) countries.

Campbel and Vuolteenaho (2004) explore that the value of a portfolio may decrease as the investors receive bad news about future cash flows, and it may also decrease as the investors increase the discount rates. Their empirical findings suggest the size premium in the stock market as the small-cap stocks covary more with cash flow than large-cap stocks.

Hahn and Lee (2006) examine the relationship of size premium (SMB) to the alternative risk factors (e.g. term spread and default spread). Their time series regression suggests that consistent with Petkova (2006), shocks to the term spread is insignificant when explaining size premium. The study of Petkova (2006) investigates whether shocks in macroeconomic variables that predict time-varying investment opportunities have impacts on size premium. Their findings suggest that SMB is significantly related to macroeconomic variables that predict the excess market return and its variance. More specifically, her time series regression model indicates a negative and significant default spread (credit spread) in explaining SMB factor. However, term spread is found to be insignificant in explaining the SMB factor. The interest rate is found to be positive with a very low coefficient (0.01) but insignificantly related to SMB.

Mouselli, Michou and Stark (2008) examine the linkage between size and value premiums to shocks in macroeconomic variables that predict future investment opportunities. They find that future economic growth has the significant positive effect on the SMB factor. Contradicting to the findings of Perez-Quiros and Timmermann (2000) and Hahn and Lee (2006) they find a significant positive loading of default spread (credit spread) with SMB factors. However, terms spread and the risk-free interest rate is found to be positive but insignificant, and negative but insignificant with SMB factor respectively.

The study of Aretz, Bartram and Pope (2010) examines the multivariate relationship between size, value, and momentum premiums with the macroeconomic factors. They report that size of the firm conveys information about the term structure risk and there is a positive relationship between size premium and term structure of interest rates. The relationship between size premium and unexpected inflation is found to be negative in their study.

Switzer (2010) provides evidence of small firm anomalies in US and Canadian stock market and examines whether or not this anomaly is due to three risk variables: default spread (credit spread), term spread, and inflation. He used the data of the US and Canadian stock market for the period of 1926 to 2010. His results of the US market show that even the coefficients of term structure and inflation are positive, they are not significant. But default risk is positive and significant for small firm premium or size premium.

Chung et al. (2012), perform the Multivariate Markov-Switching model of the US market over the period of 40 years (January 1966 to December 2005). They find a positive credit spread (default) for the size premium (SMB) both in economic expansion and recession. During economic expansion, the interest rate is found to be significantly positive with SMB but during the recession, the interest rate is found to be positive although insignificant.

2.2.5.2 Value Premium and Macroeconomic Variables

According to the model of Maio and Santa-Clara (2011), value stocks have higher return than growth stocks because of the interest rate risk (higher negative loadings on the hedging factor). They argue that value stocks have higher expected returns than growth stocks because value stocks are more exposed to the change in macroeconomic variables, i.e. value stocks have more negative loadings on the hedging factors. The reason behind the sensitivity (negatively) to unexpected rises in short-term interest rates is that value firms are near financial distress as a result of successive negative shocks to their cash flows, (Fama and French, 1992) and hence are more sensitive to the rises in short-term interest rates. According to the credit channel theory of monetary policy (Bernanke and Gertler, 1995), monetary tightening increases the financial costs and restricts the access to external financing. This monetary tightening has a stronger effect on the firms in poorer financial positions, typically the firms with higher cost of external financing and relatively depressed asset values. An increase in short-term interest rates would thus constrain the access to financial markets and restricts investments in profitable projects. This argument is consistent with the analysis of Lettau and Wachter (2007) who showed that value stocks are more sensitive to near-term cash flow shocks whereas the growth stocks are sensitive to discount rate (long-term expected return) shocks.

Black (2002) used TGARCH model in addition to Regression analysis to find out the impact of monetary policy on the mean and conditional variance of the return of value and growth stocks. He used data from 1975-2000 of 17 countries and find that monetary policy has asymmetry effect on growth and value stocks. He suggests that Federal Reserve Bank do react by adjusting the interest rates to protect stock market price. Intuitively, an increase in the short-term interest rate also increases the opportunity cost of holding money and causes substitution between stocks and interest-bearing securities which leads to the fall of stock market prices. However, the empirical findings of Black (2002) suggest the evidence of an asymmetric relationship between monetary policy and the return of growth and value stocks.

Worsening economic conditions, a measure by interest rates and default spread, has significant effect on value premium, specifically on recessionary periods, Gulen, Xing, and Zhang (2011). They argue that value firms are riskier than growth firms in the recession because they are less flexible than growth firms in mitigating recessionary shocks, and this inflexibility increases the cost of equity in the cross section. A positive relationship between default spread and the expected value premium (HML) is also found in the study of Chen, Petkova and Zhang (2008). Chung et al. (2012) also look for the asymmetric relationship between macroeconomic variables and value premium as suggested by Gulen, Xing, and Zhang (2011). In their study, for value premium (HML) credit spread (default) is found to be positive during the economic recession and negative during the economic expansion, although both are insignificant. However, the interest rate is found to be positive but insignificant for HML factor in both economic expansion and recession. The findings of Arshanapalli, Fabozzi and Nelson (2006) coincide with asymmetric behaviours of value premium during economic conditions. In the study of style premiums under different macroeconomic regimes in the US market over the period of January 1962 to June 2005, their findings confirm a positive relationship between credit spread and value premium. They argue that value stocks perform poorer during high credit spread than low credit spread.

Kelly (2003) investigates the relationship of Fama-French factors with real economic growth and unexpected inflation in 18 countries. His empirical findings confirm the positive and significant relationship between HML and GDP growth. He also finds that the unexpected inflation is positively correlated with HML at five (ten) percent level of significance in one (one) country. Wei (2009) argue that increasing inflation is ‘good news’ for stocks during economic expansions and ‘bad news’ during economic contractions, and hence stock market exhibits asymmetric behaviour to unexpected inflation across business cycles. His empirical findings suggest the cyclical pattern of inflation betas across value and size portfolios. Moreover, the growth firms (low book-to-market ratios) are bad hedges for unexpected inflation during recessions and hence are more negatively correlated with unexpected inflation.

Liew and Vassalou (2000), test for the possible relationship of future GDP growth and value premium. Using univariate and bivariate regression in ten countries they find that value premium contains significant information about future GDP growth. They document these findings both good and bad states of business cycles in ten sample countries. Gregory, Harris and Michou (2003) go through a comprehensive investigation to look for the relationship between macroeconomic state variables with the value investment strategy. Consistent with Liew and Vassalou (2000) and Vassalou (2003), they find positive correlation of future GDP growth with both value and size premium. They also find a positive relation between value premium and Treasury bill rate, but the relation is negative with lagged yield and again positive with term structure. Vassalou (2003) argue that news related GDP growth is an important factor in explaining the value portfolios. Consistent with the findings of Liew and Vassalou (2000); and Kelly (2003), she confirms that value premium is correlated with nominal GDP growth.

Hahn and Lee (2006)) investigate the relationship between size and book-to-market factors with alternative macroeconomic factors (e.g. term spread and default spread). They argue that innovations of term and default spread capture the market's expectations about the future credit market conditions and interest rates. Since value firms are vulnerable to worse credit market conditions and high interest rates, they tend to have high financial leverage and cash flow problems, Fama and French (1992, 1995). Fama and French (1992) assert that, the book-to-market ratio is the difference of market leverage (the ratio of book value of asset to market value of equity) and book leverage (the ratio of book value of asset to book value of equity). Hence the value firms i.e. firms with high book-to-market ratios (high market leverage relative to book leverage) have a huge amount of market-imposed leverage. A decrease in interest rates is likely to have a larger positive impact on high levered firms than on less levered firms. Since when the interest rate decreases (increases) the term spread increases (decreases), we can expect that an increase (decrease) in the term spread is associated with higher (lower) return in average value premium. Their empirical findings suggest a shock to the term spread is positive and significant when explaining value premium.

In a similar manner, Petkova (2006) investigates whether shocks in macroeconomic variables that predict time-varying investment opportunities have an impact on value premium. Their findings suggest that value premium (HML) is significantly related to macroeconomic variables that predict the excess market return and its variance. More specifically, she finds a significant positive relationship between term spread and value premium. Whereas, default spread (credit spread) is found to be positive but insignificant, and the interest rate is found to be negative but insignificantly related to value premium. Similar to Petkova (2006), Mouselli, Michou and Stark (2008) also examine the relationship between size and value premium to shocks in macroeconomic variables that predict future investment opportunities. They find that HML factor covaries negatively (and significantly) with future economic growth. Moreover, default spread (credit spread) is found to be positively and significantly related to HML, suggesting that firms with high book-to-market ratios (with persistently poor earnings) are adversely affected by default risk than those of low book-to-market ratios. However, terms spread is found to be positive but insignificant, and the risk-free interest rate is found to be negative but insignificant with HML factor.

Alternatively, Akbas et al. (2010) argue that if investors tend to switch riskier to safer asset during bad economic conditions (if the flight to quality) there will exist a negative coefficient on credit (default) spread and positive coefficient on term spread because credit spread is countercyclical and term spread is procyclical. Their study of the US market over the period 1927-2008 also confirms the relationship.

Aretz, Bartram and Pope (2010) hypothesise the risk exposure of a firm’s value characteristics to the macroeconomic factors as systematic reflections. Based on the US data, they find that value premium is significantly related to the changes in economic growth, unexpected inflation and slope of the term structure (term spread). Both the unexpected inflation and slope of the term structure are found to be positively related to value premium.

Black and McMillan (2002) extended the literature by examining the relationship of macroeconomic variables with long-run value premium of US, UK and Japan monthly data over the period January 1975 to December 2000 (For US January 1975 to June 2006). They sought the literature where IP, Interest rates and Inflation are theoretically and empirically co-integrated with stock market prices. They used Vector Error Correction Model (VECM) to test the co-integration between macroeconomic variables and stock prices. Their results suggest a significant negative relationship between value premium and interest rates, and value premium and industrial production in UK and US. Also, the relationship between inflation and value premium are positive and significant in both US and the UK. While in Japan, the value premium shows positive relations with both the industrial production and interest rates but negative relation with inflation.

2.2.5.3 Momentum Premium and Macroeconomic Variables

The ignorance of momentum effect by Fama and French (1992) is criticised by Cochrane (2005). He argued that momentum effect is correlated with value effect and it is tempting to extend macroeconomic explanation of value effect to momentum effect. Several other empirical studies prove his argument. Aretz, Bartram and Pope

(2010) look for the evidence of theoretically motivated multivariate relationship of momentum effects to the macroeconomic variables. Their empirical findings reveal the significant negative relationship of momentum premium with term structure of interest rates, but find a negative but insignificant relationship with economic growth and unexpected inflation.

If the Fisher theory holds and stocks provide hedge against inflation then the relationship between inflation and stock return supposed to be positive, Biglova and Rachev (2009). Hence, the momentum premium should be positively related to inflation. However, the money supply should also positively relate to stock prices as the growth in money supply will also increase the inflation. Consistent with this argument, Biglova and Rachev (2009) find a positive relationship between momentum premium and inflation; and momentum premium and money supply.

Chordia and Shivakumar (2002) show that momentum premium can be explained by macroeconomic factors that are related to business cycles. They find a positive relationship between term spread and momentum premium in both regressions that excludes and include January dummy. However, the credit spread (default spread) is found to be negatively related to momentum premium in both the regressions, suggesting that controlling the credit spread should increase the momentum returns. On the contrary, Arshanapalli, Fabozzi and Nelson (2006) find a positive relationship between credit spread and momentum premium. Their empirical findings suggest that momentum premium provide twice the premium in low credit spread as high credit spread: confirming the asymmetric behaviour of momentum premium with different economic conditions.

Chelley-Steeley and Siganos (2004) also investigate whether the macroeconomic factors account for time variation in the magnitude of momentum returns in the UK market over the period of January 1975 to July 2001 by using the LSPD listed companies. Their results show that winner returns are positively related with real GDP and nominal interest rates, but negatively related with portfolio outflows. Hence prior winners continue to perform better during economic upturn. They also find a negative relation between market volatility and winner return; hence conclude that during economic downturn (higher volatile period) the winner portfolio has lower return.

Maio and Santa-Clara (2011) went long way forward to explain the momentum anomalies. They explained momentum factor based on short-term interest rates. According to their model, past winners have higher return than past losers because of conditional market risks, i.e. past winners have higher market betas when the short-term interest rates are high. According to their model, past winners have higher expected returns than past losers because past winners have greater conditional market risk, i.e. they have higher market betas during the time of high short-term interest rates. The possible explanation is that winners and losers stocks have different characteristics during the business cycle. More specifically, during economic expansions (associated with higher short-term interest rates) winners tend to be cyclical firms with high market betas. On the other hand, winners tend to be non-cyclical firms with low market betas during recessions (associated with low short-term interest rates). This reasoning is consistent with the literature that momentum premium is pro-cyclical, i.e. momentum premium in economic expansion is higher than the recession.

2.2.6 Summary and Gaps in the Literature

Perez-Quiros and Timmermann (2000), Gulen, Xing and Zhang (2011), and Kim et. al. (2014) explore the asymmetric behaviour of size, value and momentum premium, respectively, in the US market. However, they only explain the asymmetric behaviours with the credit market variables, and hence other macroeconomic variables left unexplained in the asymmetrical relationship and economic nature of style premiums. Moreover, they didn't compare the asymmetric behaviours across the style premiums which would have provided overall picture of style premiums. Size, value, and momentum anomalies are relatively less explored in the UK market compared to the US market. As a whole, the UK market provides evidence that value and momentum premiums are relatively more stable and persistent than size premium. The economic sources of size, value, and momentum premiums are still debatable. However, the understanding of the possible sources of size, value, and momentum effects might be handy to distinguish the information content of Fama-French and Carhart model and vice-versa. If the risk-based explanation of size, value, and momentum premiums holds then those premiums should vary with some risk factors. The exact identification of those risk factors is still debatable and under investigation. On the other hand, if the mispricing-based explanation holds for the outperformance of style premiums then the investors under or overreaction might be influenced by the economic conditions. Chung et al. (2012) argue that the investors' uncertainty over the economic states might create overreaction to mispricing during good economic conditions and underreaction to mispricing during bad economic conditions and generates asymmetries across economic cycles.

The literature reviewed so far motivates our first essay (chapter three) where we investigate these asymmetries of size, value and momentum premiums and the determinants of mostly studied macroeconomics variables in those premiums. In the second essay, we study the survival time of momentum in style portfolios and derive the style timing strategy to exploit the momentums for excess returns. Section 2.3. reviews the relevant literature for second essay (chapter four).

2.3 Momentum Based Style Timing

Since the seminal papers on market timing by Treynor and Mazuy (1966) and Henriksson and Merton (1981) a number of studies investigate whether investment styles can be timed (e.g. Copeland and Copeland, 1999; Kao and Shumaker, 1999; Levis and Liodakis, 1999; Chen and De Bondt, 2004; Desrosiers et al., 2004; Knewtson et al., 2010; Bird and Casavecchia, 2011; Gallagher et al., 2015; Miller et al., 2015; etc.). The emphasis has been on the popularised four factors: market, size (SMB), value (HML), and/or momentum (UMD). Recently, practitioners have been focusing on timing the underlying style factors (SFs) i.e. 'factor timing', using fundamental and/or macroeconomic information. However, there are small amount of literature that investigates the timing of the style portfolios.

Most of the existing literature focuses on determining whether individual styles can be timed and evaluation of fund managers' market and/or style timing skill (e.g. Daniel and Titman, 1997; Kao et al., 1998; Bollen and Busse, 2005; etc.). The literature of style timing is mostly based on the concept of style momentum. Style momentum refers to the momentum of style based portfolios. The objectives of chapter four (Essay Two) are in twofold: extend the literature of style momentum of the portfolios that are used to construct style factors; and incorporate survival based econometrical model in the style timing literature that identifies potential momentum of style portfolios. Based on our research objectives, we looked into the literature of style momentum and then style timing with an intention to contribute to style timing literature by analysing the timing of style portfolios (that are used to construct the style factors) based on momentum survival. This is the first study which incorporates survival based econometrical model in the style timing literature that identifies potential momentum of style portfolios. This study also investigates whether the survival of momentum is associated with macroeconomic variables.

2.3.1 Style Momentum

Since Jegadeesh and Titman (1993) reported momentum profits in the equity market, momentum has been extended to different asset classes, portfolios, and international equity markets. Some scholars also looked into style momentum. Style momentum refers to the momentum of style portfolios, i.e. to a portfolio of asset or security that share similar characteristics. The Economic significance of style momentum is that an investor can achieve extra return by buying (selling) those portfolios whose past performances were better (worse) than other style portfolios in the presence of style momentum. The discovery of style momentum (or portfolio momentum) led to the formulation of three alternative theories of momentum, i.e. underreaction theory, excess comovement theory of Lewellen (2002) and the style investing theory of Barberis and Shleifer (2003). Earlier behavioural theories, (e.g. DeBondt and Thaler, 1985; Daniel, Hirshleifer and Subrahmanyam, 1998; Hong and Stein, 1999; etc.) identified investors' underreaction as the source of momentum profits. Whereas, style investment theory of Barberis and Shleifer (2003) identifies the tendency of fundamentally unrelated stocks to co-move simply because investors classify them into different asset styles based on market capitalization, book-to-market ratios and dividend yield. Moreover, excess comovement theory of Lewellen (2002) argues that the autocorrelation patterns in stock returns are empirically inconsistent with portfolio specific underreaction. He reports negative auto-correlation and cross-serial correlation in style portfolios and argues that stronger cross-serial correlation between style portfolios rather than auto-correlation generates momentum profits.

In the earlier study, Haugen and Baker (1996) suggest that style investment strategies with superior prior performance earn higher risk-adjusted returns. Asness (1997) also studies value strategies with prior momentum. He finds that value strategies perform well with loser stocks and show weak performance with winner stocks. These studies find the evidences, although weak, of style momentum.

Kim (2012), investigates the excess comovement theory of Lewellen (2002) in cross-asset style momentum profits, i.e. profit of momentum strategy applied to style portfolios in multiple asset classes (equity, debt, FX, commodity, and money market). Using the framework of Lewellen (2002), they find the significance of cross-asset style momentum, however, argue that this cross-asset style momentum is consistent with the underreaction theory rather than the style investing or the excess comovement theory. Nonetheless, Chen and Hong (2002) argue that the explanation of style momentum returns by Lewellen (2002) does not hold out-of-sample and that, his results are methodology driven rather than excess co-movement hypothesis. They also provide evidence that negative autocorrelation of style portfolios do not necessarily discard under-reaction based explanation of momentum. Together with Chen and Hong (2002), Chan and Docherty (2015) also disagree with the findings of Lewellen (2002) based on the study of 25 size and book-to-market style portfolios over the period 1975 to 2008. They report robust evidence of momentum in the Australian market and ascertain that this momentum is predominately explained by positive autocorrelation in returns (consistent with the return continuation behavioural models of momentum).

Chen and DeBondt (2004) examine the style related trends in equity returns by looking at the market value of equity, book-to-market ratio, and dividend yield of all firms in the Standard and Poor's-500 index from January 1976 to December 2000. They form nine size (ME) - book-to-market portfolios as the intersections of the three size (small, medium & large) and three book-to-market (growth, value/growth blend & value) groups. They find significant return differentials between portfolios. More specifically, returns are found to be lower for large firms and for glamour stocks. Value and no-dividend stocks earn exceptionally large returns in January. With a return of 1.20% per month (1.22% per month between February and December), the large-growth portfolio performs worst of all style portfolios. Overall, small-value portfolio performs the best. They further employ a trading strategy that go long in past winner stocks (i.e., the securities that belong to the one or two style portfolios that performed best) and short in past loser stocks (i.e., the securities that belong to the one or two portfolios that performed worst) in the subsequent test periods range between one quarter and 3 years. Their report of average return per month of the different buy, sell, and arbitrage (i.e., buy minus sell) portfolios confirm that style momentum profits are strong over intermediate horizons (3 to 12 months) however are statistically indistinguishable from 0 beyond 1 year.

To assess the performance of small-cap stocks, Gorman (2003) analyses small-cap oriented portfolios. Similar to the findings of Jegadeesh and Titman (1993), he concludes that small-cap portfolios demonstrate momentum and that small-cap portfolios with strong performance in the last 12 months continue to outperform in the next 3 to 12 months, followed by a performance reversal.

Nijman, Swinkels and Verbeek (2004) examine country, industry and individual momentum effects in European stock market. They find that European momentum strategies are most profitable for small growth stocks, whereas the large value stocks exhibit least return continuation. However, in the study of the UK market, Aarts and Lehnert (2005) didn’t find the evidence that style momentum strategies, based on equally weighted or market cap weighted portfolios, earn higher average return. They conclude that individual momentum strategies are found to be more profitable than the style momentum strategies. However, their study has the drawbacks of studying limited style based portfolios which give us the scope of studying style momentum in the UK market.

In the study of style momentum in the Australian market, O’Brien, Brailsford and Gaunt (2010) find that momentum premium is evident for large and middle sized portfolio, but losers outperform winners (negative momentum premium) by a considerable margin in the smallest size portfolios.

In the context of the global market, Chao, Collver and Limthanakom (2012) investigate the proposition of Barberis and Shleifer (2003) which claims that style-level momentum strategies should profitable as asset-level momentum strategies at the presence of style-switchers on a risk-adjusted basis. They find considerable evidence of style momentum in the US market as well as global market. However, although they find some evidence of outperformance along with value-growth portfolios, there is less evidence of style momentum within size portfolios.

In a most recent study, Chan and Docherty (2015) find that style momentum strategies with investment periods of up to 12 months generate significant momentum profits. Moreover, they observe monotonous decrease of the magnitude of returns as the investment period increases. However, the 60-month average return is found to be statistically insignificant, which indicates that the marginal returns on the momentum strategy are negative for investment periods that are greater than 12 months. Five out of eight portfolios with 3-month and 6-month formation period generate significant positive returns; indicating that style momentum returns are robust when a shorter window is used to sort the winners and losers.

2.3.2 Style Timing

Timing strategies based on size, style and the market have long been attractive to investors as potential sources of added value. Although the outperforming ability to a benchmark by accurately timing these dimensions remains debatable, long-term excess return premiums are reportedly associated with either value along the style dimension, or small cap along the size dimension, or equity among the market choices. Mutooni and Muller (2007) compared the performance of timing strategies with perfect foresight (taking long position in higher returning asset or short in lower returning asset) based on the market, size and style (value/growth) during 1979 to 1997 in the US market. They find the evidence that the timing strategy based on asset class and size outperform the value/growth strategy. More specifically, monthly timing strategies based on market dimension yields 48.24% on Cash and 43.23% on Bonds. Style dimension, controlling value/growth, yields 20.86% on large-cap and 27.30% on small-cap stocks. Whereas size dimension, controlling small/ large cap, yields 24.58% on value and 34.52% on growth stocks.

Copeland and Copeland (1999) explore timing strategy based on implied volatility between six style portfolios: large-cap/growth, medium-cap/growth, small-cap/growth, large-cap/value, medium-cap/value, and small-cap/value. They used two different timing strategies: 1) switching between value stocks and growth stocks, and 2) switching between small-cap stocks and large-cap stocks. In the first strategy when the estimate of expected future volatility increased (decreased), they shifted the portfolio into value (growth) stocks. Whereas, in the second strategy when the estimate of expected future volatility increased (decreased), they shifted the portfolio into large-cap (small-cap) stocks. Following the timing signal of market volatility index, they find that excess portfolio returns can be obtained considerably by allocating asset between the style portfolios. The timing/rotation strategy of Levis and Liodakis (1999) also consist of rotating between value and growth, and between large-cap and small-cap portfolios. They demonstrate that investors would have better chance to beat a buy-and-hold strategy if they rotate between value and growth portfolios than if the rotate between small-cap and large-cap portfolios. They use logit and OLS model to inspect the profitability of style rotation strategy in the UK from 1968 to 1997. However, they argue that value/growth rotation strategy requires 80% forecasting accuracy, whereas large-cap/small-cap rotation strategy requires 65-70% forecasting accuracy.

The trading strategies of Copeland and Copeland (1999) are further analysed by Boscaljon, Filbeck and Zhao (2011) by using daily data over the period 17th April 1990 to 31st December 2008. They conclude that portfolio returns derived from switching from value to growth stocks based on changes in the VIX (Volatility Index) appear to exhibit economically significant trading strategies for longer holding periods. However, they don't find the significance of shorter holding periods trading strategies that was suggested by Copeland and Copeland (1999). For longer holding periods of 30 days or more using the one-day percentage change in the VIX from its 75-day moving average as a signal to switch to value from growth style portfolios resulted in positive returns. However, no consistent trading strategies persisted for decreases in the VIX index.

Reinganum (1999) finds the considerable economical benefits of managing market capitalisation exposure. He argues that the variability in small-cap premiums can be exploited to improve returns. He finds the significant return differentials of allocation strategy comparing to passive buy-and-hold and rebalanced fixed weight strategies.

Managers with superior timing tactics could produce significantly better performance by shifting their assets according to market capitalisation exposure.

Some studies incorporate macroeconomic variables in style timing/switching literature. For example, Oertmann (2000) finds that the return difference between value and growth stocks is predictable to some extent on the basis of lagged macroeconomic variables. He uses style switching strategy to test whether this predictability can be exploited. He compared active style switching strategy with passive value and passive growth strategies of 18 countries over the period January 1986 to March 1999. The timing of style switching on his study are determined on the basis of fitted values of the instrument regression models. The active style switching strategies between value and growth stocks are found to outperform the respective passive strategies. Arshanapalli, Switzer and Panju (2007) also study multinomial timing strategy based on macroeconomic and fundamental public information over the period January 1979 to April 2005. They find the outperformance of style rotation strategies over the best performing buy-and-hold portfolio even accounting the transaction costs. They conclude that the success of effective market timing strategies is dependent on the ability to capture either inefficiencies, or disequilibria associated with changes in the investor opportunity set. Based on macroeconomic factors, Bird and Casavecchia (2011) contributed to the literature of style timing by developing a model (weighted least square) to identify periods during which value or growth portfolios will perform best. Their study analyses to what extent an investor's portfolio return can be extended by rotating between value and growth stocks within the European markets. They find that, over a 12-month holding period, the rotation portfolio generates an excess return of 9.5%, which is 4% greater than that realised by the value portfolio. The added value from style rotation is also strongly evident over holding periods of 3 and 6 months, but appears to lose its efficacy when the holding period is extended to 24 months. However, although the forecasting ability of their model is high but that its timing leverage (ability to accurately forecast at the right time) is relatively poor.

Ahmed, Lockwood and Nanda (2002) show that the performance of stocks classified by market capitalisation and growth factors shows significant variability over time. Their multi-style rotation strategy exploits the variability of market cap, and value/growth spread simultaneously and outperforms passive and active strategies. They also show that smart investors can improve their portfolio performance by integrating style shifts based on the timing strategies. Similar to the study of Reinganum (1999) and Ahmed, Lockwood and Nanda (2002); L'Her, Mouakhar and Roberge (2007) investigate the timing strategies of Value versus Growth stocks, however, used non-parametric Artificial Intelligence (AI) model such as recursive partitioning, neural networks, and genetic algorithms. They argue that the classic small-minus-big (SMB) strategy, which systematically favours small-caps, might well be too naive, and size timing, even if risky, can present an opportunity to add further value. They show that strategies based on their artificial intelligence approaches could successfully time the U.S. size premium over the period January 1990 to December 2004. Considering only extreme bets, i.e. 100% long in small-caps and 100% short in large-caps, and vice versa, they find that, five out of six timing strategies remain profitable even after transaction costs.

Amenc et al. (2003) use econometric forecasts based on multi-factor recursive modelling approach to generate systematic style timing allocation decisions of four equity style indexes: S&P 500 Large Cap, S&P 500 Large Cap-Growth, S&P 500 Large Cap-Value, and S&P 500 Small Cap. They document strong evidence of significant predictability in equity style returns. They also provide strong evidence that style timing strategy enhances the portfolio performances. The average net performance of the tactical asset allocation is 10.90% with a 4.71% volatility, an attractive risk-return trade-off with higher Sharpe ratio.

Desrosiers, L'Her and Plante (2004) study style diversification and style timing strategy over the period January 1975 to August 2003. They find that style timing provides consistent superior risk-adjusted performance to the fixed-style strategies or style diversification. Their study suggests the potentiality of style timing on size effect (small-cap versus large-cap). In a similar manner, Nalbantov, Bauer and Sprinkhuizen-Kuyper (2006) investigate whether short-term directional variations in the size and value premium are sufficiently predictable to be exploited by means of a tactical timing strategy in the US market. Their style timing strategies are documented based on technical and macroeconomic variables with the use of Support Vector Regression (SVR). They conclude that in terms of realised information ratios, a combination of both value-growth and small-large timing produces the superior results.

Based on the UK market, Clare, Sapuric and Todorovic (2010) examine the profitability of a number of long-only and long/short multi-style rotation strategies based on quantitative and momentum approaches. They argue that style rotation can be implemented by using simple momentum approach rather than a complex quantitative one. By using multinomial ordered logit for timing they find that simple short-term momentum strategies generate higher returns even after transaction cost. Momentum strategies outperform in shorter holding period and medium-term (6 months) formation period even after considering the transaction costs. However, they find relatively higher return on long-only multi-style rotation than long/short strategy both in momentum and quantitative trading.

Efremidze, DiLellio and Stanley (2014) revisit the methodology of Copeland and Copeland (1999), and Boscaljon, Filbeck and Zhao (2011). They examine the style rotation feasibility by using Sample Entropy[3] (SaEn) and Approximate Entropy (ApEn) calculated from the CBOE Volatility Index (VIX) time series. They find that these two entropy-based timing (signals) produce better performing value minus growth (or growth minus value) portfolios than trading strategies based on VIX percentage change signals.

The timing strategy of Gallagher, Gardner and Schmidt (2015) also generates higher annual average than the mean for book-to-market, ROE, and size yet slightly lower than the average returns of momentum factor. However, the Sharpe ratio of momentum factor return is 17 % higher than the associated timing strategies. On average they find that the timing strategy generates around 2 % significantly (at 5% level of significance) higher return, and conclude that stock return timing strategy is fruitful to generate higher return based on investor's combined risk/return objectives. Additional studies that provide evidence effective style timing strategies are (Asness

[3] The theory of entropy was initially developed in the field of thermodynamics as a way to measure the level of randomness in the late 1850s. In that context, it was used to characterise the amount of energy in a system that was no longer available for doing work. Subsequently, the definition has been expanded to characterise a level of randomness and disorder.

et al., 2000; Bauer, Derwall and Molenaar, 2004; Bollen and Busse, 2005; Holmes, Faff and Clacher, 2010).

2.3.2.2 Momentum Survival

Since the study of Jegadeesh and Titman (1993), a large body of academic research has supported evidence on medium-term stock price continuations. Similar to the findings of Jegadeesh and Titman (1993), Gorman (2003); and Chen and DeBondt (2004) also confirm that style momentum is strong over intermediate horizons (3 to 12 months).

However, a general problem of momentum related studies is that they use no arbitrage argument to identify momentum effects by depending on zero investment portfolios. Jochum (2000); and Kos and Todorovic (2008) investigates momentum effects by constructing economic survivorship curves (Kaplan–Meier (KM) estimator) that allow measuring to an extent in which an existing trend will persist beyond the present day. The advantage of this method is that it circumvent the no-arbitrage argument of the zero-investment portfolio.

The study of Jochum (2000) uses survival methods and answers the useful instrument in the investment decision by investigating how likely a positive (negative) return survives based on the post positive (negative) returns. He uses the daily stock market return of London, New York and Zurich over the period January 1973 to December 1997. His empirical evidences show that positive momentum (upward trend) persists (survives) more pronouncedly than negative momentum (downward trend). He concludes that the probability of return continuation (upward or downward) is too high to be explained by commonly used return generating model (Random Walk, ARMA and EGARCH).

Kos and Todorovic (2008) extend the study of Jochum (2000) by investigating the survival of S&P Global 1200 sector index returns. They use daily returns over the period 1 January 1998 to 6 December 2006 that allows 2230 data points. They find that momentum effect survives on an average a little more than 2 days after it has been established. Technology, Utilities, Financials and Industrials sectors show considerably longer positive momentum survival times than suggested by theoretical benchmark models (random walk and ARMA), whereas Consumer Discretionary sector shows strong negative survival rates. They also find that the Random Walk model underestimates empirical positive momentum survival times considerably, implying a violation of the market efficiency theory.

2.3.3 Summary and Gaps in the Literature

In the style timing or market timing literature the effectiveness of the timing strategy depends on identifying the trends early and react quickly. If we can identify how long the trend (positive or negative) will survive (based on the survival methodology) this can be easily exploited (long or short trading) to time the market and gain higher returns. However, the application of survival methodology is rare in the investment management literature although the application could be very helpful and intuitive. Jochum (2000) and Kos and Todorovic (2008) explore the survival methodology in the stock returns and sector returns, respectively. However, to the best of our knowledge, no study in the style timing literature uses the survival methodology. The study of Jochum (2000) is somewhat basic in the sense that it only identifies whether the empirical and theoretical survival curves are identical or not to explore whether the market momentum (empirical) survives longer than it should (theoretical). Kos and Todorovic (2008) extend the study of Jochum (2000) and derive trading strategies to exploit the misaligned theoretical and empirical momentum survival of sector returns. However, they didn't test whether the empirical momentum survival are equal across business cycles and also didn't test whether the momentum survival varies for the change in the macroeconomic variables. Our study, hence, fills up the gaps in the literature and extends the application of survival methodology in the investment management, specifically in the style timing literature.

Our study argues that, if empirical survival curves[4] are under-or over-estimate the theoretical curves than simple trading strategies can be implemented to generate higher return. The literature review of section 2.3 motivates our second essay (chapter

[4] A survival curve is a statistical plot of the survival (here survival of positive or negative momentum) showing the percentage surviving versus time.

four) where we incorporate survival based econometrical model in the style timing literature that identifies potential momentum of style portfolios. In contrast to the previous studies, we also investigate whether the survival of momentum is associated with macroeconomic variables.

On the other hand, in the 'style investing' literature the empirical virtues of different asset pricing models (one factor (CAPM), three-factor (Fama-French), four-factor (Carhart), and five-factor (Fama-French) models) and their embedded measures of risk have been raging. Practitioners are puzzled to pick one for their investment decisions. The third essay (chapter five) of this study is devoted to investigates whether newly evolved five-factor model (Fama and French, 2015) provides better descriptions of average returns than their previous three-factor model (Fama and French, 1993). We compare the risk-adjusted performance of Fama-French three-factor and five-factor model in the area of relatively less explored sector/industry portfolios. The following section (section 2.4) reviews the literature that helped to define the aims and objectives of essay three (chapter five).

2.4 Alpha Based Sector Rotation

The concept of active portfolio management largely involves portfolio rotations towards (or away from) particular assets, styles, industries, markets, or asset classes based on expectations of future performance. Where there are several asset pricing models available, academics as well as practitioners remain puzzled to pick one model for their portfolio management. In the case of performance measure of portfolios based on particular asset pricing model, risk-adjusted performance measure (alpha) is widely accepted by the academics as well as practitioners. The Alpha (intercept) of an asset pricing model is expected to be indistinguishable from zero in a regression of an asset’s excess returns on the model’s factor returns if the corresponding asset pricing model completely captures expected returns. A non-zero alpha can then be attributed to the abnormal performance, or the amount of return that cannot be captured by the model. If the alpha of a pricing model is a true alpha then based on that alpha investment strategy (in our case sector rotation) can be formulated to generate higher return.

The investment strategy based on sector rotation received comparably less attention in the academic literature although sector/industry return predictability is attractive to the practitioners. This gap is surprising with respect to the importance of sector/industry analysis in the investment process. In chapter five (Essay Two) we intend to contribute the literature by investigating sector rotation of sector/industry portfolios based on the rolling window alphas of the Fama-French models (three-factor and/or five factor). Moreover, most of the literature in performance measurement studies the performance of several funds' (mainly mutual funds). Our study also contributes to the performance measurement literature by studying the performance of sector/industry portfolios.

Nevertheless, to the best of our knowledge, there is no study that assesses the performance of portfolio(s) with five-factor models. In this section, relevant literature is surveyed and theoretical framework for the empirical study is formulated. To do so, we have reviewed some key literature of performance measurement (with a focus on performance measure of portfolios) and industry/sector rotation in this section.

2.4.1 Performance Measurement

The literature of performance measurement can be traced back to early 60s. Treynor (1965) used Treynor's ratio that measures the excess return of a portfolio that could have been earned on a riskless investment per each unit of market risk (systematic risk). Market risk is the beta of Capital Asset Pricing Model (CAPM) which is developed by Sharpe (1964) and Lintner (1965).

To measure the fund performance, Jensen (1968) proposed to add alpha (α) in CAPM. Jensen's alpha measures the excess return of a portfolio over the security's required rate of return as determined by CAPM. Jensen's alpha measure assumes that if all equities lie on Security Market Line (SML) then the alpha of market portfolio, which is benchmark portfolio, is zero. However, actively managed portfolio can produce positive alpha, indicating that active portfolios can have higher returns than the benchmark portfolio (market portfolio). Alpha defines the mathematical estimate of the return on a security when the excess market return as a whole is zero. Jensen's Alpha is derived by regressing portfolio returns with market portfolio with an intercept ($\propto_p$) as follows:

$$R_{it} - r_{ft} = \propto_{it} + \beta_{it}\left(R_{mt} - r_{ft}\right) + \varepsilon_{it}$$

Here, R_{it} is the return of portfolio *i* in month *t* (with t = 1,2, ..,T), r_{ft} is the risk-free return, R_{mt} is the return of the market portfolio, and ε_{it} an error term. Alpha ($\propto_{it}$) measures risk-adjusted return, or the actual return of a portfolio in addition to the expected return based on its beta. Beta (β_{it}) measures the portfolio's volatility in relation to its benchmark portfolio. If the actual return of a portfolio is higher than its beta the portfolio has a positive alpha and it has a negative alpha if the return is lower. CAPM can be viewed as a single-factor model since it uses only one factor (excess market return).

However, Roll (1977, 1978) criticises the use of CAPM as a benchmark in performance evaluation. He argues that single factor measure is logically inconsistent under the assumptions of the model since any measured abnormal performance can only occur when the market proxy is inefficient. Besides this, CAPM apparently oversimplifies the complex market by using a single factor to compare the excess returns of a fund with the excess returns of the market portfolio. Moreover, CAPM fails to account for non-index stock-holdings, such as small-cap stocks or value stocks. The obvious inefficiency of the usual market proxies, together with concern over the testability of CAPM, has led researchers to explore alternative theories of asset pricing. This single-factor modelling has been extended in literature to a multifactor framework in order to improve the portion of variance explained by the regression. Fama and French (1993) added two additional factors, one for size (SMB, i.e., small minus big) and the other for ratio of book-to-market value (HML, i.e., high minus low book-to-price ratio):

$$R_{it} - r_{ft} = \propto_{it} + \beta_{im}\left(R_{mt} - r_{ft}\right) + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t + \varepsilon_{it}$$

Carhart (1997) adds a momentum (UMD, i.e. up minus down) factor to the Fama and French (1993) model, which accounts for trend-following strategies in stock markets, i.e., buying stocks that were past winners and selling past losers:

$$R_{it} - r_{ft} = \propto_{it} + \beta_{im}\left(R_{mt} - r_{ft}\right) + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \beta_{iUMD} UMD_t + \varepsilon_{it}$$

More recently Fama and French (2015) extended their previous three-factor model to five-factor model with the argument that the new five-factor model describes the cross section of return better. They add two new factor profitability (RMW, i.e. robust minus weak profitability) and investment (CMA, i.e. conservative minus aggressive investment) together with size and value factors:

$$\begin{aligned} R_{it} - r_{ft} = \propto_{it} + \beta_{im}\left(R_{mt} - r_{ft}\right) + \beta_{iSMB} SMB_t \\ + \beta_{iHML} HML_t + \beta_{iUMD} UMD_t + \beta_{iRMW} RMW_t + \beta_{iCMA} CMA_t + \varepsilon_{it} \end{aligned}$$

These multifactor models changed the definition of alpha. In the single factor CAPM, alpha (Jensen's alpha) is the amount by which an active portfolio manager outperforms a broad market index. The multifactor models define alpha for equities more precisely as the return an active manager achieves above the expected return due to all corresponding equity risk factors. While Fama-French three-factor model alpha (hereafter 3F alpha) represents excess return that an active portfolio manager achieves above the expected return due to all three equity risk factors: market, size and value; Carhart's alphas (hereafter 4F alpha) then represents excess return after market risk, small cap, value and momentum associated performance is taken into account. Similarly, alpha of Fama-French five-factor model (hereafter 5F alpha) denotes the excess return that an active portfolio manager achieves above the expected return due to market, size, value, profitability and, investment risk factors. The evaluation of multifactor model doesn't reduce the application of single factor model because of its simplicity. Although most of the studies prior to the 90s use Jensen's alpha to evaluate the performance of portfolios or funds, after the evaluation of multifactor asset pricing models, some studies include Jensen's alpha together with other multifactor model alpha for comparison purpose.

Practitioners and academics use different techniques to evaluate the performance of portfolios. A typical practitioner uses benchmark indexes, e.g. S&P 500, to measure portfolio performance; whereas, an academic uses asset pricing models, e.g. Fama-French (FF) three-factor model, Carhart four-factor model etc., as a benchmark for the performance measure. Cremers, Petajisto and Zitzewitz (2012) claim that criteria for defining a “good” benchmark model for portfolio performance evaluation are not identical to those of a good pricing model, even though pricing models can also be used as benchmark models. They further argue that a pricing model should be the simplest possible model that explains the cross-section of expected stock returns. Asset pricing theory suggests that expected returns should be a linear function of betas of the portfolio with respect to one or more systematic risk factors. Empirically motivated factors, in principle, could be derived from any stock characteristic that is believed to predict returns out-of-sample.

On the contrary, a benchmark model should estimate the portfolio manager’s added value more accurately than the passive strategy. Meaning that, benchmark model should include asset pricing model so that the manager does not get applause for simply bearing more systematic risk. Cremers, Petajisto and Zitzewitz (2012) argue that a benchmark model can also include non-priced factors to reduce noise in alpha estimates, or can even encompass well-known anomalies. For instance, if value firms historically produced excess returns, but whether it will do so once it is widely known is in question, then controlling for past exposure to value premium in a benchmark model might be justified. The multifactor models are evaluated in this spirit.

The search for non-zero alpha or measuring the portfolio performance in the literature is extensive, till today. One of the first focused studies of performance measurement is done by Jensen (1968). Over the period 1945 to 1964, Jensen (1968) studies 115 mutual funds. He finds a negative alpha (average) of -1.1%. More precisely, his study finds that 98 funds have alphas that are insignificantly different from zero, among them only 3 funds with significant positive alphas and 14 significant negative alphas. The study of Ippolito (1989), however, contrast to some earlier studies (Friend et al., 1970; Jensen, 1968; Sharpe, 1966) finds the evidence that mutual funds possess enough private information to offset their expenses. By using the similar methodology (Jensen Alpha) of Jensen (1968) he finds that over the period 1965-1984 the overall alpha is positive (0.81%). More specifically, out of 142 funds, 127 funds are found to have alphas that are insignificantly different from zero, 4 have significantly negative alphas and 12 of them have significantly positive alphas. He also finds that the average alphas of S&P 500, NYSE, S&P Salomon Brothers long-term bond indexes are 83, 87 and 248 basis points respectively. The study of John and Donald (1974), who analysed the risk and return of 123 American mutual funds during 1960–1969 by applying Sharpe, Treynor and Jensen (alpha) measures, also find the evidence of fund outperformance. They conclude that more aggressive portfolios outperform the less aggressive one. However, a later study of Cumby and Glen (1990), who examined 15 U.S. based internationally diversified mutual funds over the period January 1982 to June 1988 by using Jensen measure, find no evidence of outperformance over their benchmark portfolios.

After the evolve of multifactor models (Three-factor model of Fama and French (1993) and Four-factor model of Carhart (1997)), researchers concentrate more on multifactor models (3FM and 4FM) in the literature of performance measure, however some studies include Jensen's alpha together three-factor alpha (3F alpha) for comparison purpose. In this trend, Daniel et al. (1997) measure the performance of US mutual fund over the period December 1974 to December 1994. They find that, over the entire sample period, both the one-factor alpha (Jensen's Alpha) and the four-factor alpha (Carhart alpha) measures of performance are positive, however insignificant. They argue that average mutual fund outperforms simple mechanical rule, however, the amount by which the average mutual fund beats a mechanical strategy is fairly small (under 100 basis points) and is approximately equal to the average management fee. During the same year, Cai, Chan and Yamada (1997) investigate 64 open–ended Japanese funds over a period of January 1981 to December 1992 by using Jensen's measure and also by employing value weighted single index benchmark and Fama-French 3FM. They conclude that most of the mutual funds underperformed their benchmark. The underperformance is also reported in the study of Pástor and Stambaugh (2002). They find that, across different beliefs about the asset pricing, most of the funds underperform the CAPM and Fama-French benchmarks.

The study of Wermers (2000) over the period January 1975 to December 1994 indicate that mutual funds held stock portfolios that outperform a broad market index (the CRSP value-weighted index) by 130 basis points per year. Out of that, about 60 basis points is due to the higher average returns associated with the characteristics of stocks held by the funds, whereas the remaining 70 basis points is due to the picking stocks skills of fund managers that beat their characteristic benchmark portfolios. Daniel et al. (1997); and Grinblatt et al. (1995) also attributed much of this mutual fund performance to the characteristics of stocks held by the funds: explaining that funds that use value investment strategies hold stocks with higher average returns than passive stock indexes.

In a simulated study, Kothari and Warner (2001) select 50 equity funds from Morningstar OnDisc data and construct a 75-stock mutual fund portfolio each month from January 1966 to December 1994. They report positive alpha (mean) for both Fama-French 3FM (0.04% per month) and Carhart 4FM (0.08% per month). They argue that multifactor model (e.g. Fama-French 3FM, Carhart 4FM) are the basis for performance measurement as they have high explanatory power in asset pricing tests. Baks, Metrick and Wachter (2001) investigate the performance of mutual fund from an investor perspective. The estimated four-factor alpha over the period 1962 to 1996 shows that 705 managers, out of 1437, generates positive alpha after expenses. However, overall performance evaluation analysis with their Bayesian methods couldn’t reject the null hypothesis that fund managers have skills and generate abnormal returns.

Chan, Dimmock and Lakonishok (2009), however, used characteristic-matched benchmarks as well as regression-based benchmarks using portfolio holdings to evaluate the performance of equity portfolios. They report a significant Fama-French alpha of -4.74% for Russell 2000 Growth index over a 13 year sample period. They argue that alternative performance evaluation models lead to significant performance differentials. For example, for Russell 2000 Value index, one method (Market, size and value composite model i.e. the modification of Fama-French model) reports an impressive significant mean abnormal return of 3.50%, while another equally sensible method (independent sort on the size and book-to-market) suggests that performance is a disastrous −3.18%.

Otten and Bams (2004) study the comprehensive assessment of existing mutual fund performance models by using CRSP mutual funds data. They explore the added value of introducing extra variables such as size, book-to-market, momentum and a bond index to the single factor CAPM. In the case of CRSP total market index, they observe that Fama-French 3FM generate positive alpha (over-perform the index), however, the CAPM and Carhart 4FM underperform the index by 0.45% and 0.51% per year respectively. Although the inclusion of additional factors (Fama-French 3FM to Carhart 4FM) increase the statistical significance of the model with greater R^2 , the performance of the alpha estimates decreases (however not significantly). They further investigate whether the results of CRSP total market index are biased because all funds are pooled within one portfolio. They conclude that at the investment style level the uses of richer models with more explanatory variables have an obvious impact on alpha estimates.

Berk and Green (2004) raised the question, whether active portfolio managers have skills. They find that about 80% of managers have skills to generate alpha in excess of their fees. Later in 2006, Kosowski et al. (2006) examine the statistical significance of the performance of mutual fund managers. They conclude that the performance of the mutual fund managers are not solely due to luck, that is, the significant alpha cannot be explained solely by sampling variability. However, in a later study of Barras, Scaillet and Wermers (2010) reveals that although 75.4% of the fund managers have some stock picking ability, only 0.6% fund managers are skilled who can achieve statistically significant non-zero alpha. While in the UK, Cuthbertson, Nitzsche and O'Sullivan (2008) report that top performing equity-income funds show stock picking skills (positive alpha), whereas such ability is generally not found among small stock funds and 'all company' funds. In the study of real estate, Damodaran and Liu (1993) and Kallberg, Liu and Trzcinka (2000) suggest that investment managers in real estate sector can produce positive abnormal returns because of their specific appraisal skills and information about real estate investment targets. Bollen and Busse (2004) and Kosowski et al. (2006) find short-term performance persistence, with the latter study showing that the persistence in mutual fund returns is not entirely explained by luck. In contrast, Gruber (1996), Carhart (1997), and Fama and French (2010) find little or no evidence of performance persistence and skill in active investing, especially after management fees and transaction costs, arguing that most of the observed persistence in fund returns is explained by momentum in stock returns or ''luck''.

Although the findings of fund performance are mixed; overperform, underperform, or insignificant, the search continues in the empirical studies. We summarise some of the important studies in an ascending order of publication:

Matallin-saez (2007) investigate the Russell indexes (Overall, Growth and Values indexes of Russell 3000, Russell 2500, Russell 2000 Russell 1000, Russell Midcap, Russell Top 200) over the period June 1995 to December 2004. They find that all the value indexes generates positive Jensen's alpha. The best performance is obtained in the Russell 2500 Value Index, with an alpha of 7.5%.

Cremers and Petajisto (2009) argue that an active fund manager who deviates his portfolio from the benchmark tends to perform better. They further argue that economically and statistically significant four-factor (Carhart) annual alpha of S&P 500 (1.08%) index would be inappropriate to attribute to the "skill" of fund managers as S&P 500 index is a purely mechanical index. Instead, this significant alpha suggests a misspecification in the four-factor model.

Huij and Verbeek (2009) evaluate the performance of CRSP mutual fund over the period 1962-2003. They obtain the Jensen's alpha, Fama-French 3 factor alpha, and Carhart 4 factor alpha by estimating the CAPM, Fama-French 3 factor model and Carhart 4 factor model using OLS with a rolling window over the preceding 36 months respectively. Using the pooled time-series cross-sectional methodology they test whether the style portfolios' alphas are jointly equal to zero. They found significant non-zero alpha for both Fama-French 3FM and Carhart 4FM when sorting on value beta and past return (momentum).

Cremers, Petajisto and Zitzewitz (2012) estimate the Carhart and Fama-French alphas for the major Russell, S&P, and Wilshire indexes over the period January 1980 to December 2005. They find significant positive alphas for the general and growth versions of the large-cap indexes (the Russell 1000 and S&P 500) and significant negative alphas for the general and growth versions of the small-cap indexes (the Russell 2000 and S&P 600). The alpha for the Wilshire 5000 is found to be close to zero, as they expected based on the argument that the Wilshire 5000 index approximates the CRSP value-weighted index (which is included as a factor in the Carhart model). They also find that the index alphas are similar for the Fama-French and Carhart models, reflecting generally minor loadings on the momentum factor. Furthermore, they also find that all alphas are jointly significant at any reasonable level (p-value of F-test below 0.0001%), which highlights the existence of non-zero alphas in the indexes.

Angelidis, Giamouridis and Tessaromatis (2013) revisited the mutual fund performance evaluation by using the daily return data of CRSP Mutual Fund database over the period September 1998 to January 2009. They claim that performance of Mutual fund manager should be measured relative to their self-reported benchmark rather than the return of a passive portfolio with the same risk characteristics. Their empirical study reveals that on average mutual fund managers underperform their self-designated benchmarks. The underperformance is consistent and statistically significant across all size groups. The underperformance is significant for growth and core managers but insignificant for value managers. Also, when Carhart 4 factor model is used as benchmark model the alphas are negative across all size and value/growth investment styles.

Gupta-mukherjee (2013) uses a new measure based on portfolio allocations, peer deviation, to capture a fund managers' divergence from the contemporaneously unobservable beliefs of their peers. She reports significantly positive four-factor model (4FM) alpha of US equity funds over the decile 1-10 portfolios. In her study decile 1–10 portfolio represents a strategy of going long on the funds with the lowest divergence in beliefs and short on the funds with the highest divergence in beliefs, where portfolio choices reveal beliefs. However, she argues that alphas resulting from the Fama and French 3FM and the Carhart 4FM for value funds are systematically biased downward, and those for growth funds are biased upward because of the miscalculation of the premiums of hypothetical hedge portfolios.

Apart from the US, some of the studies investigate fund performance in the European context. Otten and Bams (2002) investigate the performance of European mutual funds (France, Italy, Germany, Netherlands and UK) over the period January 1991 to December 1998 by using Carhart (1997) four-factor model. Their empirical evidence suggests that European mutual funds seem to prefer small-cap and high book-to-market stock (having positive alpha). More specifically, small-cap funds are able to generate positive alpha after taking into consideration of transaction cost. Except for

Germany, the other four countries exhibit significant outperformance at the aggregate level. When comparing the Carhart 4 factor alpha and Fama-French 3 factor alpha, it is observed that in general, 4FM generates higher alpha than 3FM in the case of small-cap stocks. The comparison between unconditional and conditional performance evaluation, however, provide mixed performance. Unconditional alpha is higher in the case of Germany, Italy and UK, whereas the conditional alpha is higher for France and Netherlands. Small-cap stocks generate higher conditional alpha than unconditional alpha for all the five countries. They also investigate the performance persistence of the mutual funds and find that only UK mutual funds exhibit strong performance persistence in mean returns.

In a recent study Vidal-garcía (2013) examines the performance and the performance persistence of style-consistent European equity mutual funds over the period January 1988 to December 2010. He finds that three-factor and four-factor alpha for value-weighted returns are negative. However, the investment style portfolios show positive performance on average if an investor evaluates the performance of mutual fund portfolios by using simple style benchmarks.

Apart from mutual funds, Alison and Tonks (2001) examine the performance of 2175 segregated UK pension funds over the period March 1983 to December 1997. They find that, over the whole period and across all funds, the average outperformance is insignificant. However, during the sub-periods 1987-1992, the pension funds outperform significantly but show significant average underperformance during the bull market of mid 1980s.

The performance of pension funds is also controversial. Coggin, Fabozzi and Rahman (1993) examine the performance of randomly selected 71 US equity pension funds over the period January 1983 to December 1990. They find that the pension funds that adopt value strategies outperform by 2.1%, but funds that adopt growth strategies underperform by -0.96%. By using a large sample of pension funds over the period 1983-97 in which there is less survivorship bias, Tonks (2005) find that strong evidence of persistence in abnormal returns generated by fund managers over one year time horizons.

A limited evidence of performance persistence for a small number of fund managers is found from the study of Brown, Draper and McKenzie (1997) who investigate the consistency of 232 UK pension funds over the period 1981 to 1990. However, in separate studies, Ippolito and Turner (1987) and Lakonishok et al. (1992) find the underperformance of pension funds in the US and UK market respectively. Blake and Timmerman (1997), who examine the performance of UK pension funds, find that large pension funds underperform small funds.

In the context of hedge fund performance, Slavutskaya (2013) selects hedge funds based on their deviations from the common mean. The Large deviation would mean that these funds follow the allocation differently from their peers. She finds an average alpha of 0.009 in the whole sample periods. However, funds with large deviations demonstrate an average alpha which is significantly larger than an average alpha in the whole sample. In contrast, the study of Brown, Goetzmann and Ibbotson (1999), that uses raw as well as risk-adjusted returns from the CAPM and excess returns over the style benchmarks, finds little performance persistence in hedge funds.

Agarwal and Naik (2000a) and Agarwal and Naik (2000b) reveal substantial persistence in quarter returns using excess returns over the average style return and (non-)parametric tests. They also find that ‘‘losers’’ are more persistent than ‘‘winners’’. Significant persistence is also found by Edwards and Caglayan (2001) for both ‘‘winners’’ and ‘‘losers’’. However, Capocci and Huebner (2004) draw opposite conclusion from their study. They find no persistence among either ‘‘winners’’ or among ‘‘losers’’, but limited evidence of persistence in returns of the middle decile funds. More recently, Kosowski, Naik and Melvyn (2007) applied Bayesian econometrics, and a bootstrap procedure to evaluate hedge fund performance and find that hedge fund returns persistence over a one-year horizon.

All the studies of performance measurement concentrate on the funds (mostly mutual funds). There are small numbers of studies concentrate on the industry or sector perspective. Dellva, DeMaskey and Smith (2001) study the timing and selectivity of the performance of 35 Fidelity sector mutual funds from the funds’ inception till December 1998. The number of positive Jensen alphas are relatively constant (varied from 24-33) with the exception of latest period 1994-1998 where the alphas declined to negative values.

Faff (2004) studies the performance of 24 Australian industry portfolios by using the daily data over the period 1st May 1996 to 30th April 1999. His study finds that there is a tendency for mining and resources to produce negative 'risk-adjusted performance' in terms of the Fama-French alpha (3F alpha) , whereas industrials tend to produce positive alpha.

Kacperczyk, Sialm and Zheng (2005) investigate the performance of industry concentrated of US mutual funds over the period January 1984 to December 1999. They argue that fund managers may deviate from the passive market portfolio by having their portfolio with specific industry concentration. They show that mutual funds that deviate more from the overall market by focusing on particular industries tend to perform better. More specifically, their results indicate that the most diversified fund portfolio generates an abnormal return of 0.09% per quarter; while the most industry concentrated fund portfolio generates an abnormal return of 0.53% per quarter. The abnormal returns of the five most concentrated portfolios are all significantly positive at the 10% level. In contrast, the abnormal returns of the five most diversified portfolios are not significantly different from zero.

2.4.2 Sector Rotation

The investment process often divided into of three steps or stages: asset allocation, group rotation, and security selection/ analysis. In the asset allocation step, funds are allocated between the major asset categories: domestically or globally on the basis of forecasts of the overall economic and market environment. In domestic asset allocation funds are allocated between common stocks, government bonds, corporate bonds and treasury bills. Whereas, in global allocation process between the equity and bond markets of different countries. In the group rotation step, funds are apportioned to groups of securities. In this step, managers attempt to identify economic sectors and industries that stand to gain or lose relative to the overall market. In the security selection/analysis step, investors or fund managers choose combinations of securities from each of several stocks or bonds groups.

Most of the research in finance that consider industry returns focus on industry "factors" or risks in security returns. The study of industry factor can be traced backed to 1960s. King (1966) studied the industry factor in stock price behaviour. He argued that a single piece of information can affect more than one security price change, perhaps even the whole market, at a given time period. Intuitively if two variables share one or more common elements in their statistical makeup, they will exhibit correlated behaviour to some extent and hence the industries co-move with the similar sector. He found that the movement of a group of security price changes can be broken down into market and industry components.

King's study was followed in the late 1960s and early 1970s by several other studies that also demonstrated the importance of industry factors in security returns. Reilly and Drzycimski (1974) provide a review of these studies and extend King's work. They conclude that there is a substantial divergence in relative performance among industries during any given time period. They also find considerable variability in relative price performance over time. From the differences in price performance among industries, they suggest that it is worthwhile to find better performing industries to get superior return. They also find substantial variation in risk across industries (as measured by the betas of industry returns relative to the S&P 500 Index) but found that the risks are reasonably stable over time for individual industries. However, they doubted that only the analysis of historical performance alone is not sufficient to determine future performance because of the lack of instability in relative price performance.

Recent studies have continued the focus on industry differences or industry factors to explain the variance of asset returns. Some of the studies focus on industry rotation strategies, others focus on industry returns in broader investigations of predictability. One of the earlier studies that focused on industry rotation strategies is done by Sorensen and Burke (1986). They rank 43 industry groups by relative price performance over the period 1972 to 1984. They form equality weighted industry portfolios based on the top-ranked industries. They find that, while individual industry rankings varied considerably, industry-specific stock price movements tend to persist for at least two quarters. A naive strategy based on rotating portfolio holdings in each quarter among the three, five or ten best performing industry groups resulted in superior returns. They use Sharpe index, the Treynor index and the portfolio alpha to measure the performance of group rotation. They find that portfolio alphas ranged from a low of 1.34 % per year to a high of 17.15 %. The other performance measures also demonstrate the dominance of group rotation over average market returns. The second study is performed by Grauer, Hakansson and Shen (1990) who use multiperiod portfolio theory in constructing and rebalancing of portfolios composed of 12 industry indexes of the US market during the period 1934-1986. They also compare the returns on 'active', 'passive' and 'semi-passive' industry rotation strategies. They conclude that active industry rotation strategies of the multiperiod model show better performance to the value-weighted industry indexes.

To overcome the drawbacks of some earlier studies that used only in-sample test, Beller, Kling and Levinson (1998) investigate the in-sample and out-of-sample predictability of industry stock returns (55 industries of BARRA's U.S.) within the context of a Bayesian multivariate regression model over the period 1973 to 1995. They use several statistical methods to evaluate the ex-post performance of the portfolios including Sharpe ratios, differences in mean returns, and Jensen's alphas. For the portfolios that long the higher return industries and short the lower return industries have the mean excess return of 1.689% (which is significantly different from zero) with a Jensen's alpha of 1.735%; however, the beta is not found to be significantly different from zero. The empirical findings of Beller, Kling and Levinson (1998) provide evidence that industry returns are predictable- not merely in a statistical sense but also from the economically relevant standpoint of portfolio selection. In the absence of trading costs, portfolios formed by simply choosing the quintile of industries with the highest predicted returns outperformed the benchmarks. Trading costs, however, eliminated the trading profits. Optimised portfolios formed by using the predicted returns and predicted covariance matrixes of returns significantly outperformed the benchmarks even in the face of trading costs.

Moskowitz and Grinblatt (1999) document that industry factors drive cross section momentum effect in the U.S equity market and consequently industry momentum strategies are more profitable than individual stock momentum strategies. They also document that industry portfolios exhibit significant momentum even after controlling for size, book-to-market equity (BE/ME), individual stock momentum, and the cross-sectional dispersion in mean returns. Their results further suggest that serial autocorrelations in industry portfolio return largely contribute to profits on strategies based on cross-section momentum. Using a different method of decomposing momentum profits into the components, Pan, Liano and Huang (2004) provide direct support to the findings of Moskowitz and Grinblatt (1999).

Conover et al. (2008) examine the sector rotation strategy of 10 U.S. equity sector over the period January 1973 to December 2005. They report unambiguous evidence that a simple sector rotation strategy improves risk-adjusted portfolio performance significantly. Simple sector rotation strategy outperforms benchmark portfolio (equally weighted across all sectors) by 3.49% (annualised), and the market portfolio by 3.78% (annualised). They also found the outperformance of sector rotation strategy over the best performing individual sectors (Resource and Financials). In their previous study, Conover et al. (2005) incorporate business conditions with the sector returns and argue that, sectors that are considered to be closely related to general business conditions display the most obvious patterns whereas sectors that are considered to be relatively invariant to changes in business conditions display relatively weak patterns in term of returns. Their findings demonstrate that the pattern of sector return is prominent for cyclical sectors and least distinct for utilities, resources and noncyclical consumer goods. Cyclical consumer goods sector is reported to have the most prominent return. In a recent study, Dou et al. (2014) also examine the regime dependency of sectors. Their regime-switching sector rotation strategy is found to be economically important. In their out-of-sample analysis over the period 2003 to 2010, the regime-dependent sector allocation delivers an average annual return of 13.13%, compared to the annual returns on a static mean–variance sector allocation 7.31% and the world market portfolio 7.03%.

Baca, Garbe and Weiss (2000) study the sector effect in the major equity market. Their empirical findings of 10 sector index within seven largest counties suggest that industry sector effect dominates industry effect in explaining variations in the stock returns. With a similar argument, Shynkevich (2013) studies the industry momentum in the US market. Using the daily returns of 49 industry portfolios over the period 1991 to 2011 he finds that, trend continuation is predominantly an intra-industry rather than a market-wide or a single-company effect. After adjusting for data snooping bias, trend chasing trading rules achieve superior predictability for a number of sectors and industries in the 1990s. Shynkevich (2013) argues that if trend continuation is an industry-specific rather than a market-wide or single-stock phenomenon, returns on sectors and industries can be predictable even when returns on the aggregate market portfolio and individual stocks are not.

Fidelity Investments pushed sector investing into the mainstream by launching the slate of sector mutual funds referred as the “Select” series during the 1980s. However, the modern era of sector investing began in December' 1998 when the first sector exchange-traded funds were introduced to equity investors. Based on the Fidelity Select Sector picking as selection criteria, Sassetti and Tani (2006) uses three simple market-timing techniques: Rate of Change, alpha, and Relative Strength; on 41 funds of "Fidelity Select Sector" over the period January 1998-September 2003. They conclude that a sector rotation based on the Alpha indicator appear more regular and stable than those obtained using the Rate of Change. Based on the alpha indicator 186% return comes from 5 funds / 60 days strategy (42 trades per annum).

2.4.3 Summary and Gaps in the Literature

To sum up, it can be argued that sector based asset allocation is gaining importance and will continue to gain prominence into the future. Intuitively, companies in the same sector or industry would exhibit higher pairwise return correlations than companies from different sectors. Firms within the same sector that operate under the same regulatory environment are likely to react similarly to technological innovations, and also exhibit similar sensitivity to macroeconomic shocks and/or government policy. Because of highly correlated returns on the stocks of the same sector and integrated financial markets, it would be sensible to look for any added benefit for sector asset allocation, more specifically by performing sector rotation which is a relatively less explored area of asset allocation.

Most of the studies of performance measurement concentrate on the funds (mostly mutual funds). However, there are small numbers of studies (Dellva, DeMaskey and Smith, 2001; Faff, 2004; Kacperczyk, Sialm and Zheng, 2005; Dou et al., 2014; etc) that concentrate on the industry or sector perspective. Although sector/industry return predictability is attractive to the practitioner it has received comparably less attention in academic literature. This gap is surprising with respect to the importance of sector/industry analysis in the investment process. Furthermore, most of the performance literature uses factor models like one factor model (CAPM), three factors model (Fama-French three-factor model) or four factor model (Carhart's four factor model). The newly evolved five-factor model of Fama-French (Fama and French 2015) is widely acknowledged by the academics; however, to the best of our knowledge, no body uses the five-factor model to evaluate the performance of sectors portfolios.

To the best of our knowledge, our study is the first that compares the portfolio performance by using newly evolved Fama-French Five-Factor Model (5FM) with their previous Three-Factor Model (3FM) in the industry/sector perspective. In the essay three (chapter five) of this study, together with the portfolio performance evaluation by using multi-factor models (3FM and 5FM), we also contribute to the scarce literature of sector rotation strategies. Our sector rotation strategies of sector portfolios are formulated based on the rolling alphas of Fama-French models (three-factor and/or five factor). Our argument is that, if the factor models of Fama-French (whether three-factor and/or five-factor model) generate true alpha (intercept) then we can incorporate investment strategies (sector rotation strategies) to ‘beat the market’.

2.5 Conclusion

To recapitulate, time-variations in expected size, value and momentum premiums have received attention in empirical studies. A large amount of empirical studies looks for the relation between value, size, and momentum premiums and macroeconomic phenomena across different economic states. Systematic differences in variations over the economic states in small and large firms (Kim and Burnie, 2002; Perez-Quiros and Timmermann, 2000; Switzer, 2010, Scheurle and Spremann, 2010; etc.); value and growth firms (Black and McMillan, 2005; Arshanapalli et al., 2006; Gulen, Xing, and Zhang, 2011; Scheurle and Spremann, 2010; Chung et al., 2012; etc); and winner and loser firms (Chordia and Shivakumar, 2002; Griffin et al., 2003; Arshanapalli et al., 2006; Li et al., 2008; Scheurle and Spremann, 2010; Kim et al., 2014; etc.) are documented. To incorporate the asymmetries of size, value, and momentum premiums this study adopts a flexible econometric framework of Perez-Quiros and Timmermann (2000); Gulen, Xing, and Zhang (2011); and Kim et al. (2014) that allows time variations in expected size, value, and momentum premiums. The Time-Varying Markov Switching model of this study captures the asymmetries of expected return premiums that are predicted by theories.

While regular price momentum is already a well-documented characteristic of financial markets, style momentum (momentum among style portfolios) can be considered as a new empirical study defying the theory of efficient markets. Lewellen (2002); Chen (2003); Chen and De Bondt (2004); Froot and Teo (2004); and Chen et al. (2012) studied style momentum in the US context; whereas Aarts and Lehnert (2005); and Clare et al. (2010) studied in the UK context. On the other hand, numerous studies investigate whether investment styles can be timed (e.g. Copeland and Copeland, 1999; Kao and Shumaker, 1999; Levis and Liodakis, 1999; Chen and De Bondt, 2004; Desrosiers et al., 2004; Knewtson et al., 2010; Bird and Casavecchia, 2011; Gallagher et al., 2015; Miller et al., 2015; etc.). However, a very small amount of literature investigates the timing of the style portfolios. The literature of style timing is mostly based on the concept of style momentum. Hence, there are scopes to contribute to the style timing literature by identifying momentum of style portfolios. To incorporate survival based econometrical model in the style timing literature that identifies potential momentum of style portfolios, we use Kaplan-Meier (KM) estimator by following the study of Jochum (2000) and Kos and Todorovic (2008). This approach sheds light on momentum effect from a trader's perspective, rather than portfolio manager's perspective. Trading rules are then carried out based on the momentum effect of style portfolios that has been identified by the positive and negative return sequentials.

On the other hand, in the literature different asset pricing models (CAPM, Fama-French three-factor model, Carhart four-factor model, Fama-French five-factor model) are widely acknowledged by academics as frameworks for the conceptualisation of equity risk, and often accepted as a conventional perception among academics as well as practitioners. However, the empirical virtues of these asset pricing models and their embedded measures of risk have been raging for decades. Although a universal accepted asset pricing model has not yet been found, Fama-French 3FM and Carhart 4FM alpha, along with Jensen's alpha, have been used as standard measures of portfolio performance among. Kothari and Warner (2001) argue that multifactor benchmark models (e.g. Fama-French 3FM, Carhart 4FM) are the basis for performance measurement as they have high explanatory power in asset pricing tests. Fama and French (1993) characterised the multifactor benchmark models as 'simple' and 'straightforward' method of performance measurement. If an asset pricing model completely captures expected returns, the intercept (alpha) is expected to be indistinguishable from zero in a regression of an asset's excess returns on the model's factor returns. However, a non-zero alpha can be attributed as the abnormal returns in excess of what could have been achieved by a matched investment in the benchmark portfolios. In this argument, it would be interesting to examine whether the newly evolved Fama-French five-factor model can capture the performance of portfolio returns better than previous Fama-French three-factor model. Moreover, if either of the factor models produces true alpha then based on the time series of alphas (rolling window alpha) we can generate rotation based trading strategies to gain higher returns. We investigate these rotation strategies to the less explored sector/industry portfolios in our study (chapter five).

CHAPTER THREE: ASYMMETRIES IN THE UK SMALL, VALUE AND MOMENTUM PREMIUMS

3.1 Introduction

Chapter three contributes to the style literature by extending the study in the UK market and investigates the asymmetries of size, value and momentum premiums over the economic cycles and their macroeconomic determinants. We use Markov Switching approach to perform the comparative analysis of the asymmetries over the UK economic cycles. To the best of our knowledge, this is the first study that examines how all three equity premiums (size, value and momentum) are influenced by macroeconomic factors across business cycles, including recent financial crisis in the UK.

Since Fama and French, (1993) and Carhart (1997) related a small-cap premium (small-minus-big company returns [SMB]), value premium (high book to market minus low book to market ratio stock returns [HML]) and momentum premium (winner or up-momentum minus loser or down-momentum stock returns [UMD]) to excess returns, a vast body of literature that analyses determinants of those premiums has emerged. While, for instance, DeBondt and Thaler (1985) and Daniel, Hirshleifer and Subrahmanyam (1998) argue that the value premium arises due to the overreaction of investors, a number of academic studies point that the value and size premium are proxies for some non-diversifiable risks not captured by the standard CAPM model, such as risks resulting from variations in macroeconomic factors (see Kelly, 2003; Liew and Vassalou, 2000; Petkova, 2006; Vassalou, 2003; Zhang et al. 2009;Black and McMillan, 2005; Gulen Xing and Zhang, 2011, Kim et al., 2014 and Perez-Quiros and Timmermann, 2000). The literature on variety of macroeconomic sources that can cause asymmetries in expected returns of value, small-cap and winner portfolios over different phases of economic cycle focuses on the US market. We expand this literature by investigating the determinants of the cyclical variations in size, value and momentum premiums in the UK. The UK asset management industry accounts for more than one-third (37%) of European assets under management and it is globally second only to the US. Thirty nine percent (39%) of those assets are managed on behalf of the overseas clients and 32% of all equity mandates are placed in the UK equity[5]. Therefore, we believe that examining cyclicality of premiums in the UK market is of interest to investors and asset managers domiciled both in the UK and overseas. To the best of our knowledge this is the first comprehensive study of the asymmetry of the three premiums in the UK, which scrutinises the relative differences in the cyclical behaviour of the three premiums and their macroeconomic determinants. Last but not least, our study is the first that encompasses the period of the recent global financial crisis.

Let us first take a look at the existing evidence on how small, value and momentum premiums in the US market are affected by different economic conditions. We will also review why small, value and loser firms may be more sensitive when it comes to recessionary shocks than their counterparts[6]. Research focusing on cyclical asymmetries in small and large size firms reveals that their sources of finance are different, implying they should not be affected in the same manner by the credit market constraints. Perez-Quiros and Timmermann (2000) argue that worsening credit market conditions in the US during economic downturns have an adverse effect on the small-cap firms, suggesting greater risk and increase in the risk premium. Chan and Chen (1991) prove that characteristics of a firm rather than its size matter for the US size premium. Specifically, they find a large proportion of marginal firms (with lower production efficiency and higher financial leverage) in the small-cap portfolio. Since marginal firms have low price, while having higher financial leverage and cash flow problems; their price tends to be more sensitive to the changes in market conditions. Similar is confirmed more recently by Kim and Burnie (2002). This evidence implies that one should expect the small-cap premium to differ across economic states.

As far as asymmetry in value premium is concerned, the US evidence shows that value portfolio returns respond more to the changes in interest rates and money

[5]The Investment Association Annual Survey ‘Asset Management in the UK’ available from: http://www.theinvestmentassociation.org//assets/files/research/2015/20150914-ams2014-2015-fullsurvey.pdf

[6] Comprehensive literatures are reviewed in chapter two.

supply over the recessionary periods than expansionary periods, supporting the asymmetric behaviour hypothesis (see Black and McMillan, 2005). Three distinct sources, namely, costly reversibility, operating leverage and financial leverage have been identified as the sources of relative inflexibility of value firms in mitigating recessionary shocks. Hence, these firms are riskier in recessions leading to higher expected value premiums. First, costly reversibility implies there is higher cost of firms' to reduce the scale of productive assets than it is to expand. Value firms want to disinvest more in economic downturn because their assets are less profitable than those of growth firms; such disinvesting is less important for growth firms Gulen, Xing, and Zhang (2011). Since disinvesting is restricted by costly reversibility, the fundamentals of value firms are affected more severely than the fundamentals of growth firms in economic downturn when the credit market conditions are unfavourable. In similar spirit, Gala (2005) argues that investment irreversibility plays a vital role in explaining the size effects in stock returns and their relation to risk and firms' fundamentals. Second, in recessions, the stock prices and revenues of value firms fall more relative to book values and average market level, respectively, so the value firms ought to have higher operating leverage than growth firms. The operating leverage will have adverse effect on value firms by the negative aggregate shocks during economic downturn as suggested by Gulen, Xing and Zhang (2011). Third, Livdan, Sapriza and Zhang (2009) find that value firms are characterised with higher financial leverage and investors require higher expected returns to hold higher levered stocks during economic downturn when the value firms are more exposed to the financial constraints. All this evidence is pointing that a higher value premium should be expected in recessions compared to expansions.

Looking at the variations in momentum returns across economic states, Kim et al. (2014) suggest that winner stocks are more impacted in economic expansions while loser stocks are more sensitive to economic conditions during recessions. Johnson (2002) argues that stock price is a convex function of expected growth, meaning that risk increases with growth rates and hence the winner stock returns are supposed to be more sensitive to the changes in expected growth during the expansions and higher momentum premium should be expected. Hence, past winners (past losers) tend to have higher (lower) growth rate changes in the recent past, as well as higher (lower) subsequent expected returns, according to Kim et al. (2014). They find that momentum profits are pro-cyclical and can be explained by time-varying risk. A similar link between momentum returns and risk is documented in Maio and Santa-Clara (2011), who argue that momentum anomaly could be explained by time-varying betas, reinvestment risk and interest rates.

Using size, value, and momentum premiums data from Gregory, Tharyan and Christidis, (2013) and Markov switching model methodology, this chapter seeks to contribute to the literature by providing the first comprehensive study of the effect of a set of relevant macroeconomic variables on those premiums in the UK market over varying economic regimes. The Markov switching framework in this study is closely related to Perez-Quiros and Timmermann (2000) and Gulen, Xing and Zhang (2011), where the former investigate the systematic difference in variation of size premium while the latter focusses on variations in value premium over the US business cycles. In this study, we comparatively examine the impact of UK macroeconomic variables, such as GDP growth, interest rates, money supply, credit spreads etc. on all three UK equity premiums (small, value and momentum) across high and low-volatile market states. We also explore whether cyclical differences in premiums lead to asymmetries in the economic value added (Sharpe ratios) to investors across the two states. To do this, we apply a simple trading rule that allows us to switch between a style/size portfolio and UK 3-month Treasury bill, depending on the sign of the portfolio's forecasted return. We then assess the differences in Sharpe ratios of the strategy during recessions, expansions and the full sample period relative to a buy-and-hold benchmark. We evaluate whether the trading is feasible at a reasonable level of transaction costs.

We relate Markov switching low volatility regime (regime 1) with market expansion and high volatility regime (regime 2) with recession, using OECD UK Recession Indicator. Our findings reveal that the most pronounced asymmetry across market states is associated with the size premium, followed by the value premium, while the least asymmetric is the momentum premium. The size premium changes sign from positive in expansions to negative in recessions. Overall, in our sample, macroeconomic variables have more significant impact on the three premiums in the recessions. We document that credit market conditions variables, namely interest rates, term structure and credit spread have the greatest significant impact on the level of the three premiums, particularly in the downmarket. In addition, GDP growth has strong significant impact on small and value premium in both market states, while money supply growth has significant effect on the two premiums only in economic downturns. Momentum premium is unaffected by unexpected inflation, GDP and money supply growth regardless of the market state, but remains influenced by credit market variables in both states. Our trading rule results confirm the asymmetry of the premiums over economic cycles, particularly the size premium. The Sharpe ratios are lower in recessions than in expansions, which is in line with our Markov switching model results that suggest lower premiums in recessions, and in turn lower returns for investors. Nevertheless, compared to buy and hold strategy, our trading rule fares well, particularly during recessionary periods. Specifically, portfolios of small capitalisation stocks sorted by book-to-market ratios and momentum generate greater Sharpe ratios than the corresponding buy-and-hold strategy in recessions, while in expansions their economic value added is at best equal to that of the buy-and-hold. This simple trading application shows that our model is able to successfully differentiate between the two market states and can lead to profitable trading in the down-market after transaction costs are taken into account. These findings show that economic indicators can be utilised particularly by UK small-cap investors at a very reasonable level of transaction costs, implying that these costs are unlikely source of the limits to arbitrage.

The remainder of the chapter is organised as follows: Section 3.2 outlines the methodological framework and describes the data; Section 3.3 discusses the findings before concluding the chapter in Section 3.4.

3.2 Data and Methodology

3.2.1 Style Premiums

This study uses monthly UK market data from July 1982 to June 2014. The UK SMB, HML and UMD premium data are from Gregory, Tharyan and Christidis (2013)[7], which is comparable with the Fama-French's and Carhart's US equivalents. After sorting on market capitalization, Gregory, Tharyan and Christidis (2013) form two size groups of UK stocks, namely 'S'-small and 'B'-big by using the median market

[7] Downloadable from: http://business-school.exeter.ac.uk/research/areas/centres/xfi/research/famafrench/files/ (Accessed on 20/07/2015)

capitalization of the largest 350 companies in the year ‘t’ as the size break point. Similarly, three book-to-market groups, named ‘H’-High, ‘M’-medium and ‘L’-Low are formed by using the 30th and 70th percentiles of book-to-market of the largest 350 firms as break points for the book-to-market. Six intersecting portfolios: SH, SM, SL, BH, BM and BL are formed (where 'SH' is the small size high book-to-market portfolio, 'SL' is the small size low book-to-market portfolio, 'BL' is the big size low book-to-market portfolio and so on). SMB and HML factors are then calculated as

SMB= (SL + SM + SH)/3 – (BL + BM + BH)/3

and,

HML= (SH + BH)/2 – (SL + BL)/2

UMD (momentum) factor is constructed using size and prior (2-12 month) returns[8]. Gregory, Tharyan and Christidis (2013) create six portfolios, namely SU (small size and high momentum portfolio), SM (small size and medium momentum portfolio), SD (small size and low momentum portfolio), BU (big size and high momentum portfolio), BM (big size and medium momentum portfolio) and BD (big size and low momentum portfolio). The UMD (i.e. high minus low momentum return) factor is then calculated as

UMD= (SU + BU)/2 - (SD + BD)/2,

Note that the components used to form the SMB, HML and UMD factors are equally weighted.

3.2.2 Macroeconomic Factors

A selection of the UK macroeconomic factors in this study, namely GDP growth, inflation, interest rate, term spread, credit spread and money supply, are commonly used in the literature of the predictability of stock returns. Table 3.1 lays out the variables used in this chapter as potential determinants of the changes is style premiums across economic regimes; their expected relationship with the SMB, HML

[8]The prior return at the end of month t is the cumulative return from month t-12 to month t-2. January is excluded from the calculation to adjust for the seasonal anomalies.

and UMD premiums respectively, the literature that identifies those relationships, the source of data and definition for each variable.

GDP indicates real economic growth and a positive relationship between GDP growth and return premium (size, value and momentum) is identified by many (e.g. Chelley-Steeley and Siganos, 2004; Kelly, 2003; Liew and Vassalou, 2000; Zhang et al., 2009).

The relationship between unexpected inflation and size premium is assumed to be negative, because small firms are affected more in the environment of unexpected inflation (Zhang et al., 2009); whereas, the relationship with value premium is expected to be positive. This is because value firms pay high dividends relative to growth firms, they perform better in higher inflationary periods, Zhang et al. (2009). According to Fisher's theory if the stocks are hedged against inflation one would expect a positive relationship between inflation and stock returns. Hence the intuitive relationship between momentum premium and inflation is positive. We follow Fama and Gibbons (1984) and Zhang et al. (2009) to calculate the unexpected inflation as per Table 3.1.

Further, the increase in the short-term interest rates affects badly value firms and small-cap firms due to their high leverage, uncertainty of cash flows and low durations in general. Moreover, rising interest rate reflects the worsening of credit market conditions (Perez-Quiros and Timmermann, 2000) and thus interest rates are likely to be negatively correlated with stock returns (Gulen, Xing, and Zhang, 2011). In this study, we use the UK 3-month Treasury bill as a proxy for the risk-free interest rate.

The term spread can be viewed as an economic activity indicator and it is a proxy for risk premium. In economic upturn, the term spread decreases because short-term interest rates increase more than long-term interest rates. Whereas, during economic downturn short-term interest rates decrease and the spread between long and short-term interest rates increases. Term spread may, therefore, affect expected stock return because it affects the company earnings (Lucas et al., 2002). The intuitive relationship between term spread and style premium is positive. We define term spread as the difference between the yield on a 10-year UK government bond and the UK 3-month Treasury bill.

Table 3. 1: Macroeconomic variables

The table grids all macroeconomic variables used in this study; their expected relationship to SMB, HML and UMD; academic studies that report the relationship; how the variable is transformed for the purpose of this study and the source of data

Variable name	Relationship with SMB	Relationship with HML	Relationship with UMD	Study which reports the relationship	Variable used in our study defined as:	Data source
GDP growth	Positive	Positive	Positive	Chelley-Steeley and Siganos (2004), Kelly (2003), Aretz, Bartram and Pope (2010), Liew and Vassalou (2000), Zhang et al. (2009), etc.	$\mathrm{GDPgrowth} = \ln(\mathrm{GDP_t}) - \ln(\mathrm{GDP_{t-1}})$	OECD (2014)
Unexpected Inflation (INF)	Negative	Positive	Negative	Kelly (2003), Kim et al. (2014), Zhang et al. (2009)	$\text{Unexpected INF}_t = \text{Realized INF}_t - \text{Expected INF}_t$ $\text{Realized INF}_t = \ln(\mathrm{CPI_t}) - \ln(\mathrm{CPI_{t-1}})$ $\text{Expected INF}_t = \mathrm{T-bill} - \sum_{j=1}^{12} \mathrm{T-bill}_{t-j}$ where CPI is the consumer price index, taking 2005 as base year	Datastream
Interest rate	Negative	Negative	Negative	Gulen, Xing, and Zhang (2011), Kim et al. (2014), Maio and Santa-Clara, (2011), Zhang et al. (2009), etc.	3-month UK Treasury bill	Datastream
Term spread	Positive	Positive	Positive	Aretz, Bartram and Pope (2010), Chordia and Shivakumar (2002), Lucas, van Dijk and Kloek (2002), Hahn and Lee (2006), Petkova (2006), etc.	Term spread = 10-year UK government bond yield – 3 months T-bill yield	Datastream
Credit spread	Negative	Positive	Positive	Chordia and Shivakumar (2002), Gulen, Xing, and Zhang (2011), Perez-Quiros and Timmermann (2000), Hahn and Lee (2006), Petkova (2006), etc.	Credit spread = Moody's US BBA yield – 10-year UK government bond yield	Datastream
Money supply (M2)	Positive	Positive	Positive	Gulen, Xing, and Zhang (2011), Perez-Quiros and Timmermann (2000), Steiner (2009),etc.	$\mathrm{M2} = \ln(\mathrm{M2_t}) - \ln(\mathrm{M2_{t-1}})$	Datastream

Credit spread or default spread has long been used in the literature as a proxy of credit market conditions, see for example Chen, Roll and Ross (1986); Gertler, Hubbard and Kashyap (1990); Kashyap, Lamont and Stein (1994); Keim and Stambaugh (1986); Perez-Quiros and Timmermann (2000); Griffin, Ji and Martin (2003); Gulen, Xing and Zhang (2011); etc. We define credit spread as the difference in yields between high yield corporate bond[9] and 10-year UK government bond. The intuitive relationship between credit spread with value and momentum premiums are positive. However, since small firms tend to be newcomers, poorly collateralized and don't have full access to the external financial markets, they have relatively stronger adverse effects than large firms to the worsening credit market conditions. On average, an increase (decrease) in the credit spread is expected to be associated with lower (higher) returns of SMB. Moreover, asymmetries are expected for the credit spread variables since small firms are likely to be more exposed to credit market conditions during recession, (Perez-Quiros and Timmermann, 2000).

Finally, the change in money supply variable proxies the liquidity changes and monetary policy shocks, (Gulen, Xing, and Zhang, 2011). It also measures the monetary policy shocks that might affect aggregate economic conditions. Intuitively, changes in money supply affect the economic conditions and investment premium as they indicate the credit market conditions. One could expect a higher return when there's an increase in money supply. Smallest firms are found to be particularly strongly positively affected by money supply growth during recessions in the study of Perez-Quiros and Timmermann (2000).

3.2.3 Relationship Between the Premiums and Macroeconomic Factors

To get an indication of the relationship between a set of macroeconomic variables selected and each of the three premiums for the overall sample period, we run three separate multi-factor Ordinary Least Squares (OLS) regressions of the following form:

[9]Note that the high yield corporate bond data are not available for the UK market a period longer than 11 years. To cover longer span of varying economic regimes, we resort to Moody's US BAA corporate bond index as a proxy for the UK data. The correlation coefficient Thomson Reuter UK Corporate Benchmark BBB (available since April 2002) and Moody's US BAA is 0.871085 over the 11 year period.

$$r_{it} = \alpha_1 + \beta_{i1}GDPG_{t-1} + \beta_{i2}INF_{t-1} + \beta_{i3,}IR_{t-1} + \beta_{i4}TERM_{t-1} + \beta_{i5}CREDIT_{t-1} + \beta_{i6}\Delta M_{t-2} + \varepsilon_{it}\ ;\ i = (SMB, HML, UMD);\ \ \varepsilon_{it} \sim N(0, \sigma_{it}^2) \quad \text{..... (3.1)}$$

While OLS can serve as an indicator of the relationship between factor premiums and macroeconomic variables, if asymmetries in the data do exist, the OLS is not the appropriate model to use, as it does not account for different economic states. To test for any presence of asymmetry in relationships given in equation (3.1) in high- and low-volatility regimes, we adopt the Markov Switching Model methodology.

3.2.4 Econometric Framework for Markov Switching Model

We assume that investors' investment decisions vary across different economic regimes and further, we assume the relationship between style returns (size, value and momentum) and macroeconomic variables also varies. To characterise economic regimes in style investment return, Perez-Quiros and Timmermann (2000), Guidolin and Timmermann (2008), Gulen, Xing, and Zhang (2011), Chung, Hung and Yeh (2012) adopt a two-stage Markov switching model approach. The Markov Switching model was pioneered by Hamilton (1989) and over the years gained popularity for studying the asymmetries across business cycle regimes (Layton and Smith, 2007). The model allows shifts from one regime to another and gives probabilities of such transitions. It also takes into account certain types of non-stationarity inherent in economic or financial time series data that cannot be captured by classical linear models. These economic and financial time series might obey to different economic regimes characterised by economic events such as financial crisis (Jeanne and Masson, 2000) or abrupt economic policy changes (Hamilton, 1988), which is relevant for our study. From the econometrics point of view, the main challenge of estimating Markov Switching model is the unobservability of the prevailing regime (Ammann and Verhofen, 2006).

The Markov Switching framework of this study closely related to Perez-Quiros and Timmermann (2000) and Gulen, Xing and Zhang (2011). We model size, value and momentum premiums as follows:

$$r_{it} = \alpha_i + \beta_{i1,s_t}GDPG_{t-1} + \beta_{i2,s_t}INF_{t-1} + \beta_{i3,s_t}IR_{t-1} + \beta_{i4,s_t}TERM_{t-1} + \beta_{i5,s_t}CREDIT_{t-1} + \beta_{i6,s_t}\Delta M_{t-2} + \varepsilon_{it} \quad ;\ i = (SMB, HML, UMD) \quad \text{...... (3.2)}$$

Here, $r_{it} = (SMB_t, HML_t, UMD_t)'$ is the (3×1) vector of three different style premiums, and ε_{it} is normally distributed error term with mean 'zero' and variance $\sigma^2_{is_t}$, with $S_t = \{1, 2\}$, namely regime 1 and regime 2. *GDPG* is the GDP growth rate, *INF* is the unexpected inflation; *IR* is a 3-month Treasury bill, used as a proxy of short-term interest rate; *TERM* is the difference between the 10-year Government bond and 3-month Treasury bill, representing a term spread; *CREDIT* is the credit spread defined as the difference in yield between high yield bond and ten year Government bond; ΔM is the log change in money supply, used as a proxy for liquidity changes in the economy.

Following the study of Perez-Quiros and Timmermann (2000), Gulen, Xing and Zhang (2011) and Kim et al. (2014), this study uses the lag of one-month for GDP growth, Inflation, Interest Rates, Term Spread and Credit Spread; whereas, money supply growth is lagged by 2-months to allow the publication delay of this variable. The model is estimated by the two-state Markov switching model with time-varying transition probabilities, which is feasible estimation method with non-normal data (See, Hamilton, 1988; Hamilton, 1994; Kim and Nelson, 1999; and Jeanne and Masson, 2000).

We can denote the Markov Switching framework of our study in matrix approach, considering the equation (3.1), as:

$$r_t = \alpha_{s_t} + \beta_{s_t} X_t + \varepsilon_t \; ; \quad \text{...} (3.3)$$

$\varepsilon_t \sim N(0, \sigma^2_{s_t})$

Where, $r_t = \begin{pmatrix} SMB_t \\ HML_t \\ UMB_t \end{pmatrix}, \alpha = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{pmatrix}, \; \beta = \begin{pmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} & \beta_{15} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} & \beta_{25} \\ \beta_{31} & \beta_{32} & \beta_{33} & \beta_{34} & \beta_{23} \end{pmatrix},$

$$X_t = \begin{pmatrix} GDPG_{t-1} \\ INF_{t-1} \\ IR_{t-1} \\ TERM_{t-1} \\ CREDIT_{t-1} \\ \Delta M_{t-2} \end{pmatrix} \varepsilon_t = \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{pmatrix} \text{ and } S_t = \{1, 2\}$$

The observation of economic regimes (either 1 or 2) at time t depends on the realizations of unobserved Markov Chain, denoted by $S_t, S_{t-1}, \ldots S_{t-k}$. The regime at time $\tau < t$ that will be observed at time $'t'$ is not known with certainty.

Prior literature shows that the transition probabilities between regimes are time varying and depend on information variables such as economic leading indicator Filardo (1994); Perez-Quiros and Timmermann (2000); Gulen, Xing, and Zhang (2011); Chung et al. (2012). Layton (1998) argues that such transition probabilities adjusted by information variables or leading indicators provide very close correspondence to the business cycle chronology. To ensure transition probabilities accurately defined prior studies used logarithmic lag difference of Composite Leading Indicators ($\Delta LNCLI_{t-1}$). The Composite Leading Indicators is designed to anticipate the turning point of economic cycles relative to trend and continue to signal diverging growth patterns across the corresponding economy (OECD, 2014). However, The indicator suffers from back-filling bias, as it is published when 60% of its data are available and revised as more data are included. There is a 2-month publication lag for input data for this indicator so that the data for month ‘t’ is available in month ‘t+2’[10]. To avoid back-filling bias, we apply CLI indicator with lag 2 in this study (as in Perez-Quiros and Timmermann, 2000 and Gulen, Xing and Zhang, 2011).

If S_t is a first order Markov Process and the transition of one regime to another depends on the transition variable, observed at time $t-k$, (Z_{t-k}) than the Time Varying Transition Probabilities (TVTP) can be defines as (Diebold, Lee and Weinbach, 1995):

[10]http://www.oecd.org/std/compositeleadingindicatorsclifrequentlyaskedquestionsfaqs.htm

$$
\begin{array}{cc}
 & \textbf{Time } \boldsymbol{t} \\
 & \begin{array}{cc} \text{State 1} \qquad\qquad\qquad & \qquad\qquad\qquad \text{State 2} \end{array} \\
\begin{array}{c} \text{State 1} \\ \\ \\ \textbf{Time } \boldsymbol{t}\textbf{-1} \\ \\ \\ \text{State 2} \end{array} &
\left[\begin{array}{c:c}
\begin{array}{c} P_{11}(z_{t-k}) \\[1ex] P(s_t = 1 | s_{t-1} = 1, z_{t-k}) \\[1ex] \dfrac{\exp(a_1 + b_1 z_{t-k})}{1 + \exp(a_1 + b_1 z_{t-k})} \end{array} &
\begin{array}{c} P_{12}(z_{t-k}) \\[1ex] P(s_t = 1 | s_{t-1} = 2, z_{t-k}) \\[1ex] 1 - \dfrac{\exp(a_1 + b_1 z_{t-k})}{1 + \exp(a_1 + b_1 z_{t-k})} \end{array} \\ \hdashline
\begin{array}{c} P_{21}(z_{t-k}) \\[1ex] P(s_t = 2 | s_{t-1} = 1, z_{t-k}) \\[1ex] 1 - \dfrac{\exp(a_2 + b_2 z_{t-k})}{1 + \exp(a_2 + b_2 z_{t-k})} \end{array} &
\begin{array}{c} P_{22}(z_{t-k}) \\[1ex] P(s_t = 2 | s_{t-1} = 2, z_{t-k}) \\[1ex] \dfrac{\exp(a_2 + b_2 z_{t-k})}{1 + \exp(a_2 + b_2 z_{t-k})} \end{array}
\end{array}\right]
\end{array}
$$

Here, $P_{ij}\,(z_{t-k})$ is the probability of moving regime i to regime j, conditional to the transitional variable (Z_t). Note that, the likelihood of the transition from regime 1 (2) to regime 2 (1) depends on the changes on variable (Z_t). A positive change in z_{t-k} will increase (decrease) the likelihood of a transition from regime 1 to regime 2 when the coefficient $b_1 > 0(< 0)$. Likewise, a positive change in z_{t-k} will increase (decrease) the likelihood of a transition from regime 2 to regime 1 when the coefficient $b_2 > 0(< 0)$, Agnello, Dufrénot and Sousa (2013).

Following the procedure of Filardo (1994, 1998) and Agnello, Dufrénot and Sousa (2013) the TVTP of Markov Switching Model can be estimated by Maximum Likelihood method.

Let,

$\Omega_t = (X_t, Z_{t-k})$ = Vector of observed independent variables and transition variables at time $t - k$

$\Psi_t = (y_t, y_{t-1}, \dots, y_{t-k}, \dots, y_1)$ = Vector of dependent variables. And

θ= Vector of parameters to estimate.

The conditional likelihood function of Ψ_t can be defined as:

$L(\theta) = \prod_{t=1}^{T} f(y_t|\Omega_t, \Psi_{t-1}; \theta)$;

Where,

$$f(y_t|\Omega_t, \Psi_{t-1}; \theta) = \sum_i \sum_j f(y_t|s_t = i, s_{t-1} = j, \Omega_t, \Psi_{t-1}; \theta) \times P(s_t = i, s_{t-1} = j|\Omega_t, \Psi_{t-1}; \theta) \qquad \text{..............} \ (3.4)$$

By applying Bayes' rule we can get the conditional state probabilities:

$$\begin{aligned} &P(s_t = i|\, s_{t-1} = j|\mathrm{z}_t)\, P(s_{t-1} = j|\Omega_t, \Psi_{t-1}; \theta) \\ &\quad = P_{ij}(z_t)\, P(\, s_{t-1} = j|\Omega_t, \Psi_{t-1}; \theta) \end{aligned} \qquad \text{......} \ (3.5)$$

And,

$$\begin{aligned} P(s_t = i|\Omega_{t+1}, \Psi_t; \theta) &= P(s_t = i\,|\Omega_t, \Psi_t; \theta) \\ &\times \frac{1}{f(y_t|\Omega_t, \Psi_{t-1}; \theta)} \sum_j f(y_t|s_t = i, s_{t-1} = j, \Omega_t, \Psi_{t-1}; \theta) \\ &\qquad \times P(s_t = i, s_{t-1} = j|\Omega_t, \Psi_{t-1}; \theta) \end{aligned} \qquad \text{.......} \ (3.6)$$

Equation (3.5) and (3.6) can be iterated by applying the recursion technique to obtain the conditional function:

$$f(y_t|s_t = 1, s_{t-1} = j, \Omega_t, \Psi_{t-1}; \theta) = \frac{\phi\left(\frac{y_t - x_t^{'}\beta_1}{\sigma_1}\right)\Phi\,(a_j + z_t^{'}b_j)}{\sigma_1 P_{1j}(z_t)} \qquad \text{...............} \ (3.7)$$

$$f(y_t|s_t = 2, s_{t-1} = j, \Omega_t, \Psi_{t-1}; \theta) = \frac{\phi\left(\frac{y_t - x_t^{'}\beta_2}{\sigma_2}\right)\Phi\,(a_j + z_t^{'}b_j)}{\sigma_2 P_{2j}(z_t)} \qquad \text{..............} \ (3.8)$$

3.2.5 Identification of the States

Figures 3.1, 3.2 and 3.3 provide an indication of the relation between the Markov switching states and economic regimes. All three figures display the regime probabilities of being in low-volatile regime (regime 1) and high-volatile regime (regime 2) for size, value and momentum premiums respectively at time t with the conditional information at time t - 1. Here, *P(S(t)=1)* and *P(S(t)=2)* are the probability of being in regime 1 and regime 2 respectively. The shaded area is the OECD based Recession Indicators for the United Kingdom taken from Federal Reserve Bank of St. Louis. It can be observed that the predicted probabilities of being in the high-volatile (low output) regime coincide with the recessionary period. Figure 3.1 and 3.2 illustrate that the smoothed regime probabilities display clear time variation of small-cap and value premium across the states of the economy and the probabilities of being in regime 2 are high during the recessions. Figure 3.3 also displays the time variation of momentum premium across the economic states but the probabilities of being in regime 2 when there is economic downturn are notable however not as high as those for small and value premium. The least time variant across economic states is the value premium (Figure 3.2). Most variation in value premium is observed at the start of 2001/02, around the dot-com bubble burst. During that time, we note a very high probability of value premium being in regime 2 (downturn). These results overall give support to the fact that the regime 1 can be classified as the state of economic upturn and regime 2 as the state of economic downturn.

Moreover, we find that that the regime 2 is associated with the high conditional volatility, measured by conditional standard deviation reported in Table 3.4 for the size, value and momentum premiums. These findings are in alignment with those of Schwert (1990), Hamilton and Lin (1996), Gulen, Xing and Zhang (2011), Perez-Quiros and Timmermann (2000) and Kim et al. (2014). Given this, it can be inferred that the regime 1 corresponds to economic upturn and regime 2 to the economic downturn, which are characterised by low and high volatilities, respectively.

Figure 3. 1: Time-Varying Probability of Being in High and Low-volatile Regimes for Size Premium

This figure displays the regime probabilities of being in low-volatile regime (regime 1) and high-volatile regime (regime 2) for size premium at time *t* with the conditional information at time *t-1*.here, p(s(t)=1) and p(s(t)=2) are the probability of being in regime 1 and regime 2 respectively. The shaded area is the OECD based recession indicators for the united kingdom.

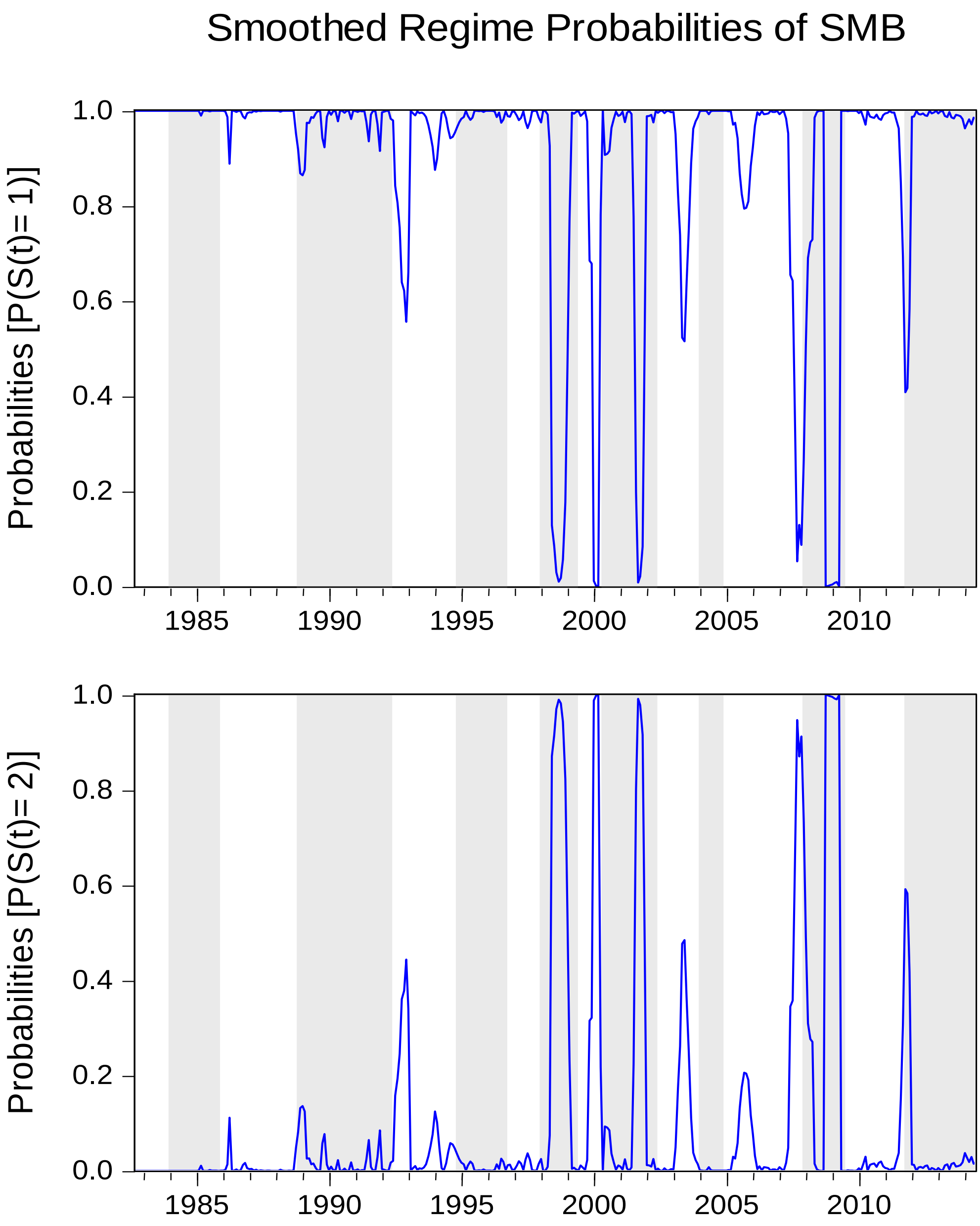


Figure 3. 2: Time-Varying Probability of Being in High and Low-volatile Regimes for Value Premium

This figure displays the regime probabilities of being in low-volatile regime (regime 1) and high-volatile regime (regime 2) for value premium at time t with the conditional information at time t-1.here, p(s(t)=1) and p(s(t)=2) are the probability of being in regime 1 and regime 2 respectively. The shaded area is the OECD based recession indicators for the united kingdom.

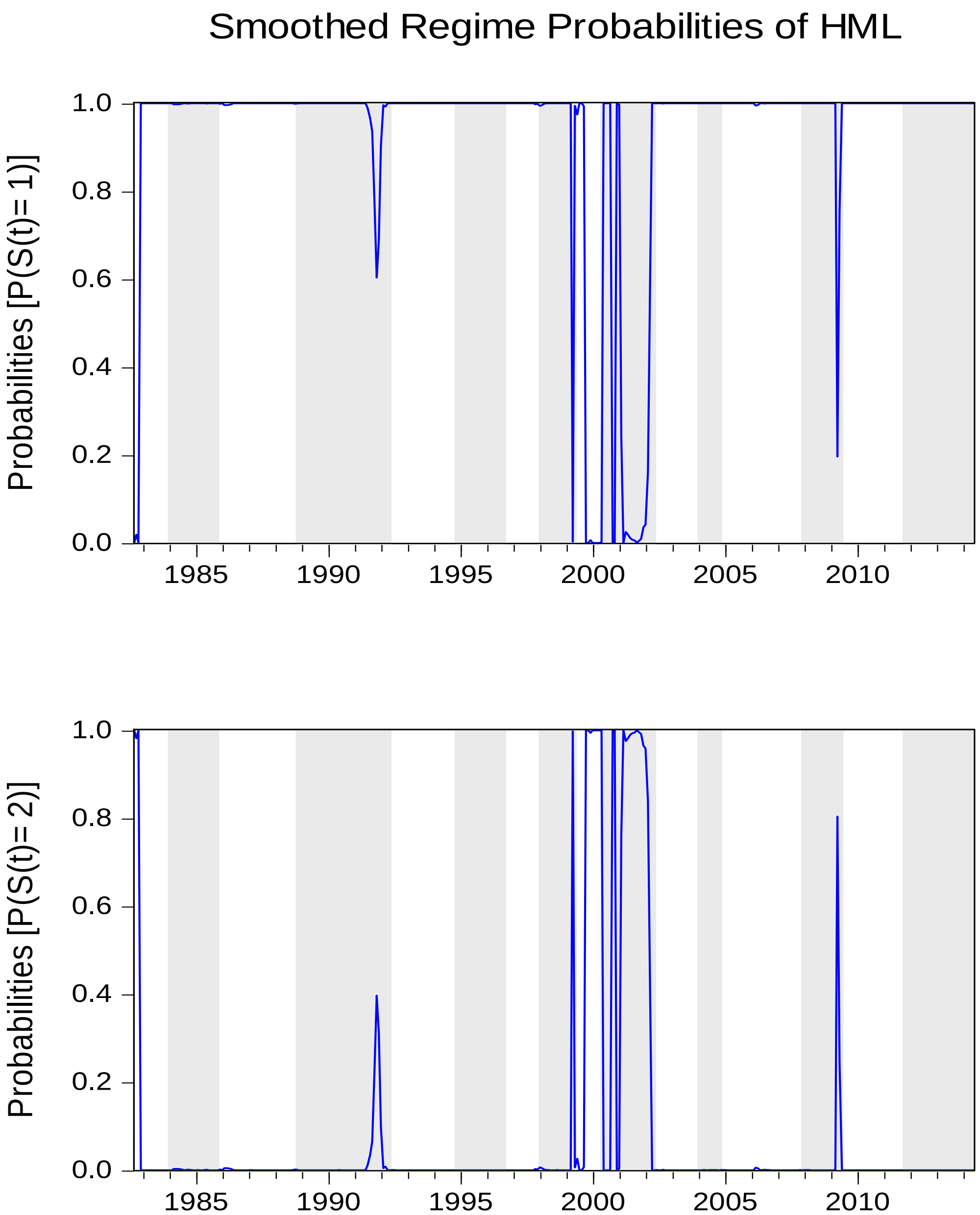
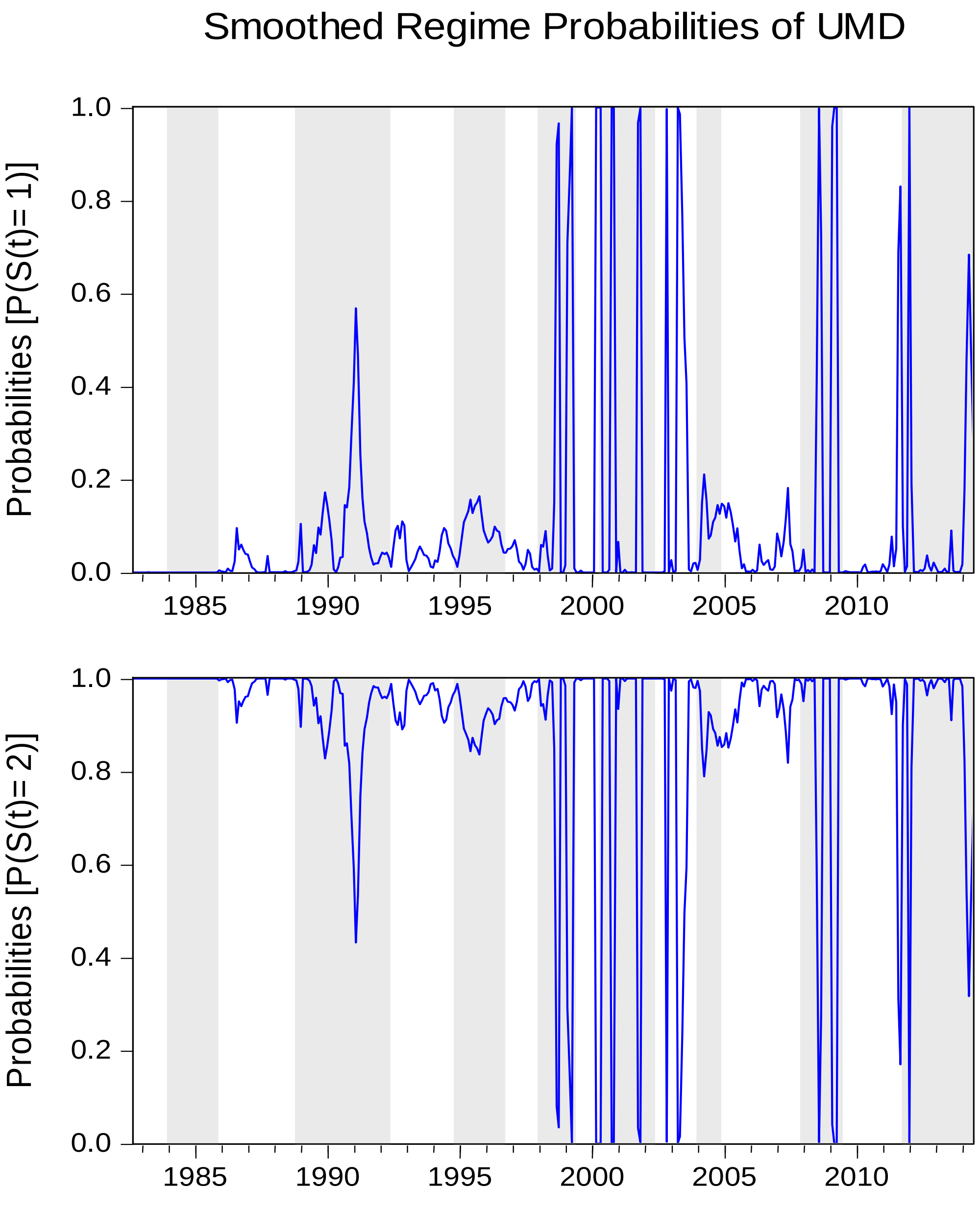


Figure 3. 3: Time-Varying Probability of being in High and Low-volatile Regimes for Momentum Premium

This figure displays the regime probabilities of being in low-volatile regime (regime 1) and high-volatile regime (regime 2) for momentum premium at time *t* with the conditional information at time *t-1*.here, p(s(t)=1) and p(s(t)=2) are the probability of being in regime 1 and regime 2 respectively. The shaded area is the OECD based recession indicators for the united kingdom.



3.3 Empirical findings

3.3.1 Descriptive Statistics

Table 3.2 presents the descriptive statistics (mean, standard deviation, skewness and kurtosis) of the UK size, value and momentum premiums in the overall sample period (Panel A) and in economic downturns and upturns[11] separately (Panel B). The monthly mean returns of size, value and momentum premiums in the overall sample period reported in Panel A are 0.12%, 0.34% and 0.95% with the standard deviation of 3.1%, 3.2% and 4.4% respectively.

Table 3. 2: Descriptive Statistics of Style Premiums

This table reports the Mean, Standard Deviation, Skewness and Kurtosis of different style based factor returns over the full sample period (1982M07 to 2014M06). Panel A reports the values of the overall sample period. Panel B reports the values over the business cycles. St. Louis fed's recession index is used to define recessions and expansions. The values in the parentheses represent the p-values of Skewness-Kurtosis test for normality. The mean standard deviations are in percentage.

Panel A

	Mean	Standard Deviation	Coefficient of Skewness	Coefficient of Kurtosis
SMB	0.1232	3.1157	0.1146 (0.3519)	5.1296*** (0.0000)
HML	0.3425	3.2387	-0.5941*** (0.0000)	9.5733*** (0.0000)
UMD	0.9480	4.3678	-0.9542*** (0.0000)	8.6358*** (0.0000)

Panel B

		Mean	Standard Deviation	Coefficient of Skewness	Coefficient of Kurtosis
Expansion	**SMB**	0.3381	2.9851	0.1099 (0.5309)	3.9093 (0.0316)
	HML	0.3502	3.3782	-1.9291*** (0.0000)	12.543*** (0.0000)
	UMD	0.9276	3.7708	-0.1064 (0.5442)	8.7245*** (0.0000)
Recession	**SMB**	-0.0706	3.2239	0.1446 (0.3879)	5.9317 (0.0000)***
	HML	0.3360	3.1164	0.9386*** (0.0000)	5.7750*** (0.0000)
	UMD	0.9658	4.8526	-1.2870*** (0.0000)	7.9820*** (0.0000)

***Implies the significance at 1% level of significance
** Implies the significance at 5% level of significance
*Implies the significance at 10% level of significance

[11] As defined by OECD's Composite Leading Indicator (CLI) described in section 3.4 of the paper

Panel B shows the domination of momentum premium with the mean return (and standard deviation) being highest in both regimes. Panel B documents that while the fall in value and momentum premiums in recessions is very marginal, the size premium exhibits a notable change. It shifts from positive (0.34%) in expansions to negative (-0.07%) in recessions, which indicates the poor performance of small firms during the tight credit market conditions. Decrease in size premium in the downmarket state is also documented by Kim and Burnie (2002). Further, in the overall sample period (Panel A), all but the SMB premium are significantly negatively skewed with kurtosis higher than 3 in all the cases, implying non-normal distribution. Similar characteristics are also observed during the two economic cycles.

3.3.2 Multiple OLS Results

Table 3.3 provides a summary of the relationship between each of the return premiums and macroeconomic variables used in this chapter. It is apparent that increases in GDP, inflation, credit spread and money supply growth are causing significant increase in the size premium. Similarly, short-term interest rates and credit spread have a significant positive impact on value premium. However, the OLS results show that no macroeconomic variable impacts momentum premium over our sample period. The intuition behind some of these relationships will be explained in the next section.

These OLS results are only indicative of the relationship between the premiums and macroeconomic variables but they do not tell us anything about the change in the size of the premium in recessions and expansion, or about variables that may be more (or less) influential across the two regimes. The low level of R^2 shows that OLS as a method of estimation has limitations when asymmetries in the data are present and when the assumptions of the normal distribution are violated (note that descriptive statistics in Table 3.2 illustrates that the data are not normal).

Table 3. 3: Parameter Estimates of Multiple OLS Regression Model

This table reports the parameter estimation of multiple regression model over the sample period 1982M07 to 2014M06. The estimated model is:

$$r_{it} = \alpha_1 + \beta_{i1} GDPG_{t-1} + \beta_{i2} INF_{t-1} + \beta_{i3,} IR_{t-1} + \beta_{i4} TERM_{t-1} + \beta_{i5} CREDIT_{t-1} + \beta_{i6} \Delta M_{t-2} + \varepsilon_{it}$$

$i = (SMB, HML, UMD)$; $\varepsilon_{it} \sim N(0, \sigma_{it}^2)$;

Here, r_{it} = monthly return of SMB, HML and UMD, GDPG is the GDP growth rate, INF is the realized inflation, IR is the short-term interest rate, TERM is the term spread, CREDIT is the credit spread and ΔM is the growth of money supply.

	SMB	**HML**	**UMD**
α_1	-0.003718 (0.5534)	-0.010698 (0.1112)	0.013285 (0.1448)
$GDPG_{t-1}$	2.972630** (0.0153)	1.901194 (0.1457)	1.818247 (0.3048)
INF_{t-1}	0.385759** (0.0122)	0.119489 (0.4659)	-0.179156 (0.4205)
IR_{t-1}	-0.848198 (0.2940)	1.698680** (0.0497)	-0.379323 (0.7461)
$TERM_{t-1}$	-0.080550 (0.5733)	0.085839 (0.5745)	-0.111149 (0.5921)
$CREDIT_{t-1}$	0.250738* (0.0934)	0.329427** (0.0394)	-0.135733 (0.5307)
ΔM_{t-2}	0.576761*** (0.0038)	-0.150828 (0.4771)	0.256228 (0.3735)
Standard Error	0.030222	0.032308	0.043843
R-Squared	0.076441	0.018950	0.012809

***Implies the significance at 1% level of significance
** Implies the significance at 5% level of significance
*Implies the significance at 10% level of significance

3.3.3 Markov Switching Model Results

Table 3.4 reports the parameter estimation of the equation (3.2) by the Markov switching model. The constant term (α_1) in regime 2 is lower than those of regime 1 universally for all the style premiums. This indicates lower expected value of the SMB, HML and UMD after adjusting for the macroeconomic risk factors in the regime 2 then in regime 1. Except for the size in regime 1, all of the constant terms are statistically significant across the regimes. The highest constant is the one associated with the momentum premium in both regimes. The most notable change is associated with size premium both in terms of its magnitude (a change of 0.26%) and its sign, which changes from positive in expansion to negative in recession. This conclusion is consistent with the one associated with mean values of the three premiums in expansions and recessions reported in Table 3.2. The constants in Table 3.4 therefore imply that the investors in the UK market would benefit more from investing in large capitalization firms with good growth opportunities in the recessions, but that the premium on holding winners will be lower than in expansions. This is in line with Arshanapalli, D'Ouville and Nelson (2004) and Fama and French (1993) who argue that firms with small capitalization, high book-to-market ratios (value firms) and past winners are more likely to be distressed and vulnerable during bad economic conditions and investors will be better off avoiding them.

What becomes apparent from Table 3.4 is that macroeconomic variables popularly used in the literature as determinants of size, style or momentum premiums are of greater significance in the recessions than in expansions. For instance, looking at the SMB or HML premium in recessions, all explanatory variables are significant at 1% level (the only exception being the impact of inflation on value premium); while for UMD premium the variables describing credit market conditions (interest rates, term structure and credit spread) fare as the most significant ones. In expansions, both the number of significant variables and their level of significance is lower for each of the three premiums. Out of six explanatory variables commonly considered in the style premiums literature, the significant positive drivers of the small-cap premium in the upmarket are GDP growth (significant at 10%) and inflation (significant at 5%) while the increase in the term structure decreases small-cap premium (significant at 10%). GDP growth, interest rates, term structure and credit spread all have positive and significant impact on value premium in expansions; while at the same time momentum premium is highly negatively influenced by the increase in interest rates (significant at 5%) and the increase in credit spread (significant at 1%), but remains unaffected by the remaining variables.

Table 3. 4: Parameter Estimation of Markov Switching Model

The estimated two-state Markov switching model is:

$$r_{it} = \alpha_1 + \beta_{i1,s_t} GDPG_{t-1} + \beta_{i2,s_t} INF_{t-1} + \beta_{i3,s_t} IR_{t-1} + \beta_{i4,s_t} TERM_{t-1} + \beta_{i5,s_t} CREDIT_{t-1} + \beta_{i6,s_t} \Delta M_{t-2} + \varepsilon_{it}$$

$i = (SMB, HML, UMD)$, $\varepsilon_{it} \sim N(0, \sigma_{it}^2)$, $S_t = \{1, 2\}$

$P_{11} = P(s_t = 1 | s_{t-1} = 1, z_{t-1}) = \Phi(\pi_0 + \pi_1 CLI_{t-2})$, $P_{12} = 1 - P_{11}$

$P_{22} = P(s_t = 2 | s_{t-1} = 2, z_{t-1}) = \Phi(\pi_0 + \pi_2 CLI_{t-2})$, $P_{21} = 1 - P_{22}$

Here r_{it} = monthly return of SMB, HML and UMD, GDPG is the GDP growth rate, INF is the realized inflation, and IR is the short-term interest rate. TERM is the term spread, CREDIT is the credit spread and ΔM is the growth of money supply; and CLI is the OECD's Composite Leading Indicator. The model is estimated over the sample period 1982M07 to 2014M06.
The values in the parentheses represent the p-values.

		SMB	HML	UMD
Regime 1 (Expansion)	α_1	0.003474 (0.5550)	-0.017747*** (0.0006)	0.167793*** (0.0058)
	$GDPG_{t-1}$	2.344566* (0.0844)	3.520900*** (0.0004)	-4.712032 (0.2992)
	INF_{t-1}	0.369968** (0.0121)	0.120493 (0.3541)	0.348204 (0.6243)
	IR_{t-1}	-1.192405 (0.1103)	2.506955*** (0.0001)	-23.82852** (0.0122)
	$TERM_{t-1}$	-0.231651* (0.0996)	0.273211** (0.0181)	-1.871451 (0.1256)
	$CREDIT_{t-1}$	0.205820 (0.1418)	0.298536** (0.0217)	-6.290640*** (0.0000)
	ΔM_{t-2}	0.196170 (0.2981)	0.085135 (0.5902)	1.167759 (0.1607)
	Conditional Standard Deviation	0.041940	0.011578	0.020489
Regime 2 (Recession)	α_1	-0.259131*** (0.0000)	-0.240148*** (0.0000)	0.022916*** (0.0020)
	$GDPG_{t-1}$	22.46944*** (0.0000)	-66.49195*** (0.0000)	-1.834958 (0.2580)
	INF_{t-1}	1.554869** (0.0165)	0.408614 (0.5143)	0.094883 (0.5975)
	IR_{t-1}	26.23414*** (0.0017)	17.55085*** (0.0000)	-1.827687** (0.0493)
	$TERM_{t-1}$	2.938451*** (0.0004)	-8.521932*** (0.0000)	-0.495384*** (0.0041)
	$CREDIT_{t-1}$	5.151615*** (0.0000)	6.749098*** (0.0000)	0.426099** (0.0137)
	ΔM_{t-2}	4.461694*** (0.0000)	-3.170360*** (0.0000)	0.054154 (0.7741)
	Conditional Standard Deviation	0.188605	0.226901	0.053830

*** Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
* Implies the significance at 10% level of significance.

Let us now examine the further impact of each of the macroeconomic variables on the three premiums and provide some rationale behind the documented relationships. Table 3.4 reveals the significant positive relationship between the GDP growth and small and value premium in regime 1. When the economy is doing well a further increase in the GDP growth signals increase in small-cap and value premium as the literature (see Table 3.1) suggests. While this relationship holds for small-cap premium in regime 2 as well, we find that the growth in GDP decreases premium on the UK value stocks in recessions. This can be explained by the fact that value companies are concentrated in industries that are cyclical in nature (utilities, banking, etc.) and heavily affected by recessions, so even if the GDP grows in the recession it does not improve returns of value companies until the end of the recession cycle. We do not observe any significant relationship between momentum premium and GDP growth in either economic state.

The inflation coefficient is only significant for size premium, taking positive values during both regimes. Such positive and significant relationship imply that small capitalization stocks benefit from inflation, as the small firms find it relatively easier to pass along price increases in inflationary times, as argued by Anderson (1997). Since value firms pay higher dividends than growth firms, they perform better when inflation increases, as suggested by Zhang et al. (2009). While we find the relationship between value premium and unexpected inflation to be positive, it is insignificant in both economic states; the same is observed for the momentum-unexpected inflation relation.

According to the credit channel theory of monetary policy (Bernanke and Gertler, 1995), monetary tightening increases the financial costs and restricts the access to external financing. This monetary tightening has stronger effect on the firms in poorer financial positions. Our findings are in line with this theory, suggesting that since small firms tend to be low-duration firms with high leverage and cash flow problem, higher interest rates will restrict their access to external financing, which is particularly relevant during economic downturns. The small-cap premium – interest rates relationship, therefore, exhibits asymmetry and turns from negative (albeit insignificant) in expansions to positive (significant at 1%) in recessions. Similarly, we find support for a positive relationship between value premium and interest rates in both market regimes, significant at 1% level. This is consistent with Black and McMillan (2005), indicating that value investors seek higher returns to compensate increased returns on competing assets, such as fixed-income instruments. Finally, the increase in interest rates by 1% decreases momentum premium by 23.83% in regime 1 and 1.83% in regime 2, both values being significant at 5% level. Hence, past winners are more adversely affected by the increases in short-term interest rates than past losers in both economic states, however notably more so in expansions.

The relationship between the term structure and size exhibits asymmetries over economic regimes. The relationship turns from negative in regime 1 to positive in regime 2. Aretz, Bartram and Pope (2010) argue that shocks to term structure will have greater effect on larger firms than on the smaller ones and hence a positive relationship is expected between term spread and size premium. Our results confirm this view in economic downturn. In the upturn, the negative relationship between term spread and size premium may be explained by the fact that small firms often do not have as much collateral as large firms and have lesser ability to raise external funds, hence restricting the potential growth.

Further, similar to Gregory, Harris and Michou (2003), we find that during expansions, an increase in term structure has greater positive effect on value premium. The effect turns to negative in recessions, implying that increase in term spread is decreasing the value premium. Note that in expansions, even if the term structure increases, the yield curve is still relatively flat. However, in economic downturns, when the yield curve steepens, it affects more adversely growth stocks than value stocks due to their non-payment of dividends and longer durations. Hence, it is expected that investors ask for greater premium on growth stocks in recessions, which is in line with our findings from Table 3.4. Finally, we document the negative relationship between the term spread and momentum premiums in recession indicating that the past losers benefit from the steepening of the yield curve. One plausible explanation of this relationship is that winner firms tend to have higher market betas, moving more in line with the market than loser stocks. Hence, in a situation when short-term interest rates fall below long-term interest rates, winner stocks are adversely affected because of the cyclical behaviour of winner stocks.

An increase in credit spread is commonly interpreted as a sign of worsening credit market conditions. One would expect positive relationship between credit spread and style premiums. We find evidence that corroborates this in both regimes and document a positive coefficient of credit spread with size and value premiums during both economic states. This finding coincides with the findings of Fama and French

(1988, 1989). This might indicate that small and value firms require greater compensation for taking higher risk when the credit spread is higher. Higher magnitudes of credit spread during recessions for size and value premiums indicate that firms exposed to tightening credit market conditions respond more to increased credit risk. Nevertheless, contrary to Kim et al (2014), we find that the credit spread coefficient is negative for momentum premium in expansions, indicating that past losers enjoy higher return than past winners during economic upturn.

Money supply growth shows asymmetries with value premium. The relationship turns from insignificant in market upturns to negative during downturns. One possible explanation can be that value investors interpret increase in the growth of money supply in recessions as a positive indicator of expansionary monetary policy that will stimulate growth in the economy and make the environment more suitable for value firms, thus causing value premium to drop. At the same time, growth firms take the advantage of higher money supply despite of the higher risk in economic downturn. A positive relationship of growth in money supply and size premium is found during downmarket, indicating that when there is expansion in monetary growth in recessions, the small-cap stocks are at their highest level in terms of risk premiums, as noted by Perez-Quiros and Timmermann (2000). This can be explained by the fact that even though growth in money supply signals acceleration of economic growth, the lack of small firm’s access to credit markets may lead to prolonged effect of the recession on those firms and in turn requirement of the higher risk premium.

Overall, our results clearly show that the cyclical asymmetry in size, value and momentum premiums and their determinants are present in the UK market. The greatest cyclicality is documented with the size premium, which changes sign from being positive in expansion to negative in recession and exhibits the greatest magnitude change. Momentum premium is comparatively the least cyclical one in the UK. Overall, we document more significant impact of macro factors on all the three premiums in the recessions. Macroeconomic variables that proxy credit market conditions (interest rates, term spread and credit spread) are found to have more profound effect on size, value and momentum premium, particularly in the high-volatile market state (downmarket). In addition, the strong impact of GDP growth in both states and money supply growth in recessions is found for both small and value premium. Momentum premium is not affected by unexpected inflation, growth in GDP and money supply regardless of the market state; putting credit market conditions variables as the lead contributors to the changes in this premium in the UK in up- and downmarkets.

3.3.4 Model Diagnostics

While Table 3.4 shows that there are differences in how size, value and momentum premiums respond to changes in macro variables across the two regimes, the differences in intercepts or coefficients are not statistically verified. To test for significance of asymmetries in our sample and significance of our Markov switching model overall, we start by employing a Wald test to assess if the intercepts and coefficients of six conditioning variables (GDP growth, inflation, interest rates, term spread, credit spread and money supply growth) are identical across regimes for the size, value and momentum premiums, applying the following hypothesis:

For size premium:

$$H_{01}: \beta_{SMB,j,(s_t=1)} = \beta_{SMB,j,(s_t=2)};\ j = 1, 2, 3, 4, 5, 6$$

For value premium:

$$H_{02}: \beta_{HML,j,(s_t=1)} = \beta_{HML,j,(s_t=2)};\ j = 1, 2, 3, 4, 5, 6$$

For momentum premium:

$$H_{03}: \beta_{UMD,j,(s_t=1)} = \beta_{UMD,j,(s_t=2)};\ j = 1, 2, 3, 4, 5, 6$$

Table 3.5 reports that Wald test values of Chi-Squared distribution with 6 degrees of freedom and the p-values. The significant Chi-Square statistics reject the null hypothesis in favour of regime dependency for all the size, value and momentum premiums. These results identify that the switching model is statistically significant, implying the differential response of style premiums and their determinants to aggregate economic conditions in the economic downturn and economic upturn. Our results fare well with Perez-Quiros and Timmermann (2000), Gulen, Xing and Zhang (2011) and Kim et al. (2014).

To identify the significance of regressors in the model, the likelihood ratio test for redundant variables is performed. Likelihood ratio test is being performed under the null hypothesis $\beta_{ij} = 0,\ i = SMB, HML, UMD;\ j = 1, 2, 3, 4, 5, 6;$ to identify the significance of each regressor, namely IP growth, inflation, interest rates, term spread, credit spread and money supply growth. Table 3.6 reports the likelihood ratio test of redundant variables for the estimated Time Varying Markov Switching model.

Table 3. 5: Wald Test

This table reports the Wald test's outcome for the hypothesis testing of switches in the intercept and switches in the slope.

The test statistics for the Wald test are:

For, $H_0: \alpha_{i1} = \alpha_{i2};\ \frac{(\hat{\alpha}_1 - \hat{\alpha}_2)^2}{Var\ (\hat{\alpha}_1) + Var\ (\hat{\alpha}_1) - 2cov\ (\hat{\alpha}_{1,}\hat{\alpha}_2)} \approx \chi^2(1)\ ;\ i = SMB, HML, UMD$

For $H_0: \beta_{j1} = \beta_{j2};\ \frac{(\hat{\beta}_1 - \hat{\beta}_2)^2}{Var\ (\hat{\beta}_1) + Var\ (\hat{\beta}_1) - 2cov\ (\hat{\beta}_1, \hat{\beta}_2)} \approx \chi^2(6)\ ;\ J = 2,3,4,5,6,7$

Hypothesis	SMB (Chi-Square)	HML (Chi-Square)	UMD (Chi-Square)
Switches in the Intercept $H_{01}: \alpha_{SMB,(s_t=1)} = \alpha_{SMB,(s_t=2)}$ $H_{02}: \alpha_{HML,(s_t=1)} = \alpha_{HML,(s_t=2)}$ $H_{03}: \alpha_{UMD,(s_t=1)} = \alpha_{UMD,(s_t=2)}$	21.65018*** (0.0000)	41.75555*** (0.0000)	5.689131** (0.0171)
Switches in the Slope $H_{01}: \beta_{SMB,j,(s_t=1)} = \beta_{SMB,j,(s_t=2)}$ $H_{02}: \beta_{HML,j,(s_t=1)} = \beta_{HML,j,(s_t=2)}$ $H_{03}: \beta_{UMD,j,(s_t=1)} = \beta_{UMD,j,(s_t=2)}$ $j = 2,3,4,5,6,7$	92.26251*** (0.0001)	315.8468*** (0.0000)	79.42191*** (0.0000)

*** Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
* Implies the significance at 10% level of significance.

Table 3. 6: Likelihood Ratio Test for Redundant Variable

This table reports the likelihood ratio test for the redundant variables to identify the significance of the regressors in the models. The estimated two-state Markov switching model, over the sample period 1982M07 to 2014M06, is:

$$r_{it} = \alpha_1 + \beta_{i1,s_t} GDPG_{t-1} + \beta_{i2,s_t} INF_{t-1} + \beta_{i3,s_t} IR_{t-1} + \beta_{i4,s_t} TERM_{t-1} + \beta_{i5,s_t} CREDIT_{t-1} + \beta_{i6,s_t} \Delta M_{t-2} + \varepsilon_{it} ;$$

$i = (SMB, HML, UMD)$; $\varepsilon_{it} \sim N(0, \sigma_{it}^2)$, $S_t = \{1, 2\}$

$P_{11} = P(s_t = 1 | s_{t-1} = 1, z_{t-1}) = \Phi(\pi_0 + \pi_1 CLI_{t-2})$, $P_{12} = 1 - P_{11} = P(s_t = 1 | s_{t-1} = 2, z_{t-1})$

$P_{22} = P(s_t = 2 | s_{t-1} = 2, z_{t-1}) = \Phi(\pi_0 + \pi_2 CLI_{t-2})$, $P_{21} = 1 - P_{22} = P(s_t = 2 | s_{t-1} = 1, z_{t-1})$

Here r_{it} is the return of size (SMB), value (HML) and momentum (UMD) factors. GDPG is the GDP growth rate, INF is the realized inflation, and IR is the short-term interest rate. TERM is the term spread, CREDIT is the credit spread and ΔM is the growth of money supply; and CLI is the OECD's Composite Leading Indicator. The p-value of likelihood ratio test indicates the probability of the insignificance of corresponding regressor.

Likelihood Ratio	SMB	HML	UMD
Unrestricted Log Likelihood	828.1365	859.6611	721.5690
Log Likelihood with $\beta_{i1} = 0$, $i = SMB, HML, UMD$	818.5313*** (0.0000)	841.1312*** (0.0000)	720.7072* (0.1892)
Log Likelihood with $\beta_{i2} = 0$, $i = SMB, HML, UMD$	814.5014*** (0.0000)	858.9896 (0.2465)	721.3299 (0.4892)
Log Likelihood with $\beta_{i3} = 0$, $i = SMB, HML, UMD$	818.0224*** (0.0069)	846.2138*** (0.0000)	719.5768** (0.0459)
Log Likelihood with $\beta_{i4} = 0$, $i = SMB, HML, UMD$	809.9817*** (0.0659)	853.3821*** (0.0000)	717.4515*** (0.0041)
Log Likelihood with $\beta_{i5} = 0$, $i = SMB, HML, UMD$	812.7886*** (0.0000)	846.8765*** (0.0001)	709.2969*** (0.0000)
Log Likelihood with $\beta_{i6} = 0$, $i = SMB, HML, UMD$	814.8402*** (0.0000)	841.0220*** (0.0000)	720.3951 (0.1255)

*** Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
* Implies the significance at 10% level of significance.

With the exception of inflation in determining value and momentum premiums and money supply growth in determining the momentum premium, the likelihood ratio test is significant for all of the remaining regressors of size, value and momentum premiums. These results corroborate the overall significant impact our chosen macroeconomic variables have on the three premiums.

3.3.5 Regimes Robustness Check

We test the robustness of our model by estimating model parameters using the change in the UK IP index with one period lag as an alternative information variable in modelling transitions probabilities instead of CLI lagged by two periods. IP index is often used as a proxy for economic activity. The results in Table 3.7 indicate that our model is robust to the variable used to define the state of the economic cycle. The most asymmetry is present in the SMB intercept, which changes from positive (albeit insignificant) to negative, while HML and UMD change magnitude but not the sign. By and large, the signs of the coefficients remain unchanged compared to Table 3.4. Credit market conditions variables (interest rates, term and credit spread) still have the greatest and most significant overall impact across regimes for all the premiums. They are followed by the change in the money supply, which has a significant impact on the premiums in the recessions.

Table 3. 7: Parameter Estimation of Markov Switching Model: Using IP Index as an Alternative Information Variable in Modelling Transitions Probabilities

The estimated two-state Markov switching model, over the sample period 1982M07 to 2014M06, is:

$r_t = \alpha_1 + \beta_{i1,s_t} GDPG_{t-1} + \beta_{i2,s_t} INF_{t-1} + \beta_{i3,s_t} IR_{t-1} + \beta_{i4,s_t} TERM_{t-1} + \beta_{i5,s_t} CREDIT_{t-1} + \beta_{i6,s_t} \Delta M_{t-2} + \varepsilon_{it}$;

$i = (SMB, HML, UMD)$; $\varepsilon_{it} \sim N(0, \sigma_{it}^2), S_t = \{1, 2\}$

$P_{11}=P(s_t = 1|s_{t-1} = 1, z_{t-1}) = \Phi(\pi_0 + \pi_1 IP_{t-1})$, $P_{12}=1 - P_{11}$

$P_{22}=P(s_t = 2|s_{t-1} = 2, z_{t-1}) = \Phi(\pi_0 + \pi_2 IP_{t-1})$, $P_{21}=1 - P_{22}$

Here r_{it} is the return of size (SMB), value (HML) and momentum (UMD) factors, GDPG is the GDP growth rate, INF is the realized inflation, and IR is the short-term interest rate. TERM is the term spread, CREDIT is the credit spread and ΔM is the growth of money supply; and IP is the change in the Industrial Production index of UK. The values in the parentheses represent the p-values.

		SMB	HML	UMD
Regime 1(Expansion)	α_1	0.002317 (0.6855)	-0.017625*** (0.0007)	0.018694*** (0.0097)
	$GDPG_{t-1}$	1.463355 (0.2597)	3.502783*** (0.0004)	-1.164752 (0.4037)
	INF_{t-1}	0.453465*** (0.0027)	0.143064 (0.2762)	0.043448 (0.7206)
	IR_{t-1}	-1.212458* (0.0984)	2.514588*** (0.0001)	-1.367553 (0.1389)
	$TERM_{t-1}$	-0.240752* (0.1039)	0.266736** (0.0214)	-0.380272** (0.0158)
	$CREDIT_{t-1}$	0.291675** (0.0363)	0.298651** (0.0230)	0.428205** (0.0110)
	ΔM_{t-2}	0.234085 (0.2265)	0.073415 (0.6149)	0.102880 (0.6185)
	Conditional Standard Deviation	0.008518	0.001460	0.027747
Regime 2 (Recession)	α_1	-0.144048** (0.0128)	-0.234666*** (0.0000)	0.069190* (0.0575)
	$GDPG_{t-1}$	16.43552*** (0.0000)	-66.50175*** (0.0000)	-4.946730 (0.3071)
	INF_{t-1}	-0.110192 (0.8378)	0.444140 (0.4909)	0.704047 (0.4701)
	IR_{t-1}	13.29070 (0.1417)	16.44003*** (0.0001)	-0.040574 (0.8089)
	$TERM_{t-1}$	2.184715** (0.0491)	-8.454087*** (0.0000)	1.652218** (0.0537)
	$CREDIT_{t-1}$	2.259204** (0.0329)	6.746357*** (0.0000)	-6.892137*** (0.0000)
	ΔM_{t-2}	4.042608*** (0.0000)	-3.133290*** (0.0000)	2.277822*** (0.0075)
	Conditional Standard Deviation	0.143565	0.190502	0.251312

*** Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
* Implies the significance at 10% level of significance

3.3.6 Economic Value of the Model and Limits to Arbitrage

Efficient market hypothesis assumes that all investors are rational. However, in practical world irrational investors can co-exist with rational ones. Meaning that risk based explanation and mispricing based explanation can explain the size, value and momentum premiums simultaneously. Existence of these premiums may be justified by the limits to arbitrage process, which can be constrained in various ways. According to the efficient market hypothesis mispricing in the market should be eliminated by the arbitrageurs who exploit any misalignment opportunity in the stock market. Arbitrage is, hence, significant for the maintenance of efficient markets as it keeps fundamental values of the firms aligned with the market price. In practice, arbitrage leads to costs as well as risk, and for these reasons there are limits to the effectiveness of arbitrage in eliminating certain security mispricing. These limits to arbitrage can provide us opportunity to trade against any mispricing or behavioural biases. We identify such identify such limits to arbitrage in our study.

In the previous sections, we have identified the presence of asymmetries in the size/style premiums in the UK. It is of interest to practitioners to explore the economic significance of these findings by testing the profitability of a trading strategy based on our model's predictions. It is important to note that some of the economic indicators we find significant in the Markov Switching model might be proxies for the limits of arbitrage. This implies that size/style premiums we have identified in recessions and expansions will persist as investors are not able to exploit them due to certain constraints. Barberis and Shleifer (2003) argue that the arbitrage opportunities will not be adequately seized if the idiosyncratic risk is high, if noise trading momentum risk is present and if transaction costs associated with trading strategies are high. While assessment of the idiosyncratic risk and noise trading risk is beyond the scope of this chapter, we will assess the impact of transaction costs to profitability of our strategy as an indicator of the presence of limits to arbitrage.

We acknowledge that a pure arbitrage strategy will involve long-short investing, but given that typical investors in the UK market are long-only (mutual funds for instance) and pursuing conservative strategies (pension funds for instance), investing in Fama-French factors that are based on long and short positions will not be possible for them. Having this in mind, we employ long-only asset allocation strategy feasible for the typical UK investors, similar to that given in Perez-Quiros and Timmermann

(2000). We start by applying our model to each of the eight size/style portfolio returns available from Gregory, Tharyan and Christidis (2013) database, namely: small cap-value, small cap-growth, large cap-value, large cap-growth, small-cap with-negative momentum, small-cap with-positive momentum, large-cap with-negative momentum and large-cap with-positive momentum. Our data sample is split into 306 in-sample months and 78 out-of-sample (trading) months from July 1982 to June 2014. Using our model and the data July 1982 – December 2007, we forecast the return for January 2008 for each of the eight portfolios. If the forecasted return for a portfolio is positive, we invest in that portfolio in January 2008. In the case of negative forecast returns, the funds are invested in the proxy for the risk-free asset UK 3-month Treasury Bill. The procedure is then repeated recursively out-of-sample over 78 trading months, until June 2014. Our investment strategy is, therefore, a switching strategy based on alternating between the given size/style portfolio and the T-bill, depending on the sign of the forecast. There are 52 recession months and 26 expansion months in our trading period.

We compare each portfolio switching strategy to the corresponding buy-and-hold benchmark. Buy-and-hold is defined as the investment in the relevant size/style sorted portfolio over the entire 78-month trading period. The risk-adjusted profitability of the switching strategy for each portfolio versus its buy-and-hold benchmark is measured by the Sharpe ratios. To assess the feasibility of our allocation strategy for investors, we calculate the break-even level of transaction costs per switch for each portfolio. Those are maximum costs per trade that will equalise the Sharpe ratio of the switching strategy to that of the buy and hold benchmark. The higher the break-even transaction costs are, the more feasible our strategy is. Following Chandrashekar (2006); Kritzman, Page and Turkington (2012); Boudt et al., (2015), it can be calculated as

$$\frac{\bar{r}_{Switching} - \bar{r}_f}{\sigma_{Switching}} = \frac{\bar{r}_{Buy-hold} - \bar{r}_f}{\sigma_{Buy-hold}}$$

Here mean return is calculated as: $\bar{r}_{Switching} = \sum_{t=1}^{n} \frac{r_t - C}{n}$, where C takes the value of zero if no transaction has been made and value of breakeven transaction cost if trading occurred in month 't' and 'n' is the number of periods. This calculation is similar to the approach of Bessembinder and Chan (1998). They calculate break-even transaction cost that makes an investor indifferent between the buy and hold benchmark returns and the trading rule returns. Limitation of their approach is that, trading rules could have different amounts of risk and the return could be the compensation of such risk. As the investors as well as academics consider the risk adjusted performance, this study computes the break-even transaction cost that will equalise the Sharpe ratio of switching strategy to that of the buy and hold benchmark.

Table 3.8 reports annualised mean return, standard deviation, Sharpe ratio, the number of switches and break-even transaction costs per switch for each of the eight switching portfolios. Comparative figures (where applicable) are reported for the buy and hold portfolios. Panel A (Panel B) lays out results for four strategies involving small-cap (large cap) portfolio groups: with low book-to-market ratio, with high book-to-market ratio, with down momentum and with up momentum. Results are split into full period, expansion and recession sub-periods.

Given the Sharpe ratios in Panel A, all four small-cap switching portfolio categories outperform their buy-and-hold benchmarks in the out-of-sample period January 2008-June 2014. The average Sharpe ratio of switching portfolios in the full sample in Panel A is 0.65, compared to that of 0.55 of the relevant benchmarks. Break-even transaction costs are well above at least 100 basis points per trade for all but small-cap with up momentum switching portfolio (18.55 bps), showing that our small size/style switching strategy is both profitable and feasible. In contrast, Panel B documents that while switching strategies of portfolio of large firms sorted on momentum are not underperforming the buy-and-hold in any instance, their outperformance is not that notable. Large-cap portfolio with down momentum generates only marginally higher Sharpe ratio (0.16) than their benchmark (0.15) in the full sample and a less negative Sharpe ratio in recessions. Alternating between large-cap firms sorted on book to market and the risk-free rate does not lead to above-benchmark profitability in any instance. Overall, we show that the forecast from our model has economic value for small-cap strategies and is not subject to the limits of arbitrage proxied by transaction costs; while this is less pronounced in the large-cap space.

Looking at the differences in profitability across economic regimes, the key findings in Table 3.8 can be interpreted as absolute (level changes of Sharpe ratios in expansions and recessions) and relative (compared to that of the buy and hold). In absolute terms, excess returns per unit of risk (Sharpe ratios) on all portfolios decrease when we move from expansion to recession state. This is coherent with our

Markov switching model results which show a drop in size, value and momentum premiums in recession, indicating lesser opportunities for investors pursuing those strategies. Note that in our out-of-sample trading period, the drop in Sharpe ratios is highly influenced by the strong negative returns during the period of global financial crisis 2007-2010. Tightening of credit market conditions, which we found to have the strongest impact in determining the size of the three premiums, is a likely cause of this drop. Our findings are in line with those of Perez-Quiros and Timmermann (2000).

When compared to buy-and-hold, our trading strategies show better overall relative performance in recession as opposed to expansion. This finding is more pronounced among switching strategies with small-cap portfolios (Panel A) than large-cap portfolios (Panel B). Specifically, the average Sharpe ratio across four small size switching portfolios is by 0.12 higher than that of the buy-and-hold strategies in recessions. In expansions, it is lower by 0.02 on the average. Their outperformance in recession is distinct at a feasible level of break-even transaction costs per trade, even for smaller investors. This finding is of particular importance to practitioners, as it proves that our model can successfully differentiate between economic states and that economic indicators used for forecasting are unlikely proxies for the limits of arbitrage[12]. Investors would be benefited if they buy small firms with low book-to-market (SL) and small firms with high book-to-market (SH), particularly in recession period and follow our trading strategy i.e. take long position in the relevant style portfolio is taken if its return from the recursively predicted by the Markov Switching model is positive, otherwise, we invest in 3-month T-Bill.

Note that, although the justification of efficient market hypothesis is beyond the scope if this study, one can interpret the economic significance of our trading strategies as the limits to arbitrage holding the behavioural explanation of style premiums or can interpret the market as 'not perfectly efficient' and there are scopes to beat the market.

[12]Note that the conclusion regarding limits to arbitrage relates to transaction costs only. Presence of higher idiosyncratic risk and noise trading remains to be tested in future research.

Table 3. 8: Trading Strategy Results for Eight Portfolios

Trading results are based on the monthly switching between the eight style portfolios and T-bills. Our in sample estimation period is July 1982 - December 2007 and out of sample trading period is January 2008 - June 2014. A long position in the relevant style portfolio is taken if its return from the recursively predicted by the model is positive, otherwise, we invest in 3-month T-Bill. The buy-and-hold strategy represents the investment in the corresponding style portfolio over the trading period. Annualised mean returns, standard deviations and Sharpe ratios are reported for each style portfolio switching strategy and its buy-and-hold benchmark. The number of switches denotes the number of times we switch between the given style portfolio and 3-month T-bill during the trading period. Break-even transaction costs are maximum costs an investor would pay per switch that equalises the Sharpe ratio of the switching strategy and that of the buy-and-hold. Negative (zero (0.0)) break-even transaction costs imply the Sharpe ratio of the switching strategy was lower (equal to) the Sharpe of the buy-and-hold. Bold denotes the break-even transaction costs per switch that are large enough to imply the switching strategy is feasible. Panel A reports findings for Small size portfolios and their subgroups while Panel B for large-cap portfolios and their subgroups. All results are reported for the full out-of-sample period, expansions and recessions separately.

PANEL A		Small firms with low book-to-market (SL)		Small firms with high book-to-market (SH)		Small Firms with down momentum (SD)		Small Firms with up momentum (SU)	
		Buy and Hold	Switching Portfolio	Buy and Hold	Switching Portfolio	Buy and Hold	Switching Portfolio	Buy and Hold	Switching Portfolio
Full Period	Mean Return	12.85	14.71	8.53	11.60	7.28	8.56	19.71	19.82
	Std. Dev.	17.60	17.01	24.06	22.52	29.62	25.14	18.41	18.40
	Sharpe Ratio	0.67	0.80	0.31	0.47	0.21	0.30	1.01	1.02
	No. of Switches	-	5	-	11	-	13	-	3
	Break-even TC	-	**278.56 BPS**	-	**196.66 BPS**	-	**108.50 BPS**	-	**18.55 BPS**
Expansions	Mean Return	22.51	22.51	19.07	16.15	11.99	9.32	31.76	31.76
	Std. Dev.	15.73	15.73	21.29	20.72	21.62	17.56	17.97	19.13
	Sharpe Ratio	0.78	0.78	0.50	0.43	0.31	0.29	0.94	0.94
	No. of Switches		0		4		5		0
	Break-even TC	-	0.00	-	Negative	-	Negative	-	0.00
Recessions	Mean Return	8.02	10.81	3.27	9.33	4.93	8.18	13.69	13.85
	Std. Dev.	18.45	17.66	25.40	23.54	33.07	28.34	18.55	18354
	Sharpe Ratio	0.30	0.44	0.06	0. 28	0.09	0.20	0.54	0.55
	No. of Switches	-	5	-	7	-	8	-	3
	Break-even TC	-	**258.12 BPS**	-	**383.96 BPS**	-	**199.12 BPS**	-	**22.65 BPS**

PANEL B		Big firms with low book-to-market (BL)		Big firms with high book-to-market (BH)		Big Firms with down momentum (BD)		Big Firms with up momentum (BU)	
		Buy and Hold	Switching Portfolio	Buy and Hold	Switching Portfolio	Buy and Hold	Switching Portfolio	Buy and Hold	Switching Portfolio
Full Period	Mean Return	10.41	-1.04	5.96	5.27	4.50	4.93	10.28	10.28
	Std. Dev.	12.59	7.38	17.78	16.23	23.81	23.78	19.85	19.85
	Sharpe Ratio	0.74	-0.27	0.28	0.26	0.15	0.16	0.46	0.46
	No. of Switches	-	6	-	9	-	3	-	1
	Break-even TC	-	Negative	-	Negative	-	**68.85 BPS**	-	0.00
Expansions	Mean Return	20.22	3.10	20.52	20.66	19.13	19.13	24.16	24.16
	Std. Dev.	10.80	3.84	16.86	16.84	18.03	18.03	21.21	21.21
	Sharpe Ratio	0.98	0.39	0.67	0.67	0.59	0.59	0.63	0.63
	No. of Switches	-	2	-	2	-	0	-	0
	Break-even TC	-	Negative	-	Negative	-	0.00	-	0.00
Recessions	Mean Return	5.50	-3.11	-1.32	-2.42	-2.81	-2.18	3.35	3.35
	Std. Dev.	13.27	8.60	18.02	15.61	26.13	26.11	19.03	19.03
	Sharpe Ratio	0.26	-0.41	-0.12	-0.19	-0.13	-0.11	0.09	0.09
	No. of Switches	-	4	-	7	-	3	-	1
	Break-even TC	-	Negative	-	Negative	-	**108.28 BPS**	-	0.00

3.4 Summary and Conclusions

This study is the first to shed light on asymmetries in the UK size, value and momentum premiums and identifies the main drivers of these premiums in both expansions and recessions. It is the first comprehensive study in the UK contexts to measure the effect of a set of relevant macroeconomic variables on style premiums. It is the only study that includes all three premiums and compares their responsiveness over business cycles. We focus on UK SMB, HML and UMD factors defined by Gregory, Tharyan and Christidis (2013) in the period January 1982 - June 2014. Employing Markov switching methodology, we find evidence in strong support of asymmetry in the three premiums across the two Markov switching regimes. Our analysis of regimes related to OECD's UK Recession Indicator prompts us to conclude that Markov switching regime 1, associated with lower conditional volatility coincides by and large with economic upturns and vice versa for regime 2. We find that all three premiums vary across regimes but that most asymmetries are observed in the size premium and the least in the momentum premium. The UK momentum premium result is in contrast to Kim et al. (2014), who document clear asymmetry in the US market. Nevertheless, ours is the only study that provides direct comparison of all three premiums and their relationship with a set of macroeconomic variables.

Following the US literature, we test whether the growth in GDP, inflation, interest rates, term structure, credit spread and money supply growth are valid determinants of those cyclical variations in UK equity return premiums. We corroborate findings from the US markets in that macroeconomic factors are drivers of equity premiums in both economic upturn and downturn but have more pervasive and more significant influence in the economic downturn. The strongest impact on size, value and momentum premiums have variables that proxy credit market conditions, namely interest rates, term structure and credit spread. Our results are similar to those documented for the US size and value premiums, but when it comes the relationship between momentum premium and interest rates, credit spread and money supply, we find the opposite relationships to those documented in Kim et al. (2014) for the US expansionary periods.

To test the significance of our Markov switching model, we apply the Wald test and redundant variable test (Likelihood Ratio Test). Wald test shows that the intercept and slope of the Markov Switching model are regime dependent and hence there is differential response of style premiums in economic upturn and downturn. Given the Likelihood Ratio Test, all macroeconomic variables across the three premiums are being deemed as significant ones, at the minimum 5% level of significance, with the exception of inflation (which is adequate regressor for small-cap premium only) and monetary growth (which is weak in explaining momentum).

Finally, we examine the economic implications of our model in forecasting size/style portfolio returns and of the asymmetries in size, value and momentum premiums on those portfolios. Using eight portfolios sorted on distinctive size/style/momentum combinations we find that conservative trading strategy with portfolios featuring small-cap characteristics generates better risk-adjusted performance relative to the buy and hold strategy and relative to the comparable large-cap portfolios. Further, we find evidence of cyclicality of equity premiums in both absolute and relative terms. In absolute terms, all trading strategies based on eight style/size portfolios exhibit a drop in Sharpe ratios in the recession. In relative terms, all small-cap switching strategies and large cap/negative momentum switching display relative outperformance over their buy and hold benchmarks in recessions, but not in expansions. This implies that forecasts based on our model have considerable economic significance for investors, particularly for trading strategy involving small-cap stocks. Transaction costs per trade are at the feasible level, making these costs unlikely cause for the limits to arbitrage, at least in small-cap portfolio trading space.

These findings are relevant for the UK size, style and momentum investors interested in determining how to maximise their profits across economic cycles by applying adequate market timing or asset allocation strategies to exploit the changes in the three premiums over time. With this in mind, our study has some limitations and can be extended in several ways. For instance, one limitation of this study is that the factor portfolios are constructed using the same breakpoints as described in Fama and French (1993). Given that recent literature points to the fact that those breakpoints are arbitrarily chosen (see for instance Cremers, Petajisto and Zitzewitz, 2013), it would be beneficial to consider if the results are robust to the use of alternative breakpoints. Further, Avramov et al. (2016) document that factor portfolios may exhibit momentum. While exploring momentum in premiums is not the focus of this study, our further research in this area is focusing on measuring the survival time of momentum in Fama-French factor portfolios. Additionally, this study can be extended to include the two newly available factors from Fama and French (2015) five-factor model: operating profitability and investment.

CHAPTER FOUR: STYLE TIMING

4.1 Introduction

Chapter four contributes to the equity momentum and style timing literature by examining and exploiting the survival time of momentum in the UK style portfolio returns. The seminal paper of Jegadeesh and Titman (1993) was the first to document the outperformance of momentum trading strategies. While a significant body of research finds that trading strategies based on predictive firm characteristics (such as size, book to market ratio, leverage etc.) weaken in performance over time (see for instance recent study of Chordia, Roll and Subrahmanyam, 2011 and McLean and Pontiff, 2016), robustness of momentum investment strategy is confirmed in a number of US studies, such as Chan, Jegadeesh, and Lakonishok (1996), Jegadeesh and Titman (2001, 2002) and Asness, Moskowitz and Pedersen (2013). Momentum profits are not restricted to the US market only; a point verified by Hon and Tonks (2003), Chelley-Steeley and Siganos (2004), Gregory, Tharyan, and Christidis (2013) and Liu, Strong, and Xu (1999) who all find evidence of momentum effect in UK stock market, while Rouwenhorst (1998) documents momentum for 12 European countries.

One stream of momentum literature focuses on investigating the presence of momentum in the US style (value, growth, small cap) portfolios (see for instance Lewellen , 2002; Chen , 2003; Chen and De Bondt, 2004; Froot and Teo, 2004 and Chen, Jiang and Zhu, 2012). Similarly, Clare, Sapuric and Todorovic (2010) find that exploiting momentum in UK style portfolios proves to be a profitable investment strategy for investors following style rotation strategy. More recently, Avramov et al. (2016) investigate momentum among 15 market anomalies in the US (total accruals, net operating assets, momentum, gross profitability, book-to-market among others). They document that while the profitability of momentum in individual anomalies fades over time, a long-short trading strategy based on a combination of winner (best performing, long position) and loser (worst performing, short position) anomalies according to lagged one-month returns generate significantly positive risk-adjusted returns and outperform the naive benchmark. Further, they show that momentum profits are time varying and are stronger following high investor sentiment periods, similar to Stambaugh, Yu and Yuan (2012).

Previous literature is in agreement that 1) momentum is present across various markets and across style portfolios and that 2) momentum profits diminish over time. However, there is a clear gap in the literature as to how long do momentum returns persist, particularly in style portfolios, i.e. portfolios where stocks are selected based on firm characteristics that resemble a particular 'investment style'. In this chapter, we contribute to the literature by measuring the longevity (survival time) of momentum on the UK equivalents of six Fama-French size/style portfolios based on popular market anomalies: size and book to market ratio. To investigate the survival of the momentum we follow Jochum (2000) and Kos and Todorovic (2008) approach by constructing survival curves[13]. Specifically, we apply Kaplan–Meier estimator (Kaplan and Meier, 1958; KM hereafter), a non-parametric method that in our setting measures the likelihood that a positive/negative momentum will persist beyond the current day. Additionally, to estimating survival time, this model enables us to identify profit potential and feasibility of momentum trading in style portfolios. Kos and Todorovic (2008) emphasise that the KM survival methodology has clear advantage over the Jegadeesh and Titman (1993) approach as it does not depend on zero-cost, no arbitrage portfolios which only hypothetically have zero betas and leave investors exposed to systematic risk.

Moreover, in the literature of market timing, pioneered by Treynor and Mazuy (1966) and Henriksson and Merton (1981), a number of studies investigate whether investments on size, book-to-market can be timed (Gallagher, Gardner and Schmidt, 2015; Miller et al., 2015; Bird and Casavecchia, 2011; Chen and De Bondt, 2004;

[13] Kiefer (1988) provides a survey of economic survival and hazard functions

Copeland and Copeland, 1999; Desrosiers et al., 2004; Kao and Shumaker, 1999; Knewtson et al., 2010; Levis and Liodakis, 1999)[14]. Although the outperforming ability to a benchmark by accurately timing these dimensions remains debatable, long-term excess return premiums are reportedly associated with either value (high book-to-market) along the style dimension, or small cap along the size dimension, or equity among the market choices. Mutooni and Muller (2007) compared the performance of timing strategies with perfect foresight (taking long position in higher returning asset or short in lower returning asset) based on the market, size and style (value/growth) in the US market. They find the evidence that the timing strategy based on asset class and size outperforms the value/growth strategy. The outperformance of market timing of style portfolios (hereafter style timing) is also documented in the study of Bird and Casavecchia (2011); Clare, Sapuric and Todorovic (2010); Arshanapalli, Switzer and Panju (2007); L'Her, Mouakhar and Roberge (2007); Amenc et al. (2003); Ahmed, Lockwood and Nanda (2002); Oertmann (2000); Copeland and Copeland (1999); Reinganum (1999) etc[15].

Similar to momentum trading, the core of market timing or style timing lies in identifying the trends early and react quickly, hence academics and as well as the financial institutions spend a considerable amount of time into this phenomenon. This study contributes to the literature of style timing by incorporating survival analysis of biostatistics to identify style portfolio momentums early and derive timing strategies to exploit the momentums. The survival methodology that is used in this study allows identifying and quantifying the momentum. Simple trading strategies are then formulated to exploit the potentials of momentum trading and gauging their feasibility.

This study, to the best of our knowledge, is the first to address survival time of momentum in the style portfolio returns. We use monthly data in the period October 1980 to June 2014 for six UK style portfolios: Small Size & Low BTM (SL), Small Size & Medium BTM (SM), Small Size & High BTM (SH), Big Size & Low BTM (BL), Big Size & Medium BTM (BM) and Big Size & High BTM (BH)[16]. We

[14] Extended literature review on style timing is documented in chapter two

[15] Detail literature review is explored in the second chapter.

[16] As defined in Gregory, Tharyan and Christidis (2013)

construct empirical survival curves for momentum in each portfolio and calculate average momentum survival time (in months). We compare the empirical mean of momentum survival with the one obtained with simulated theoretical benchmarks. To establish theoretical (benchmark) momentum survival times, we deploy Monte-Carlo simulation of two commonly cited models in the description of stock returns: the Random Walk and ARMA (1,1) model. Any departure of empirical survival time obtained with KM estimator from the theoretical one presents an arbitrage opportunity. By timing strategies, we exploit this opportunity for each style portfolio separately and for a combination of style portfolios. For each style portfolio, we apply long-only trading rule that buys that style portfolio once a positive momentum signal is triggered and holds it for average survival time of the positive momentum. Similarly, the short-only trading rule calls for selling/short-selling of a style portfolio upon initiation of a negative momentum signal and holding that portfolio for the average negative momentum survival time. In addition, combine the long-only and short-only rule for each style portfolio separately into a long-short rule. Finally, we form a long-short 'winner-loser' rule that implies switching across style portfolios so that: in month '*t*' we buy the winner style portfolio (highest positive momentum) and hold it for the average positive momentum survival time, and short-sell the loser style portfolio (lowest negative momentum) and hold the position over average negative momentum survival time. The winner/loser strategy implies that investors are engaged in exploiting momentum through style-rotation, an approach proven profitable in the UK in Clare, Sapuric and Todorovic (2010) and Levis and Liodakis (1999). We gauge the profitability of our strategies by comparing its Sharpe ratio to the buy-and-hold of the corresponding style portfolio. We estimate the feasibility of our trading rule by calculating break-even transaction costs, which represent costs that equalise the Sharpe ratio of the trading strategy to that of the buy and hold. Additionally, given that strength of momentum profits varies over time (Stambaugh, Yu and Yuan, 2012; and Avramov et al., 2016) and that UK momentum premium exhibits cyclical behaviour (see chapter three), we evaluate if there are any differences in the probabilities of momentum trading across UK business cycles.

Our findings reveal that positive momentum lasts longer than the negative one; a result consistent with Jochum (2000) and Kos and Todorovic (2008). The difference in survival probabilities between empirical and theoretical models (Random Walk and ARMA (1,1) process) is strongly statistically significant for momentums lasting up to eight months. The average empirical survival time of positive momentum across all portfolios is 4 months, while for negative momentum it is 3 months for small-cap group of portfolios and 2 months for the large-cap ones. Comparative analysis of average survival times using empirical data and benchmark model simulations shows that empirical survival time of positive momentum is underestimated by theoretical models; while it is marginally overestimated for negative momentum. This implies lesser ability of theoretical models to explain empirical price patterns on the positive momentum side, which leads us to more profitable positive momentum trading in our study. We show that long-only positive momentum is a feasible strategy even for small investors as the level of transaction costs that would make positive momentum trading unprofitable are much higher than what investors would be asked to pay in reality. Long-short strategies in our study show the most consistent risk-adjusted performance across portfolios and highest incremental Sharpe ratios relative to naive buy and hold strategies. Finally, we show that survival probabilities are not significantly different across economic regimes in most of the portfolios, implying persistence in momentum strategies. Our trading rule results corroborate this.

The remainder of this chapter is organised as follows: Section 4.2 outlines the data and methodological framework; Section 4.3 discusses the findings and Section 4.4 provides conclusions to the chapter and recommendations for further research.

4.2 Data and Methodological Framework

In many studies, especially in medical studies, the main outcome of the assessment is the time-to-event (time until an event occurs) of interest. 'Survival Time' is the generic name of this time-to-event. Survival time may be applicable to the time 'survived' from death, disease incidence, relapse from remission, recovery (e.g., return to work) or any designated experience of interest that may happen to an individual. 'Survival time analysis' or simply 'survival analysis' can be performed in the situation where the population of objects that stay in certain state (survive) can be observed for some time until an exit (death or failure) happens. In the survival study, since the data are collected over a finite period of time, it is usual that time-to-event may not be observed for all the individual of the study sample (or population), and thus their true time-to-event is unknown. These observations are called censored observations. The analysis of such time-to-event data with censoring characteristics cannot be handled properly by the standard statistical methods, but the survival analyses. Survival analysis studies the time of survival or failure and the probability of survival or failure in a given time period.

Survival function and the hazard rate are the key concepts of survival analysis (Hensler, 1997; Jenkin, 2005; Kleinbaum and Klein, 2012). The concept of survival function is to model a probability curve for the survival rate of the study sample (or population). The aim of estimating survival function is to calculate the time span in which an object is alive. This time span or length of time-to-event is the realisation of a continuous random variable $'T'$ with a cumulative distribution function (cdf), $F(t)$, and probability density function (pdf), $f(t)$; Jenkin (2005).

The survival function $S(t)$ can be defined as 1' minus the failure function $F(t)$, i.e.:

$$S(t) = 1 - F(t) \qquad \text{...... (4.1)}$$

Here $'t'$ is the elapsed time since the entrance of the object in the study. If the probability function (cdf) of time-to-event can be represented by:

$$\Pr(T < t) = F(t) \qquad \text{...... (4.2)}$$

Hence the survival function can be represented as:

$$S(t) = 1 - F(t) = 1 - \Pr(T < t) = \Pr(T > t) \qquad \text{.......................... (4.3)}$$

Here $'T'$ is the life time of interest. Hence the survivor function $S(t)$ represents the probability that the object of interest survives from time origin to a specific future time $'t'$.

The slope of failure (cumulative density function) function is the probability density function (pdf) of $'T'$. That is:

$$f(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \leq T \leq t + \Delta t)}{\Delta t} = \frac{\partial F(t)}{\partial t} = -\frac{\partial S(t)}{\partial t} \qquad \text{.......... (4.4)}$$

Given that $f(t)$ is continuous at t and note that,

$f(t) \geq 0$, $\int_0^\infty f(t)dt = 1$ and $F(t) = \int_t^\infty f(s)ds$

An alternative characterisation of the distribution of $'T'$ is given by the hazard function. The hazard function, denoted by $h(t)$, gives instantaneous potential per unit time (rate) of occurrence of the event, given that the individual or object has survived up to the time $'t'$. Note that, hazard function focuses on ‘failing’ (i.e. the event of occurring) in contrast to survival function which focuses on ‘not failing’. The hazard function can be defined as:

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \leq T \leq t + \Delta t | T \geq t)}{\Delta t} \qquad \text{.......... (4.5)}$$

Here the conditional probability $\Pr(t \leq T \leq t + \Delta t | T \geq t)$, numerator of equation (4.5), is the probability that the individual/object fails in the interval $[t, t + \Delta t]$ given that the individual/object survived up to time t.

From (4.5) and the definition of density function, it can be written that (Kalbfleisch and Prentice, 2002):

$$h(t) = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{S(t)} = \frac{-\frac{dS(t)}{dt}}{S(t)} = \frac{-dlog\, S(t)}{dt} \qquad \text{..........(4.6)}$$

By integrating the equation (4.6) with respect to $'t'$, we obtain

$$-log\,S(t) = \int_0^t h(u)du = \Lambda(t) \quad \text{...(4.7)}$$

Here $\Lambda(t)$ is the cumulative hazard function and can be defined from (4.7) as:

$$S(t) = e^{-\Lambda(t)} \quad \text{.. (4.8)}$$

Regardless of the functions $[S(t), F(t), f(t), h(t) or\ \Lambda(t)]$ the distribution of the continuous survival time $'T'$ has a clearly defined relationship among them. However, this study, similar to Jochum (2000) and Kos and Todorovic (2008), emphasises on the 'survival probabilities' as this best confines the intuition behind the financial concept of momentum.

The survival probabilities can be estimated by non-parametrically by using Kaplan-Meier method, proposed by Kaplan and Meier (1958), from the observed survival time. Since, Kaplan-Meier method, also known as product limit method, is a non-parametric method the assumptions about the distribution of survival curve is not necessary to be made. This non-parametric characteristic gives Kaplan-Meier estimator a higher degree of flexibility.

4.2.1 Data

This study utilises monthly UK style factor portfolios data from Gregory, Tharyan and Christidis (2013) in the period October 1980 – June 2014. The data is a UK equivalent of the Fama-French's US market data[17] and is obtained from the Xfi Centre for Finance and Investment[18], University of Exeter. To form the portfolios, Gregory, Tharyan and Christidis (2013) sort the sample firms on market capitalisation into 'B'-big and 'S'-small and book-to-market ratio into 'H'-high, 'M'- Medium and

[17] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[18] http://business-school.exeter.ac.uk/research/areas/centres/xfi/research/famafrench/files/ (Accessed on 20.07.15)

'L'-low[19]. Six intersecting style portfolios are used in this study: SH; SM; SL; BH; BM; BL (where "SH" is the small size high book-to-market portfolio, "SL" is the small size low book-to-market portfolio, "BL" is the big size low book-to-market portfolio and so on).The portfolios are formed at the beginning of October in year '*t*' so we select October 1980 as the start of our sample period.

4.2.2 Methodological Framework

4.2.2.1 Momentum Signal

For momentum based style timing, we need to delineate the definition of the momentum signal used in this study. Following Jochum (2000) and Kos and Todorovic (2008), we consider momentum a technical trading rule according to which a buy (sell) signal is triggered if a positive (negative) return is realised over two consecutive periods. Any returns of the same sign following immediately are then added to the duration of this momentum signal and a (positive or negative) trend is formed. We consider the trend to be broken if the return changes to the opposite sign. This definition implies that positive and negative momentum trends are not necessarily alternative of each other (Jochum, 2000). For each trend, the number of periods (months) it persisted is counted (e.g. 3, 4, 5 etc.) and the direction of the trend is taken into account. The Kaplan-Meier estimator uses this information to calculate the survival probability of a positive (negative) trend to last, 3 or 4 periods.

Empirical evidence shows that profitability of momentum strategies is wiped out by high transaction costs (see for instance Carhart, 1997). To successfully link the momentum survival probability to a trading rule feasible for investors, the trade-off between rigidness of momentum definition (in particular definition of what constitutes a break of trend) and transaction cost has to be considered (Kos and Todorovic, 2008). A more rigid definition of a trend change (as in our case - where a trend is broken if a return changes sign), will imply higher degree of transaction cost due to more frequent buy/sell decisions. By relaxing the trading rule and considering

[19] For methodology refer to Gregory et. al (2013)

a trend change not only when the return changes sign but also when it goes over a predetermined threshold level– the transaction costs are likely to decrease. Note that the same definition of momentum signal and trend reversal/break will be applied to both actual style portfolio returns and simulated returns series, to ensure comparability.

Table 4.1 illustrates sequence of momentum signals and generation of trend. We define momentum as 1 in the table and no momentum as 0. For a positive trend, we identify two momentum signals, one surviving two months and one surviving three months. For the negative trend, only one momentum signal lasting 1 period is identified in the example.

Table 4. 1 Return Changes and Trend Construction

Month	1	2	3	4	5	6	7	8	9	10
Return Changes	0.01	0.01	0.04	-0.01	0.09	0.07	0.12	0.01	-0.01	-0.01
Pos. Trend	0	1	1	0	0	1	1	1	0	0
Neg. Trend	0	0	0	0	0	0	0	0	0	1

4.2.2.2 Survival Time Estimation

Survival analysis studies the time of survival or failure of an event/object (in our case - the momentum) and the probability of survival or failure in a given time period. Survival analysis originates in medical research studies, but it has been successfully applied in economics and finance (see for instance Kiefer (1988) and Jochum (2000) among others) in the context of duration analysis for instance. In the survival study, since the data are collected over a finite period of time, it is usual that time-to-event (survival time) may not be observed for all the individual of the study sample (or population), and thus their true time-to-event is unknown. These observations are called censored observations[20]. The analysis of such time-to-event data with censoring characteristics cannot be handled properly by the standard statistical methods, but the survival analysis. This study, similar to Jochum (2000); and Kos and Todorovic

[20] In this study left censoring means that the event of interest (momentum) has already occurred before enrolment, whereas, right censoring means that event of interest (momentum) remained after the sample period.

(2008), focuses on the 'survival probabilities' as this best confine the intuition behind the financial concept of momentum. They are estimated by Kaplan-Meier estimator, as described in the next section.

4.2.2.2.1 Kaplan-Meier Estimator

The survival probabilities can be estimated using Kaplan-Meier (KM) method, proposed by Kaplan and Meier (1958), from the observed survival time. The KM method (also known as product limit method) is non-parametric, hence no assumptions about the distribution of survival curve have to be made.

In the KM estimator, the momentum observations of the portfolios can be ordered in accordance to the duration of momentum survival (time-to-event). The estimator also gives the probabilities of those durations. Hence, the Kaplan-Meier estimator resembles the censored generalisation of the empirical distribution function.

The proportion of the observations which have survived to the first observed survival time t_1, $\hat{S}(t_1)$, is simply one minus the proportion of observation which have failed by the time t_1. The latter proportion can be estimated by the number of observations that have failed (momentum trends that were broken), d_1, divided by the number of observations which were at the risk of failure, n_1. That is, d_1/n_1. Similarly the proportion of momentums surviving to the second observed survival time t_2, $\hat{S}(t_2)$, is one minus the proportion of observations which failed between t_1 and t_2, multiplied by $\hat{S}(t_1)$; i.e. $S(t_2) = S(t_1)(1 - \frac{d_1}{n_1})$. The equation can be generalised as:

$$\hat{S}(t_j) = \prod_{j \mid t_t < t} (1 - \frac{d_j}{n_j}) \quad \text{......} (4.9)$$

Where, t_j = Ordered failure time. At $t = t_j$; $t(1) \leq t(2) \leq t(k)$

d_j = Number of failures at time $t = t_j$

n_j = Number of observations which are alive at time $t = t_j$, i.e. the observations at risk of exit.

Hence, the survival function of KM method is the product of one minus the ‘failure rate’ at each of the survival times. $S(t)$ is constant between the time of events, and hence the estimated survival probably is a step function which changes only at each time when event occurs. Therefore, every step in the survival function represents the change in probability of momentum surviving beyond a given time horizon $t(j)$. This probability is conditional upon surviving, provided that the momentum is alive.

The standard error of K-M estimator at time t can be calculated as:

$$Std.Error = \sqrt{Var\left(\hat{S}(t)\right)} = \sqrt{\hat{S}^2(t)\sum_{t_t<t}\frac{d_j}{n_j\,(n_j - d_j)}} \qquad ....(4.10)$$

The survival/event probability at a specific time point *'t'* is a summary measure, however, it does not contain information regarding the event time distribution profile during the time interval (0, t*). Mean survival time or restricted mean survival time is the useful alternative which summarises the survival process using information beyond the survival probability only at a single time t (Zhao et al., 2016; Royston and Parmar, 2013). The mean survival time or restricted mean survival time, let's say 'μ', up to time *t*>0* is the area under the survival curve s(t) from *t=0* to *t=t**:

$$\mu = E(X) = E[\min(T, t^*)] = \int_0^{t^*} S(t)dt \qquad .... (4.11)$$

The mean survival time or restricted mean is estimated from the area under the corresponding Kaplan–Meier product-limit survivor curve up to time t^*. This study assumes T as the time to event i.e. when the trend is broken and hence μ is the t^* months momentum expectancy.

4.2.2.3 Log-rank and Wilcoxon Test to Compare Survivals

It is interesting to compare the survival functions of two or more groups, that is, to determine whether or not the survival functions of two or more groups are identical. The non-parametric tests can be performed to compare two or more survival curves. Log-rank test , proposed by Peto et al. (1977), is the frequently used method to compare the survivals of two or more groups. In this study, the groups are the different value weighted style portfolios. At each time-to-event, for each group, this method calculates the number of expected events since the previous event if there were no differences between the groups. The number of events is then summed up for all event time to get the total expected number of events for each group. If E_i is the expected number of events for group i , O_i is the observed expected number of events for group i; then the Log-rank test statistics can be defined as:

$$Log - rank\ statistics = \sum_{i=1}^{g} \frac{(O_i - E_i)^2}{E_i} \approx \chi^2 \qquad \text{.................................... (4.12)}$$

Here 'g' is the number of groups. Log-rank statistics follows chi-square (χ^2) distribution with (g-1) degrees of freedom. Log rank test uses $O_i - E_i = \sum_j (m_{ij} - e_{ij})$; by weighting the test statistics for two groups we get:

$$\chi^2 = \frac{(\sum_j w(t_j)(m_{ij} - e_{ij}))^2}{Var(\sum_j w(t_j)(m_{ij} - e_{ij}))} \qquad \text{.. (4.13)}$$

Here, $'i'$ & $'j'$ represents the groups and failure time respectively; m_{ij} and e_{ij} is the observed and expected number of failures in $'i'$ th group at $'j'$ th ordered failure time. Whereas, $w(t_j)$ is the weight at jth failure time. For Log-rank test this weight is '1' ,however, Wilcoxon test (also called the Breslow test) weights the observed minus expected score at time $t(j)$ by the number at risk $n(j)$ over all groups at time $t(j)$. Thus, the Wilcoxon test places more emphasis on the information at the beginning of the survival curve where the number at risk is large allowing early failures to receive more weight than later failures. This type of weighting may be used to assess whether the effect of a treatment on survival is strongest in the earlier phases of administration and tends to be less effective over time.

The Log-rank and Wilcoxon tests are performed to compare the equality of survival for each style portfolios stratified by business cycles. That is, we test the null hypothesis that the style portfolio survivals are identical across business cycles.

4.2.2.4 Logit Model

Lewellen (2002) claims that macroeconomic factors rather than firm-specific factors must be responsible for the size and book-to-market momentum. In the previous chapter (essay one) we also found that the strongest impact on size, value and momentum premiums have variables that proxy credit market conditions, namely interest rates, term spread and credit spread. We used Logit model to determine how much these variables affect the survival of style momentum. In this model, the dependent variable is denoted by 1' ('0' otherwise) if the momentum survives longer than or equal to the mean survival. The multinomial Logit model can be formulated as:

$$L = Log(\frac{p}{1-p}) = \alpha + \beta_1 IR + \beta_2\ TERM + \beta_3\ CREDIT \qquad \text{.................... (4.14)}$$

Here,

$L =$ Log of the odds ratio

$p =$ Probability of positive (negative) momentum for two consecutive period

The odds of momentum can be written as:

$$\frac{p}{1-p} = e^{\alpha+\beta_1 IR+\beta_2\ TERM+\beta_3\ CREDIT} = e^{\alpha+\beta_i X_i} \qquad \text{................................(4.15)}$$

Hence e^{β_i} represents the change in odds of a momentum for per unit increase in the credit market condition variable X_i. If β_i is positive then $e^{\beta_i} > 1$ which implies that the odds ratio in favour of positive (negative) momentum are increased. Whereas, if β_i is negative then $e^{\beta_i} < 1$ suggesting that the odds are decreased, while the odds will be unchanged if $\beta_i = 0$ since $e^{\beta_i} = 1$.

4.2.2.5 Simulating Style Portfolio Returns

One of the objectives of this study is to assess whether theoretical models used in describing price behaviour can explain variations in empirical survival functions. To do so, empirical survival function for each of the six style portfolios is compared with simulated theoretical survival curves. The initial step of Monte-Carlo simulation is to formulate the model to be used for data simulation. Following Jochum (2000) and Kos and Todorovic (2008) we apply simulation using Random Walk and Auto Regressive Moving Average (ARMA(1,1)); widely used models that describe stock return behaviour. Random walk is extensively analysed in efficient market literature since Fama (1965), while the ARMA (1,1) model finds its support in Pagan (1996) and Fama and French (1988) among others.

According to Random Walk literature, the market is not predictable and the price changes are independent of each other. Random walk model can be formulated as:

$$p_t = \mu + p_{t-1} + \varepsilon_t; \qquad \varepsilon_t \sim N(0, \sigma_\varepsilon{}^2) \qquad \text{.....................................} (4.16)$$

Here, μ is the drift constant, p_{t-1} is the lagged price and ε_t is the random error term.

ARMA model uses returns rather than prices and takes into account both the lagged value of the stock return and the random error term. An ARMA (1, 1) is a combination Autoregressive (AR) process and Moving average (MA) process. Both AR and MA processes are based on the simple concept of random error or stochastic errors (shocks or innovations). A shock occurs between the two observations in a series and can affect the level of the series. ARMA model describes these shocks or disturbance of the time series data. AR process assumes that each value of the times series is a linear function of the lagged value(s) and a random shock. In MA process each value is determined by the average of current shocks or disturbance and lagged shocks. The order of moving average specifies the number of lagged shocks to be included in the model.

An ARMA (1, 1) is a combination of AR (1) and MA (1) process and can be defined as:

$$r_t = \mu + \alpha_1 r_{t-1} + \beta_1 \varepsilon_{t-1} + \varepsilon_t \qquad \text{..} (4.17)$$

Where, r_t is the portfolio return, μ is constant and ε_t is the shocks or innovation of portfolio return and is a white noise, i.e. $E(\varepsilon_t) = 0$.

In the second step of Monte-Carlo simulation, we estimate the parameters of both Random-Walk and ARMA (1, 1) process for the period October 1980 to June 2014.

10,000 simulated time series of the same length as the empirical data are produced for six style portfolios. For each of the simulated series, the survival curve is obtained.

The comparison of empirical survival curves with theoretical (simulated) ones allows us to infer whether the survival of an existing trend (positive or negative) is higher or lower than the values gained from Random Walk with drift and ARMA (1,1). We compare the mean survival times of theoretical and empirical curves. In the case of identical theoretical and empirical survival curves we expect that the market reflects all available information and there are less possibilities to exploit the discrepancies. However, if there are discrepancies between actual (empirical) survival time and theoretical survival time, we treat it as a sign of inefficiency as theoretical models are unable to fully capture the complexity of the empirical data. This would further imply that and one could employ simple momentum trading rules (timing/rotation strategies) to generate higher returns using style portfolios. The trading rules applied in this study and their implementation is described in section 4.4 of this chapter.

4.3 Empirical Results

4.3.1 Kaplan-Meier Estimator

The results of the step-wise calculation of Kaplan-Meier estimator for both positive and negative momentum are reported in Table 4.2 for Small Size and Low Book-to-Market (SL, i.e. small-growth) portfolio. To save space and repetition, tables showing results for the remaining five portfolios[21], namely- Table A4.1, A4.2, A4.3, A4.4, and A4.5 are in the appendix A4. The second column of each of the aforementioned tables represents ordered failure time, i.e. the number of consecutive months momentum has survived. We note that across all portfolios positive momentum survives longer than the negative, consistent with Jochum (2000) and Kos and Todorovic (2008). In Table 4.2, the maximum positive momentum sequential for SL portfolio is 11 months. The longest positive return sequential in our sample of

[21] Small Size & Medium BTM (SM), Small Size & High BTM (SH), Big Size & Low BTM (BL), Big Size & Medium BTM (BM), and Big Size & High BTM (BH)

Table 4. 2: KM estimator of Small Size & Low book-to-market (SL) Portfolio

This table reports the stepwise calculation (ex-post) of Kaplan-Meier estimator for Small Size & Low book-to-market **(SL)** Portfolio, estimated over the sample period October 1980 to June 2014. This calculation allows a thorough description of survival curves. The survival function (S_t) can be interpreted as the probability of trend continuation until failure time $t(j)$ months conditioned upon the fact that the momentum is alive in $t(j)$, where $t(1) \leq t(2) \leq t(k)$. With simple t-test we checked whether the survival function is significantly different from zero. The values in the parentheses reports the p-values of the t-test.

j	Ordered failure time, $t(j)$	Intact before t (n_j)	Ending at time t (d_j)	Survivor function (S_t)	Std. Error $[\sqrt{Var\ S(t)}]$
Survival Function of Positive Portfolio Momentum					
1	2	174	55	0.6839*** (0.0000)	0.0352
2	3	119	34	0.4885*** (0.0000)	0.0379
3	4	85	25	0.3448*** (0.0000)	0.0360
4	5	60	20	0.2299*** (0.0000)	0.0319
5	6	40	13	0.1552*** (0.0000)	0.0274
6	7	27	8	0.1092*** (0.0001)	0.0236
7	8	19	6	0.0747*** (0.0015)	0.0199
8	9	13	6	0.0402* (0.0194)	0.0149
9	10	7	6	0.0057 (0.3559)	0.0057
10	11	1	1	0.0000 (N/A)	-
Survival Function of Negative Portfolio Momentum					
1	2	71	36	0.4930*** (0.0000)	0.0593
2	3	35	16	0.2676*** (0.0000)	0.0525
3	4	19	9	0.1408*** (0.0031)	0.0413
4	5	10	5	0.0704** (0.0458)	0.0304
5	6	5	2	0.0423 (0.1515)	0.0239
6	7	3	1	0.0282 (0.2868)	0.0196
7	8	2	1	0.0141 (0.4977)	0.0140
8	9	1	1	0.0000 (N/A)	-

*** Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
* Implies the significance at 10% level of significance

portfolios lasts 14 months and is observed in SH and BH portfolios, reported in Tables A3.2 and A3.5 respectively. This is similar to the findings of Lewellen (2002) who observes that style portfolios exhibit momentum for up to 17 months. The longest negative return sequential has been identified for 9 months in SL portfolio in Table 4.2. Positive and negative return continuation over a horizon of 3 to 12 months is also reported in the study of Jegadeesh and Titman (1993).

The third column of Table 4.2 shows the number of ‘alive’ momentums before ordered failure time, t(j). In the sample of 405 observations, 174 positive momentums that survive (n_j) for two months are identified. Out of those, 55 momentums (d_j, column 4) dies at 2 months and hence the probability of surviving at least 2 months is 68.29% ($1-d_j/n_j$). The remaining 119 momentums continue to survive for at least three months, where 34 observations die after three months of momentum etc. Only one momentum survived 11 months in Table 4.2. For negative momentum, out of 405 observations only 71 have been identified with two months of negative momentum, of which 36 of them die after two months etc.

The survival function (S_t) can be interpreted as the probability of trend continuation until failure time t(j) months conditioned upon the fact that the momentum is alive in t(j), where $t(1) \leq t(2) \leq t(k)$. So for instance, the probability that the negative momentum survived at least 2 months is 49.30%; however, the probability of it surviving at least 3 months diminishes by almost 50% to 26.76%. Overall, our findings reveal that the probability of positive momentum surviving at least 2 successive months is 60% or more for all the portfolios. For negative momentum the equivalent probability is only 33% or more for all the portfolios. The standard error of Kaplan-Meier estimators are low for all the style portfolios such that the statistical significance of survival probabilities are not at risk. We perform simple t-test to check whether the survival function is significantly different from zero. We observe that, survival function is statistically significant for until 9 months for positive survival. Negative survival function is statistically significant for until 5 months. Similar findings are found for rest of the portfolios.

4.3.2 Empirical vs. Theoretical Survival Curves and Scope for Arbitrage

In this section, empirical momentum survival probabilities of style portfolios are compared with those of simulated theoretical benchmark curves. If the theoretical models fully explain the empirical momentum survival process, there should be no statistically significant difference between empirical and theoretical survival probabilities. Should the survival times of the empirical curves prove to be different than for the benchmark simulations, we may conclude that the Random Walk Model and the ARMA(1,1) model do not capture the full complexity of the empirical price generating process and that exploitable arbitrage opportunities exist.

Table 4.3 reports the survival function of theoretical survival curves (Monte-Carlo Simulation of Random Walk and ARMA (1,1) process) for both positive and negative momentum for SL portfolio. Equivalent tables for the remaining five portfolios are in the appendix table A4.6, Panel A-E. We use t-test to signify the difference between theoretical and empirical survival functions of corresponding ordered failure time for both positive and negative momentum. To illustrate the interpretation of Table 4.3, let us use ordered failure time of two periods. According to empirical survival curve, there is 68.39% probability that positive momentum will last for two months.

Compared to the theoretical curves, the probability of survival of positive momentum for two months according to random walk and ARMA (1,1) is considerably smaller at 50.26% and 56.94% respectively. The empirical survival time of positive momentum of portfolio SL is up to 11 months, while the Random Walk model suggests it is up to 9 months; hence zeros in the table denote zero probability of momentum surviving in the corresponding ordered failure time. Simple t-test is performed to investigate whether the positive (negative) theoretical survival functions are identical to the positive (negative) empirical survival functions of corresponding ordered failure time. We observe that the positive momentums of theoretical survival function are statistically different than those of empirical function are at 1% level. However, the theoretical survival functions are not found to be significantly different from empirical functions in case of negative momentum at any ordered failure time.

Table 4. 3: Theoretical Survival Function for SL portfolio

This table reports the survival function of theoretical survival curve (simulated Random Walk and ARMA (1,1) process). The empirical survival curve is reported here for comparison purpose. Simple t-test is performed to investigate whether the theoretical survival functions are identical to the positive or negative empirical survival functions of corresponding ordered failure time. P-value less than the significance level means that the theoretical survival function is significantly different from their corresponding empirical function.
Survival functions/probabilities are reported in decimal points.

Ordered failure time, $t(j)$	Empirical Survival Function		Theoretical Survival Function			
			Random Walk		ARMA(1,1)	
	Positive Momentum	Negative Momentum	Positive Momentum	Negative Momentum	Positive Momentum	Negative Momentum
Small Size & Low book-to-market (SL) Portfolio						
2	0.6839	0.493	0.5026*** (0.0000)	0.4959 (0.9667)	0.5694*** (0.0101)	0.5675 (0.2769)
3	0.4885	0.2676	0.2461*** (0.0000)	0.2496 (0.7687)	0.3178*** (0.0002)	0.3223 (0.3716)
4	0.3448	0.1408	0.1188*** (0.0000)	0.1266 (0.7675)	0.1748*** (0.0000)	0.1784 (0.4374)
5	0.2299	0.0704	0.0582*** (0.0000)	0.0609 (0.7874)	0.0936*** (0.0002)	0.0974 (0.4523)
6	0.1552	0.0423	0.0257*** (0.0000)	0.0296 (0.6424)	0.047*** (0.0006)	0.0522 (0.7239)
7	0.1092	0.0282	0.0124*** (0.0003)	0.0118 (0.4543)	0.0235** (0.01426)	0.0261 (0.9261)
8	0.0747	0.0141	0.0048*** (0.001928)	0.0037 (0.4993)	0.0088*** (0.003)	0.0108 (0.8361)
9	0.0402	0	0	0	0	0.0014
10	0.0057					0.0007
11	0					0

*** Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
* Implies the significance at 10% level of significance

Both Table 4.3 and A4.6 show that maximum survival time of positive momentums of simulated benchmark returns is lower than those for the empirical portfolios. The difference is by and large statistically significant across portfolios. In contrast, the negative momentums of simulated portfolios have longer survival times than empirical ones. However, this difference is not significant for portfolio SL (Table 4.3) and BL (Table A4.6, Panel C), while it is significant for shorter ordered failure times for the remaining portfolios in Table A4.6. Theoretical models are supposed to show us how the market is behaving and fairly priced. If the survival probabilities of theoretical models are significantly different from empirical ones, there might be arbitrage opportunities to explore.

Table 4.4 presents the mean survival time (restricted mean survival time) for the empirical (KM) as well as simulated (Random Walk and ARMA (1,1)) curves. The survival probability we have analysed in Table 4.2 and 4.3, S(t) is given for the specific point in time ‘t’ and is a summary measure. It does not, however, contain the information regarding the survival time distribution profile during the whole time interval (0, t). Mean survival time or restricted mean survival time is the useful alternative which summarizes the survival process using information beyond the survival probability only at a single time t, representing the area under the survival curve S(t) from period 0 to period t (Zhao et al., 2016; Royston and Parmar, 2013). Table 4.4 documents that in the case of positive portfolio momentum, the mean survival time given by theoretical Random Walk or ARMA (1,1) model is shorter than the empirical one; while the opposite is found for negative portfolio momentum. Note that, all the empirical and theoretical mean survival time are found to be statistically significant.

Moreover, in support of findings from Table 4.2, estimated empirical mean survival for positive momentum is longer than that for the negative momentum. Positive momentum in style portfolios survives on the average around four months[22], while the negative average survival time is two or three months, depending on the portfolio. Kos and Todorovic (2008) point that Grinblatt, Titman and Wermers (1995) argue that fund managers tend to buy 'winning' stocks but do not sell 'losing' stocks. This stronger tendency to buy upward moving securities reinforces positive market moves and thus creates stronger positive market momentum. These empirical findings suggest profit potentials for investors that can be exploited by adequate trading strategy.

[22] The rounding is done to the nearest whole number

Table 4. 4: Mean Values of Portfolio Survival Times

This table reports the mean survival time for the empirical as well as simulated curve. The estimating period for the empirical curve is October1980 to June2014. Theoretical survival curves are calculated from the Monte-Carlo simulation of 10,000 time series. The mean survival times are calculated from corresponding survival curve of Kaplan-Meier estimator. With simple t-test we check whether the mean survival time is significantly different from zero. The values in the parentheses reports the p-values of the t-test.

Portfolios	Mean Empirical Survival Time	Mean RW Survival Time	Mean ARMA Survival Time
Positive Portfolio Momentum			
Small Size & Low BTM (SL) Portfolio	4.132184*** (0.000)	2.968687*** (0.000)	3.234758*** (0.000)
Small Size & Medium BTM (SM) Portfolio	4.172043*** (0.000)	3.028482*** (0.000)	3.236601*** (0.000)
Small Size & High BTM (SH) Portfolio	4.281081*** (0.000)	3.00712*** (0.000)	3.232162*** (0.000)
Big Size & Low BTM (BL) Portfolio	4.045977*** (0.000)	2.989682*** (0.000)	3.022612*** (0.000)
Big Size & Medium BTM (BM) Portfolio	3.539394*** (0.000)	3.022577*** (0.000)	2.894845*** (0.000)
Big Size & High BTM (BH) Portfolio	4.095808*** (0.000)	2.981913*** (0.000)	2.975143*** (0.000)
Negative Portfolio Momentum			
Small Size & Low BTM (SL) Portfolio	3.056338*** (0.000)	2.978084*** (0.000)	3.27121*** (0.000)
Small Size & Medium BTM (SM) Portfolio	2.438597*** (0.000)	2.985441*** (0.000)	3.226335*** (0.000)
Small Size & High BTM (SH) Portfolio	2.693548*** (0.000)	2.921293*** (0.000)	3.197999*** (0.000)
Big Size & Low BTM (BL) Portfolio	2.847458*** (0.000)	2.974138*** (0.000)	3.07943*** (0.000)
Big Size & Medium BTM (BM) Portfolio	2.521739*** (0.000)	2.92324*** (0.000)	2.791115*** (0.000)
Big Size & High BTM (BH) Portfolio	2.52*** (0.000)	2.943633*** (0.000)	2.975496*** (0.000)

*** Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
* Implies the significance at 10% level of significance

Underestimated theoretical positive survival time of Random walk model for all the portfolios (and overestimated negative empirical survival time of Random walk model for some portfolios) can be viewed as the misalignment of efficient market hypothesis with empirical data. As the efficient market hypothesis primarily based on the random walk model, these under- and over-estimation violates the efficient market theory to some extent. However, one can view these misalignments as the limits to arbitrage with the argument that, cost and fundamental risk limits the effectiveness of arbitrage in eliminating certain security mispricing. Although the justification of efficient market hypothesis is beyond the scope of this study, we gauge the impact of transaction cost (break-even transaction cost) to the profitability of our trading strategies as an indicator of the presence of limits to arbitrage.

The potentiality of exploiting the misalignment of theoretical and empirical momentum curves (as suggested in the Table 4.4), particularly for the positive momentum, is explored in the following section. We implement simple trading rules as described in 4.3 and assess the profitability of positive (long-only), negative (short-only) and combined (long-short) style portfolio momentum trading.

4.3.3 Trading Strategy Design, Profitability and Limits to Arbitrage

We implement momentum based timing strategies derived from mean survival times of both positive and negative momentum for each of the six style portfolios. Mean survival time for positive and negative momentum used for trading rule design is estimated in-sample in the period October 1980 to December 2000 for each of the six portfolios and reported in Table 4.5. The out-of-sample trading period is then January 2001 to July 2014.

Table 4.5 shows that the mean survival times are almost identical to those in the overall sample (Table 4.4) and also are highly significant. For positive momentum, it is approximately four months for all the style portfolios. However, mean survival times vary in case of negative momentum. For small size portfolios (SL, SM and SH) mean survival time is approximately three months; whereas, for big size portfolios (BL, BM and BH) it is two months.

Given these mean survival times, we design timing strategies (trading rules) that are easily implementable by practitioners. The trading rule implies that in the case of positive momentum, we take a long position in the relevant portfolios if a positive momentum signal is triggered (see section 4.1 for description of momentum signal) and hold it for four months (mean survival time for positive momentum). Whereas for negative momentum, we take a short position once the momentum is triggered and hold it for two months in case of large-cap portfolios and three months in case of small-cap portfolios (according to the mean survival time of relevant portfolios). The trigger of momentum signal depends on whether we observe a positive (negative) momentum or not, i.e. whether the positive (negative) return is observed for two consecutive periods or not. If no momentum signal is observed, we invest in the risk-free asset, proxied by UK three month T-Bill. Note that we do not say that these is the only, the best or optimal trading rule, but we simply use it to illustrate whether exploiting empirical momentum survival times is profitable in the UK style portfolios at a feasible level of transaction costs. Using this rule, we design four strategies: 1) Long-only exploiting positive momentum in each portfolio, 2) Short-only exploiting negative momentum in each portfolio, 3) Long positive/Short negative momentum in each portfolio and 4) Long in winner style (portfolio with highest positive momentum) and Short in loser style (lowest negative momentum portfolio). Note that the last strategy implies style rotation, i.e. that investor switches style portfolios over investment horizon.

Table 4. 5: Mean Values of Portfolio Survival Times

This table reports the mean survival time of positive and negative momentum for style portfolios (SL, SM, SH, BL, BM and BH) over the in-sample estimating period October 1980 to December 2000. These mean survival time are used in the trading strategies. With simple t-test we check whether the mean survival time is significantly different from zero. The values in the parentheses reports the p-values of the t-test.

Portfolios	Positive Mean Empirical Survival Time	Negative Mean Empirical Survival Time
Small Size & Low BTM (SL) Portfolio	4.185185*** (0.000)	2.888889*** (0.000)
Small Size & Medium BTM (SM) Portfolio	4.278261*** (0.000)	2.514286*** (0.000)
Small Size & High BTM (SH) Portfolio	4.45082*** (0.000)	2.6875*** (0.000)
Big Size & Low BTM (BL) Portfolio	4.2*** (0.000)	2.387097*** (0.000)
Big Size & Medium BTM (BM) Portfolio	3.679245*** (0.000)	2.384615*** (0.000)
Big Size & High BTM (BH) Portfolio	4.486487*** (0.000)	2.304348*** (0.000)

*** Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
* Implies the significance at 10% level of significance

The risk-adjusted profitability of the strategies vis-à-vis their respective buy-and-hold benchmark is measured by the Sharpe ratios. As the benchmark for strategies 1) - 3) we use buy-and-hold of the corresponding style portfolio, while for strategy 4) the buy-and-hold of FTSE All Share Index. However, one could argue the importance of transaction costs in profitability of active strategies, particularly those active strategies based on frequent trading, such as the ones presented in this study. Determining whether such strategies are robust, implementable, and sizeable or whether they face significant practical hurdles is vital. Profitability of our trading strategies after trading cost may indicate the presence of limits to arbitrage.

However, the transaction cost is not fixed and can be different for individual investor, and large institutional investors (Frazzini, Israel and Moskowitz, 2012). Hence, using fixed transaction cost may be a very poor proxy for the trading cost our strategies that can be exploited by marginal investors as well institutional investors. To assess the feasibility of our strategies, we calculate the break-even level of transaction costs per trade for each portfolio following the formulae of Chandrashekar (2006); Kos and Todorovic (2008); Kritzman, Page and Turkington (2012); and Boudt et al. (2015):

$$\frac{\bar{r}_{Trading\ \ Rules}-\bar{r}_f}{\sigma_{Trading\ \ Rules}}=\frac{\bar{r}_{Buy-hold}-\bar{r}_f}{\sigma_{Buy-hold}}$$

Here mean return is calculated as: $\bar{r}_{Trading\ \ Rules}=\sum_{t=1}^{n}\frac{r_t-C}{n}$, where C takes the value of zero if no transaction has been made and value of breakeven transaction cost if trading occurred in month 't' and 'n' is the number of periods. Contrary to the method of Bessembinder and Chan (1998), we use Sharpe ratio rather than return with the argument that, investors are risk averse and care about risk adjusted returns i.e. Sharpe ratios for choosing among strategies. The costs are deducted from the portfolio return in the months in which trading occurs. The higher these break-even transaction costs are, the more feasible our strategy is. The mechanics, profitability and feasibility of each strategy are discussed in the sub-sections that follow.

4.3.3.1 Strategy 1) and 2): Long-only Positive Momentum and Short-only Negative Momentum in Each Portfolio

In the long-only positive momentum strategy, we buy a style portfolio once the momentum signal is established and hold it for four months. In the short-only negative momentum, we short a style portfolio once a negative momentum is triggered and hold it for three months if small-cap and two months if large-cap portfolio. When no momentum is observed, both strategies assume investment in the UK 3 month T-bill. The strategies are applied in each portfolio separately.

Tables 3.6 and 3.7 reports annualised mean return, standard deviation, Sharpe ratio, the number of switches over the trading period and break-even transaction costs per switch for each of the style portfolios and for positive and negative momentum respectively. Comparative figures (where applicable) are reported for the buy and hold portfolios.

The results in table 4.6 reveal that applying long-only positive momentum strategy results in higher returns and Sharpe ratios in all style portfolios, at a feasible level of transaction costs per trade even for smaller investors. Exploiting positive momentum is most profitable in SH (small-value) portfolio, generating Sharpe ratio of 1.23 and break-even level of transaction costs of 444 bps per trade. This means that momentum trader can pay up to 4.44% transaction costs per trade and still generate higher Sharpe ratio than the buy and hold of the SH portfolio. We also show that positive momentum trading has lower risk (standard deviation) than the buy-and-hold strategy for all the portfolios.

In contrast, Table 4.7 shows that although strategy based on negative portfolio momentum generates lower risk (standard deviation) than the corresponding buy-and-hold, only half of the portfolios (SL, BL and BM) outperform the buy-and-hold strategy at a reasonable level of break-even transaction costs. This is not surprising because theoretical negative momentum survival curves are almost identical with the empirical curves for most portfolios. Hence there are less possibilities to exploit the market using the negative momentum.

Table 4. 6: Trading Rule Results of Positive Portfolio Momentum

Trading results of this table are based on the positions of SL, SM, SH, BL, BM and BH portfolios and T-bills (monthly) according to positive momentum survivals. We estimate the mean survival time over the in-sample period October 1980 to December 2000 (243 months) and used the estimated mean to trade upon the trading period January 2001 to June 2014 (162 trading months). The buy-and-hold strategy represents the investment in the relevant portfolios. Whereas, timing portfolio take long position in the relevant portfolios if a positive momentum is observed and hold it for 4 months (means survival time), otherwise invest in T-Bills.
Mean returns and standard deviations (Std. Dev.) have been annualised and are expressed in percentages.

	Small Size & Low BTM (SL) Portfolio		Small Size & Medium BTM (SM) Portfolio		Small Size & High BTM (SH) Portfolio	
	Buy and Hold	Timing Portfolio	Buy and Hold	Timing Portfolio	Buy and Hold	Timing Portfolio
Mean Return	4.00	12.81	12.17	18.80	10.98	21.05
Std. Dev.	19.85	14.01	17.84	12.45	20.37	14.12
Sharpe Ratio	0.16	0.73	0.58	1.22	0.48	1.23
No. of Switches	-	29	-	31	-	32
Break-even TC	-	375.87 BPS	-	337.78 BPS	-	444.65 BPS

	Big Size & Low BTM (BL) Portfolio		Big Size & Medium BTM (BM) Portfolio		Big Size & High BTM (BH) Portfolio	
	Buy and Hold	Timing Portfolio	Buy and Hold	Timing Portfolio	Buy and Hold	Timing Portfolio
Mean Return	5.06	11.79	6.97	13.26	6.12	11.94
Std. Dev.	12.17	7.72	16.46	10.65	17.34	12.10
Sharpe Ratio	0.23	1.12	0.32	0.96	0.27	0.76
No. of Switches	-	24	-	32	-	31
Break-even TC	-	372.17 BPS	-	284.32 BPS	-	263.65 BPS

Table 4. 7: Trading Rule Results of Negative Portfolio Momentum

Trading results of this table are based on the positions of SL, SM, SH, BL, BM and BH portfolios and T-bills (monthly) according to negative momentum survivals. We estimate the mean survival time over the in-sample period October 1980 to December 2000 (243 months) and used the estimated mean to trade upon the trading period January 2001 to June 2014 (162 trading months). The buy-and-hold strategy represents the investment in the relevant portfolios. Whereas, Timing portfolio takes short position according to mean survival time of the relevant portfolios if a negative momentum is observed, otherwise invest in T-Bills. The mean negative momentum survival time of SL, SM, SH, BL, BM and BH portfolios are 3, 2, 3, 3, 2, and 2 months respectively. Mean returns and standard deviations (Std. Dev.) have been annualised and expressed in percentages.

	Small Size & Low BTM (SL) Portfolio		Small Size & Medium BTM (SM) Portfolio		Small Size & High BTM (SH) Portfolio	
	Buy and Hold	Timing Portfolio	Buy and Hold	Timing Portfolio	Buy and Hold	Timing Portfolio
Mean Return	4.00	11.65	12.17	6.97	10.98	6.83
Std. Dev.	19.85	13.20	17.84	11.67	20.37	14.55
Sharpe Ratio	0.16	0.69	0.58	0.40	0.48	0.34
No. of Switches	-	31	-	27	-	29
Break-even TC	-	305.04 BPS	-	Negative	-	Negative

	Big Size & Low BTM (BL) Portfolio		Big Size & Medium BTM (BM) Portfolio		Big Size & High BTM (BH) Portfolio	
	Buy and Hold	Timing Portfolio	Buy and Hold	Timing Portfolio	Buy and Hold	Timing Portfolio
Mean Return	5.06	8.98	6.97	7.56	6.12	4.94
Std. Dev.	12.17	7.21	16.46	8.39	17.34	9.84
Sharpe Ratio	0.23	0.86	0.32	0.58	0.27	0.25
No. of Switches	-	23	-	24	-	35
Break-even TC	-	257.44 BPS	-	127.39 BPS	-	Negative

In general, results for the positive momentum effects are more pronounced than negative momentum effects. However, the results suggest that the model works well for both positive and negative momentum where the empirical survival curves are not identical with theoretical survival curves. Hence, the survivorship model can be seen as a compelling indicator of profitable trades.

4.3.3.2 Strategy 3): Long Positive/Short Negative Momentum in Each Portfolio

This strategy is a combination of strategy 1) and 2) for each portfolio. Hence, the long (short) position in the relevant portfolios involves buying (shorting) that portfolio if a positive (negative) momentum is observed and holding it according to mean survival time. Note that we are never long and short at the same time in this strategy, but we rather alternate long and short position in each portfolio. We compare this strategy to the buy and hold of each portfolio and report Sharpe ratios as well as break-even transaction costs. The performance and feasibility of the strategy are presented in Table 4.8. It is clear that risk-adjusted performance of our long-short strategy in each portfolio separately significantly outperforms buy-and-hold strategy. The highest

Table 4. 8: Long Positive/Short Negative Momentum in Each Style Portfolio

This table reports the annualised Mean Return, Standard Deviation, Sharpe Ratio and break-even transaction costs (in basis points) of Long-Short trading of style portfolios based on the positive and negative momentums. Long (short) position in the relevant portfolios means buying (shorting) the portfolio if a positive (negative) momentum is observed and hold it according to mean survival time, otherwise invest in the UK 3 month T-Bills. In-sample estimation period is October 1980 to December 2000 (243 months) which is used to estimate the mean survival time. The estimated mean are then used to trade upon the trading period January 2001 to June 2014 (162 trading months).

	Small Size & Low BTM (SL) Portfolio		Small Size & Medium BTM (SM) Portfolio		Small Size & High BTM (SH) Portfolio	
	Buy and Hold	Timing Portfolio	Buy and Hold	Timing Portfolio	Buy and Hold	Timing Portfolio
Mean Return	4.00	7.85	12.17	10.77	10.98	10.68
Std. Dev.	19.85	9.19	17.84	7.68	20.37	9.01
Sharpe Ratio	0.16	0.56	0.58	1.00	0.48	0.87
No. of Switches	-	51	-	40	-	47
Break-even TC	-	199.93 BPS	-	226.98 BPS	-	205.05 BPS

	Big Size & Low BTM (BL) Portfolio		Big Size & Medium BTM (BM) Portfolio		Big Size & High BTM (BH) Portfolio	
	Buy and Hold	Timing Portfolio	Buy and Hold	Timing Portfolio	Buy and Hold	Timing Portfolio
Mean Return	5.06	10.09	6.97	10.33	6.12	10.27
Std. Dev.	12.17	4.93	16.46	6.25	17.34	6.68
Sharpe Ratio	0.23	1.42	0.32	1.15	0.27	1.08
No. of Switches	-	42	-	51	-	46
Break-even TC	-	367.09 BPS	-	276.35 BPS	-	318.26 BPS

Sharpe ratio of large-growth (BL) long-short momentum strategy is 1.42, which is more than six times that of its buy-and-hold benchmark. The level of break-even transaction costs that equalises the Sharpe ratio of our momentum strategy to that of the buy and hold is very high, at 367.09bps. Hence, as long as one pays less than

3.67% per each switch, they will outperform the buy-and-hold, which is verifying the feasibility of our strategy.

4.3.3.3 Strategy 4): Long Winner/Short Loser Portfolio Style Rotation Strategy

This strategy implies buying the winner portfolio (a portfolio with highest positive momentum) in month t and holding it for mean survival time of four months (until period *t+3*). Once the four-month holding period expires, we look for portfolio with the next positive momentum trigger. If more than one portfolio exhibits momentum signal in the same month, we buy the one with the highest historical return, i.e. the highest momentum. And so on. The strategy also involves simultaneously shorting a loser portfolio (a style portfolio that has the lowest negative momentum) in month t. We hold the short position for the average negative momentum survival time (two months for large or three months for small-cap portfolios). Once the short position is closed, similarly to the winner leg of the strategy, we search for the next loser style portfolio to short. In months when we are neither long nor short, the investment is in the UK T-bill.

During the trading period, there is 61 'buy' and 59 'sell' signals. Most traded portfolio is small-growth (SL) with 34 buy/sell signals and the least traded one is SM with 4 signals. Note that, we are not long (or short) in more than one portfolio at the time, but we can be short in one and long in another portfolio at the time 't' [23]. Hence, this results in style rotation strategy. Such rotation across investment styles causes inconsistent risk parameters in a portfolio; which does not comply with traditional mutual fund risk constraints. For this reason, style rotation strategies are more suitable for hedge funds than for funds pursuing traditional, long-only, approach to investing. Style rotation applied in the context of momentum investing is found to be profitable in the UK in Clare, Sapuric and Todorovic (2010). A number of other studies document profitability of style rotation strategies in the UK (Levis and Liodakis, 1999 and Levis and Tessaromatis, 2004) and the US (Kao and Shumaker, 1999; Arshanapalli, Switzer and Panju, 2007) among many others.

[23] Also, note that we do not allow the long and the short position to be in the same portfolio.

Table 4.9 reports the results of the long winner/short loser style rotation strategy, including both the (long) winner and (short) loser trading results separately. We show annualised mean return, standard deviation and Sharpe ratio of the strategy and the buy-and-hold of the benchmark. As the benchmark, we chose FTSE All Share index, as a representative index for the UK market given that we switch across portfolios representing various investment styles and hence covering all segments of the market.

Table 4. 9: Winner/Loser Style Rotation

This table reports the annualised Mean Return, Standard Deviation, Sharpe Ratio and break-even transaction costs (in basis points) of winner/loser momentum trading over the trading period January 2001 to June 2014. In-sample estimation period of October 1980 to December 2000 is used to estimate the mean survival time. The switching between portfolios is determined by two criteria: long position in the highest positive momentum and short position in the lowest negative momentum in month t. If the positive (negative) momentum is not observed we invest in UK three month T-Bill. The portfolios are rebalanced based on the mean survival time of positive and negative momentum (4 months if positive and 2-3 months if negative momentum). Buy-and-hold is the FTSE All Share index.

	Mean Return (%)	**Std. Dev (%)**	**Sharpe Ratio**	**Break-even TC**
Winner/loser Style Rotation Long	20.24	16.29	1.04	304.60 BPS
Winner/loser Style Rotation Short	19.42	13.18	1.21	145.57 BPS
Winner/loser Style Rotation Long-Short	20.63	8.76	1.89	216.61 BPS
Buy-Hold of FTSE All Share	4.90	14.62	0.21	

Our long winner/ short loser rotation strategy consistently outperforms buy-and-hold FTSE All Share index. The winner/loser strategy annualised mean return in Table 4.9 is around four times higher (20.63%) than that of the FTSE index (4.90%), with 6% lower standard deviation, making the strategy's annualised Sharpe ratio (1.89) nine-times that of the index (0.21). Both long and short segment of the strategy separately generate considerably higher Sharpe ratios than the buy-and-hold. Break-even transaction costs that equalise Sharpe ratio of the strategy to that of the FTSE All Share index buy-and-hold are at a feasible level for all investors.

Investors can follow our trading strategies based on their risk tolerance and whether they prefer long position, or short position, or prefer rotation strategies. The investors who prefer long position can generate higher return by taking long position in any of the style portfolios (SL, SM, SH, BL, BM and BH), based on their individual preference, if a positive momentum is observed and hold it for the months according to their mean survival time, otherwise invest in T-bills. Investors who prefer short position are advised to follow our short trading strategies (take short position if a negative momentum is observed and hold it for the months according to their mean survival time, otherwise invest in T-bills) for the SL and BL portfolios only, as they produce higher break-even transaction cost with higher Sharpe ratio. Although, investors who prefer rotation strategies can be benefited by following our strategy (i.e. taking long (short) position in the relevant portfolios by buying (shorting) the portfolio if a positive (negative) momentum is observed and hold it according to mean survival time, otherwise invest in the UK 3 month T-Bills) in all the style portfolios, they are suggested to take long-short position on big size portfolios (BL, BM, BH) where the Sharpe ratio of the long-short strategies are higher than those of small size portfolios. However, if an investor intends to take all the style portfolios into consideration but want to build his/her portfolio with the highest (lowest) positive (negative) return, they are advised to take either long or long-short position of the winner/loser style rotation strategy as these strategies produce higher return.

4.3.4 Survival across Business Cycles

Stambaugh et. al (2012) and Avramov et al. (2016) show that the strength of momentum profits varies over time. In addition, there is evidence that momentum in the UK exhibits a degree of cyclical behaviour (see first essay). Given this evidence, it is possible that the power of momentum and hence momentum profits in UK style portfolios could be different across varying economic and market conditions. To assess this, we use the Log-rank and Wilcoxon tests, proposed by Peto et al. (1977), to test the null hypothesis that the style portfolio survival curves are identical across business cycles. Log Rank test is more sensitive than the Wilcoxon test to differences between groups in later points in time. Whereas, Wilcoxon test is more sensitive than the log-rank test to differences between groups that occur in early points in time.

Table 4.10 reports that the null hypothesis of the equality of empirical survivor functions across business cycles. Looking at the positive momentum, only SM and BH portfolios significantly exhibit unequal survival function over economic regimes according to both Log rank and Wilcoxon test. In Table 4.10, 1 indicates recession and '0' indicates expansion periods. To differentiate between recession and expansion periods we use OECD based Recession Indicators for the United Kingdom taken from Federal Reserve Bank of St. Louis[24]. The survival curve of SH and BM portfolios are found to be significantly unequal using Log-rank test, however, this is rejected by Wilcoxon test. BL and SL portfolios do not exhibit cyclical differences in momentum survival curves. Reverting the analysis to negative momentum, the survival curves are different across economic regimes only for BM portfolio leading us to conclude that overall there is no strong evidence that style portfolios have different momentum survival time under different market conditions.

Given this evidence, one can infer that momentum strategies in style portfolios whose survival curve is statistically the same across economic cycles are expected to exhibit similar profitability irrespective of the economic regimes. That is, one can trade on either positive or negative momentum utilising its survival time without being concerned about the recession or expansion state of the market. We test this assumption during the trading period January 2001 to June 2014 where there is 49% of peak and 51% of trough months in the UK economy. To save space and repetition, we present profitability across economic cycles for long winner/short loser style rotation strategy only. Note that the remaining strategies presented in this chapter lead to the same qualitative conclusions.

[24] For the procedure visit: https://fred.stlouisfed.org/series/GBRRECDM

Table 4. 10: Equality of Empirical Survival Function

Log rank and Wilcoxon test is performed to check whether or not the survival functions are similar across the business cycles. We test the following hypothesis over the full sample period (October 1980 to June 2014).
H_0= Survival functions of style portfolio is equal across the economic regimes
The economics regimes are the OECD based Recession Indicators for the United Kingdom taken from Federal Reserve Bank of St. Louis. '1' indicates recession and '0' indicates expansion periods.

	Economic Regimes	Log Rank Test (χ^2)	Wilcoxon Text (χ^2)
Panel A: Positive Portfolio Momentum			
SL	0	0.41	1.97
	1	(0.5223)	(0.1607)
SM	0	17.24***	14.17***
	1	(0.0000)	(0.0002)
SH	0	3.09*	2.22
	1	(0.0789)	(0.1365)
BL	0	0.24	0.00
	1	(0.6250)	(0.9679)
BM	0	3.71*	1.24
	1	(0.0541)	(0.2662)
BH	0	9.45***	4.91**
	1	(0.0021)	(0.0268)
Panel B: Negative Portfolio Momentum			
SL	0	1.46	0.08
	1	(0.2265)	(0.7784)
SM	0	0.19	0.02
	1	(0.6654)	(0.8909)
SH	0	0.84	0.84
	1	(0.3592)	(0.3600)
BL	0	0.34	0.16
	1	(0.5578)	(0.6873)
BM	0	3.33*	2.98*
	1	(0.0680)	(0.0843)
BH	0	0.16	0.01
	1	(0.6917)	(0.9043)

* ** Implies the significance at 1% level of significance
** Implies the significance at 5% level of significance
* Implies the significance at 10% level of significance

Table 4. 11: Winner/Loser Style Rotation Across Business Cycles

This table reports the annualised Mean Return, Standard Deviation, Sharpe Ratio and break-even transaction costs (in basis points) of winner/loser momentum trading. In-sample estimation period of October 1980 to December 2000 (243 months) is used to estimate the mean survival time. The estimated mean are then used to trade upon the trading period January 2001 to June 2014 (162 trading months, 79 of them were in expansion period and 83 of them were in recession period). The switching between portfolios is determined by two criteria: long position in the highest positive (negative) momentum and short position in the lowest negative momentum in month *'t'*. If the positive (negative) momentum is not observed we invest in the UK 3 month T-Bill. The portfolios are rebalanced based on the mean survival time of positive and negative momentum (4 months if positive and 2-3 months if negative momentum). Buy-and-hold is the FTSE All Share index. The economic regimes are the OECD based Recession Indicators for the United Kingdom taken from Federal Reserve Bank of St. Louis.

	Mean Return (%)	**Std. Dev (%)**	**Sharpe Ratio**	**Break-even TC**
Panel A: Recession				
Winner/loser Style Rotation Long Winner	15.91	15.72	0.4676	404.53 BPS
Winner/loser Style Rotation Short Loser	23.14	14.82	0.7708	256.50 BPS
Winner/loser Style Rotation Long-Short	20.23	9.58	0.9397	272.28 BPS
Buy-Hold of FTSE All Share	-1.01	14.73	-0.2603	-
Panel B: Expansion				
Winner/loser Style Rotation Long Winner	24.97	16.88	0.7225	212.25 BPS
Winner/loser Style Rotation Short Loser	15.64	11.22	0.5681	49.12 BPS
Winner/loser Style Rotation Long-Short Loser	21.07	7.87	1.0967	143.38 BPS
Buy-Hold of FTSE All Share	11.49	14.38	0.2970	-

Earlier in this study, Table 4.9 has shown that both long and short segment of the winner/loser style rotation strategy separately generate considerably higher Sharpe ratios than the buy-and-hold in the overall trading period January 2001 to June 2014. Consistent with what one would expect intuitively, Table 4.11 shows that in the recessions it pays more to be short, while in expansions the long side of the portfolio has the edge. Nevertheless, in both expansion and recession, the highest Sharpe ratios (well above those of the FTSE All Share index) are generated by the long winner/short loser strategy. Investors can pay transaction costs up to 2.7% per trade in recessions (1.4% in expansions) and still generate better performance than FTSE All Share benchmark. Hence, regardless of the economic state, our momentum strategies continue to generate strong risk-adjusted performance at a feasible level of transaction costs.

4.3.5 Impact of Macroeconomic Variables on Momentum Survival

In chapter three we observe that credit market variables, namely interest rate, credit spread and term spread, has the strongest impact on momentum premium (also on size and value premium). We hypotheses that, these credit market variables can also influence the momentum survival of the style portfolios. Influences of credit market variables in the likelihood of mean portfolio momentums are tested by Logit model. Table 4.12 reports the estimated coefficients from the logit regression analysis, which examines the likelihood of style portfolios being exhibit positive (negative) momentum survival. In the multinomial logistic regression, a positive β_i implies that the odds ratio in favour of positive (negative) momentum is increased. It can be observed that, (7 out of 9 cases) credit market variables (interest rate, term spread and credit spread) increase the likelihood of positive momentum survival of small size portfolios (SL, SM and SH). On the contrary, for big size portfolios (BL, BM and BH) the odds of positive momentum survival are decreased by the increase of credit market variables. However, all the credit market variables are only significant for BL portfolio.

On the other hand, the likelihood of negative momentum survival of (almost) all style portfolios decreases by the upsurge of credit market variables. Nevertheless, credit market variables significantly decrease the odds only for negative momentum survival of SM, SH and BL portfolios.

These findings can be of interest to the investors who want to trade according to the survival time. These macroeconomic variables can be used to introduce one extra layer in the style timing strategies which can lead to more accurate timing.

Table 4. 12: Logit Model

This table summarises the coefficients of Logit model. We examine whether the mean survival time is affected by the credit market conditions over the sample period (October 1980 to June 2014). The multinomial Logit model can be formulated as:

$$L = Log(\frac{p}{1-p}) = \alpha + \beta_1 IR + \beta_2\, TERM + \beta_3\, CREDIT$$

Here, $L =$ Log of the odds ratio, p =Probability of positive (negative) momentum for the corresponding mean survival period. In this model, the dependent variable is denoted by 1' ('0' otherwise) if the momentum lives longer than or equal to the mean survival. The mean survival for positive momentum is 4 months for all style portfolios, however the negative momentum for SL, SM, SH, BL, BM and BH portfolios are 3,2,3,3,3 and 3 months respectively.

Panel A: Positive Portfolio Momentum

	Small Size & Low BTM (SL) Portfolio	Small Size & Medium BTM (SM) Portfolio	Small Size & High BTM (SH) Portfolio	Big Size & Low BTM (BL) Portfolio	Big Size & Medium BTM (BM) Portfolio	Big Size & High BTM (BH) Portfolio
Intercept	-1.3976*** (0.001)	-2.1703*** (0.000)	-1.8406*** (0.000)	0.1960 (0.723)	-1.3308*** (0.008)	-0.9245* (0.058)
Interest rates	-1.1636 (0.981)	95.220** (0.037)	75.710 (0.106)	-171.20** (0.013)	-26.727 (0.652)	-23.124 (0.690)
Term Spread	3.6676 (0.696)	14.444 (0.114)	-0.1799 (0.984)	-22.070** (0.042)	-6.3524 (0.549)	-15.367 (0.125)
Credit Spread	3.0446 (0.786)	16.147 (0.135)	10.341 (0.341)	-39.698*** (0.003)	-11.024 (0.393)	-22.813* (0.066)

Panel B: Negative Portfolio Momentum

	Small Size & Low BTM (SL) Portfolio	Small Size & Medium BTM (SM) Portfolio	Small Size & High BTM (SH) Portfolio	Big Size & Low BTM (BL) Portfolio	Big Size & Medium BTM (BM) Portfolio	Big Size & High BTM (BH) Portfolio
Intercept	-1.5707** (0.030)	-0.2730 (0.671)	-0.3848 (0.707)	-3.1756*** (0.000)	-2.5421 (0.008)	-2.3196 (0.270)
Interest rates	-124.86 (0.158)	-175.76** (0.029)	-239.96* (0.071)	-79.402 (0.382)	-48.942 (0.675)	-130.836 (0.270)
Term Spread	-30.990* (0.041)	-37.557*** (0.003)	-14.974 (0.417)	-42.708** (0.018)	5.6259 (0.778)	-19.982 (0.330)
Credit Spread	2.6227 (0.886)	-26.084* (0.096)	-65.463*** (0.008)	60.233*** (0.006)	-29.241 (0.230)	2.7255 (0.912)

* ** Implies the significance at 1% level of significance
** Implies the significance at 5% level of significance
* Implies the significance at 10% level of significance

4.4 Summary and Conclusions

This study contributes to the literature of style momentum and style timing by studying the survival time of momentum in UK style portfolios. To the best of our knowledge, this is the first study that incorporates survival analysis model in the style momentum and style timing literature. The probability of positive and negative momentum survival is quantified by using the Kaplan-Meier estimator. This method is non-parametric so it does not require assumption regarding return distribution and it does not depend on the construction of zero-investment portfolios; bypassing the general problem of momentum related studies that use no-arbitrage argument. We estimate momentum survival times for six UK style portfolios used for the construction of Fama-French factors, for the period January 1980 - June 2014. Consistent with the findings of Jochum (2000); Kos and Todorovic (2008); Lewellen (2002), we report that positive momentum survives longer than negative momentum. The longest positive return sequential (momentum) is identified for 14 months and is observed in Small-size & High book-to-market (SH) and Big-size & High book-to-market (BH) portfolios. Small-size & Low book-to-market (SL) portfolio, however, found to has the longest negative momentum for 9 months. The probability that a positive momentum survives at least 2 months is found to be more than 60 percent for all the style portfolios. Whereas, this probability fluctuates between 33 to 49 percent in case of negative momentum of the same length. The estimated mean survival of positive momentum is 4 months, whereas the mean survival of negative momentum varies between 2 months for large-cap portfolios to 3 months for small-cap portfolios. In addition, we simulate the theoretical survival curves using Random Walk and ARMA (1, 1) process. If the theoretical models fully capture returns behaviour, theoretical and empirical survival times should not differ. Nevertheless, we show that the empirical curves are underestimated by theoretical models in case of positive momentum, and (marginally) overestimated in case of negative momentum.

We apply four simple trading strategies by timing the style portfolios to exploit mean momentum survival times based on these empirical findings: long only positive momentum in each style portfolio; short only negative momentum in each style portfolio; long positive/short negative momentum in each style portfolio; and long winner/short loser portfolio - a style rotation strategy based on investing in portfolios with highest positive or lowest negative momentum. With the exception of short only negative momentum, all strategies perform better than their buy and hold benchmarks and a feasible level of transaction costs for all investors. This is not surprising as the theoretical survival curves are almost identical with the empirical ones of the negative momentum across our style portfolios. Strongest performance, in terms of incremental Sharpe ratios relative to buy-and-hold, is detected in long winner/short loser strategy, contributing to the evidence that style rotation strategies are profitable in the UK; a finding consistent with Levis and Liodakis (1999) and Clare, Sapuric and Todorovic (2010).

This chapter looks at differences in survival times and performance of strategies across economic states and we document that momentum trading based on survival times works well in both recessions and expansions, generating higher Sharpe ratios than buy-and-hold portfolios at a feasible level of transaction costs for all investors. Overall, we believe that our survival model can be seen as persuasive indicator for trading decisions, particularly where the empirical survival curves are different than the corresponding theoretical ones.

This study also investigates the association of momentum mean survival with macroeconomic variables that describe credit market conditions. It is found that, in general, credit market variables increase (decrease) the likelihood of positive (negative) momentum mean survival for small size portfolios (SL, SM & SH). However, in case of big size portfolios (BL, BM & BH) the likelihood of both positive and negative momentum mean survival decreases for any upsurge of credit market variables. Although only 36.11 percent coefficients are found to be significant, these macroeconomic variables can be used to introduce one extra layer in the style timing strategies.

Our findings have useful implications for both traders and portfolio managers in that 1) momentum in style portfolios in the UK is present; 2) momentum survival time can be successfully exploited in each style portfolio separately (relevant for those interested in style-consistent investing in more traditional funds); 3) momentum survival time leads to profitable trading in style rotation strategy when switching between winner and loser style portfolios (relevant for hedge fund managers) and 4) momentum trading based on mean survival times is feasible even if transaction costs are high.

CHAPTER FIVE: SECTOR ROTATION

5.1 Introduction and Background of the Study

In this chapter, we investigate the risk-adjusted performance of US sector/industry portfolios in terms of Fama-French three-factor (Fama and French, 1993) and five-factor (Fama and French, 2015) models. The argument is that, if three-factor and/or five-factor model generate true alpha (intercept) then we can incorporate investment strategies to generate higher return. With this argument, we formulate sector rotation strategies based on the rolling alphas of Fama-French models and compare the portfolio performances. We also investigate if the two models provide us any different information.

The contribution of this chapter to the literature is twofold: first, performance measurement (evaluating the performance of sectors plus comparing 3 and 5 factor model of Fama-French) and second, sector rotation. Investment strategies based on sector rotation received comparably less attention in the academic literature although sector/industry return predictability is attractive to the practitioners. This gap is surprising with respect to the importance of sector/industry analysis in the investment process. In this chapter, we contribute to the literature by investigating alpha-based sector rotation of sector/industry portfolios. To the best of our knowledge, this is the first study that compares Fama-French (1993) three-factor and newly evolved Fama and French (2015) five-factor model as a benchmark model of performance evaluation. Moreover, most of the literature in performance measurement studies the performance of different variety of funds (mainly mutual funds). Our study also contributes to the performance measurement literature by studying the performance of sector/industry portfolios.

The concept of active portfolio management largely involves portfolio rotations towards (or away from) particular assets, styles, industries, markets, or asset classes based on expectations of future performance. In case of the availability of several asset pricing models, academics as well as practitioners remain puzzled to pick one particular model for their portfolio management. To measure the performance of portfolios based on a particular asset pricing model, risk-adjusted performance measure (alpha) is widely accepted by the academics as well as practitioners. The Alpha (intercept) of an asset pricing model is expected to be indistinguishable from zero in a regression of an asset's excess returns on the model's factor returns if the corresponding asset pricing model completely captures expected returns. A non-zero alpha can then be attributed as the risk-adjusted abnormal performance of the corresponding portfolio. Our argument is that, if the alpha of a pricing model is a true alpha, i.e. explains cross section of expected stock return in greater accuracy, then based on that alpha investment strategy (in our case sector rotation) can be formulated to generate higher return.

Since the introduction of Capital Asset Pricing Model (CAPM) by Sharpe (1964) and Lintner (1965), the empirical asset pricing model is in the state of turmoil. The pre-eminence of CAPM has been challenged by academics as well as practitioners who identified the empirical deficiencies and also because the observed anomalies are un-explainable. Market capitalization and related financial ratios have been a challenge to CAPM because of their ability to predict the cross section of returns. Fama and French (1993) proposed two additional factors (explanatory variables) to include in CAPM. They argue that in CAPM the market beta (β) carries little information about the average return; meanwhile size and book-to-market do explain the cross-section of expected return. Regardless of its frequent use in empirical research, there are evidence to suggest that the Fama-French three-factor model cannot completely explain the cross-section of stock returns[25] and the hunt to include additional factors remained. Carhart (1997) got into this hunt and advocate to add one additional factor (momentum factor) to the Fama-French 3 factor model (hereafter Fama-French 3FM). The proposed 4 factor model of Carhart (1997) (hereafter Carhart 4FM) is also widely acknowledged by the academics, however also been criticised because it goes against the conventional contrarian investment strategies. Although, Fama-French 3FM was a

[25] Some anomalies such as, positive relationship with momentum returns and earnings surprises, negative relationship with financial distress, net stock issues and asset growth, left unexplained by Fama-French three-factor model (see for example, Chen, Novy-Marx and Zhang, 2011; Fama and French, 1996, 2008; Cooper, Gulen and Schill, 2008; Daniel and Titman, 2006; Campbell, Hilscher and Szilagyi, 2008; Chen and Zhang, 2010; etc.).

significant improvement over the CAPM because it adjusted for outperformance tendency but academics questioned about its ability to explain some anomalies as well as the cross-sectional variation in expected returns particularly related to profitability and investment. Motivated by this argument, Fama and French (2015) proposed five-factor model that added two additional factors, profitability and investment, in addition to their previous three-factor model. They argue that three-factor model was an inadequate model for expected returns because it overlooks the variation in average returns related to profitability and investment. Their empirical evidence suggests that, for portfolios formed on size, B/M, profitability, and investment, the five-factor model provides better descriptions of average returns than the Fama-French 3FM.

In the literature, these models are widely acknowledged by academics as frameworks for the conceptualization of equity risk, and often accepted as a conventional perception among academics as well as practitioners. However, the empirical virtues of these asset pricing models and their embedded measures of risk have been raging for decades. Although a universally accepted asset pricing model has not yet been found, Fama-French 3FM and Carhart 4FM alpha, along with Jensen’s alpha, have been used as standard measures of portfolio performance among both academics and practitioners. The argument of the alpha based performance measurement is that, if an asset pricing model completely captures expected returns, the intercept (alpha) is expected to be indistinguishable from zero in a regression of an asset’s excess returns on the model’s factor returns. A non-zero alpha can then be attributed to the abnormal performance or fund managers' skill.

Most of the studies of performance measurement concentrate on the funds (mostly mutual funds). There are small numbers of studies (Dellva, DeMaskey and Smith, 2001; Faff, 2004; Kacperczyk, Sialm and Zheng, 2005; Dou et al., 2014; etc) that concentrate on the industry or sector perspective. Although sector/industry return predictability is attractive to the practitioner it has received comparably less attention in academic literature. This gap is surprising with respect to the importance of sector/industry analysis in the investment process. To the best of our knowledge, we couldn’t find any literature that investigates the performance of industry/sector portfolios. However, the study of industry/sector rotation is closest alternative literature that we have found[26].

It can be argued that sector/industry based asset allocation is gaining importance and will continue to gain prominence into the future. Intuitively, companies in the same sector or industry would exhibit higher pairwise return correlations that companies from different industries. Firms within the same industry that operate under the same regulatory environment are likely to react similarly to technological innovations, and also exhibit similar sensitivity to macroeconomic shocks and/or government policy. Because of highly correlated returns on the stocks in the same industry and integrated financial markets, it would be sensible to look for any added benefit for sector asset allocation, more specifically by performing sector rotation which is a relatively less explored area of asset allocation.

In this study, together with the evaluation and comparison of portfolio performance by factor models (3FM and 5FM); we also contribute to the scarce literature of sector rotation strategies. This is also the first study that compares the portfolio performance by using newly evolved Fama-French Five-Factor Model (5FM) with their previous Three-Factor Model (3FM) in the industry/sector perspective. We perform sector rotation by following the study of Sassetti and Tani (2006), who claim that a sector rotation based on the alpha indicator appear to be more regular and stable.

Our findings reveal that 5FM is better than 3FM in the case of containing additional information. 5FM is statistically better fitted model and two addition factors (RMW and CMA) significantly increase the log-likelihood of the model. Sector rotation strategies based on 3FM alphas and 5FM alphas outperform S&P 500 benchmark by 5.53% and 5.40% respectively. However, when we integrate business cycles into our trading strategy by taking long position to the corresponding sectors with positive alpha (based on 3FM and 5FM) during expansion period and invest in risk-free T-bonds during recession period outperform S&P 500 benchmark by 7.21% in case of 3FM and 7.12% in case of 5FM. The sector rotation strategies, with Fama-French sector portfolios, based on 3FM alphas have slightly higher returns than 5FM alphas. However, we observe that trading Select Sector SPDR ETFs with 5FM alpha

[26] Comprehensive literatures are reviewed in chapter two.

provides higher annualised return than trading with 3FM alpha. Similar to the Fama-French sector portfolios, the highest outperformance is observed in the rotation strategies that integrate business cycles into consideration. Nevertheless, although trading Fama-French sector portfolios based on 3FM alphas produces slightly higher return, we do not find any statistical difference between the mean return of trading strategies based on 3FM and 5FM alphas.

5.2 Data and Methodology

5.2.1 Data

This study uses monthly data of the US market that covers the period January1964 to December 2014. The Fama-French factors data and the data of 10 sector (industry) portfolios are obtained from Kenneth French's website[27]. Ten sectors are: Consumer Non Durables or NoDur (firms that produce Food, Tobacco, Textiles, Apparel, Leather, Toys), Consumer Durables or Durbl (firms that produce Cars, TV's, Furniture, Household Appliances), Manufacturing or Manuf (firms that manufacture Machinery, Trucks, Planes, Chemicals, Office Furniture, Paper, Computer Printing), Energy or Enrgy (firms that produce Oil, Gas, and Coal Extraction and Products), Business Equipment or HiTech (firms that produce Computers, Software, and Electronic Equipment), Tele-communication or Telcom (Telephone & TV Transmission companies), Shops (Wholesale, Retail, & Some Services -Laundries, Repair Shops companies), Health or Hlth (Healthcare, Medical Equipment, & Drugs based companies), Utilities or Utils (Companies in Utilities sector) and Others (Companies in Mines, Constructions, Building materials, Trans, Hotels, Bus Services, Entertainment, Finance sectors). Industry definition and SIC codes of sector portfolios are reported in Table A5.3 in the appendix A5. Fama-French assign each NYSE, AMEX, and NASDAQ stock to an industry portfolio based on its four-digit SIC code. Although the data of factors are available from July 1963, the data for

[27]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html [Accessed on 16.04.15]

sector portfolios are available from July 1926. Business cycle and S&P500 composite index data are obtained from NBER[28] and DataStream respectively.

5.2.2 Methodological Framework

5.2.2.1 Performance Measurement

The most basic performance measurement model is Jensen's alpha, based on an ex-post test of the classical CAPM. Jensen's Alpha is derived by regressing portfolio returns with market portfolio with an intercept ($\propto_p$) as follows:

$$R_{it} - r_{ft} = \propto_{it} + \beta_{it}\left(R_{mt} - r_{ft}\right) + \varepsilon_{it} \qquad \text{(5.1)}$$

Here, R_{it} is the return of portfolio *i* in month *t* (with t = 1,2, ..,T), r_{ft} is the risk-free return, R_{mt} is the return of the market portfolio, hence, $\left(R_{mt} - r_{ft}\right)$ is the excess market return and ε_{it} an error term. In CAPM, alpha ($\propto_{it}$) measures risk-adjusted return or the actual return of a portfolio in relation to the expected return based on its beta. The slope of the regression line is the beta (β_{it}) that measures the portfolio's volatility in relation to its benchmark portfolio. If the actual return of a portfolio is higher than its expected return, the portfolio has a positive alpha, and if the return is lower it has a negative alpha. CAPM can be viewed as a single-factor model since it uses market proxy as the only factor. The assumption of such single factor model is that a fund's investment behaviour can be approximated by using a single market index, e.g. S&P 500.

Multifactor models have been developed from this single-factor model in order to improve the portion of variance explained by the regression. The rationale of using multifactor model lies in the literature of cross-sectional variation of stock returns (see for example Fama and French, 1992; Fama and French, 1993; Fama and French, 1996; Carhart, 1997; Fama and French, 2015). To explain the cross-sectional

[28]http://www.nber.org/cycles.html [Accessed on: 18.11.15]

variation of stock returns, Fama and French (1993) added two additional factors, one for size and one for the ratio of book-to-market value

$$R_{it} - r_{ft} = \propto_{it} + \beta_{im}\left(R_{mt} - r_{ft}\right) + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \varepsilon_{it} \qquad \text{.... (5.2)}$$

Here, $\left(R_{it} - r_{ft}\right)$ is the excess sector return, SMB is the difference between Small-cap and large-cap firms that meant to mimic risk factor in returns related to the size of the firms. HML, on the other hand, is the difference between high book-to-price and low book-to-market ratio; and is meant to mimic risk factor in returns related to the value of the firms.

More recently Fama and French (2015) extended their previous three-factor model to five-factor model with the argument that the new five-factor model describes the cross section of return better. They add two new factors, profitability and investment, with their previous size and value factors:

$$\begin{aligned} R_{it} - r_{ft} = \propto_{it} &+ \beta_{im}\left(R_{mt} - r_{ft}\right) + \beta_{iSMB} SMB_t \\ &+ \beta_{iHML} HML_t + \beta_{iRMW} RMW_t + \beta_{iCMA} CMA_t + \varepsilon_{it} \end{aligned} \qquad \text{........ (5.3)}$$

Here RMW is the profitability factor which is the return spread of most profitable firms (Robust profitability) minus least profitable firms (Week profitability). CMA is the investment factor calculated as return spread of firms that invest conservatively minus aggressively. That is, RMW stands for robust minus weak profitability and CMA stands for conservative minus aggressive investment.

These multifactor models change the definition of alpha. In the single factor CAPM, alpha (Jensen’s alpha) is the amount by which an active portfolio manager outperforms a broad market index. The multifactor models define alpha for equities more precisely as the return an active manager achieves above the expected return due to all corresponding equity risk factors. While the alpha of three-factor model (three-factor alpha) implies performance of funds or portfolios after adjusting for the size and value risk factors; the alpha of Fama-French five-factor model (five-factor alpha) denotes the excess return that an active portfolio manager achieves above the expected return due to market, size, value, profitability and investment risk factors.

Multifactor models are advocated as the basis of performance measurement because of their high explanatory power in asset pricing tests, with greater R-squared. The explanatory power (measured by R-squared) of Fama-French 3FM exceed 90 percent to explain cross-sectional variation of expected returns (Fama and French, 1996). This explanatory power for the five-factor model (5FM) is between 71 to 94 percent (Fama and French, 2015). The multifactor models have a direct application in measuring portfolio or fund performance. In analysing portfolio risk according to various dimensions, it is possible to identify the sources of risk associated with the portfolio and to evaluate the associated reward. These models contribute more information to performance analysis than the Jensen alpha. With these models, the asset returns could be decomposed linearly according to several risk factors common to all the assets, but with specific sensitivity to each. Once the model has been determined, we can attribute the contribution of each factor to the overall portfolio performance.

In the literature, Fama-French 3FM is widely acknowledged by academics as frameworks for the conceptualization of equity risk, and often accepted as a conventional perception among academics as well as practitioners. Although a universal accepted asset pricing model has not yet been found, Fama-French 3FM, along with Jensen's alpha and Carhart 4FM alpha, have been used as standard measures of portfolio performance among both academics and practitioners. Kothari and Warner (2001) argue that multifactor benchmark models (e.g. Fama-French 3FM, Carhart 4FM) are the basis for performance measurement as they have high explanatory power in asset pricing tests. Fama and French (1993) characterised the multifactor benchmark models as 'simple' and 'straightforward' method of performance measurement. The studies that use Fama-French 3FM model to measure fund performance include Cai, Chan and Yamada (1997); Daniel and Titman (1997); Kothari and Warner (2001); Otten and Bams (2002, 2004); Faff (2004); Chan, Dimmock and Lakonishok (2009); Huij and Verbeek (2009); Cremers, Petajisto and Zitzewitz (2012);Vidal-garcía (2013), etc, among others. This study uses the most recent five-factor model of Fama-French in the sector portfolio return and compares the three-factor model to examine whether the addition of two factor conveys any additional information to the asset pricing. We interpret the estimated Alpha in this study as abnormal returns in excess of what could have been achieved by a matched investment in the benchmark portfolios. To the best of our knowledge, this is the first study that compares the performance of sector portfolios and more specifically with 3FM and 5FM of Fama-French.

5.2.2 Sector Rotation Strategy

We incorporate trading strategy based on the rolling window alphas of sector portfolios over the period January 1967 to December 2014. We use the first 36 months of the sample period to estimate the first set of alphas based on the 3FM and 5FM. Our rotation strategy takes the long position in the sector portfolios that have positive alpha of 36 months rolling window regression. The Long-Short rotation strategy buys sector portfolios that have positive alpha and sell those with negative alpha. We rebalance the portfolio every month based on the rolling window alpha of previous 36 months. For example, for the first trading in January 1967 we use the rolling window alpha over the period January 1964 to December 1966, and for the trading in February 1967 the rolling window alpha, over the period February 1964 to January 1967, is used. In another strategy, we incorporate economic recession and expansions in our trading rule. In this strategy we buy corresponding sectors with positive alpha based on 3FM and 5FM in the expansion period, otherwise, invest in risk-free bonds. We compare the trading strategies with the buy-and-hold strategy that represents the investment in the S&P 500 index; a commonly known and used benchmark in performance evaluation literature. Overall, there are 576 trading months.

5.3 Empirical Findings

Descriptive statistics (Mean, Standard Deviation, Skewness and Kurtosis) of the factors (Panel A) and the 10 sector portfolios (Panel B) over the sample period are reported in Table 5.1. Returns of the factors and sector portfolio are monthly rate of return, in percent. Rmt (Market excess return), SMB (Small minus Big), HML (High minus Low Book-to-market), RMW (Robust minus week profitability) and CMA

(Conservative minus Aggressive investment) are the five factors of Fama-French five-factor model; whereas NoDur, Durbl, Manuf, Enrgy, HiTec, Telcm, Shops, Hlth, Utils and Other sector portfolios are the portfolio of Consumer Non-Durables (Food, Tobacco, Textiles, Apparel, Leather, Toys), Consumer Durables (Cars, TV's, Furniture, Household Appliances), Manufacturing (Machinery, Trucks, Planes, Chemicals, Office Furniture, Paper, Com Printing), Energy (Oil, Gas, and Coal Extraction and Products), High Technology Business Equipment (Computers, Software, and Electronic Equipment), Telecom (Telephone and Television Transmission), Shops (Wholesale, Retail, and Some Services like Laundries, Repair Shops), Health (Healthcare, Medical Equipment, and Drug), Utility and Others (Mines, Construction, Building Materials, Transport, Hotels, Bus Service, Entertainment, Finance) industries respectively.

Market excess return found to be higher than other factors with a mean return of 0.50% (monthly). HML has the second highest monthly mean return of 0.36%. However, if we consider the risk (standard deviation) CMA seems to have the highest return (0.33%) with a lowest standard deviation. Market excess return (Rmt) and profitability factor (RMW) are negatively skewed, while the others are positively skewed. However, except Value factor (HML) all the other factors are found to be significantly skewed. The coefficient of Kurtosis in the right column of Table 5.1 indicates the peakedness of distribution. All the factors showed leptokurtic distribution (sharper than normal distribution). The significant Leptokurtic shape suggests high probability of extreme values in the factor returns.

Table 5. 1: Descriptive Statistics

This table reports the descriptive statistics (Mean, Standard Deviation, Skewness and Kurtosis) of the factor return (Panel A) and the 10 sector portfolios returns (Panel B) over the period January 1964 to December 2014. Returns of the factors and sector portfolios are monthly excess return, in percent.
The values in the parentheses represent the p-values of Skewness-Kurtosis test for normality.

Panel A: Five-Factor Returns

	Mean	Standard Deviation	Coefficient Of Skewness	Coefficient of Kurtosis
Rmt	0.5015	4.4721	-0.5343*** (0.0000)	4.9189*** (0.0000)
SMB	0.2840	3.0824	0.3850*** (0.0001)	6.5559*** (0.0000)
HML	0.3623	2.8731	0.0100 (0.9187)	5.5163*** (0.0000)
RMW	0.2457	2.1471	-0.4053*** (0.0001)	14.436*** (0.0000)
CMA	0.3288	1.9949	0.2505** (0.0116)	4.3630*** (0.0000)

Panel B: Sector Portfolio Returns

	Mean	Standard Deviation	Coefficient Of Skewness	Coefficient of Kurtosis
NoDur	0.6820	4.3034	-0.3161*** (0.0016)	5.1108*** (0.0000)
Durbl	0.4561	6.3366	0.1592* (0.1058)	7.9030*** (0.0000)
Manuf	0.5724	4.9686	-0.4945*** (0.0000)	5.5911*** (0.0000)
Enrgy	0.6420	5.4176	-0.0081 (0.9340)	4.4112*** (0.0000)
HiTec	0.5702	6.5339	-0.2251** (0.0230)	4.2958*** (0.0000)
Telcm	0.4603	4.6470	-0.1894* (0.0549)	4.2634*** (0.0000)
Shops	0.6389	5.2272	-0.29187*** (0.0035)	5.4181*** (0.0000)
Hlth	0.6899	4.8708	0.0161 (0.8693)	5.5127*** (0.0000)
Utils	0.4504	4.0465	-0.1156 (0.2389)	4.0215*** (0.0002)
Other	0.5382	5.3302	-0.4858*** (0.0000)	4.8271*** (0.0000)

* **Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
*Implies the significance at 10% level of significance.

Similar non-normal pattern can be observed in the normality test of sector portfolios. All the sector portfolios seem to have highly significant leptokurtic shape. Only durable and health sector has positive skewness in the distribution. These distribution statistics indicate the probability of extreme values in the sector returns, most of the time they are on the left tail. The mean returns of 10 sector portfolios are almost similar with a minimum return of 0.45% (Utility) and a maximum return of 0.69% (Health) in monthly observations. However, utility sector portfolio shows lowest standard deviation, whereas hi-technology sector shows highest standard deviation.

5.3.1 Performance of Sector Portfolios

The alphas that are obtained from the rolling window regression by applying 3FM and 5FM to 10 sector portfolios are analysed to evaluate the performance of the sectors. We start our analysis by looking at the mean of 3FM and 5FM rolling alphas. To calculate the mean of rolling alphas, we first regress the excess return of sectors portfolios with 3FM and 5FM, respectively, over 36 months rolling window period. We then calculate the mean and standard deviation of these time series of alphas. The second column of Table 5.2 represents the average alphas of 10 sector portfolio in case 3FM and 5FM. The results are quite interesting. Non-Durable, Telecom and Utility sectors have opposite signs in case 3FM and 5FM mean alphas. Mean of Hi Tech sector alpha is almost double in case of 5FM than 3FM. Apart from Durable, Manufacturing and 'other' sectors, at least one factor model indicates positive average alpha. The positive average alpha is also reported in the study of Dellva, DeMaskey and Smith (2001) for 35 Fidelity sector funds. However, their positive alpha is the average alpha of 35 sector funds, but they didn’t specify sectors with positive and negative alphas. With MSCI sector return data, Dou et al. (2014) report positive alpha of Energy, HiTech, and health sectors; and negative alphas of Durable and Manufacturing sectors both in regime 1 (bull market) and regime 2 (bear market). We also report similar findings of those sectors and interestingly the alphas are consistent with 3FM as well as 5FM model.

Table 5. 2: T-Test of Sector Alphas between Five and Three-Factor Model

This table reports the t-test for the equality of means of rolling window alphas applying 3FM and 5FM with the null hypothesis that the mean differences are equal. 10 sector portfolios are regressed with Fama-French 3 factors and 5 factors separately over the sample period January 1964 to December 2014 in 36 months rolling window basis. The factor models can be expressed as:

$R_{it} - r_{ft} = \propto_{it} + \beta_{im}\left(R_{mt} - r_{ft}\right) + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t + \varepsilon_{it}$

$R_{it} - r_{ft} = \propto_{it} + \beta_{im}\left(R_{mt} - r_{ft}\right) + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t + \beta_{iRMW}RMW_t + \beta_{iCMA}CMA_t + \varepsilon_{it}$

Here, $R_{it} - r_{ft}$ is the excess return of sector portfolios, Rmt (Market excess return), SMB (Small minus Big), HML (High minus Low Book-to-market), RMW (Robust minus week profitability) and CMA (Conservative minus Aggressive investment) are the factors of Fama-French models. Alpha (intercepts) is the average returns unexplained by exposures to the factors of the corresponding model. Time series of alphas (3F alpha & 5F alpha) are obtained from the 36 months rolling window regressions. Mean and standard deviations of the time series of alphas are reported in the second and third column. Fourth column reports the test statistics of t-test (p-values of t-test are in parentheses). Mean and standard deviations are in percentage.

Variables	**Mean**	**Std. Dev**	**Ho: diff = 0 Ha: diff ≠ 0 (P-value)**
NoDur-3F	19.35	39.92	10.6386***
NoDur-5F	-6.12	41.42	(0.0000)
Durbl-3F	-27.78	52.68	-0.8688
Durbl-5F	-24.99	56.23	(0.3852)
Manuf-3F	-0.38	30.83	2.3234**
Manuf-5F	-5.03	36.82	(0.0203)
Enrgy-3F	13.44	64.09	1.6610*
Enrgy-5F	6.69	73.06	(0.0970)
HiTec-3F	19.11	53.40	-5.3179***
HiTec-5F	37.21	61.92	(0.0000)
Telcm-3F	2.02	47.14	4.4397***
Telcm-5F	-11.46	55.67	(0.0000)
Shops-3F	11.76	42.21	4.7899***
Shops-5F	0.29	39.08	(0.0000)
Hlth-3F	41.01	35.16	1.4340
Hlth-5F	37.73	42.30	0.1518
Utils-3F	-3.49	46.11	-3.6640***
Utils-5F	6.41	45.68	(0.0003)
Other-3F	-16.72	25.49	-4.5404***
Other-5F	-9.20	30.55	(0.0000)

* **Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
*Implies the significance at 10% level of significance.

With a simple t-test, we further check whether the mean alphas of the sector portfolios for both factor models are significantly different from each other or not. Last column of Table 5.2 illustrates the results of t-test with the null hypothesis that the mean differences of 3FM and 5FM alphas are equal. We can observe that only for durable and health sector the mean alphas of 3FM and 5FM are statistically equal. For all the other sectors the hypotheses of equal mean alpha are rejected at 10% level of significance, i.e. the alphas of 3FM and 5FM are statistically different. These may indicate that the 5FM add additional information than the 3FM. The opposite signs in case 3FM and 5FM mean alphas of Non-Durable, Telecom and Utility sectors are also significant.

To look more insights of the performance of sector funds, we plot the rolling alphas of sectors over the sample period. Figure 5.1 and 5.2 illustrates the time series of sector alphas for 3FM and 5FM. If we look at figure 5.1 that plots the three-factor alphas, we can observe that health sector perform during the late 60s and continue to perform well, not the best, in most of the time period if after adjusting the risk of 3 factors. During the period 1979 to 1981 energy sector provide significant higher alpha than others, however, experienced powerful rebounds until the end of 1986. We can also observe the dominance of Hitec sector alpha during the period 1994 to 2003. Although 5FM alpha exhibits the similar pattern (figure 5.2), the dominance of alpha for Hitec sector is observable more rigidly. This performance of Hitec sector is inevitable as the world observe a boom in technology sector during the late 1990s. The negative alphas of the energy sector are more visible than other sectors in 5FM compare to 3FM. However, in case of 'others' sector's performance, that includes Mines, Construction, Building Materials, Transport, Hotels, Bus Service, Entertainment, Finance industries, are negative over most of the sample period regardless of whether the average returns with the exposures to 3 factors or 5 factors.

If we look at the figure that plots the difference of alphas between 3FM and 5FM (figure 5.3) for the 10 sectors, we can have better insights about the performance of portfolios. Positive difference means the superior performance of the corresponding portfolio adjusting the risk of 3FM, whereas, the negative alpha indicates the superior performance after adjusting the risk of 5FM. We can observe from the figure 5.3 that, 3FM provides higher alpha than 5FM in the case of Telecom, energy and shops sectors. In general, 3FM alpha is dominant in most of the cases. These findings can be confirmed by looking at the box-plots of 3FM and 5FM alphas (figure A5.1 & figure A5.2 in the Appendix A5). 5FM alphas in Telecom, energy and shops sectors have more negative outliers than 3FM. Moreover, the negative outliers of 5FM alphas are more than 3FM in general. The alphas of Health, Manufacturing and Utility sector seems to be relatively more stable and don’t have outliers (health, and utility sector has only one outlier in 5FM) in case of both the factor models.

We examine whether the sector portfolio returns are better explained by Fama-French three-factor model or the five-factor model. To do so, as mentioned earlier, we obtain the time series of alphas by regressing 10 sector portfolios separately with Fama-French three factors (Rmt, SMB & HML) and five factors (Rmt, SMB, HML, RMW & CMA) over a rolling window span of 36 months with 1-month step size. The null hypothesis of equal mean differences, i.e. hypothesis that portfolios performance is same for both models, is rejected (at 10% level of significance) almost for every sector, apart from durable and health sector (see Table 5.2). Moreover, although the sign of mean alpha, apart from Telecom and Utility sector, are similar for 3FM and 5FM, the magnitude doesn’t have any pattern to claim 5FM fits better than 3FM or vice versa. These may indicate that the 3FM and 5FM convey different information. We further perform unpaired t-test to examine whether the 3FM and 5FM alphas are different across the sectors. Table A5.1 (in appendix A5) reports the unpaired t-test of the rolling window alphas (by using 3FM) of 10 sector portfolios. 89% of 3FM alphas (40 out of 45 pairs) are found to be significantly different from each other. In the case of 5FM alphas, we can also observe the similar results (Table A5.2 in appendix A5). However, we can’t observe any specific pattern in either of the model's alphas.

Figure 5. 1: Sector Alphas of Three-Factor Model (3FM)

This figure display the time series of alphas that is obtained by regressing the sector portfolios with Fama-French 3 factors over the sample period January1964 to December 2014 in 36 months rolling window basis.

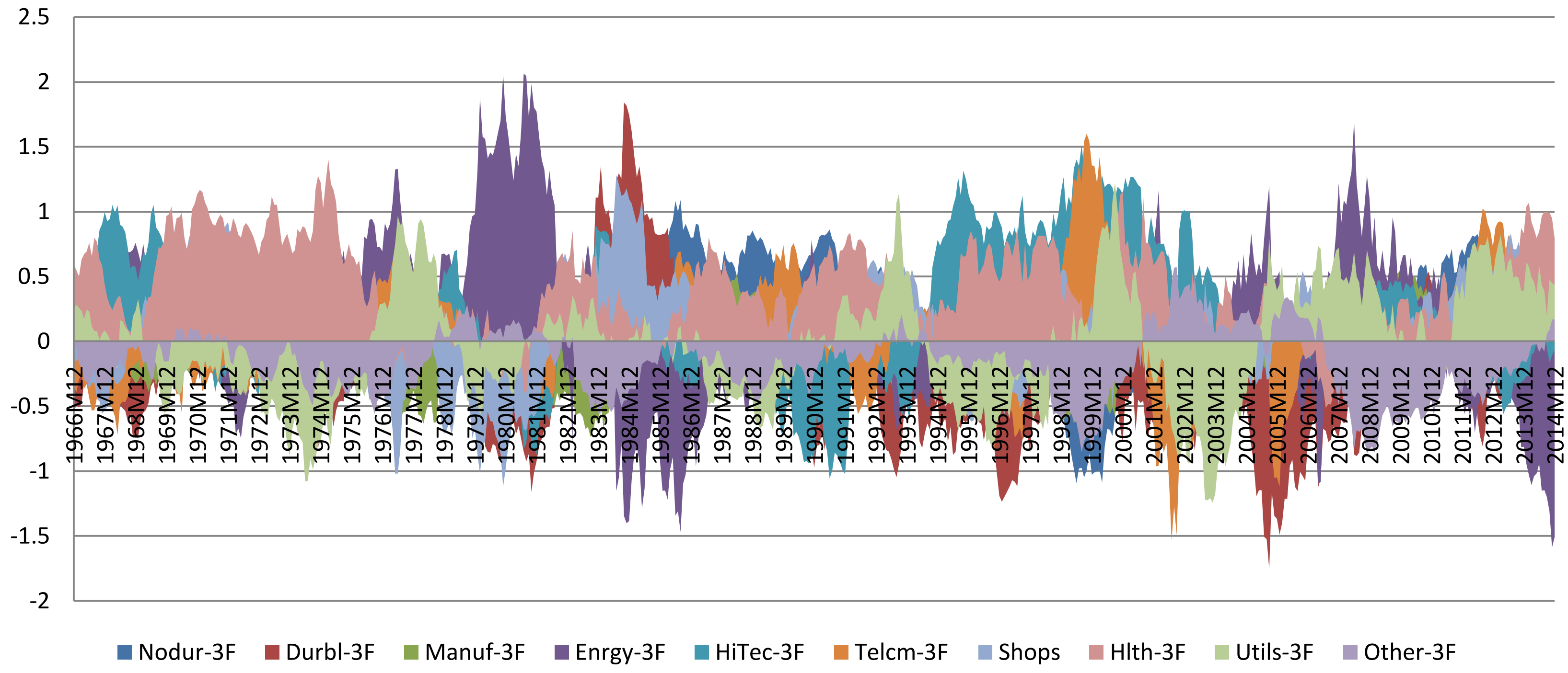


Figure 5. 2: Sector Alphas of Five-Factor Model (5FM)

This figure display the time series of alphas that is obtained by regressing the sector portfolios with Fama-French 3 factors and 5 factors separately over the sample period January 1964 to December2014 in 36 months rolling window basis.

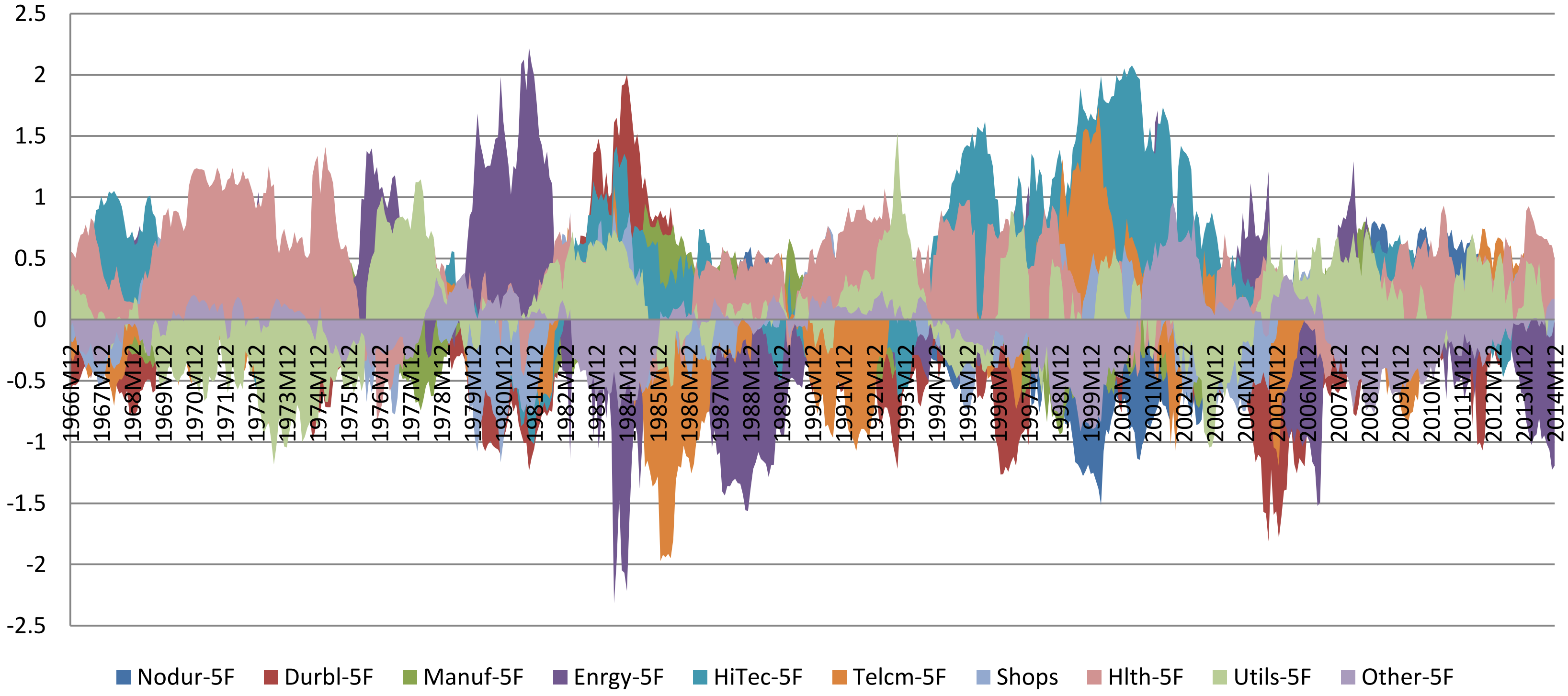
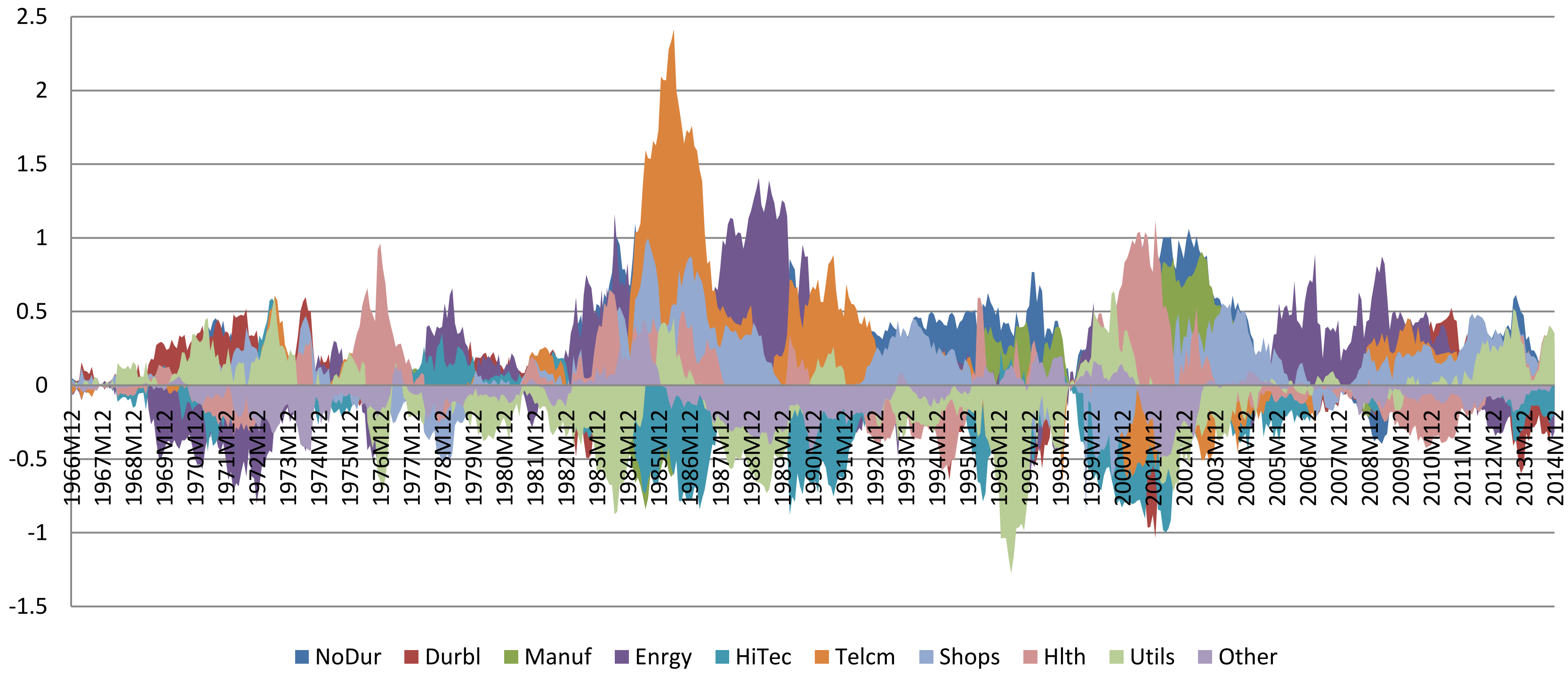


Figure 5. 3 : Difference between Alphas (3FM-5FM)

This figure illustrates difference between 3FM and 5FM rolling alphas that are obtained by regressing the sector portfolios with Fama-French 3 factors and 5 factors separately over the sample period January1964 to December2014 in 36 months rolling window basis.



To look for any superior performance we further looked at the significance of sector portfolio alphas, over the rolling windows, for both the three-factor and five-factor model. We regress the sector portfolios with one factor (market), three factors and five factors separately over 36 months rolling window (577 regressions for each portfolio) and count the number of times the alphas are significant or insignificant. Here, we include one factor model (Jensen's alpha) for illustration purpose. The percentage of sectors with statistically significant and insignificant coefficient estimates under the models (CAPM, Fama-French 3F and Fama-French 5F) are reported in Table 5.3. Manufacturing, Energy and HiTech sectors have increasing pattern of significant alphas from Jensen's alpha to 5F alpha. In the case of manufacturing sector, the total significant alpha is 9.36% in case of CAPM. However, this 'percentage of significant alphas' doubled when it is estimated by 5FM, where the negative alphas increase the most by 4.85%. We observe similar pattern in the case of Energy and HiTech sector. In regards to Telecom sector, the percentage of significant 5F alpha (total) is lower than Jensen's alpha, but higher than 3F alpha. This is because the telecom sector couldn't achieve positive alpha (also significantly positive alpha) over the sample period, however, the percentage of negative alpha (also significantly negative alpha) has increased. This performance of Telecom sector is also visible in figure 5.1 & 5.2, where the time series of alpha is negative over most of the period. However, 3FM alpha of Telecom sector was significantly higher during mid 80s until the beginning of 90s (figure 5.3). For Utility sector, the significant alpha of 5FM is lower than 3FM for the marginal amount, although the percentage of positive (negative) alpha is higher (lower) than 3FM. Although all other sectors have increasing pattern in the significance of alpha, total significant rolling window alphas decreased almost by 1% from 3FM to 5FM (percentage of significant alphas are 14.94% and 13.99% respectively for 3FM to 5FM) when considering all the sectors. The highest decrease is in Non-Durable sector, where the percentage of significant alphas is 27.21% for CAPM but decreased to 9.88% in case of 5FM.

Table 5. 3: Significance of Alphas' over the Rolling Window

This table reports the significance of 10 sector portfolio alphas for both the three-factor and five-factor model at 90% confidence, based on the two-tailed t-test. Jensen Alpha is reported for illustration purpose. We regress the each sector portfolio with one factor (market), three factors and five factors separately over 36 months rolling window over the period January 1964 to December 2014 (577 regression for each portfolio); and count the number of times the alphas are significant, positively significant, negatively significant, positive, or negative. The overall positive and negative portfolio alphas (in percentage) under the models (CAPM, Fama-French 3FM and Fama-French 5FM are reported. We also report the statistically significant sector portfolio alphas (also categorised by positive and negative alpha). Average R-squared (average of the 577 rolling window regressions) for each sector portfolios are reported in the last column.

Sectors		Significant			Overall (total)		Average R-Squared
		Positive	Negative	Total	Positive	Negative	
NoDur	Jensen Alpha	26.34%	0.87%	27.21%	74.00%	26.00%	71.26%
	3F Alpha	20.28%	3.81%	24.09%	72.62%	27.38%	77.81%
	5F Alpha	4.68%	5.20%	9.88%	46.27%	53.73%	82.17%
Durbl	Jensen Alpha	1.04%	10.75%	11.79%	37.95%	62.05%	67.26%
	3F Alpha	3.29%	9.71%	13.00%	26.86%	73.14%	75.56%
	5F Alpha	2.60%	9.88%	12.48%	23.74%	76.26%	78.00%
Manuf	Jensen Alpha	6.76%	2.60%	9.36%	50.61%	49.39%	87.61%
	3F Alpha	6.59%	7.45%	14.04%	49.22%	50.78%	89.83%
	5F Alpha	10.57%	8.15%	18.72%	36.22%	63.78%	91.02%
Enrgy	Jensen Alpha	4.68%	2.43%	7.11%	69.15%	30.85%	45.46%
	3F Alpha	8.32%	2.95%	11.27%	57.89%	42.11%	57.12%
	5F Alpha	10.92%	7.80%	18.72%	57.02%	42.98%	65.12%
HiTec	Jensen Alpha	5.03%	8.84%	13.86%	42.63%	57.37%	76.36%
	3F Alpha	16.64%	2.95%	19.58%	57.54%	42.46%	85.15%
	5F Alpha	23.05%	1.21%	24.26%	71.75%	28.25%	87.59%
Telcm	Jensen Alpha	12.48%	4.85%	17.33%	59.62%	40.38%	56.26%
	3F Alpha	7.11%	2.25%	9.36%	47.83%	52.17%	62.52%
	5F Alpha	2.95%	7.97%	10.92%	37.09%	62.91%	66.50%
Shops	Jensen Alpha	21.66%	5.55%	27.21%	58.23%	41.77%	73.78%
	3F Alpha	13.52%	2.25%	15.77%	63.08%	36.92%	78.87%
	5F Alpha	6.93%	2.60%	9.53%	50.43%	49.57%	82.49%
Hlth	Jensen Alpha	14.73%	1.21%	15.94%	67.94%	32.06%	61.11%
	3F Alpha	21.49%	0.00%	21.49%	89.25%	10.75%	70.21%
	5F Alpha	20.45%	0.00%	20.45%	77.99%	22.01%	73.17%
Utils	Jensen Alpha	11.79%	1.21%	13.00%	67.07%	32.93%	38.92%
	3F Alpha	4.51%	1.21%	5.72%	48.01%	51.99%	56.25%
	5F Alpha	3.29%	0.87%	4.16%	57.02%	42.98%	62.35%
Other	Jensen Alpha	5.55%	7.11%	12.65%	51.30%	48.70%	87.17%
	3F Alpha	0.17%	14.90%	15.08%	27.21%	72.79%	92.48%
	5F Alpha	1.56%	9.19%	10.75%	43.67%	56.33%	93.32%

Nevertheless, the average R-squared for each sector portfolios (reported at the last column in Table 5.3) is always higher for 5FM. This corroborates that using additional two FF factors in the Fama-French 5FM has enhanced the explanatory power when it comes to sector returns. In summary, a significant percentage of sectors appear to have both significantly positive and significantly negative alphas in case of CAPM, 3FM and 5FM. Some of the alphas lose their significance (6 out of 10 sectors) when additional factors are included in the model. Undeniably, overall positive alpha has decreased for 7 out of 10 sector portfolios when we move from 3FM to 5FM model, while this amount is 8 out of 10 when we move from CAPM to 5FM model. If the 5FM alphas are comparatively more accurate then these alphas might be exploitable in certain kind of investment strategies, for example, sector rotation strategies.

From the analysis that has been done so far in this study, it is observed that the risk-adjusted performance of sector portfolios in terms of three-factor model (3FM) is significantly different than those with five-factor model (5FM). The significant difference between time series of alphas may indicate to convey different information across two different models. Fama and French (2015) argue that "if an asset pricing model completely captures expected returns, the intercept is indistinguishable from zero in a regression of an asset's excess returns on the model's factor returns". To investigate their claim we regress the ten sector portfolios with three factors and five factors separately.

Table 5.4 and Table 5.5 reports the Ordinary Least Square (OLS) estimates of three-factor model and five-factor model respectively for 10 sector portfolios. The tables report the alpha, beta and R-squared of the regressions for the overall time period from January 1664 to December 2014. Betas of excess market return are found to be significantly higher and positive across 10 sector portfolios. From the higher beta of excess market return in Table 5.4, it can be argued that sector portfolios follow the market quite closely. In the case of 3FM, 50% of sector alpha is significantly different from zero ('0'). However, only three sectors (Durable, Manufacturing & 'others') show underperformance after adjusting for market, size and value factors. Almost all of the betas are found to be significant.

Table 5. 4: Regression of 3 Factor Model with 10 Sector Portfolios

This table reports the Ordinary Least Square estimates of 10 sector portfolios by Fama-French three-factor model (3FM) over the sample period January 1664 to December 2014.The 3FM is expressed as:

$$R_{it} - r_{ft} = \propto_{it} + \beta_{im}(R_{mt} - r_{ft}) + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \varepsilon_{it}$$

Here, $R_{it} - r_{ft}$ is the excess return of sector portfolios, Rmt (Market excess return), SMB (Small minus Big), and HML (High minus Low Book-to-market), are the factors of Fama-French models. Alpha (intercepts) is the average returns, expressed in percentage, unexplained by exposures to the Rmt , SMB, and HML. The values in the parentheses represent the p-values.

Sector Portfolio	Alpha	Market Beta	SMB Beta	HML Beta	R^2
NoDur	0.2088** (0.031)	0.8420*** (0.000)	-0.0381 (0.234)	0.1704*** (0.000)	0.7067
Durbl	-0.3915*** (0.006)	1.2134*** (0.000)	0.1587*** (0.001)	0.5353*** (0.000)	0.7071
Manuf	-0.0379 (0.582)	1.0701*** (0.000)	0.0285 (0.2113)	0.1808*** (0.000)	0.8879
Enrgy	0.1453 (0.374)	0.8974*** (0.000)	-0.2154*** (0.000)	0.2975*** (0.000)	0.4711
HiTec	0.1916* (0.098)	1.0935*** (0.000)	0.2039*** (0.000)	-0.6286*** (0.000)	0.8170
Telcm	0.0567 (0.649)	0.8391*** (0.000)	-0.2046*** (0.000)	0.1128*** (0.012)	0.5811
Shops	0.0907 (0.402)	0.9880*** (0.000)	0.1391*** (0.000)	0.0363 (0.348)	0.7507
Hlth	0.4430*** (0.000)	0.8265*** (0.000)	-0.2404*** (0.000)	-0.2741*** (0.000)	0.6273
Utils	0.0062 (0.960)	0.6550*** (0.000)	-0.1785*** (0.000)	0.4593*** (0.000)	0.4611
Other	-0.2019*** (0.004)	1.1658*** (0.000)	0.0670*** (0.004)	0.3766*** (0.000)	0.9001

* **Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
*Implies the significance at 10% level of significance.

Table 5. 5: Regression of 5 Factor Model with 10 Sector Portfolios

This table reports the Ordinary Least Square estimates of 10 sector portfolios by the Fama-French five-factor model (5FM) over the sample period January 1964 to December 2014.The 5FM is expressed as:

$$R_{it} - r_{ft} = \propto_{it} + \beta_{im}\left(R_{mt} - r_{ft}\right) + \beta_{iSMB}\, SMB_t + \beta_{iHML}\, HML_t + \beta_{iRMW}\, RMW_t + \beta_{iCMA}\, CMA_t + \varepsilon_{it}$$

Here, $R_{it} - r_{ft}$ is the excess return of sector portfolios, Rmt (Market excess return), SMB (Small minus Big), HML (High minus Low Book-to-market), RMW (Robust minus week profitability) and CMA (Conservative minus Aggressive investment) are the factors of Fama-French models. Alpha (intercepts) is the average returns unexplained by exposures to the Rmt , SMB, HML, RMW and CMA. The values of alpha are in percentage.
The values in the parentheses represent the p-values.

Sector Portfolio	Alpha	Market Beta	SMB Beta	HML Beta	RMW Beta	CMA Beta	R^2
NoDur	-0.0842 (0.325)	0.9103*** (0.000)	0.1029*** (0.000)	-0.0124 (0.760)	0.6310*** (0.00)	0.3949*** (0.00)	0.7860
Durbl	-0.4545*** (0.002)	1.2245*** (0.000)	0.1987*** (0.000)	0.5239*** (0.000)	0.1754** (0.016)	0.0215 (0.839)	0.7100
Manuf	-0.1643** (0.014)	1.0953*** (0.000)	0.1010*** (0.000)	0.1357*** (0.000)	0.3203*** (0.000)	0.0938** (0.051)	0.9031
Enrgy	0.0980 (0.562)	0.9155*** (0.000)	-0.2116*** (0.000)	0.2128*** (0.008)	0.0235 (0.780)	0.1887 (0.122)	0.4732
HiTec	0.4224*** (0.000)	1.0306** (0.000)	0.1175*** (0.003)	-0.4130*** (0.000)	-0.3953*** (0.000)	-0.4736*** (0.000)	0.8344
Telcm	0.1491 (0.238)	0.8273*** (0.000)	-0.2754*** (0.000)	.09419 (0.116)	-0.3076*** (0.000)	0.0484 (0.596)	0.5997
Shops	-0.1080 (0.291)	1.0233*** (0.000)	0.2644*** (0.000)	-0.0018 (0.970)	0.5502*** (0.000)	0.0732 (0.322)	0.7925
Hlth	0.2533** (0.041)	0.8732*** (0.000)	-0.1558*** (0.000)	-0.4117*** (0.000)	0.3807*** (0.000)	0.2999*** (0.001)	0.6508
Utils	-0.0148 (0.908)	0.6653*** (0.000)	-0.1828*** (0.000)	0.4042*** (0.000)	-0.0143 (0.822)	0.1233 (0.181)	0.4631
Other	-0.2258*** (0.001)	1.1605*** (0.000)	0.1076*** (0.000)	0.4463*** (0.000)	0.1717*** (0.000)	-0.1597*** (0.002)	0.9074

* **Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
*Implies the significance at 10% level of significance.

We can observe similar performance when we regress the sector portfolios by five factors (Table 5.5). Similar to the findings of 3FM, the least square estimates of 5FM also indicate that all the sectors closely follow the market close as the beta of excess market return is higher. Some sectors i.e. non-durable, durable, shops, utility and ‘others’ underperform by 0.08%, 0.45%, 0.11%, 0.01% and 0.23% respectively, after adjusting for the market, size, value, profitability and investment risk. Similar to 3FM, 5FM also shows 50% significant non-zero sector alphas. Interestingly, the alphas that are significant in 3FM (NoDur, Durbl, HiTec, Hlth & Other) remains significant in 5FM apart from Non-Durable sector. It also can be observed that, apart from HiTec, the significant alphas are lower in case of 5FM comparing those of 3FM. This might indicate that 5FM capture some of the unsystematic risk that 3FM cannot capture: leaving less amount (but more accurate) of information for active managers. Moreover, the R-squareds of 5FM are also higher than those of 3FM for all ten sectors. The higher R-squareds clearly indicate a better fit of five-factor model in the sector portfolios, as also seen in Table 5.3. It can also be observed that the inclusion of 2 additional factors in five-factor model decreases the alpha estimate (apart from HiTech and Telecom sectors). Hence from the statistical point of view, we can argue that, in an unconditional setting Fama-French five-factor model measure the sector performance better than their previous three-factor model. However, the significant alphas indicate that, there are some returns left unexplained beyond the exposures to Market, Size, Value, Profitability, and Investment factors and that they can be exploited.

5.3.2 Model Diagnostics

In model diagnostics, we perform redundant variables test to check the statistical significance of two addition factors (RMW and CMA) in Fama-French 5FM. This test is a Likelihood Ratio test that assumes Fama-French 3FM is a nested model of Fama-French 5FM model; and hypothesise that the variable of interest has zero coefficient and might thus be deleted from the equation. The test statistics of redundant variables test (F-statistic) has an exact finite sample F-distribution under null hypothesis. Panel A of Table 5.6 consist the results of redundant variables (Likelihood ratio) test under the null hypotheses:

$H_{01}: \beta_{RMW} = 0;$
$H_{02}: \beta_{CMA} = 0;$
$H_{03}: \beta_{RMW} = \beta_{CMA} = 0$

We can observe that, eight out of ten portfolios exhibits significant profitability beta whereas five out of ten portfolios exhibit significant investment betas. However, both profitability and investment factor are jointly significant in all but two portfolios (Energy and Utility).

It is a custom to believe that aggregate shocks such as business cycles will cause a structural break in a time-series. A structural change in second moments will produce a change in asset betas that might result in a spuriously significant alpha (Turtle and Zhang, 2015). During model diagnostics we check whether there exhibits structural change in the Fama-French asset pricing models due to the business cycles; with an intention to derive trading strategies accordingly. In this manner, we perform Factor Breakpoint test that splits an estimated equation's sample into a number of subsamples classified by one or more variables and examines whether there are significant differences in equations estimated in each of those subsamples. A significant difference indicates a structural change in the relationship. The Wald statistics is the Table 5.6 test whether there has been a structural change in a subset of the parameters due to the business cycles. Panel B of Table 5.6 indicates that both 3FM and 5FM exhibits structural change due to business cycles; 5FM differs more significantly than 3FM between economic states. Given the results of the factor breakpoint test for structural break, we develop a trading strategy that incorporates business cycles for more accurate trading with a potential of generating better performance. Please be apprised that, although our research objectives do not include in-depth analysis of structural change in the sector returns, we perform factor breakpoint test for simple model diagnostics and hence derive any possible simple sector rotation strategies.

Table 5. 6: Model Diagnostics

This table reports the Likelihood Ratio test and Wald Test for Factor Break Point for the corresponding hypothesis. We perform likelihood ratio test for the redundant variables to identify the significance of the two added factors (RMW and CMA) in the Fama-French 5FM. We also perform the Factor Break Point test to examine whether the subset of parameters differs due to the business cycles (BC). The test statistics is computed from a standard Wald test of the restriction that the coefficients on the equation parameters are the same in all subsamples. The Factor Breakpoint test splits an estimated equation's sample into a number of subsamples classified by one or more variables and examines whether there are significant differences in equations estimated in each of those subsamples. A significant difference indicates a structural change in the relationship.
The p-value of Wald test and Likelihood Ratio test indicates the probability of the insignificance of corresponding regressor.

	NoDur	**Durbl**	**Manuf**	**Enrgy**	**HiTec**	**Telcm**	**Shops**	**Hlth**	**Utils**	**Other**
Panel A: Likelihood Ratio Test for Redundant Variable										
$H_{01}: \beta_{RMW} = 0$	220.0168*** (0.0000)	5.7850** (0.0165)	93.8751*** (0.0000)	0.0784 (0.7795)	48.3847*** (0.0000)	23.9610*** (0.0000)	116.9313*** (0.0000)	38.3021*** (0.0000)	0.050946 (0.8215)	24.53581*** (0.0000)
$H_{02}: \beta_{CMA} = 0$	40.8665*** (0.0000)	0.0413 (0.8391)	3.8220* (0.0510)	2.3927 (0.1204)	32.9377*** (0.0000)	0.2814 (0.5940)	0.9815 (0.3222)	11.2710*** (0.0008)	1.796862 (0.1806)	10.07030*** (0.0016)
$H_{03}: \beta_{RMW} = \beta_{CMA} = 0$	112.2745*** (0.0000)	3.0312** (0.0490)	47.3725*** (0.0000)	1.2130 (0.2945)	31.6660*** (0.0000)	14.1011*** (0.0000)	61.0811*** (0.0000)	20.4472*** (0.0000)	1.108467 (0.3307)	23.99183*** (0.0000)
Panel B: Factor Break Point Test										
Structural change due to BC (5FM)	7.5203 (0.2754)	5.9712 (0.4264)	9.5444 (0.1452)	36.9510*** (0.0000)	11.1681* (0.0833)	8.2301 (0.2217)	23.5365*** (0.0000)	9.3835 (0.1531)	25.95887 (0.0002)***	9.007625 (0.1731)
Structural change due to BC (3FM)	16.0655*** (0.0029)	5.9624 (0.2020)	10.5225** (0.0325)	35.2219*** (0.0000)	7.8421* (0.0975)	10.4302** (0.0338)	22.0615*** (0.0002)	11.3597** (0.0228)	15.82159*** (0.0033)	12.72868** (0.0127)

***Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
*Implies the significance at 10% level of significance.

5.3.3 Sector Rotation Based Trading Strategy

Sorensen and Burke (1986) argue that, application of a sector rotation strategy requires at least two assumptions. First, we must assume that sector-specific effects cause price movements to differ from one group to another. Second, sector rotation assumes that the firms within a sector exhibit some homogeneity in their relative price movements, aside from overall market influences. Intuitively, companies in the same sector or industry would exhibit higher pairwise return correlations that companies from different industries. Firms within the same industry that operate under the same regulatory environment are likely to react similarly to technological innovations, and also exhibit similar sensitivity to macroeconomic shocks and/or government policy. These firms are also likely to be exposed equally to the fluctuations in the supply & demand or across the consumer-supplier chain of their corresponding market. We hypothesised that, if the either 3FM or 5FM produces true alpha then these rolling alphas can be used as information to perform sector rotation strategies.

If 5FM contains additional information than 3FM the alpha of this model, theoretically, will contain less information to exploit by the investors. However, if these alphas are accurate then we can exploit them to gain additional return. We perform sector rotation based trading strategies to test whether the alphas of 3FM and 5FM can be exploited and compare between the superiority of either of the model to produce true alpha. Although the analyses that have been done so far in this study indicate a better fit of 5FM with higher R-squared, the inclusion of 3FM is for comparison purpose and because 3FM is widely used in performance measurement literature. Note that, sectors portfolios are not investable as they have asset weights that are not in convenient units for investment and our trading strategies with Fama-French sector portfolios are for illustration purpose rather than finding the best strategy to trade upon. These strategies can be replicated in practice by using sector indexes or even sector ETFs. These sector rotation strategies are then replicated in sector ETFs to test the feasibility and profitability of our findings, later in this study.

Our rotation strategies take long position in the sector portfolios that have positive alpha of 36 months rolling window regression. The Long-Short rotation strategies buy sector portfolios that have positive alpha and sell those with negative alpha. In another trading strategy we buy corresponding sectors with positive alpha based on 3FM and 5FM in the expansion period, otherwise invest in risk-free bonds. The portfolio is rebalanced every month based on the rolling window alpha of previous 36 months. For example, for the first trading in January 1967 we use the rolling window alpha over the period January 1964 to December 1966, and for the trading in February 1967 the rolling window alpha, over the period February 1964 to January 1967, is used. We compare the trading strategies with the buy-and-hold strategy that represents the investment in the S&P 500 index.

Table 5.7 provides the annualised returns (geometric), standard deviation, and Sharpe ratios of long-only and long-short trading strategies with 3FM and 5FM. We observe that Long-only based sector rotation trading provide almost double than the buy-and-hold return of S&P 500 with similar standard deviation (in two decimal places). Sharpe ratios of these strategies are also higher (almost four times) than the Sharpe ratio of S&P 500. Interestingly, rotation based trading with the 3FM rolling window alpha provides slightly higher annual return than trading with 5FM alpha. However, the t-test for equality of mean returns indicates that trading strategies with 3FM alphas are not statistically different with those of 5FM alphas. The long-only trading based on the positive alphas of 3FM provides 0.1298% higher return than the long-only strategies based on 5FM alphas. This return seems to be less riskier as the standard deviation decreases by 0.29% and the risk-adjusted performance also increases (Sharpe ratio difference is 0.00368).

The superior performance of the trading strategy based on 3FM and 5FM can be seen in figure 5.4, which displays cumulative return of sector rotation strategies and the benchmark. The superior performance of rotation strategy grows over time and is fairly consistent over the entire trading period. In the case of Long-Short trading strategies based on positive and negative alphas of 3FM also provide greater annualised return than the similar trading strategies with 5FM alphas. This superior performance is also confirmed by the lower turnover ratio of 3FM (turn-over of 3FM is found to be 6.406 and for 5FM it is 8.125).

Table 5. 7: Trading with Fama-French Sector Portfolios

This table reports the return, Standard Deviation, Sharpe Ratio and T-test based on 3FM and 5FM rolling window alphas, over the trading period January 1967 to December 2014. In the total of 576 trading months, 493 were in expansionary periods and 83 were in recessionary periods. The buy-and-hold strategy represents the investment in the S&P 500 index. Whereas, rotation strategies take long position in the sector portfolios that have positive alpha of 36 months rolling window regression. Another rotations strategy incorporates business cycles and take long position in the sector portfolios that have positive alpha of 36 months rolling window regression, however during recession it invests in risk-free T-Bills. The Long-Short rotation strategies buy sector portfolios that have positive alpha and sell those with negative alpha.
The portfolio is rebalanced every month based on the rolling window alpha of previous 36 months. For example, for the first trading in January 1967 we use the rolling window alpha over the period January 1964 to December 1966, and for the trading in February 1967 the rolling window alpha, over the period February1964 to January 1967, is used. We used NBER recession index to calculate the return in recession and expansion period. Mean returns (geometric mean) and standard deviations (Std. Dev.) have been annualised.
We further test whether the trading strategies with 3F alpha and 5F alpha are equal in mean returns. Last column reports the t-test, p-values are in parentheses.

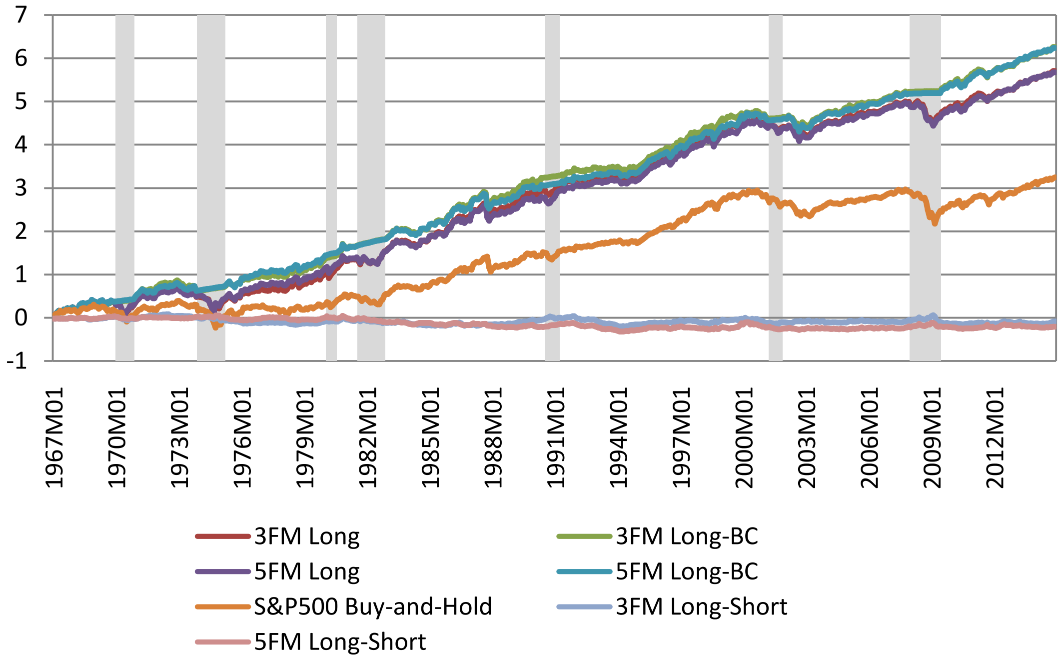
	Mean Return (%)	Std. Dev (%)	Sharpe Ratio	Ho: mean diff = 0 Ha: mean diff ≠ 0 (P-value)
Long Only Trading with **3FM**	11.20	15.54	0.1283	0.0226 (0.9819)
Long Only Trading with **5FM**	11.07	15.83	0.12462	
Long-Short Trading with **3FM**	-0.29	4.69	-0.3110	0.2686 (0.7882)
Long -Short Trading with **5FM**	-0.52	4.39	-0.3465	
Trading with **3FM** (Buy& Hold RF in Recession)	12.88	13.02	0.1786	0.0170 (0.9865)
Trading with **5FM** (Buy& Hold RF in Recession)	12.79	13.24	0.17462	
Buy & Hold of **S&P 500**	5.67	15.51	0.0333	N/A

Sorensen and Burke (1986) argue that any benefits of sector rotation may depend on existing market conditions irrespective of the particular analytical approach. We test their claims by splitting the trading periods according to the NBER business cycles. Moreover, factor breakpoint test due to business cycles (Table 5.6) also suggest the possibility of more accurate trading and generate higher return by incorporating business cycles in the trading strategies. The trading strategy where we buy corresponding sectors with positive alpha based on 3FM and 5FM in the expansion period otherwise invest in risk-free bonds, generates the superior returns. The returns are more than 7% higher than the buy-and-hold return of S&P 500 with at least 2% lower risk (standard deviation). Similar to long-only trading, it can be noted that, in rotaion strategies with 3FM alpha integrates business cycles provide slightly lower risk (by 0.22%) and slightly higher Sharpe ratio (Sharpe ratio difference is 0.00398).

Figure 5.4 depicts the superior performance of long-only trading strategies that incorporates business cycles over the entire period, in terms of cumulative returns. During all recession periods (shaded area) investing in T-bills clearly pulls the return upward. Specifically, if we compare long-only trading and trading that incorporates business cycles, we can observe that trading with 3FM (5FM) that invest T-bills during recession has higher return by 1.68% (1.72%) compared to the long only trading with 3FM (5FM) (see Table 5.7). Trading with 3FM (5FM) that incorporate business cycles also increase the Sharpe ratio from 0.1283 (0.12462) to 0.1786 (0.17426). The outperformance of sector rotation strategies (in our case except for long-short strategy) confirms the argument of Sorensen and Burke (1986) and Stangl, Jacobsen and Visaltanachoti (2009) who state that sector rotation strategy over different stages of the business cycles outperforms the market. However, the t-test for equality of mean returns indicates that trading strategies with 3FM alphas are not significantly different with those of 5FM alphas over the whole sample period.

Figure 5. 4: Cumulative Return of Sector Rotation Strategies versus Benchmark S&P500

This figure displays the cumulative return of sector rotation based on 3F alpha and 5F alpha. The returns are compared with the buy-and-hold cumulative return of S&P 500 over the trading period January 1967 to December 2014 (576 trading months; 83 recessionary periods and 493 expansionary periods).



Practitioners would be interested to explore the economic significance of these findings by testing the profitability of our sector rotation strategies based on these models' projection. Fama-french sectors portfolios are not readily investable and hence we check whether our sector rotation strategies are feasible and profitable for investors with sector ETFs. We use 'Select Sector SPDR ETFs' to replicate the sector rotation strategies. Select Sector SPDR ETFs are not perfect match of Fama-French sector portfolios. Fama-French sectors include all NYSE, AMEX and NASDAQ firms, whereas 'Select Sector SPDR ETFs' divide the S&P500 firms into 11 index funds. By matching the industry definition of Fama-French sectors and 'Select Sector SPDR ETFs', we selected Consumer Discretionary (Durable), Consumer Staples (Non-durable), Energy, Health Care, Technology (HiTech) and Utilities sectors (6 sector ETFs)[29] for trading purpose. The trading period is shorter than Fama-French sectors because of the availability of the data. The data is obtained from DataStream and the trading period is from January 1999 to December 2014, providing 192 trading periods (months).

Our rotation strategies with sector ETFs use the 3FM and 5FM alpha of Fama-French sectors. For example, when investing in Consumer Discretionary ETF with 3FM, we use the alpha of Fama-French Durable sector that is obtained by regressing (36 months rolling window basis) durable sector returns with three factors. Similar to previous sector rotation strategies, these rotation strategies take long position in the sector ETFs based on the positive alpha of corresponding Fama-French sector portfolio. The Long-Short rotation strategies buy sector ETFs that has positive Fama-French sector alpha and sell those with negative Fama-French sector alpha. Another trading strategy takes business cycles into consideration and buy corresponding sector ETFs with positive Fama-French sector alpha in the expansion period, otherwise invest in risk-free T-Bills. We compare the trading strategies with the buy-and-hold strategy that represents the investment in the S&P 500 index for the same period. Although, sector ETFs trading provide lower return than those of Fama-French sector portfolios, we observe that the return of sector rotation strategies with 5FM is higher than those of 3FM. The higher returns of the Fama-French sector portfolios may be because of the trading period. The sector ETF trading period consists of only 192 months (26 recessionary months and 166 expansionary months) compare to the 576 trading months (83 recessionary months and 493 expansionary months) of Fama-French portfolios. Note that, the S&P 500 returns for those 192 trading months is 2.0498% compare to the 5.67% return for the 576 trading periods. However, ETFs trading are readily investable and hence more comparable than Fama-French sector portfolios.

[29] Correlation coefficients between Select Sector SPDR ETFs and Fama-French sector portfolio return are: 0.828764862 (Consumer Staples/ Non-Durable), 0.816122412, (Consumer Discretionary/ Durable), 0.961186564 (Energy), 0.973998282 (Technology/HiTech), 0.705727311 (Health), 0.855138977 (Utilities).

Break-even level of transaction costs per switch for each portfolio is calculated to assess the feasibility of our allocation strategy for investors. Break-event transaction cost is the maximum cost per trade that equalises the Sharpe ratio of our rotation strategy to that of the buy and holds benchmark.[30] The higher the break-even transaction costs are, the more feasible our strategy is. Table 5.8 provides the annualised returns (geometric), standard deviation, and break-even transaction cost of long-only and long-short trading strategies with 3FM and 5FM. Similar to our previous rotation strategies we find that Long only strategies provide higher return than S&P 500 benchmark whereas the long-short strategies provide lower return. It can be observed that trading with 5FM alpha provides higher annualised return than trading 3FM alpha. The highest return is observed in the rotation strategy that takes long position in the corresponding sector ETFs during expansion period but invests in risk-free T-bills in recession period. This strategy with 5FM provides more than 7% higher return than the benchmark. The return with 5FM alpha provides 1.52% higher return than the rotation strategies with 3FM alpha. Moreover, the long-only trading strategy with 5FM alpha provides 1.74% higher return compared to the long-only trading with 3FM alpha. This justifies our argument that Fama-French 5FM provides true alphas compared to the 3FM that can be exploited through sector rotation strategies. However, the outperformance of 5FM that incorporates business cycles faded out because of the higher number of switches. Break-even transaction cost of rotation strategy that invests T-bills during recession otherwise rotation sectors based on the 5FM alpha is 326.66 BPS (114 switches) compared to the 398.27 BPS (70 switches) break-even transaction cost of trading with 3FM. Investors who want to trade based on our sector rotations strategies are advised to incorporate recessions

30 It can be calculated as: $\frac{\bar{r}_{\text{Trading Strategy}} - \bar{r}_f}{\sigma_{\text{Trading Strategy}}} = \frac{\bar{r}_{\text{Benc hmark}} - \bar{r}_f}{\sigma_{\text{Benc hmark}}}$; Here mean return is calculated as: $\bar{r}_{\text{Trading Strategy}} = \sum_{t=1}^{n} \frac{r_t - C}{n}$, where C takes the value of zero if no transaction has been made and value of breakeven transaction cost if trading occurred in month 't' and 'n' is the number of periods. We use Sharpe ratio to calculate break-even transaction cost with the argument that investors care about risk adjusted return when choosing trading strategies.

into consideration by taking long position with the positive 5FM alpha during expansion period and invest risk free T-bills during recession.

Table 5. 8: Trading with Sector ETFs

This table reports the sector ETFs return, Standard Deviation, Sharpe Ratio and Break-even Transaction cost of trading based on 3FM and 5FM rolling window alphas, over the trading period January 1999 to December 2014 (192 trading months, out of them 166 months were expansionary periods and 26 months were recessionary periods). The buy-and-hold strategy represents the investment in the S&P 500 index. Whereas rotation strategies take long position in the sector ETFs that have positive alpha, obtained by 36 months rolling window regression of corresponding (matched) Fama-French sector with Fama-French (either three or five) factors. Another rotations strategy incorporates business cycles and takes long position in the sector portfolios that have positive Fama-French sector alpha of 36 months rolling window regression, however during recession it invests in risk-free T-Bills. The Long-Short rotation strategies buy sector ETFs that have positive Fama-French alpha and sell those with negative Fama-French alpha of corresponding Fama-French sectors.
The portfolio is rebalanced every month based on the rolling window alpha of previous 36 months. For example, for the first trading in January1999 we use the rolling window alpha of Fama-French sector portfolios that is obtained over the period January 1996 to December 1998 by regressing corresponding sector portfolio with Fama-French factors, and for the trading in February 1999 the rolling window alpha, over the period February1996 to January1998, is used. We used NBER recession index to calculate the return in recession and expansion period. Mean returns (geometric mean) and standard deviations (Std. Dev.) have been annualised.
We further test whether the trading strategies with 3F alpha and 5F alpha are equal in mean returns.

	Mean Return (%)	Std. Dev (%)	Sharpe Ratio	Break-even TC
Trading with 3FM (Long Only)	3.7918	14.9667	0.055138	114.48 BPS
Trading with 5FM (Long Only)	5.5331	16.2867	0.083911	147.73 BPS
Trading with 3FM (Long-Short)	-0.0952	6.6755	-0.080490	Negative
Trading with 5FM (Long -Short)	0.5168	7.2562	-0.048748	Negative
Trading with 3FM (Buy& Hold RF in Recession)	7.6744	12.0048	0.146824	398.27 BPS
Trading with 5FM (Buy& Hold RF in Recession)	9.1910	13.7509	0.162814	326.66 BPS
Buy & Hold of S&P 500	2.0498	16.8809	0.025382	N/A

One can view the outperformance of our sector trading strategies as an implication to violates the efficient market hypothesis. Although the justification of efficient market hypothesis is beyond the scope of this study, we use the break-even transaction cost as an implication of limits to arbitrage. Break-even transaction cost in our study indentify the extent to which our trading strategy can be arbitraged.

5.4 Summary and Conclusions

This chapter contributes to the scarce literature of sector rotation strategy by studying alpha-based sector rotation with Fama-French three-factor and five-factor models. Rolling alphas of 10 sectors are used to evaluate the performance of sector portfolios. We perform sector rotation based on the rolling alphas and compare whether 3FM or 5FM produce true alphas that can be exploited through trading.

When comparing 3FM and 5FM, OLS estimates suggest that 5FM explains the variability of the sector portfolio returns slightly better than 3FM. The inclusion of two addition factors (RMW and CMA) increase the statistical significant and decrease the alpha estimate (apart from Hitech and Telecom sectors). Likelihood Ratio test for redundant variable confirms the significance of profitability (RMW) and investment (CMA) betas. Moreover, 3FM and 5FM exhibits structural change due to business cycles, suggesting that business cycles can be incorporated for more accurate trading strategies.

When comparing the time series of alphas, obtained from 36 months rolling window regression, the risk-adjusted performance of sector portfolios in terms of three-factor model (3FM) is significantly different than those with five-factor model (5FM) for 8 out of 10 sectors. The significant difference between time series of alphas may indicate to convey different information across two different models. We hypothesised that, if the either of 3FM or 5FM produces true alpha then these rolling alphas can be used as information to generate higher return.

Sector rotation strategy based on 3FM alphas in perfect world (without counting the business cycles) outperforms the S&P 500 benchmark by 5.53%, and this outperformance is 5.40% when trading with 5FM alphas. These outperformance increases when we take business cycles into consideration. In a trading strategy where we buy corresponding sectors with positive alpha (based on 3FM and 5FM) during expansion period and invest in risk-free T-bonds during recession period outperform S&P 500 benchmark by 7.21% in case of 3FM and 7.12% in case of 5FM. However, we observe that neither of long-short trading outperforms the benchmark index.

The outperformance of sector rotation based on time series of alphas (in our case except for long-short strategy) confirms the findings of Sorensen and Burke (1986) who prove that sector rotation strategy provides superior returns. Our findings also coincide with the findings of Stangl, Jacobsen and Visaltanachoti (2009) who argue that sector rotation can be benefited by integrating business cycles into the strategies. However, although trading in Fama-French sector portfolios with 3FM alphas produce slightly higher return, we do not find any statistical difference between the mean return of trading strategies based on 3FM and 5FM alphas. Although our empirical findings confirm the theoretical argument that 5FM explains the cross section of expected return with greater accuracy, i.e. the time series of 5FM alpha is more accurate then 3FM alpha; but t-test for equality of mean returns indicates that trading strategies with 3FM alphas are not statistically different with those of 5FM alphas, while trading with Fama-French sector portfolios.

However, Fama-French sector portfolios may not be representative for sectors and industries used by sector rotation investors and are not readily investable as they have asset weights that are not in convenient units for investment. With Select Sector SPDR ETFs, we therefore, assess the economic significance of our sector rotation strategies and also test our hypothesis that 5FM produces more accurate alpha to trade upon. We observe that trading sector ETFs with 5FM alpha provides higher annualised return than trading 3FM alpha. The highest outperformance is observed in the rotation strategies that take business cycles into consideration and that takes long position in the corresponding sector ETFs based on the 5FM alpha during expansion period but invest in risk-free T-bills in recession period. Annualised return with 5FM alpha provides 1.52% higher return compared to the rotation strategies with 3FM alpha. Moreover, the long-only trading strategy with 5FM alpha provides 1.74% higher return compared to the long-only trading with 3FM alpha. These findings may justify our argument that Fama-French 5FM provides truer alphas compared to 3FM that can be exploited through sector rotation strategies by the investors.

CHAPTER SIX: CONCLUSION

6.1 Summary of Findings

This thesis contributes to the literature of portfolio management over three self-contained essays. The first essay (Chapter Three) contributes to the style literature by extending the study in the UK market by investigating the asymmetries of size, value and momentum premiums over the economic cycles and their macroeconomic determinants. In addition, to the best of our knowledge, this is the first study that examines how all three equity premiums (size, value and momentum) are impacted by macroeconomic factors across business cycles, including recent financial crisis in the UK. We implement dynamic regime-based methods (Markov Switching Model) to identify the possible nonlinear phenomena of UK style factors and associate Markov switching regime 1 with economic upturn and regime 2 with the economic downturn. We find clear evidence of cyclical variations in the three premiums, most notable being that in the size premium, which changes from positive in expansions to negative in recessions. Macroeconomic indicators prompting such cyclicality the most are variables that proxy credit market conditions, namely the interest rates, term structure and credit spread. Overall, macro factors tend to have more significant impact on the three premiums during economic downturns. The results are robust to the choice of information variable used in modelling transition probabilities of the two-stage Markov switching model. We show that exploiting cyclicality in premiums proves particularly profitable for portfolios featuring small-cap stocks in recessions at a feasible level of transaction costs.

Second essay (Chapter Four) contributes to the literature of style timing and style momentum by investigating the survival time of momentums in six UK style portfolios' returns. We utilise Kaplan-Meier estimator, a non-parametric method that measures the probability of momentum persisting beyond the present day. In addition, we simulate the theoretical survival curves using Random Walk and ARMA (1, 1) process. Comparison of empirical survival times to those implied by theoretical models (Random Walk and ARMA (1, 1)) shows that there is scope for profiting from momentum trading. We illustrate this by forming long-only, short-only and long-short trading strategies that exploit positive and negative momentum and their average survival time. Our momentum based timing strategies show that utilising momentum mean survival time yields considerably higher Sharpe ratios than the naive buy-and-hold at a feasible level of transaction costs. This finding is most pronounced among the long/short strategies. This essay also looks at differences in survival times and performance of strategies across economic states. We document that momentum trading based on survival times works well in both recessions and expansions, generating higher Sharpe ratios than buy-and-hold portfolios at a feasible level of transaction costs for all investors. The survival methodology of this study can be seen as a convincing indicator for trading decisions, particularly where the empirical survival curves are different than the corresponding theoretical ones.

The contribution of essay three (Chapter Five) to the literature is twofold: first, performance measurement (evaluating the performance of sectors plus comparing 3 and 5 factor model of Fama-French) and second, sector rotation. To the best of our knowledge, this is the first study that compares Fama-French (1993) three-factor and newly evolved Fama and French (2015) five-factor model as a benchmark model of performance evaluation. The argument of essay three is that, if five-factor and/or three-factor model generate true alpha then we can incorporate investment strategies to generate higher return. With this argument, we formulate sector rotation strategies based on the rolling alphas of Fama-French three-factor and five-factor models and compare the portfolio performances. Our empirical findings suggest that 5FM explains the variability of the sector portfolio returns slightly better than 3FM. The inclusion of two addition factors (profitability and investment) increases the statistical significant and the accuracy of alpha estimate. We find that sector rotation strategies based on 3FM alphas and 5FM alphas outperform S&P 500 benchmark. However, highest outperformance can be observed in the rotation strategies that integrate business cycles by taking long position to the corresponding sectors with positive alpha (based on 3FM and 5FM) during expansion period and invest in risk-free T-bonds during recession period. We explore the economic significance of these findings by testing whether our sector rotation strategies are feasible and profitable for investors or not by means of sector ETFs data, which is readily investable. Similar to the findings with Fama-French sector portfolios we find that long only strategies provide higher return than S&P 500 benchmark whereas the long-short strategies provide lower return. It can be observed that trading with 5FM alpha provides higher annualised return than trading 3FM alpha. The highest return is observed in the rotation strategy that takes long position in the corresponding sector ETFs during expansion period but invests in risk-free T-bills in the recession period.

6.2 Implications for Efficient Market Hypothesis

The findings of this study indicate that size, value, and momentum anomalies are present in the UK market and the trading strategies based on these anomalies are profitable. In the second essay, we observe that theoretical positive (negative) survival curves of Random walk model underestimate (overestimate) the empirical survival curve for all the portfolios (for some portfolios). This under- and over-estimation can be viewed as the misalignment of efficient market hypothesis with empirical data. The efficient market hypothesis primarily based on the random walk model and these under- and over-estimation violates the efficient market theory to some extent. Trading strategies based on these misalignments are found to be profitable. Moreover, third essay also confirms the profitability of asset class (sectors). These profitability contradicts the efficient market hypothesis.

Efficient market theory assumes that the investors act rationally. However, irrational investors coexist with the rational ones in the market. Meaning that risk based explanation and mispricing based explanation can explain the size, value, and momentum premiums simultaneously. For the maintenance of efficient markets arbitrageurs are crucial as the fundamental values of firms are kept aligned with market prices through the arbitrage process. If there is any mispricing occurs in the market, because of the irrational investors or any other behavioural biases, they should be immediately eliminated by the arbitrageurs. However, these anomalies can exist because there are limits to the arbitrage process, which can be restrained in various way (Bodie, Kane and Marcus, 2011).

Nevertheless, one can view these anomalies as the limits to arbitrage with the argument that, cost and fundamental risk limits the effectiveness of arbitrage in eliminating certain security mispricing. Moreover, the justification of efficient market hypothesis involves join hypothesis problem with the fact that any of these anomalies and outperformance may reflect market inefficiency, bad asset pricing model or both. Although, the justification of efficient market hypothesis is beyond the scope of this study, we measure the impact of transaction cost (break-even transaction cost) to the profitability of our trading strategies as an indicator of the presence of limits to arbitrage. Meaning that, break-even transaction cost in our study identifies the extent to which our trading strategy can be arbitraged. Our profitable trading strategies, hence, may indicate such limits to arbitrage.

6.3 Implications for Investors

The findings of our study are relevant for the style investors who are interested in determining how to maximise their profits across economic cycles by applying adequate market timing, rotation or asset allocation strategies to exploit the changes in the style premiums, style portfolios and sector portfolios.

The first essay finds the evidence of the cyclical behaviour of style premiums and establishes that small-cap switching strategies outperform the buy and hold benchmark in overall period. Moreover, all small-cap switching strategies and large cap/negative momentum switching display relative outperformance over their buy and hold benchmarks in recessions. This implies that forecasts based on our model have considerable economic significance for investors, particularly for trading strategies involving small-cap stocks. Transaction costs per trade are found to be at the feasible level, making these costs unlikely cause for the limits to arbitrage, at least in small-cap portfolio trading space.

Findings of the second essay have useful implications for both traders and portfolio managers. We quantify the momentum survivals of style portfolios and investors can exploit the momentum survival time of style portfolio - relevant for those interested in style-consistent investing in more traditional funds. The second essay finds that momentum survival time leads to profitable trading in style rotation strategy when switching between winner and loser style portfolios - relevant for hedge fund managers. Even the naive investors can be benefited as our momentum trading based on mean survival times is feasible even if transaction costs are high.

Sector rotation trading, in the third essay, based on 3FM alphas and 5FM alphas outperform S&P 500 benchmark. This outperformance increased when we incorporate business cycles into our trading strategy by taking long position to the corresponding sectors with positive alpha (based on 3FM and 5FM) during expansion period and invest in risk-free T-bonds during recession period. These imply that our sector rotation strategies have considerable economic significance for investors. The existence of Sector ETFs facilitate the investors to apply trading strategies. The outperformance of trading with Sector ETFs clearly indicates the profitability of our rotation strategies. The outperformance of rotation strategies with an integration of business cycles is large enough to be of interest to investors.

6.4 Limitations and Future Work

The findings of the first essay are relevant for the UK size, style and momentum investors interested in determining how to maximise their profits across economic cycles by applying adequate market timing or asset allocation strategies to exploit the changes in the three premiums over time. With this in mind, this study has some limitations and can be extended in several ways. For instance, the corporate bond data is not available for the UK market longer than 11 years. To cover longer span of varying economic regimes, we use Moody’s US BAA corporate bond index as a proxy for the UK data. Although we think that Moody’s US BAA is a good proxy for UK corporate bond (the correlation coefficient Thomson Reuter UK Corporate

Benchmark BBB and Moody's US BAA is 0.871085 over the 11 year period of available data), it would be interesting to use UK corporate bond data for credit spread. Factor portfolios of this study are constructed by using the same breakpoints as described in Fama and French (1993). Given that recent literature points to the fact that those breakpoints are arbitrarily chosen (see for instance Cremers, Petajisto and Zitzewitz, 2012), it would be interesting to explore if the results are robust to the use of alternative breakpoints. Another limitation is related to the fact that factor portfolios may exhibit momentum (Avramov et al., 2016). Hence, it would be interesting to control for this effect in the study. Additionally, first essay can be extended to include the two newly available factors from Fama and French (2015) five-factor model: operating profitability and investment.

Together with the estimation of survival time (survival curve), the second essay also investigates the influences of macroeconomic variables in the likelihood of mean portfolio momentums. However, we only looked at credit market variables that are found to be significant in the first essay. It would be interesting to explore the effect of other macroeconomic variables towards the likelihood of positive/negative momentum survival. Second essay is also limited to the size and value portfolios and hence would be equally interesting to explore the momentum survival of other style portfolios, for example, the portfolios that are used to construct profitability and investment factor of newly evolved five-factor model (Fama and French, 2015). This study provides evidence that credit market variables influence the likelihood of positive and negative momentum. Hence, these macro variables can be used to introduce one extra layer in the style timing strategies.

Although first and second essay uses the UK market data, the third essay uses the US market data because of the availability of Fama-French five-factor data. Fama-French five-factor model is newly evolved and the thrid essay can be extended to the UK market. Non-normal characteristics of sector returns and Fama-French factors are reported in this study and hence non-linear models can also be employed. In addition to these ideas, it would be of interest to extend our rotation strategies to different asset classes.

APPENDIX A4

Table A4. 1: KM Estimator of Small Size & Medium book-to-market (SM) Portfolio

This table reports the stepwise calculation (ex-post) of Kaplan-Meier estimator for Small Size & Medium book-to-market **(SM)** Portfolio, estimated over the sample period October 1980 to June 2014. This calculation allows a thorough description of survival curves. The survival function (S_t) can be interpreted as the probability of trend continuation until failure time $t(j)$ months conditioned upon the fact that the momentum is alive in $t(j)$, where $t(1) \leq t(2) \leq t(k)$. With simple t-test we checked whether the survival function is significantly different from zero. The values in the parentheses reports the p-values of the t-test.

j	Ordered failure time, $t(j)$	Intact before t (n_j)	Ending at time t (d_j)	Survivor function (S_t)	Std. Error [$\sqrt{Var\ S(t)}$]
Survival Function of Positive Portfolio Momentum					
1	2	186	58	0.6882*** (0.0000)	0.0340
2	3	128	39	0.4785*** (0.000)	0.0366
3	4	89	25	0.3441*** (0.0000)	0.0348
4	5	64	18	0.2473*** (0.000)	0.0316
5	6	46	14	0.1720*** (0.0000)	0.0277
6	7	32	10	0.1183*** (0.0000)	0.0237
7	8	22	9	0.0699*** (0.0012)	0.0187
8	9	13	6	0.0376** (0.0198)	0.0140
9	10	7	5	0.0108 (0.2051)	0.0076
10	11	2	1	0.0054** (0.5000)	0.0054
11	12	1	1	0.0000 (N/A)	.
Survival Function of Negative Portfolio Momentum					
1	2	57	38	0.3333*** (0.0000)	0.0624
2	3	19	14	0.0877** (0.0311)	0.0375
3	4	5	4	0.0175 (0.3714)	0.0174
4	5	1	1	0.0000 (N/A)	.

*** Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
* Implies the significance at 10% level of significance

Table A4. 2: KM Estimator of Small Size & High book-to-market (SH) Portfolio

This table reports the stepwise calculation (ex-post) of Kaplan-Meier estimator for Small Size & High book-to-market **(SH)** Portfolio, estimated over the sample period October 1980 to June 2014. This calculation allows a thorough description of survival curves. The survival function (S_t) can be interpreted as the probability of trend continuation until failure time $t(j)$ months conditioned upon the fact that the momentum is alive in $t(j)$, where $t(1) \leq t(2) \leq t(k)$. With simple t-test we checked whether the survival function is significantly different from zero. The values in the parentheses reports the p-values of the t-test.

j	Ordered failure time, $t(j)$	Intact before t (n_j)	Ending at time t (d_j)	Survivor function (S_t)	Std. Error [$\sqrt{Var\ S(t)}$]
Survival Function of Positive Portfolio Momentum					
1	2	185	57	0.6919*** (0.0000)	0.0339
2	3	128	38	0.4865*** (0.0000)	0.0367
3	4	90	26	0.3459*** (0.0000)	0.0350
4	5	64	19	0.2432*** (0.0000)	0.0315
5	6	45	13	0.1730*** (0.0000)	0.0278
6	7	32	9	0.1243*** (0.0000)	0.0243
7	8	23	7	0.0865*** (0.0004)	0.0207
8	9	16	5	0.0595*** (0.0038)	0.0174
9	10	11	5	0.0324** (0.0319)	0.0130
10	11	6	2	0.0216* (0.0995)	0.0107
11	12	4	2	0.0108 (0.2504)	0.0076
12	13	2	1	0.0054 (0.5000)	0.0054
13	14	1	1	0.0000 (N/A)	.
Survival Function of Negative Portfolio Momentum					
1	2	62	35	0.4355*** (0.0000)	0.0630
2	3	27	16	0.1774*** (0.0011)	0.0485
3	4	11	7	0.0645* (0.0656)	0.0312
4	5	4	3	0.0161 (0.3884)	0.0160
5	6	1	1	0.0000 (N/A)	.

*** Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
* Implies the significance at 10% level of significance

Table A4. 3: KM Estimator of Big Size & Low book-to-market (BL) Portfolio

This table reports the stepwise calculation (ex-post) of Kaplan-Meier estimator for Small Big Size & Low book-to-market **(BL)** Portfolio, estimated over the sample period October 1980 to June 2014. This calculation allows a thorough description of survival curves. The survival function (S_t) can be interpreted as the probability of trend continuation until failure time $t(j)$ months conditioned upon the fact that the momentum is alive in $t(j)$, where $t(1) \leq t(2) \leq t(k)$. With simple t-test we checked whether the survival function is significantly different from zero. The values in the parentheses reports the p-values of the t-test.

j	Ordered failure time, $t(j)$	Intact before t (n_j)	Ending at time t (d_j)	Survivor function (S_t)	Std. Error [$\sqrt{Var\ S(t)}$]
Survival Function of Positive Portfolio Momentum					
1	2	174	174	0.6552*** (0.0000)	0.0360
2	3	114	114	0.4425*** (0.0000)	0.0377
3	4	77	77	0.3161*** (0.0000)	0.0352
4	5	55	55	0.2184*** (0.0000)	0.0313
5	6	38	38	0.1437*** (0.0000)	0.0266
6	7	25	25	0.1092*** (0.0001)	0.0236
7	8	19	19	0.0747*** (0.0015)	0.0199
8	9	13	13	0.0460** (0.0135)	0.0159
9	10	8	8	0.0287* (0.0583)	0.0127
10	11	5	5	0.0115 (0.2287)	0.0081
11	12	2	2	0.0000 (N/A)	.
Survival Function of Negative Portfolio Momentum					
1	2	59	32	0.4576*** (0.0000)	0.0649
2	3	27	15	0.2034*** (0.0006)	0.0524
3	4	12	5	0.1186** (0.0168)	0.0421
4	5	7	4	0.0508 (0.1260)	0.0286
5	6	3	2	0.0169 (0.4204)	0.0168
6	7	1	1	0.0000 (N/A)	.

*** Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
* Implies the significance at 10% level of significance

Table A4. 4: KM Estimator of Big Size & Medium book-to-market (BM) Portfolio

This table reports the stepwise calculation (ex-post) of Kaplan-Meier estimator for Big Size & Medium book-to-market (BM) Portfolio, estimated over the sample period October 1980 to June 2014. This calculation allows a thorough description of survival curves. The survival function (S_t) can be interpreted as the probability of trend continuation until failure time $t(j)$ months conditioned upon the fact that the momentum is alive in $t(j)$, where $t(1) \leq t(2) \leq t(k)$. With simple t-test we checked whether the survival function is significantly different from zero. The values in the parentheses reports the p-values of the t-test.

j	Ordered failure time, $t(j)$	Intact before t (n_j)	Ending at time t (d_j)	Survivor Function (S_t)	Std. Error [$\sqrt{Var\ S(t)}$]
Survival Function of Positive Portfolio Momentum					
1	2	165	63	0.6182*** (0.0000)	0.0378
2	3	102	39	0.3818*** (0.0000)	0.0378
3	4	63	24	0.2364*** (0.0000)	0.0331
4	5	39	17	0.1333*** (0.0000)	0.0265
5	6	22	11	0.0667*** (0.0025)	0.0194
6	7	11	3	0.0485** (0.0157)	0.0167
7	8	8	3	0.0303* (0.0568)	0.0133
8	9	5	2	0.0182 (0.1550)	0.0104
9	10	3	2	0.0061 (0.4163)	0.0060
10	11	1	1	0.0000 (N/A)	.
Survival Function of Negative Portfolio Momentum					
1	2	46	30	0.3478*** (0.0000)	0.0702
2	3	16	10	0.1304** (0.0195)	0.0497
3	4	6	4	0.0435 (0.2080)	0.0301
4	5	2	2	0.0000 (N/A)	.

*** Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
* Implies the significance at 10% level of significance

Table A4. 5 : KM Estimator of Big Size & High book-to-market (BH) Portfolio

This table reports the stepwise calculation (ex-post) of Kaplan-Meier estimator for Big Size & High book-to-market **(BH)** Portfolio, estimated over the sample period October 1980 to June 2014. This calculation allows a thorough description of survival curves. The survival function (S_t) can be interpreted as the probability of trend continuation until failure time $t(j)$ months conditioned upon the fact that the momentum is alive in $t(j)$, where $t(1) \leq t(2) \leq t(k)$. With simple t-test we checked whether the survival function is significantly different from zero. The values in the parentheses reports the p-values of the t-test.

j	Ordered failure time, $t(j)$	Intact before t (n_j)	Ending at time t (d_j)	Survivor function (S_t)	Std. Error [$\sqrt{Var\ S(t)}$]
Survival Function of Positive Portfolio Momentum					
1	2	167	58	0.6527*** (0.0000)	0.0368
2	3	109	34	0.4491*** (0.0000)	0.0385
3	4	75	20	0.3293*** (0.0000)	0.0364
4	5	55	15	0.2395*** (0.0000)	0.0330
5	6	40	14	0.1557*** (0.0000)	0.0281
6	7	26	9	0.1018*** (0.0002)	0.0234
7	8	17	6	0.0659*** (0.0034)	0.0192
8	9	11	4	0.0419** (0.0222)	0.0155
9	10	7	3	0.0240* (0.0882)	0.0118
10	11	4	1	0.0180 (0.1789)	0.0103
11	12	3	1	0.0120 (0.2893)	0.0084
12	13	2	1	0.0060 (0.5000)	0.0060
13	14	1	1	0.0000 (N/A)	.
Survival Function of Negative Portfolio Momentum					
1	2	50	32	0.3600*** (0.0000)	0.0679
2	3	18	12	0.1200** (0.0183)	0.0460
3	4	6	4	0.0400 (0.2083)	0.0277
4	5	2	2	0.0000 (N/A)	.

*** Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
* Implies the significance at 10% level of significance

Table A4. 6: Theoretical Survival Function

This table reports the survival function of theoretical survival curve (simulated Random Walk and ARMA (1,1) process). Empirical survival curve is reported here for comparison purpose. Simple t-test is performed to investigate whether the theoretical survival functions are identical to the positive or negative empirical survival functions of corresponding ordered failure time. P-value less than the significance level means that the theoretical survival function is significantly different from their corresponding empirical function.
Survival functions/probabilities are reported in decimal points.

Ordered failure time, $t(j)$	Empirical Survival Function		Theoretical Survival Function			
			Random Walk		ARMA(1,1)	
	Positive Momentum	Negative Momentum	Positive Momentum	Negative Momentum	Positive Momentum	Negative Momentum
Panel A: Small Size & Medium book-to-market (SM) Portfolio						
2	0.6882	0.3333	0.5142***	0.4925**	0.5677***	0.5577***
			(0.0001)	(0.0284)	(0.0054)	(0.0018)
3	0.4785	0.0877	0.2653***	0.2542***	0.3198***	0.3135***
			(0.0000)	(0.0003)	(0.0005)	(0.0000)
4	0.3441	0.0175	0.1358***	0.1327***	0.1749***	0.1772***
			(0.0000)	(0.0000)	(0.0001)	(0.0000)
5	0.2473	0	0.0671***	0.0645	0.0938***	0.0957
			(0.0000)		(0.0000)	
6	0.172		0.0304***	0.0287	0.049***	0.0512
			(0.0000)		(0.0001)	
7	0.1183		0.0121***	0.0104	0.0226***	0.0235
			(0.0001)		(0.0004)	
8	0.0699		0.0035***	0.0025	0.0088***	0.0075
			(0.0016)		(0.0038)	
9	0.0376		0	0	0	0
10	0.0108					
11	0.0054					
12	0					

Table A4.6 (Continued)

Ordered failure time, $t(j)$	Empirical Survival Function		Theoretical Survival Function			
			Random Walk		ARMA(1,1)	
	Positive Momentum	Negative Momentum	Positive Momentum	Negative Momentum	Positive Momentum	Negative Momentum
Panel B: Small Size & High book-to-market (SH) Portfolio						
2	0.6919	0.4355	0.5032*** (0.0000)	0.4826 (0.5200)	0.5598*** (0.0023)	0.5616* (0.0808)
3	0.4865	0.1774	0.2563*** (0.0000)	0.2357 (0.3075)	0.311*** (0.0001)	0.3087** (0.0216)
4	0.3459	0.0645	0.1294*** (0.0000)	0.1139 (0.1906)	0.1722*** (0.0000)	0.168*** (0.0067)
5	0.2432	0.0161	0.0676*** (0.0000)	0.0543* (0.0647)	0.0958*** (0.0001)	0.0883*** (0.0008)
6	0.173	0	0.032*** (0.0000)	0.0232	0.0543*** (0.0003)	0.0435
7	0.1243		0.0138*** (0.0001)	0.0087	0.028*** (0.0006)	0.0204
8	0.0865		0.0047*** (0.0005)	0.0029	0.011*** (0.0012)	0.0076
9	0.0595		0	0	0	0
10	0.0324					
11	0.0216					
12	0.0108					
13	0.0054					
14	0					
Panel C: Big Size & Low book-to-market (BL) Portfolio						
2	0.6552	0.4576	0.5056*** (0.0012)	0.4988 (0.5818)	0.5146*** (0.0022)	0.5204 (0.4000)
3	0.4425	0.2034	0.2544*** (0.0001)	0.2429 (0.5167)	0.262*** (0.0001)	0.2698 (0.2765)
4	0.3161	0.1186	0.127*** (0.0000)	0.1203 (0.9720)	0.1329*** (0.0000)	0.142 (0.6324)
5	0.2184	0.0508	0.0595*** (0.0000)	0.0619 (0.7399)	0.0647*** (0.0000)	0.0764 (0.4479)
6	0.1437	0.0169	0.029*** (0.0002)	0.0317 (0.4670)	0.032*** (0.0003)	0.0405 (0.2533)
7	0.1092	0	0.0115*** (0.0003)	0.0137	0.0133*** (0.0003)	0.0191
8	0.0747		0.0028*** (0.0012)	0.0047	0.0031*** (0.0013)	0.0071
9	0.046		0	0	0	0.0004
10	0.0287					0
11	0.0115					
12	0					

Table A4.6 (Continued)

Ordered failure time, $t(j)$	Empirical Survival Function		Theoretical Survival Function			
			Random Walk		ARMA(1,1)	
	Positive Momentum	Negative Momentum	Positive Momentum	Negative Momentum	Positive Momentum	Negative Momentum
Panel D: Big Size & Medium book-to-market (BM) Portfolio						
2	0.6182	0.3478	0.5053**	0.4809*	0.4759***	0.4524
			(0.0180)	(0.0984)	(0.0030)	(0.1939)
3	0.3818	0.1304	0.2569***	0.2405**	0.2214***	0.205
			(0.0072)	(0.0601)	(0.0005)	(0.1986)
4	0.2364	0.0435	0.1351**	0.1132*	0.1097***	0.0859
			(0.0111)	(0.0574)	(0.0014)	(0.2382)
5	0.1333	0	0.0716*	0.0539	0.0528***	0.0342
			(0.0516)		(0.0099)	
6	0.0667		0.0339	0.0229	0.0225*	0.0107
			(0.1554)		(0.0503)	
7	0.0485		0.0148*	0.0089	0.0094**	0.0021
			(0.0808)		(0.0405)	
8	0.0303		0.0051*	0.003	0.0033*	0.0009
			(0.0935)		(0.0728)	
9	0.0182		0	0	0	0
10	0.0061					
11	0					
Panel E: Big Size & High book-to-market (BH) Portfolio						
2	0.6527	0.36	0.4956***	0.4984*	0.4923***	0.5041*
			(0.0008)***	(0.0761)	(0.0006)	(0.0641)
3	0.4491	0.12	0.256	0.2457**	0.2563***	0.2567**
			(0.0000)	(0.0217)	(0.0000)	(0.0124)
4	0.3293	0.04	0.1266***	0.1164**	0.1263***	0.1241**
			(0.0000)	(0.0259)	(0.0000)	(0.0142)
5	0.2395	0	0.0619***	0.0519	0.0611***	0.056
			(0.0000)		(0.0000)	
6	0.1557		0.0277***	0.0211	0.0269***	0.0237
			(0.0001)		(0.0001)	
7	0.1018		0.0109***	0.0081	0.0098***	0.0089
			(0.0006)		(0.0005)	
8	0.0659		0.0032***	0.002	0.0024***	0.0019
			(0.0036)		(0.0032)	
9	0.0419		0	0	0	0
10	0.024					
11	0.018					
12	0.012					
13	0.006					
14	0					

*** Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
* Implies the significance at 10% level of significance

APPENDIX A5

Figure A5. 1: Box Plot of Sector Alphas of Three-Factor Model

This figure displays the box plot of the alphas that are obtained from the rolling regression of three-factor model.

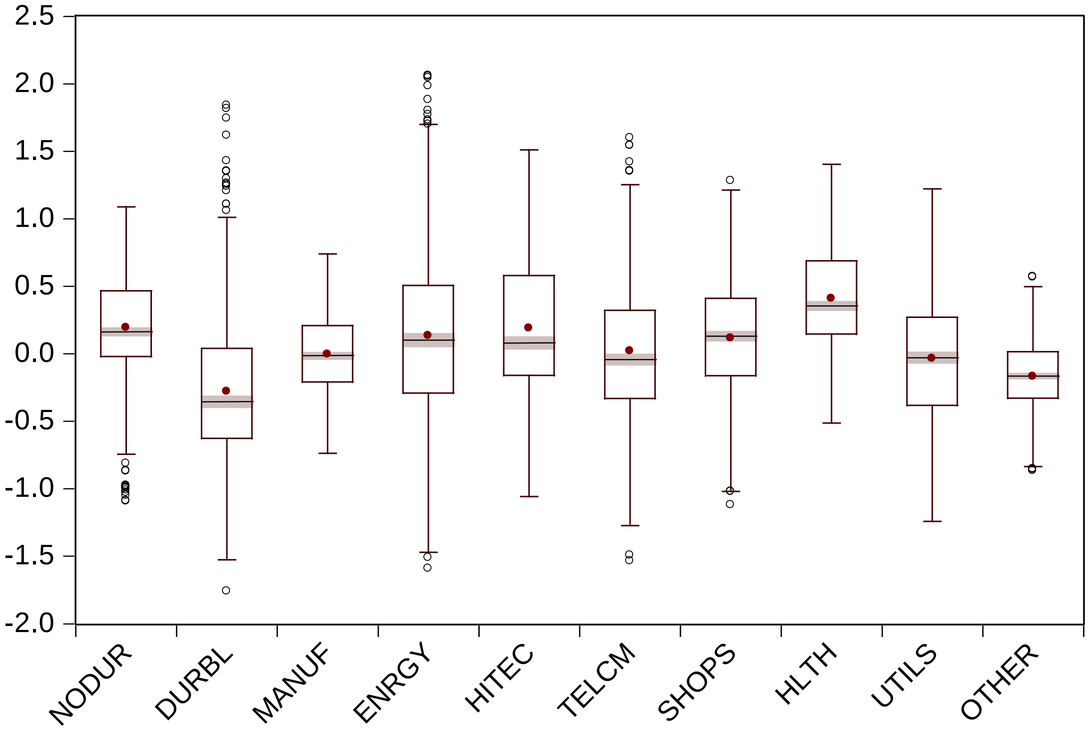


Figure A5. 2: Box Plot of Sector Alphas of Five-Factor Model

This figure displays the box plot of the alphas that are obtained from the rolling regression of five-factor model.

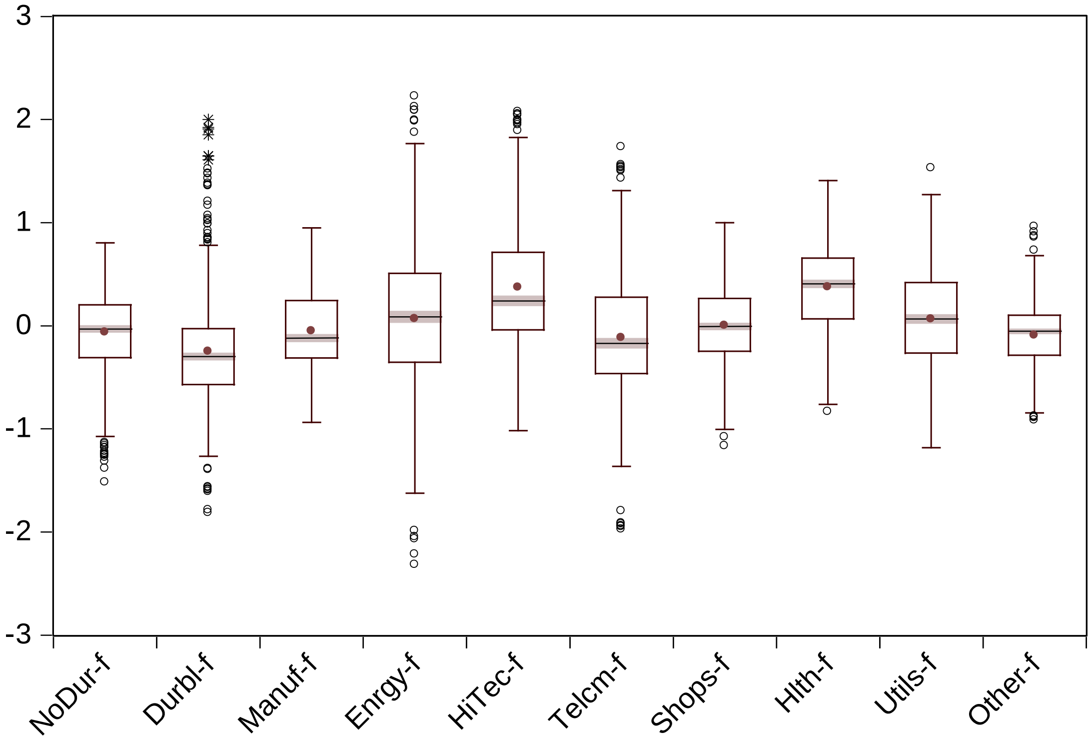


Table A5. 1: P-value matrix of Three-Factor Model Alphas

This table reports the p-value of t-test of Sector Alphas in **3FM**. The 3F alphas are obtained from the rolling window regression of 10 sector portfolio with Fama-French 3 factors over the sample period January 1964 to December 2014. We than perform t-test to check whether the alphas of 10 different sectors are different from each other.
The mean of each sector alphas are within the parentheses of 1st row and 1st column. P-value indicates level of statistical difference from each other.

	NoDur-3F (0.1935)	Durbl-3F (0-.2778)	Manuf-3F (0-.0038)	Enrgy-3F (0.1344)	HiTec-3F (0.1911)	Telcm-3F (0.0202)	Shops-3F (0.1176)	Hlth-3F (0.4101)	Utils-3F (-0.0349)	Other-3F (-0.1672)
NoDur-3F (0.1935)	-	0.0000	0.0000	0.0604	0.9296	0.0000	0.0017	0.0000	0.0000	0.0000
Durbl-3F (-0.2778)		-	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Manuf-3F (-.0038)			-	0.0000	0.0000	0.3047	0.0000	0.0000	0.1793	0.0000
Enrgy-3F (0.1344)				-	0.1033	0.0006	0.5977	0.0000	0.0000	0.0000
HiTec-3F (0.1911)					-	0.0000	0.0096	0.0000	0.0000	0.0000
Telcm-3F 0.0202)						-	0.0002	0.0000	0.0449	0.0000
Shops-3F (0.1176)							-	0.0000	0.0000	0.0000
Hlth-3F (0.4101)								-	0.0000	0.0000
Utils-3F (-0.0349)									-	0.0000
Other-3F (-0.1672)										-

Table A5. 2: P-value matrix of Five-Factor Model Alphas

T-test for the p-value of Sector Alphas in **5FM**. The alphas are obtained from the rolling window regression of 10 sector portfolio with Fama-French 5 factors over the sample period January 1964 to December 2014. We perform t-test to check whether the sector alphas are different from each other. The mean of each sector alphas are within the parentheses of 1st row and 1st column. P-value indicates level of statistical difference from each other.

	Nodur-5F (-0.0612)	Durbl-5F (-0.2499)	Manuf-5F (-0.0503)	Enrgy-5F (0.0669)	Hitec-5F (0.3721)	Telcm-5F (-0.1146)	Shops-5F (0.0029)	Hlth-5F (0.3773)	Utils-5F (0.0641)	Other-5F (-0.0919)
Nodur-5F (-0.0612)	-	0.0000	0.6353	0.0003	0.0000	0.0650	0.0069	0.0000	0.0000	0.1514
Durbl-5F (-0.2499)		-	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Manuf-5F (-0.0503)			-	0.0006	0.0000	0.0208	0.0175	0.0000	0.0000	0.0365
Enrgy-5F (0.0669)				-	0.0000	0.0000	0.0650	0.0000	0.9376	0.0000
Hitec-5F (0.3721)					-	0.0000	0.0000	0.8681	0.0000	0.0000
Telcm-5F (-0.1146)						-	0.0000	0.0000	0.0000	0.3928
Shops-5F (0.0029)							-	0.0000	0.0145	0.0000
Hlth-5F (0.3773)								-	0.0000	0.0000
Utils-5F (0.0641)									-	0.0000
Other-5F (-0.0919)										-

Table A5. 3: Industry Definition and SIC codes of Sector Portfolios

Sector Names	Abbrevia-tion	Industries	SIC Codes
NoDur	Consumer Non Durables	Food, Tobacco, Textiles, Apparel, Leather, Toys	0100-09992000-23992700-27492770-2799 3100-3199 3940-3989
Durbl	Consumer Durables	Cars, TV's, Furniture, Household Appliances	2500-2519 2590-2599 3630-3659 3710-3711 3714-3714 3716-3716 3750-3751 3792-3792 3900-3939 3990-3999
Manuf	Manufactu-ring	Machinery, Trucks, Planes, Chemicals, Office Furniture, Paper, Computer Printing	2520-2589 2600-2699 2750-2769 2800-2829 2840-2899 3000-3099 3200-3569 3580-3621 3623-3629 3700-3709 3712-3713 3715-3715 3717-3749 3752-3791 3793-3799 3860-3899
Enrgy	Energy	Oil, Gas, and Coal Extraction and Products	1200-1399 2900-2999
HiTec	Business Equipment	Computers, Software, and Electronic Equipment	3570-3579 3622-3622 (Industrial controls) 3660-3692 3694-3699 3810-3839 7370-7372 (Services - computer programming and data processing) 7373-7373 (Computer integrated systems design) 7374-7374 (Services - computer processing, data preparation) 7375-7375 (Services - information retrieval services) 7376-7376 (Services - computer facilities management service) 7377-7377 (Services - computer rental and leasing) 7378-7378 (Services - computer maintenance and repair) 7379-7379 (Services - computer related services) 7391-7391 (Services - R&D labs) 8730-8734 (Services - research, development, testing labs)
Telcm	Tele-communic-ation	Telephone & TV Transmission	4800-4899
Shops	Shops	Wholesale, Retail, & Some Services (Laundries, Repair Shops)	5000-5999 7200-7299 7600-7699
Hlth	Health	Healthcare, Medical Equipment, & Drugs	2830-2839 3693-3693 3840-3859 8000-8099
Utils	Utilities	Utilities	4900-4949
Other	Other	Mines, Constructions, Building materials, Trans, Hotels, Bus Services, Entertainment, Finance	

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