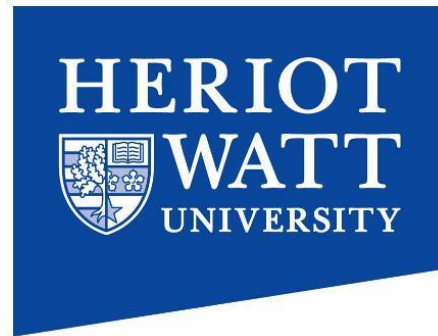


Liquidity, Momentum and Price Bubbles: Evidence From the UK

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Abstract

The asset pricing anomalies have existed in the UK stock market for a long time. This thesis aims to study different liquidity measures, liquidity commonality, systematic liquidity risk, different momentum trading strategies, asset pricing risks with momentum, investor behaviours with momentum and the causal link between financial crisis and asset pricing anomalies using various methods and tests.

The first empirical chapter examines the performance of the standard Sharpe-Lintner CAPM, the Fama-French three factor model, and the four factor model of Carhart (1997) both with, and without, the first component of multiple illiquidity measures. The results show that no individual illiquidity proxy outperforms the others, and further that the illiquidity proxies have a systematic common illiquidity component. The results also reveal that the inclusion of the illiquidity factor in the capital asset pricing model plays a significant role in explaining the cross-sectional variation in stock returns. The second empirical chapter analyses the relationship between momentum profits and stock market illiquidity. This study finds negative and significant relationship between aggregate market illiquidity and momentum profits. The model applied in this chapter captures significant bounce in varying beta coefficients changing over time. The analysis also indicates that the stocks associated with high liquidity performs better relative to illiquid stocks under systemic shocks. The final empirical chapter investigated momentum anomaly and the hypothesis that individual investors trade differently from institutional investors and significantly overreact to economic shocks, creating destabilising effect in the stock market. The results reveal that stock

market inefficiency is driven and dominated by individual investors' anchoring and adjustment biases as well as institutional investors' cognitive biases.

There are several implications for this work. The findings may be useful for both individual and institutional investors and regulators in similar markets beyond the UK, for example, the other European markets. In this study, we show that abnormal stock performance during liquidity crisis is, in part, predictable, and investors can construct portfolios of stocks that better withstand liquidity shocks. For individual investors, they can maximise their profits by holding momentum portfolios at a short horizon. For institutional investors, they might take advantage of professional expertise in making abnormal profits. Policy makers are expected to pay special attention to the differences in trading by financial institutions and individual investors.

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Chapter 1

Introduction

1.1 Research Background

The dot.com bubble in the 1990s and recent 2007-2009 global financial crisis have made the price bubble phenomena hard to ignore. Typically, the equity premium puzzle has attracted lots of attention in literature in the context of asset pricing models (e.g. (Carhart, 1997; Fama and French, 1993, 2015; Sharpe, 1964)). Although the literature have proposed several possible explanations for the puzzle, researchers haven't reached into consensus regarding a satisfactory explanation. This work therefore focuses on exploring and explaining the two most common market anomalies: liquidity and momentum. These two anomalies are often regarded as the contributing components of excess equity returns (Fama and French, 2015).

The role of liquidity in asset pricing has grown rapidly over the past few years. Liquidity is often viewed as an important feature of the investment environment and the macro economy. Recent studies find that fluctuations in various measures of liquidity are correlated across assets (e.g. (Gissler, 2016; Korajczyk and Sadka, 2008; Mancini, Ranaldo, and Wrampelmeyer, 2013)). Furthermore, the

importance of liquidity on security returns has been confirmed by numerous previous empirical studies, which have thus established liquidity as a key consideration in investment decisions. However, using liquidity-based explanations are not straightforward. A difficulty in testing the liquidity-based explanation lies in the fact that stock liquidity is a subjective concept and is very hard to measure. However, whilst liquidity is an elusive concept, most market participants agree that liquidity generally reflects the ability to buy or sell sufficient quantities quickly, at low trading cost, and without impacting the market price too much. Consequently, a vast number of measures have been used to approximate the extent to which a stock is illiquid or liquid.

Despite the increasing interest in the role of liquidity in equity markets in general, and asset pricing in particular, a universal definition for liquidity remains elusive, and the basic question of how to measure liquidity remains unsolved. For example, Hasbrouck (2002) and Goyenko, Holden, and Trzcinka (2009) find that the measures are of a different quality themselves. They find that different measures have conflicting impact on stock returns: Amihud's price to volume measure is reported to have significant impact on stock returns but Pastor and Stambaugh's γ is tested to have very little impact. In fact, if the empirical results are based solely on one particular measure, it is difficult to ascertain whether the results are driven by measure-specific components or by some common components of the measured illiquidity. Therefore, it is important to reconcile the conflict by collapsing all existing measures into one measure. This thesis therefore focuses on solving the liquidity measure puzzle and the pricing power of illiquidity in traditional asset pricing models.

Momentum effect, on the other hand, is another puzzling equity anomaly in the finance literature since it was first documented by Jegadeesh and Titman (1993). A number of studies have been carried out to attempt to clarify whether this anomaly is global and where exactly the underlying factors may derive from (e.g., (George

and Hwang, 2004; Jegadeesh and Titman, 1993; Lewellen, 2002; Moskowitz and Grinblatt, 1999; Novy-Marx, 2012)).

There are many different sources of momentum profits, including risk related explanations, data snooping and flawed methodology, and behavioural explanations. The debate initially focused on the risk-side of explanations, specifying that macroeconomic risks cause momentum (Avramov and Chordia, 2006; Bansal, Dittmar, and Lundblad, 2005; Conrad and Kaul, 1998; Fama and French, 1996; Griffin, Ji, and Martin, 2003; Liu and Zhang, 2008; Pástor and Stambaugh, 2003). Yet, this debate soon shifted to broader topics, the behavioural side to explain momentum profits by revisiting the investors' self-attributive overconfidence (Avramov, Cheng, and Hameed, 2014; Baker and Stein, 2004; Barberis, Shleifer, and Vishny, 1998; Hong, Lim, and Stein, 2000). The reason as to why researchers are yet to reach into consensus is arguably because on the one hand, psychological explanations tend to ignore the risks that drive momentum patterns. On the other hand, it is arguably challenging to make conclusions about rational risk-based explanations because it is difficult to interpret why a recent rise in a stock's price transpires to be more risky. In fact, much research fails to find direct evidence to suggest that risk drives momentum. Consequently, behavioural finance provides several possible explanations through psychological models, for example, signal model for the observed momentum profits (Daniel and Hirshleifer, 2015). Models are constructed according to how people behave: some are based on psychological biases of investors that make systematic errors in forming beliefs and preferences, while other models are built on the interactions among various investor types. Models can be generally divided into two groups: one is based on investors' under-reaction to new information and the other is based on people's overreaction to sudden news. For under-reaction, stock prices react less than they should do according to the EMH. In contrast, overreaction causes stock

prices to react much stronger than they should be according to the EMH. Therefore, both of the two biases are reflected in the models as the stock prices move gradually to the equilibrium point. This thesis therefore discusses both risk-side and behavioural-side explanations of momentum anomaly and also explores the possible link between illiquidity and momentum anomaly.

When interpreting momentum returns, the literature tend to ignore the differences between individual and institutional investors. In fact, individual investors were reported to hold 10.7% of shares listed on the London Stock Exchange by the end of 2012 (NationalStatistics, 2013). These investors are often criticised for their irrational investment decisions. For example, Barber and Odean (2011) reported that individual investors tend to excessively trade stocks, which resulting in higher transaction costs. It is also argued that due to their limited capital, individual investors are more likely to hold non-diversified portfolios (Statman, 2004). Indeed, individual investors have been treated as noise traders because of their constant decision-making errors (De Bondt, 1998). This is in line with Barber, Lee, Liu, and Odean (2009), who documented that individual investors have lost an annual average of 3.8% points in portfolio performances in Taiwan in general.

Yet, although individual investors are documented to be at a disadvantage in trading against professionals in terms of skills (Barber et al., 2009; Gao and Lin, 2015; Li, Wang, and Rhee, 2015; Tekçe, Yılmaz, and Bildik, 2016), the literature tends to neglect the fact that individuals do indeed make profits. In addition, the distinct characteristics of individual investors suggest that momentum trading can benefit this group more because such strategies do not require extensive financial knowledge. Investors only need to buy and sell based on a typical strategy. Hence, individual stocks are recommended for them to follow momentum trading patterns. The existing research mostly focuses on institutional traders who select a large amount of stocks in portfolios. Clearly, small investors are not in these

financial positions for such large portfolios. In this line, Goetzmann and Kumar (2008) document that US individual investors hold an average of only three or four shares in each portfolio. This thesis investigates the behaviours of the two types of the investors in the UK stock market and explores further on the momentum anomaly. The following section presents the background of the UK stock market.

1.2 The UK Stock Market Background

This research specifically focuses on the UK market. This section provides information about the UK stock market characteristics and briefly discusses the differences between the UK and the US stock market.

The London Stock Exchange (LSE) is home to about 2,500 companies. The Exchange is the largest stock exchange in Europe ahead of the Euronext. It consists of four markets: the Main Market, the Professional Securities Market (PSM), the Specialist Fund Market and Alternative Investment Market (AIM). This thesis mainly deals with the stocks listed in the Main Market, which includes flagship companies that are larger and more established. The Main Market represents a badge of quality for every company admitted and traded on it. It is therefore a reliable source to conduct the research. Specifically, this thesis studies the companies listed on the FTSE All-Share Index, which is a capitalisation-weighted index that include companies traded on the London Stock Exchange. The constituents of this index involves 627 companies that represent at least 98% of the full capital value of all qualified UK companies. To be qualified for FTSE All-Share Index, companies must have a full listing on the LSE with a pound sterling or Euro denominated price on SETS or SETSmm or a firm quotation on SEAQ or seats. It therefore represents the UK stock market characteristics (Opong, Mulholland, Fox, and Farahmand, 1999). Figure 1.1 shows the number of companies listed on the UK Main Market by equity market value by June 2016.

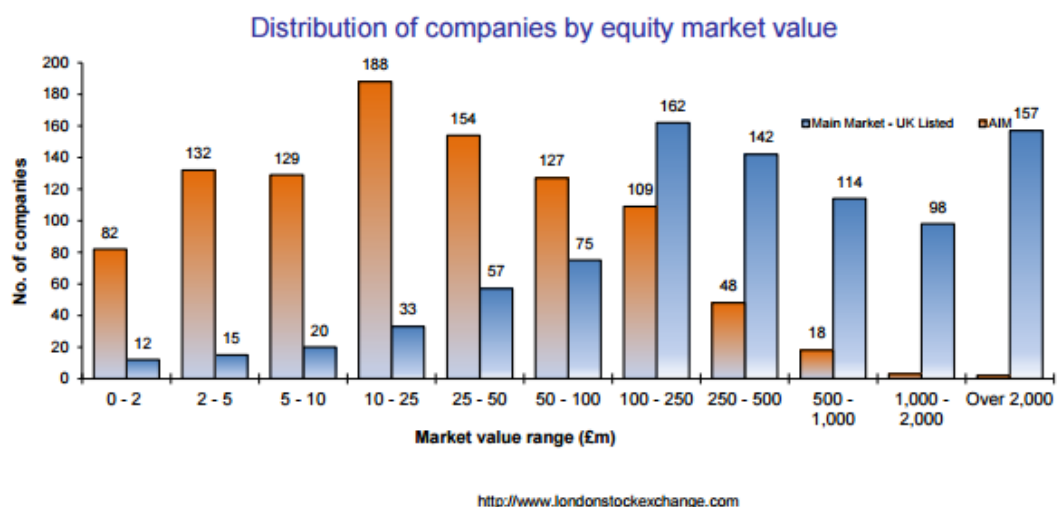


Figure 1.1: UK Main Market Statistics: June 2016

London has acquired an enviable level of global reach over the past decades and has gained significant financial influences. Therefore, it is important to conduct local research in terms of liquidity and momentum in capital market. Interestingly, although the UK equity market uniquely stands out in the global market, it is reported to have suffered from infrequent and non-synchronous trading (Hon and Tonks, 2003). This has caused biased results in efficient market researches (Barnes, 2016). It is therefore important to study equity puzzle in this market in particular. There are indeed differences between the UK and the US environment in terms of trading and market structure. In the UK, all trading takes place on the London Stock Exchange (LSE), whereas in the US stocks are traded primarily on the Nasdaq and NYSE. In the US, trading on Nasdaq is based on order book driven while the NYSE uses a hybrid system. In the case of the UK, trading on the LSE is a mix of order book driven (SETS) and a hybrid quote/order book driven system. Furthermore, the UK is a bank-based system, which is more vulnerable to liquidity crunches than capital market-based system (US) because the first-order risk is bank solvency and the level of risk lies with financial institutions (Hardie and Maxfield, 2010). Since most studies on liquidity and momentum are

predominantly based on US data, in this thesis, the author seeks to investigate if differences in market structure and liquidity characteristics of a country will lead to different results (Foran, Hutchinson, and O’Sullivan, 2014; Huang and Stoll, 2001).

1.3 Aims, Motivations and Contributions

The thesis is composed of three empirical chapters focusing on asset pricing anomalies in the UK market. They are illiquidity premium, momentum premium with illiquidity, and momentum premium with behavioural biases, representing chapters 2, 3, and 4 respectively. Each chapter has its own literature review, methodology and empirical findings.

Chapter 2 aims to provide answers to a number of questions. Firstly, based on existing illiquidity measures, is there a single illiquidity proxy that can significantly outperform other proxies with robust illiquidity premiums in asset pricing models in the UK? Secondly, does liquidity commonality exist in the UK? Thirdly, which liquidity-adjusted asset pricing model explains stock returns in the UK? Finally, do the results vary between parametric and non-parametric tests? This study reviews the effects of illiquidity on asset pricing in the UK stock market and contributes to the asset pricing literature in several ways. In contrast to the Fama and French (2015)’s indirect liquidity, the author uses UK data and examines the price of the common systematic components of illiquidity. The author defines ‘illiquidity factor’ as the spread return of equal-weighted portfolios. These portfolios are constructed on the basis of the first principal component of the first seven illiquidity measures. Further, rather than the conventional parametric tests of asset pricing models, the Hansen-Jagannathan distance is used to examine non-parametrically the level of errors associated with the liquidity capital asset pricing model (LCAPM). This helps shed light on these errors as an indication

on the efficiency of the models.

Chapter 3 aims to investigate the explanations on liquidity risks, by examining how market liquidity affects momentum payoffs. It deals with the momentum anomaly and its behavioural and risk-side explanations from the UK stock market. This chapter contributes to the seemingly contradictory impacts of illiquidity on momentum returns in several ways. First, this chapter provides empirical evidence that is consistent with recent theoretical work on the behavioural-side of explanations about momentum phenomenon, helping bolster a fairly thin research base. For example, Avramov et al. (2014) show that periods of high market illiquidity are followed by low and negative momentum returns. They argue that during market recession, overconfident investors decide to opt out of the market due to short-sale constraints and this reduces market liquidity and the momentum effect thereby becomes less powerful. The measure of illiquidity adopted in this chapter, on the other hand, combines not only liquidity impact features but also liquidity risk features. In addition to the behavioural-side of explanations, the author provides new evidence suggesting that liquidity risk provides momentum profits. Second, this study contributes to the emerging body of empirical literature on applying varying coefficient models. For momentum payoffs, the existing literature has to date not yet considered the effect during financial crisis. The semi-parametric approach is different from existing literature that mostly assumes linearity and constant beta coefficients. The results present a high heterogeneity, and as such this work increases the accuracy and flexibility of estimations. Third, this chapter contributes specifically to the UK empirical literature by exploiting local shock in 2007. The sudden bank run event of Northern Rock is market specific. The author uses the ‘difference-in-differences’ estimation method, as well as both the in- and out-of-sample experiments so as to find the predictive power of market illiquidity on momentum profits.

Chapter 4 explores the role of institutional and individual investors in momentum tradings and aims to examine both anchored and unanchored momentum strategies for each type of investors. The author uses the 52-week-high momentum strategy as a proxy for information uncertainty to investigate the behavioural differences of the two types of investors. Furthermore, by applying ‘difference in differences’ methodology, this empirical study tends to identify the causal link of momentum crash and negative economic shock and the corresponding selection bias for both institutional and individual investors. This third empirical chapter contributes to the momentum literature in the following ways. Firstly, the author examines various holding horizons of GH momentum returns for both individual and institutional investors in the UK. Although momentum pattern has been documented to have generated significant returns for investors, the existing studies mostly demonstrated the institutional investors. Notably, retail investors are often neglected because of barriers such as the relatively small amounts of capital they have invested, trading frictions and nonstandard trading horizons. However, momentum trading can be applicable to individual investors because it does not require profound investing expertise and is easy to conduct (Siganos, 2010). Therefore, in addition to conventional momentum strategies that applies to institutional investors, this study investigates the profitability of the momentum trading when only small numbers of firms are selected to construct winner and loser portfolios. Secondly, this study examines the rolling holding horizons from 3 months to 5 years of momentum profits in a 26-year sample period. The findings show significant and positive GH momentum returns for both institutional and individual investors in the UK. In particular, individual investors can profit more from the sell side loser portfolios. The momentum profits do not revert even in the long run. Thirdly, this study links the 52-week-high momentum with information uncertainty and finds that price momentum is partly driven by individual traders

who suffer from initial under-reaction to new information due to ‘anchoring biases’. During times of greater information uncertainty, individual investors tend to apply the 52-week-high price as an anchor more than institutional investors do, in particular from the sell-side. Fourthly, this study further links analysts’ forecasts with the 52-week-high momentum and find that institutional investors who have access to analysts’ earnings forecasts revisions are more likely to facilitate market efficiency. This further demonstrates that stock market inefficiency is partly driven by individual investors. Finally, this study examines the causal link between investor behaviours and momentum crashes. Importantly, the study exploits the sudden financial crisis as a negative shock. The difference-in-differences (DID) model suggests that large negative economic shock significantly affects institutional portfolio returns. In addition, this chapter confirms the presence of cognitive bias of institutional investors as evidenced by their use of ‘unanchored momentum strategy’.

1.4 Main Findings

This thesis has three empirical dimensions including illiquidity premiums and expected stock returns, semi-varying momentum payoffs and illiquidity, and the 52-week high momentum strategy and information uncertainty. The main findings of each chapter is summarized below.

1.4.1 Main Findings From the First Empirical Study (Chapter 2)

This study examined the relative importance of liquidity risk for the time-series and cross-section of stock returns in the UK. The initial investigation suggested that no individual illiquidity proxy outperforms the others, and further that the illiquidity proxies have a systematic common illiquidity component. Hence, the

author proposed a simple way to capture the multidimensionality of illiquidity. The analysis indicated that existing illiquidity measures have considerable asset specific components, which justifies this new approach. Further, the author used an alternative test of the Amihud (2002) measure and parametric and non-parametric methods to investigate whether liquidity risk is priced in the UK. The study found that the inclusion of the illiquidity factor in the capital asset pricing model plays a significant role in explaining the cross-sectional variation in stock returns, in particular with the Fama-French three-factor model. Further, using Hansen-Jagannathan non-parametric bounds, the study demonstrated that the illiquidity-augmented capital asset pricing models yield a small distance error, other non-liquidity based models failed to yield economically plausible distance values.

1.4.2 Main Findings From the Second Empirical Study (Chapter 3)

Marketwide liquidity appears to be a state variable that is important for pricing common stocks and explaining momentum profits. The study analysed the relationship between momentum profits and stock market illiquidity. The findings show that the periods of high market illiquidity are followed by low momentum profits, and very often negative returns. In the presence of aggregate illiquidity, the power of the competing state variables (for example, the down market condition) has disappeared. Furthermore, the semi-parametric tests, the time varying coefficient models and out-of-sample performance have been used to analyse the ability of the state of market illiquidity to explain and predict momentum payoffs at both the portfolio and individual levels. The study found significant bounce in varying beta coefficients changing over time. Consequently, the models captured more precise beta coefficients in the estimation compared to those linear

parametric tests, which assume linearity and smooth the line of slope coefficients. Furthermore, this study captured the significant momentum crash and the increase of liquidity risks during the financial crisis. The analysis also indicated that the stocks associated with high illiquidity are more sensitive to systemic shocks.

1.4.3 Main Findings From the Third Empirical Study (Chapter 4)

This study examined the driver of the 52-week high momentum strategy and whether this strategy's profitability can be explained by anchoring, which is a behavioral bias of both individual and institutional investors. The study demonstrated that individual investors trade differently from institutional investors and significantly overreacted to economic shocks, providing destabilising effect in the stock market due to inexperience. Institutional investors, on the other hand, are more experienced. Using analysts' earnings forecast revision ratio, the findings suggested that experienced institutional investors are more likely to incorporate momentum signals and eventually translate their forecast revisions as news. The additional tests of an unanchored strategy confirmed that the 52-week-high momentum is significantly correlated with semi-strong efficient market because unanchored strategies tend to crash and revert during periods of crowded trading caused by institutional investors. The contradictory effect of information uncertainty on winner and loser stocks implied that the 52-week-high profits are increasing with uncertainty measures. Importantly, the study found that stock market inefficiency is driven and dominated by individual investors' anchoring and adjustment biases as well as institutional investors' cognitive biases.

1.5 Outline of the Study

The thesis is organised in the following ways. Chapter 1 presents an introduction of the whole thesis. Chapter 2 details the illiquidity anomaly in asset pricing models applied in the UK. Chapter 3 details the liquidity risk in explaining momentum anomaly. The behavioural explanations of momentum is presented in chapter 4. Chapter 5 concludes this thesis.

Chapter 2

Illiquidity Premium and Expected Stock Returns: A new Approach

2.1 Introduction

The role of liquidity in asset pricing has grown rapidly over the past few years. A variety of studies have proposed different illiquidity measures as proxies for illiquidity by investors. However, although researchers are able to test whether the stock returns are statistically related to their illiquidity measures, their results generate conflicting impacts over stock returns. In other words, despite the increasing interest in the role of liquidity in equity markets in general, and asset pricing in particular, a universal definition for liquidity remains elusive, and the basic question of how to measure liquidity remains unsolved.¹ For example, Hasbrouck (2002) and Goyenko et al. (2009) find that the measures are of a different quality themselves. They find that different measures have conflicting impact on

¹Liquidity is a broad and elusive concept that generally denotes the ability to trade large quantities quickly, at low cost, and without moving the price. Financial literature indicates that rational investors who think they hold shares in exchange for lower returns with higher degree of liquidity they claim.

stock returns: Amihud's price to volume measure is reported to have significant impact on stock returns but Pastor and Stambaugh's gamma is tested to have very little impact. In fact, if the empirical results are based solely on one particular measure, it is difficult to ascertain whether the results are driven by measure-specific components or by some common components of the measured illiquidity. Therefore, it is important to reconcile the conflict by collapsing all existing measures into one measure. Given the fact that strong evidence against the reliability of a single illiquidity measure exists, in this chapter, the author adopts not only individual measures, but also constructs a comprehensive illiquidity proxy. This illiquidity proxy is used across seven different measures and examines whether the pricing of liquidity risks varies amongst these measures. In particular, the author adopts illiquidity measures introduced by Amihud (2002), Pástor and Stambaugh (2003), zero-return measures proposed by Lesmond, Ogden, and Trzcinka (1999) and Liu (2006), Roll's (1984) effective bid-ask spread measure (Roll, 1984), the price-based spread measure of Corwin and Schultz (2012) and the effective tick measure from Goyenko et al. (2009). Consistent with Korajczyk and Sadka (2008) and Kim and Lee (2014), the author finds around 33% of the variation in illiquidity proxies is explained by the first principal component, which further suggests that systematic common components exist in illiquidity measures.

This chapter contributes to understanding of the seemingly contradictory effects of illiquidity on asset pricing in several ways. It is generally the case that recent researchers have focused on new factors that contribute to traditional asset pricing models. Indeed, Fama and French (2015) propose a brand new five-factor model while adopting indirect factor to denote liquidity. In contrast, the author uses UK data and examines the price of the common systematic components of illiquidity. There are indeed differences between the UK and the US environment in terms of trading and market structure. In the UK, all trading takes place on the London Stock Exchange (LSE) whereas in the US stocks are traded primarily

on the Nasdaq and NYSE. In the US, trading on Nasdaq is based on order book driven while the NYSE uses a hybrid system. In the case of the UK, trading on the LSE is a mix of order book driven (SETS) and a hybrid quote/order book driven system. Furthermore, the UK is a bank-based system, which is more vulnerable to liquidity crunches than capital market-based system (US) because the first-order risk is bank solvency and the level of risk lies with financial institutions (Hardie and Maxfield, 2010). Since most studies on illiquidity premium and expected stock returns are predominantly based on US data, in this chapter the author seeks to investigate if differences in market structure and liquidity characteristics of a country will lead to different results (Foran et al., 2014; Huang and Stoll, 2001). This thesis defines ‘illiquidity factor’ as the spread return of equal-weighted portfolios $P10-P1$. These portfolios are constructed on the basis of the first principal component of the first seven illiquidity measures. Further, rather than the conventional parametric tests of asset pricing models, the author uses Hansen-Jagannathan distance to examine non-parametrically the level of errors associated with the liquidity capital asset pricing model (LCAPM). This helps shed light on these errors as an indication on the efficiency of the models.

This chapter aims to provide answers to a number of questions. Firstly, based on existing illiquidity measures, is there a single illiquidity proxy that can significantly outperform other proxies with robust illiquidity premiums in asset pricing models in the UK? Secondly, does liquidity commonality exist in the UK? Thirdly, which liquidity-adjusted asset pricing model explains stock returns in the UK? Finally, do the results vary between parametric and non-parametric tests?

The remainder of the chapter is set out as follows. Section 2.2 provides a brief review of the literature on the illiquidity framework. Section 2.3 provides details of the methodology and models the author used to answer all questions. Section 2.4 presents the data and variable construction. Section 2.5 presents the empirical results and section 2.6 concludes.

2.2 Literature Review

What kinds of risk systematically drive stock prices? This question has prompted vast amounts of research and continues to exist as one of the main challenges in finance. The Sharpe-Lintner CAPM (1964) was the first attempt to answer this question by quantifying the risk which is attributable to general market fluctuations (Sharpe, 1964).

Yet, although the Sharpe-Lintner CAPM provides a theoretical framework to explain stock returns, the ability of the model to describe asset returns is weak. Indeed doubts regarding the empirical validity of the model are well established and it is both frequently rejected by data and also known to ignore some well documented anomalies, see *inter alia* (Black, 1972; Fama and MacBeth, 1973; Gibbons, 1982; Hyde and Sherif, 2005; Stambaugh, 1982). Traditional tests of the CAPM assume that the market portfolio is observable, expected returns are constant, and that assets' betas are stationary over a fixed period. Further, it measures risk by beta, which is a consequence of its questionable assumption of the existence of an equilibrium in which investors display mean-variance behaviour and requires the distribution of stock returns to be symmetrical.

The failure of the Sharpe-Lintner CAPM to capture the behaviour of the data and to measure a stock's or a portfolio's volatility has led to a number of different approaches that have attempted to address the limitations of the model. For instance, the three-factor model Fama and French (1993) and the Carhart (1997) model have received significant attention in empirical research. Whilst Fama and French (1993) demonstrate that asset prices are influenced not only by market systematic risk, but also the size and value factors, Carhart (1997) argues that momentum is an important risk factor which has not been priced in assets.

Recently, much attention has been given to market friction and in particular it has been widely argued that liquidity, see *inter alia* (Amihud, 2002; Bekaert, Harvey,

and Lundblad, 2007; Chan and Faff, 2005; Chordia, Roll, and Subrahmanyam, 2001; Goyenko, Holden, and Trzcinka, 2009; Hasbrouck, 2002; Liu, 2006; Pástor and Stambaugh, 2003), appears to be a suitable candidate for a priced state variable. For example, Lillo, Farmer, and Mantegna (2002) suggest that liquidity fluctuation is a permanent market impact. However, Bouchaud, Kockelkoren, and Potters (2006) argue that the impact power is transient and will decay in time. In fact, liquidity is often viewed as an important feature of the investment environment and the macro economy, and recent studies find that fluctuations in various measures of liquidity are correlated across assets. Furthermore, the importance of liquidity on security returns has been confirmed by numerous previous empirical studies, which have thus established liquidity as a key consideration in investment decisions.

Nevertheless, using liquidity-based explanations are not straightforward. A difficulty in testing the liquidity-based explanation lies in the fact that stock liquidity is a subjective concept and is very hard to measure. However, whilst liquidity is an elusive concept, most market participants agree that liquidity generally reflects the ability to buy or sell sufficient quantities quickly, at low trading cost, and without impacting the market price too much. Consequently, a vast number of measures have been used to approximate the extent to which a stock is illiquid or liquid. The first set of illiquidity measures have been based on stock daily returns or trading volume. Amihud (2002) proposes a simple and intuitive illiquidity measure, which is defined as the absolute daily return divided by daily trading volume. Acharya and Pedersen (2005) use the illiquidity proxy of Amihud (2002) and find evidence to support the model in the US market over the period 1962-1999. Elsewhere, Pástor and Stambaugh (2003) have proposed an illiquidity measure called 'price sensitivity to order flow', which is based on return reversal due to heavy trading volume. Another illiquidity proxy is the turnover measured by daily share trading volume divided by the number of total shares outstanding.

The second set of illiquidity indicators are based exclusively on returns and provide a simple way of obtaining illiquidity proxy. For example, Liu (2006) proposes a trading volume-adjusted zero return measure and shows that the illiquidity measured by the proposed indicator is in fact priced in as far as the US market is concerned. It is worth noting that the zero return indicator is a number of zero return days scaled by the total available trading days in a given period. This measure indicates that on a day when trading cost is high, informed traders would not trade, resulting in zero return on that day. This measure is especially reliable in international finance research, as a high quality daily trading volume is not guaranteed (Bekaert et al., 2007; Lee, 2011). In addition, Lesmond et al. (1999) also propose an illiquidity measure based solely on daily returns. It was shown to be significantly correlated with the spread data and is used to show the illusionary aspect of momentum trading (Lesmond, Schill, and Zhou, 2004).

The third set of measures is based on return correlation, effective tick, and effective spread. Roll (1984) and Goyenko et al. (2009) suggest a proxy of spread based on the serial correlation of daily returns and effective spread. Also, in a recent study, Das and Hanouna (2010) create a measure of illiquidity based on ‘run length’, which totals the consecutive series of positive and negative daily returns before the sign reverses. The authors further highlight that this particular illiquidity measure acts as a proxy for price impact.

2.2.1 Illiquidity Measures

Much literature suggests a number of proxies for illiquidity that are used as time-series conditioning variables. However, there are no agreed or final measures, and researchers have not yet reached an agreement regarding the optimal illiquidity proxy. In recent studies, Liu (2009) examine seven individual illiquidity measures. According to their findings, some proxies perform better than others in asset pricing models, which shows a more significant and robust illiquid premium.

However, their results remain inconclusive regarding the most suitable illiquidity proxy. Arguably, a possible solution to find a suitable illiquidity proxy is an alternative method that extracts commonality of illiquidity risk. Indeed, recent researchers have implemented multiple illiquidity measures to gauge the robustness of their results. For example, Korajczyk and Sadka (2008) adopted multiple proxies and found that the illiquidity commonality exists among their measures. Similarly, Kim and Lee (2014) further found that the systematic common component of illiquidity measures risk in the US.

In this chapter, the author complements such approaches and adds to the field by testing illiquidity individually. This study forms a composite index of illiquidity based on the common variation of a number of proxies for illiquidity, including turnover ratio, reversal measure of illiquidity, trading volume, bid-ask spread, effective spread, and number of zero return days.

1 Return/Value Ratio (Amihud, 2002)

The first illiquidity measure is the return to volume ratio proposed by Amihud (2002) to estimate illiquidity of stocks. This measure has been widely used in empirical literature because of its easiness of construction (Acharya and Pedersen, 2005). However, it is so far not clear that Amihud's measure would be priced, due to the compensation for price impact in comparison to other proxies which is something that requires further investigation.

Amihud defines illiquidity of stock i in time t as:

$$RV_i \equiv ILLIQ_t^i = \frac{1}{Days_t^i} \sum_{d=1}^{Days_t^i} \frac{|R_t^i|}{V_t^i} \quad (2.2.1)$$

where R_t^i is the return on day d in month t , V_t^i is the dollar volume (in millions) on day d in month t , and $Days_t^i$ is the number of valid observation days in month t for

stock i . In particular, V_t^i in this chapter represents GB pound sterling (hereafter referred to as pound) volume (in millions) for the UK.

2 Reversal Measure of illiquidity (Pástor and Stambaugh, 2003)

The reversal measure of illiquidity has been advocated by Pástor and Stambaugh (2003). This measure reflects the return reversal after trading: the larger the volume, the larger the return reversal, and the larger the cost. Yet, one drawback of this measure is that it is time consuming in a real-time estimation. The measure is identified as:

$$r_{i,d+1,t} - r_{M,d+1,t} = \alpha_{i,t} + \beta_{i,t}r_{i,d,t} + \gamma_{i,t}sign(r_{i,d,t} - r_{M,d,t})dvol_{i,d,t} + \epsilon_{i,d,t}. \quad (2.2.2)$$

where $r_{i,d+1,t}$ is the return on stock i of day d at month t , $r_{M,d+1,t}$ is the market return (FTSE-All share value-weighted index return) on day d at month t , and $dvol_{i,d,t}$ is the pound trading volume (in million-pound unit). $\gamma_{i,t}$ is the coefficient of signed pound trading volume.

3 Zero Return (Lesmond et al., 1999)

Intuitively, when trading cost is higher than the benefit of trading, rational investors would choose not to trade (Lesmond et al., 1999). Therefore, people observe zero return for such days in this case. This measure is reported to be popular in international finance research, especially in emerging markets, where high-quality daily trading volume data are not available.

Lesmond et al. (1999) propose the zero return (ZR) illiquidity measure:

$$ZR_{i,t} = \frac{N_{i,t}}{T_t} \quad (2.2.3)$$

where T_t is the number of trading days at time t ; $N_{i,t}$ is the number of zero-return days of stock i in time t .

4 Turnover-Adjusted Zero-Return (Liu, 2006)

ZR measures can potentially lead to the same level of illiquidity for several stocks in multiple periods. In this case, Liu (2006) further proposed a turnover-adjusted zero-return measure, which is identified as:

$$LMx_{i,t} = \left\{ N_Z + \frac{1}{TV_x} \right\} \times \frac{21x}{N_x} \quad (2.2.4)$$

where N_Z is the number of zero-volume days in the previous x month; TV_x is the turnover over the previous x month, which is calculated as the sum of daily trading volume divided by the number of shares outstanding; N_x is the number of trading days in previous x months and DF is a deflator. Based on Liu (2006), the author adopts the *LM12* measure, which is based on the previous twelve months' data. Therefore, x is equal to twelve and this study uses the deflator of 11,000 as proposed by Liu (2006).

5 Bid-Ask Spread (Corwin and Schultz, 2012)

Amongst all of the proxies mentioned above, the bid-ask spread measure, in particular, has received extensive recognition by researchers. The data are widely available in real time and this measure can be calculated very quickly. However, the bid and ask quotes remain current only for a limited time periods. This is because the spread only measures the cost of executing a single trade of a certain size which requires complementary studies of other measures.

In a recent study, Corwin and Schultz (2012) developed the illiquidity measure from the ratio of daily high and low prices, excluding the volatility component. They define the spread estimator as:

$$S = \frac{2(e^k - 1)}{1 + e^k} \quad (2.2.5)$$

where K is identified as:

$$K = \frac{(\sqrt{2E\{\sum_{j=0}^1 [\ln(\frac{P_{t+j}^H}{P_{t+j}^L})]^2\}} - \sqrt{E\{\sum_{j=0}^1 [\ln(\frac{P_{t+j}^H}{P_{t+j}^L})]^2\}})}{(3 - 2\sqrt{2})} - \sqrt{\frac{[\ln(\frac{P_{t,t+1}^H}{P_{t,t+1}^L})]^2}{(3 - 2\sqrt{2})}} \quad (2.2.6)$$

where P_t^H and P_t^L are the high and low stock price at day t . The monthly illiquidity measure CS is identified as the average daily estimated spread s in time t .

6 Bid-Ask Spread (Roll, 1984)

Roll (1984) proposes the effective spread based on the bid-ask spread:

$$RO_{i,t} = 2\sqrt{-COV(R_{i,d}, R_{i,d-1,t})} \quad (2.2.7)$$

where $R_{i,d}$ is the return of trading day d in month t and $R_{i,d-1,t}$ is the return of the previous trading day in the same month.

To make the possibility of positive covariance, the author imposes absolute values as suggested by (Lesmond, 2005). Consequently, in this chapter, Roll's measure is defined as:

$$RO_{i,t} = 2\sqrt{|COV(R_{i,d}, R_{i,d-1,t})|} \quad (2.2.8)$$

7 Effective Tick (ET)(Goyenko et al., 2009)

Finally, this study employs the effective tick (ET) measure advocated by Goyenko et al. (2009). This measure is argued to be the simplest measure for all effective spreads. It is identified as:

$$ET = \frac{\sum_{j=1}^1 \gamma_j S_j}{\bar{P}_k} \quad (2.2.9)$$

The author obtains S_j by using the decimal grid, which is an approach similar to that of the dollar grid proposed by Goyenko et al. (2009). In this case, the possible spreads are at £0.01, £0.05, £0.1, £0.2, £0.5 and £1. \bar{P}_k is the average daily price in month k , and γ_j is defined as:

$$\hat{\gamma}_j = \left\{ \begin{array}{ll} \text{Min}[\text{Max}\{U_j, 0\}, 1] & j = 1 \\ \text{Min}[\text{Max}\{U_j, 0\}, 1 - \sum_{k=1}^{j-1} \hat{\gamma}_k], & j = 2, 3, \dots, j \end{array} \right\} \quad (2.2.10)$$

Based on

$$U_j = \left\{ \begin{array}{ll} 2F_j & j = 1 \\ 2F_j - F_{j-1}, & j = 2, 3, \dots, j-1 \\ F_j - F_{j-1} & j = j \end{array} \right\} \quad (2.2.11)$$

where

$$F_j = \frac{N_j}{\sum_{j=1}^j N_j} \quad \text{for } j = 1, 2, J.$$

N_j is the number of trades on prices to the j spread using positive volume days.

2.3 Models & Methodology

2.3.1 Models

The analysis in this chapter is based on the following standard capital asset pricing model:

$$R_t^p - R_t^f = \alpha_p + \beta_{p,MKT} MKT_t + \varepsilon_t^p \quad (2.3.12)$$

where R_t^p is the return of portfolio p in month t , R_t^f is the risk-free rate for month t , MKT_t , calculated as $(R_t^M - R_t^f)$ is the excess market portfolio return in month t and ε_t^p is the error term.

This study also bases the calculations in light of the fact that the Fama and French (1993) three-factor model is identified as:

$$R_t^p - R_t^f = \alpha_p + \beta_{p,MKT}MKT_t + \beta_{p,SMB}SMB_t + \beta_{p,HML}HML_t + \varepsilon_t^p \quad (2.3.13)$$

where SMB_t stands for size factor and HML_t is the value factor for time t .

Carhart (1997) further incorporated the momentum factor into the model as:

$$R_t^p - R_t^f = \alpha_p + \beta_{p,MKT}MKT_t + \beta_{p,SMB}SMB_t + \beta_{p,HML}HML_t + \beta_{p,MOM}MOM_t + \varepsilon_t^p \quad (2.3.14)$$

where MOM_t is the momentum factor.

In this chapter, the author incorporates illiquidity risk factor and apply the five factor model as:

$$R_t^p - R_t^f = \alpha_p + \beta_{p,MKT}MKT_t + \beta_{p,SMB}SMB_t + \beta_{p,HML}HML_t + \beta_{p,MOM}MOM_t + \beta_{p,L}L_t + \varepsilon_t^p \quad (2.3.15)$$

where L_t is the illiquidity factor.

2.3.2 Methodology

Principal Components Analysis (PCA)

Principal Component Analysis (*PCA*) is a powerful tool for analysing data as it has the ability when the data is in the form of a linear combination of optimally-weighted observed variables (Abdi and Williams, 2010). For a given stock, the

author constructs a correlation matrix of seven illiquidity measures and calculate the eigenvalue and eigen vector of the matrix. To compute scores on the first component extracted in a principal component analysis, the following model is employed:

$$COMP_1 = \beta_1(X_1) + \beta_2(X_2) + \beta_{1P}(X_P) \quad (2.3.16)$$

Or, in matrix notation:

$$COMP_1 = \beta_1^T X$$

where $COMP_1$ is the subject's score on principal component 1; $\beta_1(X_1)$ is the regression coefficient for the observed variable p , as used in creating the principal component 1; and X_p is the subject's score on the observed variable p .

The first principal component is calculated such that it accounts for the greatest possible variance in the data set. Clearly, it would be possible to make the variance of $COMP_1$ as wide as possible by choosing large values for the weights β_{11} , β_{12} , ... β_{1p} . To prevent this, weights are calculated with the constraint that their sum of squares is 1.

$$\beta_{11}^2 + \beta_{12}^2 + \beta_{13}^2 + \dots + \beta_{1p}^2 = 1 \quad (2.3.17)$$

The second principal component is calculated in the same way, with the condition that it is uncorrelated with the first principal component and that it accounts for the next highest possible variance.

$$COMP_2 = \beta_{21}(X_1) + \beta_{22}(X_2) + \beta_{2P}(X_P) \quad (2.3.18)$$

The calculation continues until a total of p principal components equal to the original number of variables has been generated. At this point, the sum of the variances of all of the principal components will equal the sum of the variances of all of the variables: that is, all of the original information has been explained.

Generalized Method OF Moment (GMM) & Fama and MacBeth (1973)

This study constructs ten portfolios on the basis of common illiquidity and then tests the joint significance of the ten portfolios' $\alpha(s)$. To reduce heteroscedasticity and serial correlation problems, this chapter estimates the $\alpha(s)$ using the systematic GMM.

For CAPM, the author defines r_t^x to be the 10×1 vector that contains excess returns of the ten portfolios, β_0 is the 10×1 vector for the constants, $B = [\beta_{MKT}]$ is the 10×1 matrix of portfolios' return sensitivities to market and $F_t = [MKT_t]$ is the 1×1 vector containing realisations of the factor. The standard CAPM can be identified as:

$$r_t^x = \beta_0 + BF_t + \varepsilon_t \quad (2.3.19)$$

To evaluate the model fit the author uses Hansen's J -test for over-identifying restrictions. The J -test provides a statistical test in cases where the moment conditions for a given model are significantly different from zero.

For the Fama-French three-factor model, $B = [\beta_{MKT}; \beta_{SMB}; \beta_{HML}]$ is the 10×3 matrix of portfolios' return sensitivities to market, size and value factor and $F_t = [MKT_t; SMB_t; HML_t]$ is the 3×1 vector. Similarly, in the Carhart four-factor model, $B = [\beta_{MKT}; \beta_{SMB}; \beta_{HML}; \beta_{MOM}]$ is the 10×4 matrix and $F_t = [MKT_t; SMB_t; HML_t, MOM_t]$ is the 4×1 vector.

This study next performs the Fama and MacBeth (1973) two framework regressions to test the cross-sectional evidence of illiquidity factor in asset pricing models. When analysing cross-sectional data, the use of Fama-MacBeth regression has a number of advantages. First, it accommodates the dynamic explanatory variables. For the Fama-MacBeth regression the betas are estimated for a time period preceding the cross-section date which allows for time varying differences in the explanatory variables, whereas in other regressions, these variables are averaged out over the sample period and may lead to the loss of valuable information. Second, by running the cross-sectional regression and calculating what the standard errors are, they will then correct for cross-sectional correlations within the panel (Cochrane, 2001). Finally, the regression can also be extended to accommodate for additional risk features, beyond the beta (Campbell, Lo, MacKinlay et al., 1997), and this is often useful if there are more risk factors to adhere to.

The first step of the Fama-MacBeth regression involves the estimation of betas after time-series regressions of the excess returns. Therefore, the illiquidity-augmented five-factor model becomes:

$$R_t^p - R_t^f = \alpha_p + \beta_{p,MKT}MKT_t + \beta_{p,SMB}SMB_t + \beta_{p,HML}HML_t + \beta_{p,MOM}MOM_t + \beta_{p,L}L_t + \varepsilon_t^p \quad (2.3.20)$$

where R_t^p is the portfolio return p at time t , R_t^f is the monthly risk-free rate in month t , and MKT , SMB , HML , MOM and L are market return, size, value, momentum and illiquidity factors.

According to the same steps as previous studies, the first step of the regression estimates the time-series factors for each of the ten portfolios using 36 months rolling windows of 240 monthly observations. The second step estimates monthly cross-sectional regressions of the ten portfolio's excess returns on the betas that are estimated in the first step. Thus the model is identified as:

$$\begin{aligned}
R_t^p - R_t^f &= \lambda_0 + \lambda_{MKT} \hat{\beta}_{p,MKT} + \lambda_{SMB} \hat{\beta}_{p,SMB} + \\
&\lambda_{HML} \hat{\beta}_{p,HML} + \lambda_{MOM} \hat{\beta}_{p,MOM} + \lambda_L \hat{\beta}_{p,L} + \omega_t^p
\end{aligned} \tag{2.3.21}$$

where λ are the risk premium parameters with each beta. The hypothesis here is that the time-series average of the estimated coefficient λ_L is positive and statistically significant. This can be interpreted as showing the evidence that the illiquidity risk factor is priced.

Hansen-Jagannathan Distance

Rather than using formal statistical tests of identification and over-identification restrictions (statistical importance), it is possible to examine the model performance (economic importance) instead. The *HJ* distance measure is the mean square distance between the fitted values (\hat{m}) and the actual value m^* . The *HJ* minimum distance can then be presented as: $E(\hat{m} - m^*)$, where the expectations are estimated in practice using the sample averages. Since

$$m - m^* = E[m(\pi)X - 1]' E(XX')^{-1} X$$

The minimum distance is given by:

$$\left[E(m(\pi)X) - 1 \right]' E(XX')^{-1} \left[E(m(\pi)X) - 1 \right] \tag{2.3.22}$$

Let

$$\mathbf{g} = [E(m(\pi)X) - 1]$$

and

$$W = E(XX')^{-1}$$

Then the minimum distance equals

$$\mathbf{g}'W\mathbf{g}$$

which is the Hansen J -test with a particular W .

Hansen and Jagannathan suggest comparing the pricing errors associated with the models in question by choosing each model's parameters θ to minimise the quadratic form:

$$h_t^{HJ} \equiv \mathbf{g}'_T(\theta)W_T^{-1}\mathbf{g}_T(\theta) \quad (2.3.23)$$

where $\mathbf{g}_T(\theta)$ is the sample average of pricing errors and W^{-1} is the sample second moment matrix of the N asset returns upon which the models are evaluated.

2.4 Data and Variable Construction

The data adopted in this study is monthly data and spans the period 1990-2012. The initial sample comprises the whole population of firms listed on the FTSE All-Share obtained from Thomson DataStream.²

For each index, the author extracts data including trading volume (turnover by volume); market value (share price multiplied by the number of ordinary shares in issue); return index (a theoretical growth in value of a share-holding over a specified period); and closing price. At the end of each month, the total number of shares outstanding, the return index, and the market value are obtained. Market to book value (market value of common equity divided by the balance sheet value of common equity in the company) is collected on an annual basis. This study uses the UK treasury bills 3-month yield rate as the risk free rate. Stocks are kept

²To avoid survivor-ship bias, this analysis covers not only presently listed stocks but also dead stocks. Dead stocks refer to those of firms that were de-listed at some point during the sample period.

if they existed for at least three years prior to the year start.

For the estimation of factor-asset pricing models, the author constructs size, value, and momentum risk factors. As for size, the author sorts all stocks based on their market capitalizations at month $t-1$ with a filter rule of 30% for portfolio formation. In other words, the value-weighted top 30% of stocks are allocated to the big-size portfolio, whereas the value-weighted bottom 30% stocks are assigned to the small-size portfolio. Therefore, the size (SMB) return is the difference between the returns of the small-size portfolio and the big-size portfolios at time t . Similarly to traditional empirical studies applied in the UK market, this study identifies the value factor (HML) by obtaining the spread between monthly returns of the MSCI Value and MSCI Growth indices (Cuthbertson, Nitzsche, and O’Sullivan, 2008; Florackis, Gregoriou, and Kostakis, 2011).

For the momentum factor, the author ranks all stocks at month $t-1$ based on their returns from month $t-13$ to $t-2$. The equally-weighted top 30% of stocks are winners and the bottom 30% are losers. Thus the difference between monthly returns of winner and loser portfolios at time t is taken as the momentum factor (MOM)(Jegadeesh and Titman, 1993).

2.5 Empirical Results

To begin with, the author analyses the persistence of market illiquidity, as investors request a premium for bearing illiquidity only when the illiquidity shock is systematic and persistent (Acharya and Pedersen, 2005; Korajczyk and Sadka, 2008; Lee, 2011; Pástor and Stambaugh, 2003). Table 1 reports the average monthly percentage returns, illiquidity, and other features for ten equally-weighted size portfolios. These are rebalanced each year based on the total market value of each stock at the end of the previous year. The existing literature reports a higher illiquidity with smaller stocks (Amihud, 2002; Amihud and Mendelson, 1986).

As seen in Table 2.1, illiquidity is generally higher for small stocks ($RV=4.6209$; $PS=0.1118$) than it is for large stocks ($RV=0.0012$; $PS=0.0001$). A similar pattern is also shown for LM , RO , and ET . The returns are higher for small stocks and the results reveal higher volatility for small stocks based on standard deviation. In line with Pástor and Stambaugh (2003), Acharya and Pedersen (2005) and Korajczyk and Sadka (2008), this study finds that the equally-weighted average of stock illiquidity is highly persistent. Given the persistence of market illiquidity, similarly to Pástor and Stambaugh (2003) and Acharya and Pedersen (2005), this study constructs the illiquidity innovations through $AR(2)$ as follows:

$$C_{M,t} \frac{MV_{M,t-1}}{MV_{M,1}} = \alpha_0 + \alpha_1 C_{M,t-1} \frac{MV_{M,t-1}}{MV_{M,1}} + \alpha_2 C_{M,t-2} \frac{MV_{M,t-1}}{MV_{M,1}} + \mu_{m,t} \quad (2.5.24)$$

where $C_{M,t}$ is the market aggregate illiquidity at month t ; and the residual $\mu_{m,t}$ is the illiquidity innovation. Notably, the author scales PS and RV by the ratio of the total market value by the end of the month $t-1$ to that in January 1990.

Table 2.1: Summary Statistics of Average Illiquidity by Size Portfolios

Note: This table presents the average monthly percentage returns and illiquidity measures for 10 equally-weighted size UK portfolios. Portfolio's size is recalculated each year based on market value of shares at the end of the previous year. The illiquidity proxies are Amihud's illiquidity (RV), Pastor and Stambaugh's measure (PS), zero return (ZR), Liu's measure (LM12), Roll's measure (RO), the spread measure of Corwin and Schultz (CS) and effective tick (ET). Market cap is the market capitalization at the end of the previous year; BTMV is the book to market ratio; and St.Dev. is the standard deviation of portfolio return in the sample period.

Portfolio	Return	RV	PS	ZR	LM12	RO	CS	ET	MarketCap	BTMV	St.Dev.
small	2.0939	4.6209	0.1118	0.0019	0.1332	0.0306	-0.0732	0.0042	1644.0017	1.1686	6.0109
2	1.4866	1.3653	0.0204	0.0013	0.1127	0.0268	-0.0624	0.0030	3145.8235	1.0700	5.5025
3	1.3134	0.9389	-0.0063	0.0012	0.1207	0.0282	-0.0627	0.0024	4731.2061	0.8846	5.4383
4	1.2193	0.5984	0.1049	0.0009	0.1116	0.0299	-0.0623	0.0018	6970.9691	0.8748	5.4623
5	1.2157	0.3619	0.0038	0.0009	0.1378	0.0285	-0.0620	0.0015	10570.0883	0.7935	5.2049
6	1.1545	0.1667	0.0032	0.0008	0.1403	0.0304	-0.0671	0.0013	15680.0039	0.7493	5.1954
7	0.8896	0.0832	0.0012	0.0006	0.1039	0.0325	-0.0707	0.0012	24416.1204	0.6775	5.5819
8	1.0252	0.0423	0.0072	0.0006	0.1154	0.0353	-0.0792	0.0008	42965.3213	0.6416	5.5332
9	0.9650	0.0058	0.0000	0.0005	0.1036	0.0374	-0.0889	0.0005	101928.4865	0.5394	5.2035
large	0.9222	0.0012	0.0000	0.0003	0.0783	0.0363	-0.0896	0.0003	781616.5530	0.4398	4.8251

This is in order to include only innovations in illiquidity, not the changes in time value of money. For other illiquidity measures, however, this study applies the general $AR(2)$ regressions to find innovations:

$$C_{M,t} = \alpha_0 + \alpha_1 C_{M,t-1} + \alpha_2 C_{M,t-2} + \mu_{m,t} \quad (2.5.25)$$

The coefficients α_1 and α_2 are both significant. Further, the residuals do not display any serial correlation. Hence, it can be claimed that $\mu_{m,t}$ accurately represents market illiquidity.

Figure 2.1 shows the time-series plots of market aggregate illiquidity innovations for each measure and provides evidence that illiquidity innovations generally coincide with liquidity events in the timeline such as the Iraq invasion of Kuwait in 1990, the Asian crisis in 1997, the long term capital management crisis in 1998, and the financial crisis from 2007 to 2009. The fact that all seven measures jointly constitute liquidity-related events suggests the possibility that the individual proxy shares a common component of illiquidity.

Table 2.2 reports the correlations between market illiquidity proxies to examine whether illiquidity measures have a common component. The author observes significant Pearson correlation tests in many cases. It measures the strength of the linear relationship between normally distributed variables. The highest correlation of 0.356 is shown between RV and RO and the lowest value among positive and significant correlations is 0.113 between ET and RV . However, RO is negatively correlated with most of the other measures in Table 2.2. The results imply that the illiquidity proxies, somehow, have systematic common components of illiquidity and this in turn justifies the use of the principal component analysis. Next this study uses the principal component analysis to extract the common components of the seven illiquidity measures. As shown in Figure 4.3, the bar

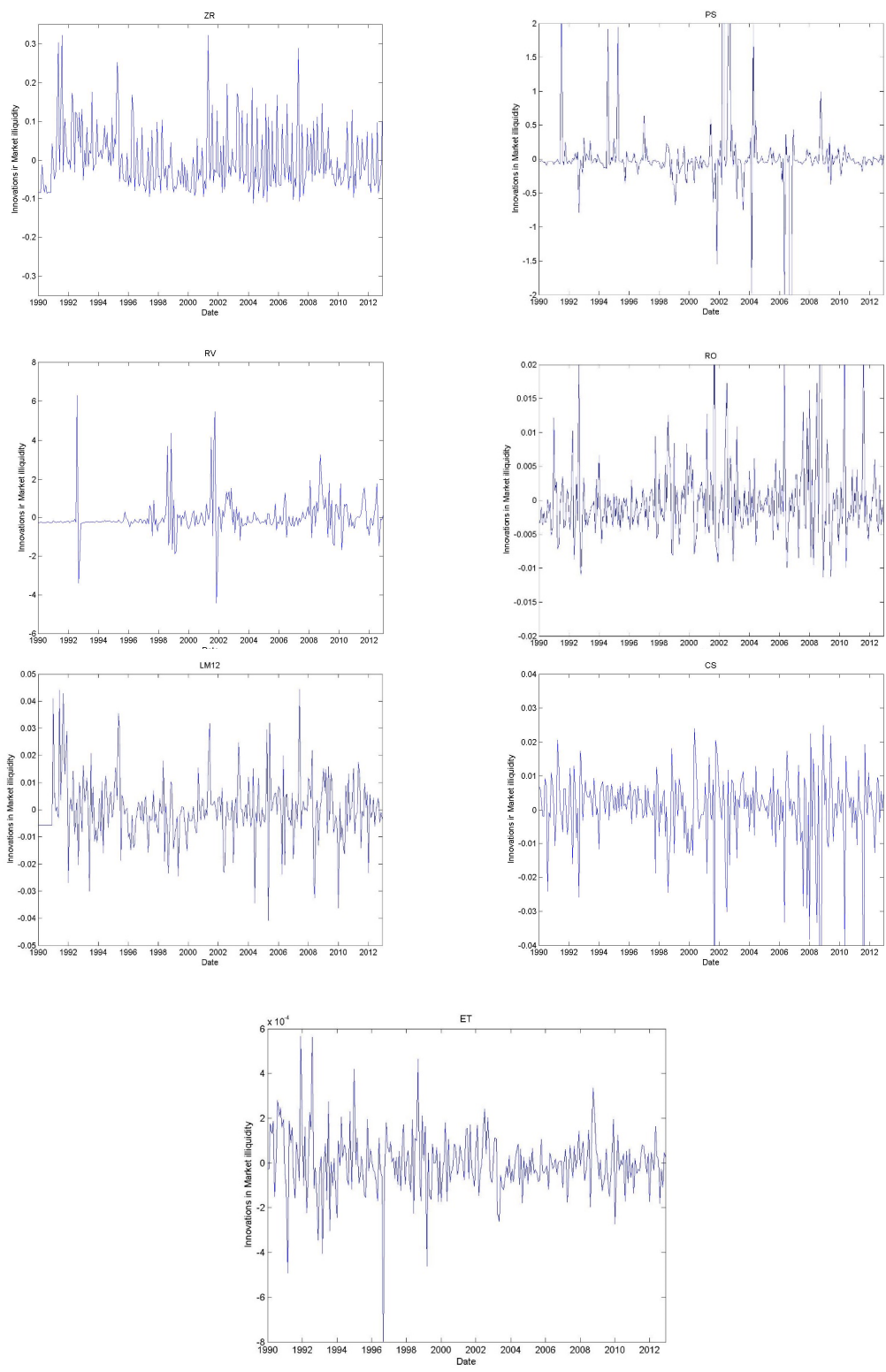


Figure 2.1: Innovations of Illiquidity Measures

graph indicates the plot of the average eigenvalue proportions of seven principal components, as well as the plot of the cumulative proportions in the corresponding line graph. This study finds that the first principal component explains 33% of the whole variation over the seven illiquidity measures, which is coincidentally similar to findings reported in Korajczyk and Sadka (2008) and Kim and Lee (2014).

Table 2.2: Pearson Correlation of Illiquidity Proxies

	RV	ZR	RO	PS	LM	CS	ET
RV	1						
ZR	0.060	1					
RO	0.356 ***	-0.048	1				
PS	0.042	0.082	-0.025	1			
LM	0.097	0.242 ***	0.064	0.047	1		
CS	-0.329***	0.093	-0.937***	0.037	0.052	1	
ET	0.113*	0.196***	-0.380 ***	0.117*	0.170 ***	0.297***	1

Table 2.3 reports the descriptive statistics of illiquid portfolio performances from February 1990 to December 2012. The study constructs decile portfolios using the first principal component of illiquidity. In particular, at the end of month $t-1$, stocks are organised according to their first principal component extracted from the seven illiquid measures. Portfolio 1 ($P1$) includes stocks with the smallest ratio, whilst Portfolio 10 ($P10$) contains stocks with the highest values of illiquidity ratio and this excess return is only calculated for for both P1 and P10. Portfolios are rebalanced on a monthly basis. This empirical findings suggest that the average portfolio return increases from $P1$ to $P10$, though not monotonically. This pattern holds for equally weighted portfolios' returns but not for value weighted portfolios' returns. The level of this differential is about 16% per annum ($t=2.896$) for equally weighted portfolio returns. The author also finds no strong relationship between common illiquidity and market capitalization, nor does she find a clear correlation between common illiquidity and book to market ratio. Such results may have occurred due to the author's focus exclusively on the first principal component of the illiquidity measures. Nevertheless, certain features may

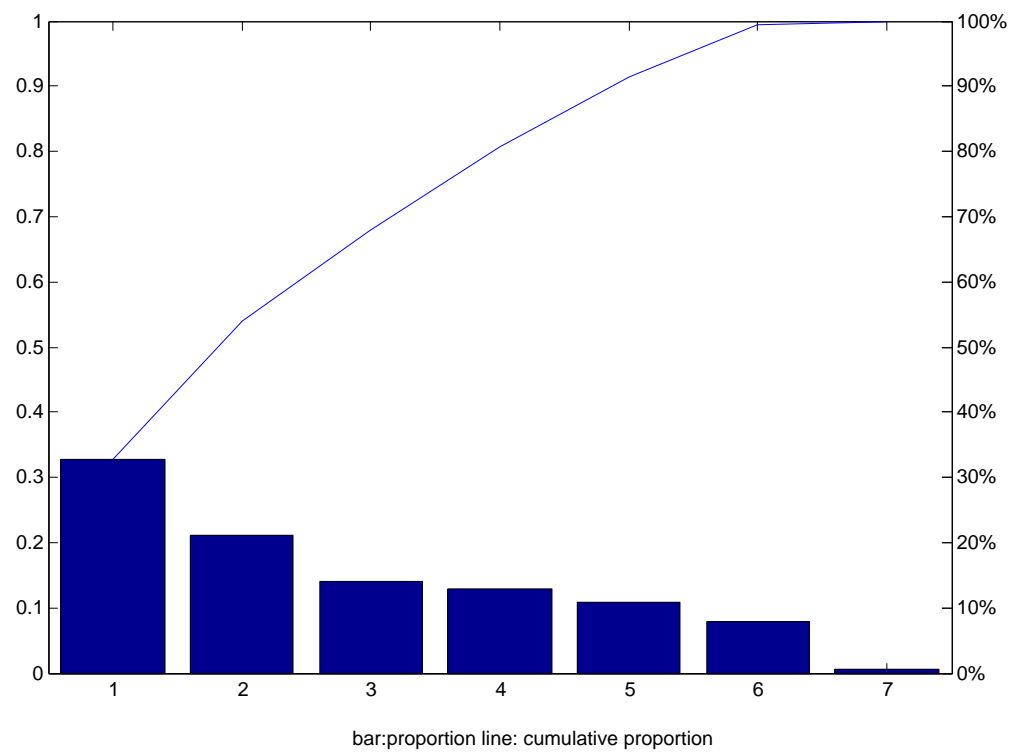


Figure 2.2: Eigenvalue proportion of principal components

continue to appear as measure-specific.³ However, this study's common illiquidity component clearly captures the change of the average β_{CAPM} associated with stocks, calculated by using a 36-month rolling window. The higher the illiquidity of the portfolio, the higher the beta the author observes. The differential between *P10* versus *P1* beta is 0.287 ($t=8.933$).

³Individual measure results are not reported but may be obtained upon request.

Table 2.3: Illiquid Portfolio Performances

Decile portfolios	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-test
<i>EW Returns(%p.a.)</i>	1.055	-0.034	-0.233	-2.146	-1.872	8.487	8.040	9.848	9.907	17.122	16.067	2.896
<i>VW Returns(%p.a.)</i>	15.263	7.405	28.979	19.866	4.434	9.891	4.365	6.261	4.380	9.714	-5.549	-0.598
ILLIQ Ratio	-0.520	-0.337	-0.174	-0.025	0.096	0.316	0.629	0.932	1.244	1.987	2.507	17.313
MV(£m)*	64657.93	62875.07	68135.25	34739.21	40886.83	82550.36	90848.25	92813.58	91646.32	70198.99	5541.064	0.89
BTMV	0.398	0.294	0.254	0.155	0.193	0.617	0.731	0.712	0.702	0.684	0.286	9.017
β_{CAPM}	0.856	0.664	0.630	0.721	1.010	0.987	1.020	1.033	1.060	1.144	0.287	8.933

Note: *P1* is the decile portfolio which has stocks with the lowest illiquidity ratio whereas *P10* has the stocks with the highest illiquidity ratio. *P10-P1* is the spread between P10 and P1. *EW* returns are the annualized average monthly returns of equal weighted portfolios and *VW* returns account for the annualized monthly returns of value weighted portfolios. *MV* is the average market value of stocks in each of the portfolios in millions measured as the average of the share price times the number of shares outstanding. *BTMV* is the average ratio of the book value of shares divided by the market value in each portfolio. β_{CAPM} is the average stock beta in each portfolio using a 36-month sliding window. The *t-test* in the last column is the null hypothesis that the means are the same between P10 and P1.

Time-series Evidence of Risk-adjusted Returns

Table 2.4 presents the alphas of the value-weighted and equal-weighted portfolios sorted by the common component of the seven illiquidity ratios. For the principal component sorted equally-weighted portfolios, The author finds that Jensen's alpha has generally increased across portfolios. Notably, most of the alphas across the portfolios (P1-P5) are with negative signs. Interestingly, *P10* has the highest and most significant alpha (CAPM) of 12.408%. Similar patterns hold for the Fama-French three-factor model and the Carhart four-factor model ($\alpha = 6.703\%$ and 8.480%) respectively. This suggests that portfolio returns increase with illiquidity. The last column presents the χ^2 statistic of the *Wald* test. The null hypothesis is that the alphas of the ten portfolios are jointly equal to zero. The author fails to reject the null hypothesis. It is also worth noting that there is no certain pattern when moving from *P1* to *P10* and there are also insignificant premiums for value-weighted portfolios. This suggests that illiquidity premiums may be subject to the size factor. However, the χ^2 of the Wald test provides strong evidence against the null hypothesis.

Table 2.4: Alphas Estimates of Value and Equally-Weighted Illiquid Portfolios

Decile portfolios	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	χ^2
Panel A:PCA Value-Weighted Portfolios											
α_{CAPM} (% p.a.)	11.400	4.564	25.888	16.360	0.857	6.009	0.599	2.138	0.337	4.931	7.182
	(1.839)	(0.472)	(2.480)	(2.471)	(0.101)	(2.431)	(0.261)	(0.879)	(0.177)	(1.848)	(0.007)
α_{FF} (% p.a.)	5.409	-2.658	21.106	11.578	-1.918	6.450	0.257	2.345	-0.109	3.496	4.526
	(0.901)	(-0.358)	(1.949)	(2.041)	(-0.238)	(2.453)	(0.107)	(1.039)	(-0.053)	(1.254)	(0.033)
$\alpha_{Carhart}$ (% p.a.)	4.575	-5.115	18.749	9.927	-2.652	6.692	0.461	3.443	0.464	5.407	3.993
	(0.766)	(-0.765)	(1.689)	(1.745)	(-0.332)	(2.218)	(0.179)	(1.322)	(0.220)	(1.987)	(0.046)
Panel B:PCA Equally-Weighted Portfolios											
α_{CAPM} (% p.a.)	-0.960	-2.409	-1.695	-2.905	-3.527	4.786	4.114	5.748	5.761	12.408	1.372
	(-0.344)	(-0.787)	(-0.684)	(-2.115)	(-1.935)	(2.210)	(1.776)	(2.744)	(2.515)	(3.677)	(0.241)
α_{FF} (% p.a.)	-2.883	-4.337	-2.901	-3.471	-5.276	1.727	0.424	2.046	1.772	6.703	0.393
	(-1.078)	(-1.425)	(-1.138)	(-2.564)	(-2.945)	(1.076)	(0.374)	(1.734)	(1.487)	(3.405)	(0.531)
$\alpha_{Carhart}$ (% p.a.)	-1.761	-3.071	-2.282	-3.511	-4.080	2.110	0.331	2.483	2.077	8.480	0.001
	(-0.710)	(-1.095)	(-0.940)	(-2.528)	(-2.370)	(1.312)	(0.271)	(2.053)	(1.655)	(4.333)	(0.986)

Note: *P1* is the decile portfolio of stocks with the lowest illiquidity ratios; *P10* is the portfolio of stocks with the highest illiquidity ratios. α is the annualized alpha estimated using the CAPM, Fama-French three-factor and Carhart four-factor models. T-statistics are reported in parentheses. The last column presents the χ^2 statistic of the *Wald* test. The null hypothesis is that the *alphas* of the ten portfolios are jointly equal to zero. The p-values are reported in the parentheses.

Cross-sectional Evidences

As a robustness test, the author further investigates the performance of the LCAPM in explaining the cross-section variations in stock returns.

Table 2.5 presents the estimated λ coefficients for the ten equally-weighted portfolios, and sorting is done based on the common component of illiquidity ratio in the UK. Panel *A* of Table 2.5 reports the unrestricted model with any value of λ_0 . The augmented illiquidity in Panel *A* is based on the first principal component. The findings are supportive of the illiquidity augmented CAPM and the Fama-French model, as these specifications produce statistically positive, significant and economically sensible coefficients (premium λ_L), thereby offering a more valuable explanation of the data.

The estimated coefficient λ_L associated with CAPM and Fama-French (FF) models are significantly positive ($\lambda_{LCAPM}=5.76$ and $\lambda_{LFF}=5.19$) respectively, but the coefficient λ_L is insignificantly positive at ($\lambda_{LCARH}=10.4$) for the liquidity-augmented Carhart model. The penultimate column in Panel *A* reports the R^2 coefficients, and the last column reports the increase in R^2 coefficients after adding the illiquidity factor to the original models. The results show a good explanatory power, as the ΔR^2 has increased across all models, $\Delta R^2=0.041, 0.021$ and 0.035 for CAPM, FF and Carhart models respectively. The high R^2 is consistent with the result reported by Acharya and Pedersen (2005) from the US ($R^2=0.942$). In Panel *B* of Table 2.5, the author presents the estimated λ coefficients from the second framework cross-sectional regression of Fama-MacBeth. This study restricts λ_0 to be zero. The results yield similar findings as those in Panel *A* of Table 2.5, indicating strong and statistically significant coefficients for the liquidity-augmented CAPM and Fama-French model.

As mentioned above (section 2.3), there are many reasonable measures that can be used to test the model specification. In section 2.3 the author studied one of these measures which depends on a non-parametric function, the Hansen J

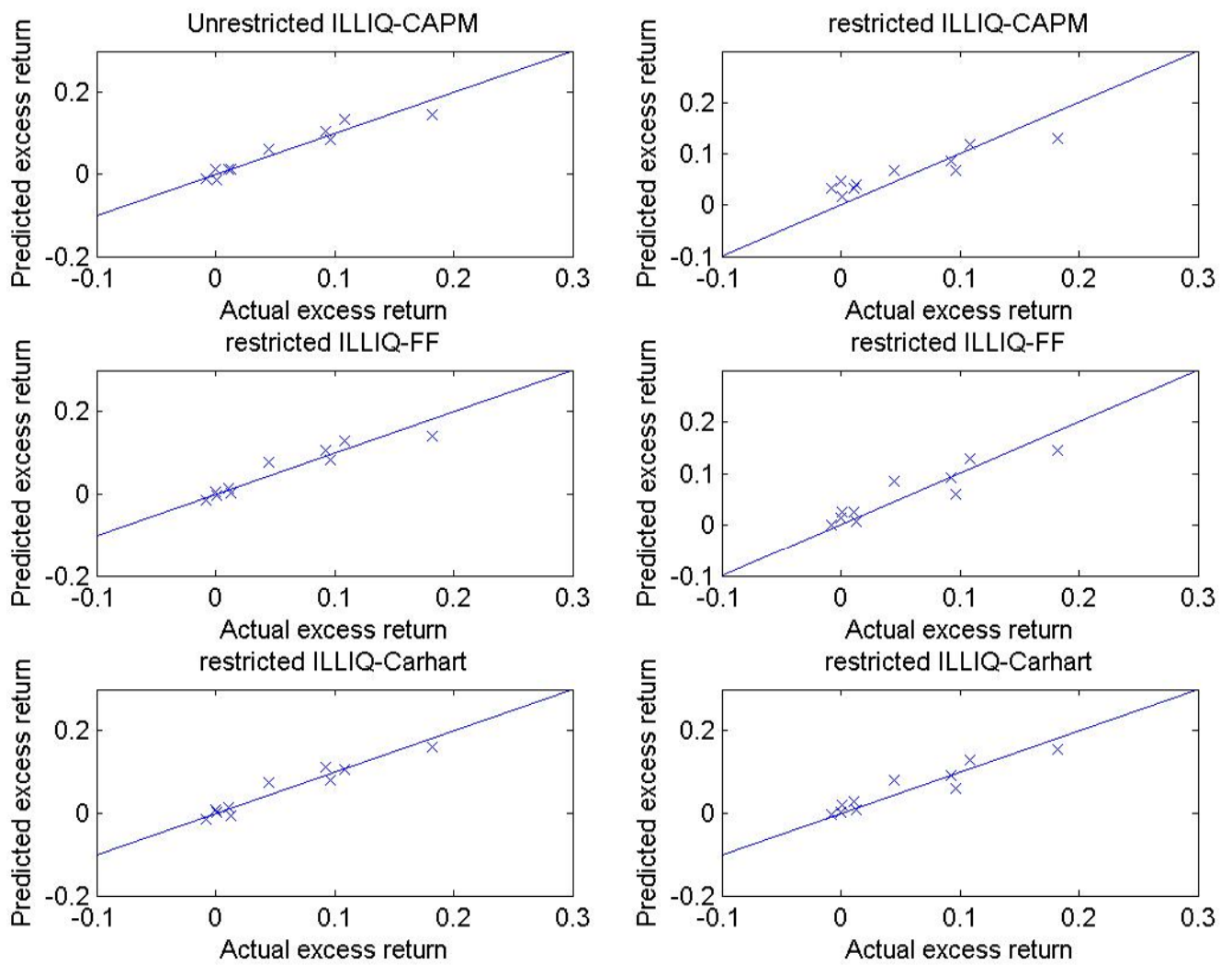


Figure 2.3: Fit of Illiquidity-augmented CAPM, Fama-French and Carhart Model

Table 2.5: Fama/MacBeth Estimates and Hansen-Jagannathan Distance

Note: λ_i is the mean of risk premium coefficients λ_i using Fama and MacBeth (1973) method. The monthly cross-sectional regressions of ten equally-weighted portfolio return premiums are estimated using the risk factors of Fama and MacBeth (1973). *ILLIQ* is illiquidity factor of the CAPMs models. Panel A and B report systematic illiquidity factor augmented asset pricing models. T-statistics are reported in parentheses. The last column reports the increase in R-squared coefficient due to the addition of the illiquidity factor. Panel C reports the Hansen-Jagannathan distance. δ measures the distance error.

	λ_0	λ_{mkt}	λ_{smb}	λ_{hml}	λ_{mom}	λ_L	R^2	ΔR^2
Panel A: PCA Unrestricted Model								
<i>CAPM_{ILLIQ}</i>	-0.434 (-2.729)	1.363 (4.338)				5.758 (3.015)	0.945	0.041
<i>FF_{ILLIQ}</i>	-0.354 (-2.622)	0.968 (1.434)	0.316 (0.267)	2.025 (1.608)		5.196 (1.976)	0.953	0.021
<i>CARHART_{ILLIQ}</i>	-0.131 (-0.916)	2.077 (1.948)	-2.155 (-1.018)	3.094 (2.716)	-5.263 (-2.492)	10.455 (1.077)	0.977	0.035
Panel B: PCA Restricted Model $\lambda = 0$								
<i>CAPM_{ILLIQ}</i>		-0.927 (-3.034)				9.338 (4.678)		
<i>FF_{ILLIQ}</i>		1.406 (1.968)	-0.1168 (-0.900)	2.739 (2.336)		10.973 (3.491)		
<i>CARHART_{ILLIQ}</i>		2.469 (2.603)	-3.149 (-1.759)	3.368 (2.929)	-6.031 (-3.358)	13.178 (1.537)		
Panel C: Hansen-Jagannathan Distance								
	CAPM	<i>CAPM_{ILLIQ}</i>	FF	<i>FF_{ILLIQ}</i>	Carhart	<i>Carhart_{ILLIQ}</i>		
δ	0.304	0.198	0.33	0.177	0.407	0.581		

test. However, Summers (1991) and Cochrane and Hansen (1992) claim that the GMM approach *J* test focuses too much on the specification of the model, and has too little focus on evaluating the accuracy of the underlying model. They argue that an increased focus on the accuracy of the model would help both reflect the purpose of understanding different types of behaviour and improve the ability of the model to make different types of predictions. To account for this criticism, the author implements two alternatives advocated by Hansen and Jagannathan (1997) to assess the performance of the models.

Panel C of table 2.5 shows the robustness results of the Hansen-Jagannathan distance tests both with and without the illiquidity factor. The author reports both the principal component as of illiquidity. With the principal component illiquidity factor, this study finds that the error decreases from 0.304 to 0.198 and from 0.330 to 0.177 for the CAPM and Fama-French three-factor model respectively. Figure 2.4 also details the distance on the Hansen-Jagannathan bound, suggesting a significant empirical improvement for the liquidity Capital asset pricing models.

Robustness Tests

In table 2.2, the author reports negative correlations of the RO measure with many other illiquidity measures, i.e. ‘Pastor and Stambaugh’s gamma’, ‘Corwin and Schultz’s spread’ and the ‘effective tick’. Such results indicate that the RO measure might differ more from other existing proxies. Therefore, this study applies the robustness tests by removing the RO and estimate the new single illiquidity measure constructed by the principal component analysis. The author reports both parametric and non-parametric results in table 2.6.

Similar to the main findings, the new single illiquidity measure that is constructed by using the common component of the six illiquidity measures excluding RO proxy performs meaningful results. As for the parametric Fama-MacBeth estimations, the author reports positive and significant coefficient λ_L for CAPM and Fama-French models ($\lambda_{LCAPM}=6.423$ and $\lambda_{LFF}=7.331$). The coefficient λ_L is still insignificantly positive at ($\lambda_{LCARH}=5.657$ for the illiquidity-augmented Carhart model. The results show a slightly better explanatory power, but not a significant change in results as the ΔR^2 has increased across all models, $\Delta R^2= 0.071, 0.075$ and 0.042 for CAPM, FF and Carhart models respectively. Panel C reports the results of Hansen-Jagannathan Distance using the new illiquidity measure generated from six illiquidity measures. The error decreases from 0.142 to 0.139, from 0.604 to 0.073, and from 0.619 to 0.168 for the CAPM, Fama-French three-factor

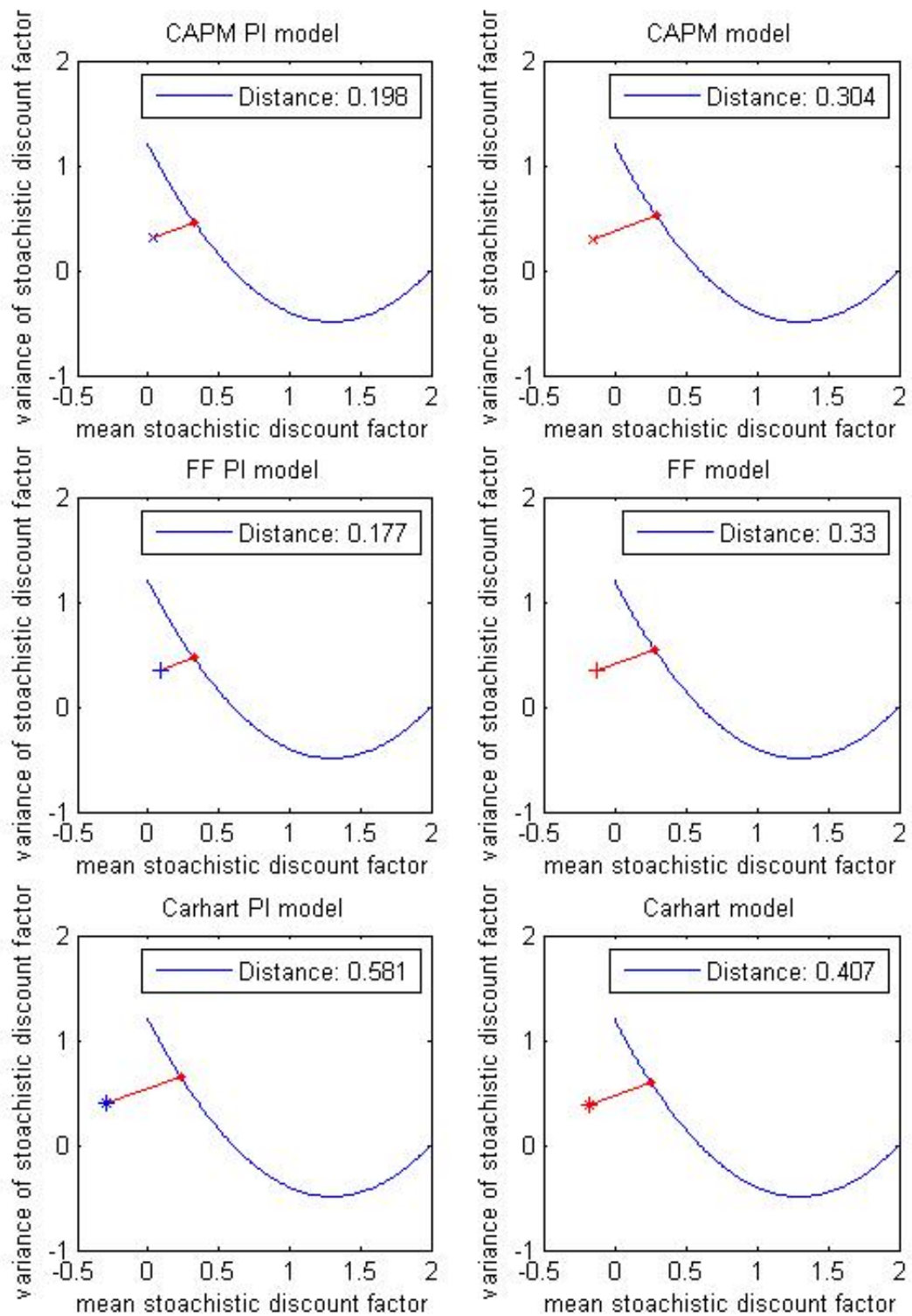


Figure 2.4: Hansen-Jagannathan Bound of Capital Asset Pricing Models

Table 2.6: Robustness Tests on Illiquidity Without RO

Note: This table reports the robustness test results of both parametric and non-parametric estimations. The illiquidity factor is constructed without RO proxy proposed by Roll (1984).

	λ_0	λ_{mkt}	λ_{smb}	λ_{hml}	λ_{mom}	λ_L	R^2	ΔR^2
Panel A: PCA Unrestricted Model								
$CAPM_{ILLIQ}$	-0.357 (-2.090)	0.818 (2.291)				6.423 (4.057)	0.957	0.071
FF_{ILLIQ}	-0.138 (-0.69)	-0.565 (-0.806)	2.27 (2.656)	2.365 (2.445)		7.331 (3.677)	0.977	0.075
$CARHART_{ILLIQ}$	-0.119 (-0.576)	-0.414 (-0.583)	2.052 (2.506)	2.059 (2.266)	-2.098 (-1.918)	5.657 (1.003)	0.972	0.042
Panel B: PCA Restricted Model $\lambda = 0$								
	λ_0	λ_{mkt}	λ_{smb}	λ_{hml}	λ_{mom}	λ_L		
$CAPM_{ILLIQ}$		0.173 (0.493)				9.742 (4.922)		
FF_{ILLIQ}		-1.135 (-1.656)	2.953 (3.347)	2.815 (3.382)		8.155 (3.372)		
$CARHART_{ILLIQ}$		-0.859 (-1.232)	2.572 (3.061)	2.412 (3.127)	-1.803 (-1.611)	6.303 (0.750)		
Panel C: Hansen-Jagannathan Distance								
	CAPM	$CAPM_{ILLIQ}$	FF	FF_{ILLIQ}	Carhart	$Carhart_{ILLIQ}$		
δ	0.142	0.139	0.604	0.073	0.619	0.168		

model and Carhart four-factor model respectively. This implies that after they are augmented with illiquidity factor, the empirical asset pricing models significantly improve their pricing powers.

2.6 Conclusion

This chapter examined the performance of the standard Sharpe-Lintner CAPM, the Fama-French three factor model (Fama and French, 1993), and the four factor model of Carhart (1997) both with, and without, the first component of multiple illiquidity measures. Further, the ability of the capital asset pricing models

(CAPMs) to explain asset returns using solely individual illiquidity measures was also analysed. The author used monthly UK data between 1990 and 2012.

The initial investigation suggests that no individual illiquidity proxy outperforms the others, and further that the illiquidity proxies have a systematic common illiquidity component. Hence, the author used the principal component analysis. According to the results of this analysis, the fact that seven measures jointly indicate liquidity-related events further suggests the possibility that the individual proxies share a common component of illiquidity. In addition, the correlations between market illiquidity proxies were considered in order to examine whether illiquidity measures share a common component. Similarly to studies by Korajczyk and Sadka (2008) and Kim and Lee (2014), the findings indicate that the first principal component explains 33% of the whole variation over the seven illiquidity measures in the UK. For illiquid portfolio and model performance, this chapter's findings are supportive of the illiquidity augmented CAPM and Fama-French model particularly with the portfolio of stocks with the highest illiquidity ratios *P10*. These specifications produce statistically positive, significant and economically coefficient estimates. For the non-parametric tests, the author finds that the illiquidity-augmented CAPM and Fama-French three-factor model yield a very small distance. These findings are supportive of the liquidity specification of the capital asset pricing models. Other non-liquidity CAPM models fail to yield economically plausible parameter values.

These findings have important implications for academic research into liquidity risk and for practical liquidity risk management alike. This chapter contributes to the literature on liquidity risk by investigating the determinants of cross-sectional stock returns during liquidity crises. In addition, this chapter analyses liquidity risk from a practical risk management standpoint. This empirical work shows that abnormal stock performance during liquidity crises is, in part, predictable, and investors can construct portfolios of stocks that better withstand liquidity shocks.

However, the results suggest that liquidity risk management comes at a cost of lower average returns during periods of relatively stable liquidity conditions.

Future research could investigate whether expected returns are related to stocks' sensitivities to fluctuations in other aspects of aggregate liquidity. It would also be useful to explore whether some form of systematic liquidity risk is priced in other financial markets, such as fixed income markets or international equity markets.

Chapter 3

Semi-varying Momentum Payoffs and Illiquidity

3.1 Introduction

Understanding and predicting the behaviour of stock markets and stock prices is a key theme in the theory of financial economics. It has received much attention from corporate financial economists and has been the basis of intense debate. One of the most intensely and widely debated subjects in financial markets has been whether markets are efficient. Malkiel and Fama (1970) argued that when markets are efficient, stock prices follow the pattern of a random walk. Therefore, it is not possible to predict future returns under an efficient environment. This means that investment strategies of past information on stock prices will not correspondingly generate abnormal returns. However, many studies have recently documented that such strategies do in fact generate significant profits (see for example, (Asness, Moskowitz, and Pedersen, 2013; Chou, Chen, and Hsieh, 2014; Hirshleifer, 2014; Vidal-García, 2013)).

Indeed, such investment strategies and their momentum effect remain one of the

most puzzling equity anomalies in the finance literature since they were first documented by Jegadeesh and Titman (1993). Since then, several studies have been carried out to attempt to clarify whether this anomaly is global and where exactly the underlying factors may derive from (e.g., (George and Hwang, 2004; Jegadeesh and Titman, 1993; Lewellen, 2002; Moskowitz and Grinblatt, 1999; Novy-Marx, 2012)).¹

As empirical evidence associated with previous momentum studies have provided different explanations to question fundamental financial theories, it might therefore be of value to further examine whether other assumptions underlying the EMH might be rejected in order to generate an even higher abnormal return. Moreover, different variables may affect the profitability of the momentum strategy, the importance of which has been proven in many finance literature (e.g., (Avramov, Chordia, Jostova, and Philipov, 2007; Lee and Swaminathan, 2000; Sadka, 2006). One of these assumptions and variables is that of liquidity and trading volume. For example, poor liquidity is therefore associated with higher bid-ask spread and risk for an investor. In addition, the EMH assumes liquidity to be perfect, implying that there is never a bid-ask spread. Thus, no participants on the market can push prices by blocking trades. It might therefore be of value to further clarify whether a relationship exists between momentum and liquidity, and if the addition of any liquidity strategy can generate even higher abnormal return than a plain momentum strategy.

To date, the momentum effect has been researched in many stock markets. However, none of the previous literature is able to explain why such an effect occurs. Instead, many different sources of momentum profits are suggested by different researchers, including risk related explanations, data snooping and flawed methodology, and behavioural explanations. The debate initially focused on the risk-side

¹Momentum strategies by definition involve buying stocks with a recent history of over performance and selling stocks that have fallen values.

of explanations, specifying that macroeconomic risks cause momentum (Avramov and Chordia, 2006; Bansal et al., 2005; Conrad and Kaul, 1998; Fama and French, 1996; Griffin et al., 2003; Liu and Zhang, 2008; Pástor and Stambaugh, 2003). Yet, this debate soon shifted to broader topics, the behavioural side attempted to explain momentum profits by revisiting the investors' self-attributive overconfidence (Avramov et al., 2014; Baker and Stein, 2004; Barberis et al., 1998; Hong et al., 2000). The reason as to why researchers are yet to reach into consensus is arguably because on the one hand, psychological explanations tend to ignore the risks that drive momentum patterns. On the other hand, it is arguably challenging to make conclusions about rational risk-based explanations because it is difficult to interpret why a recent rise in a stock's price transpires to be more risky. In fact, much research fails to find direct evidence to suggest that risk drives momentum. Consequently, behavioural finance provides several possible explanations through psychological models for the observed return continuation effect. Models are constructed according to how market participants behave: some are based on psychological biases of investors that make systematic errors in forming beliefs and preferences while some are built on the interactions among various investor types. Models can be generally divided into two groups: one based on investors' under-reaction to new information and the other based on people's overreaction to sudden news. In the case of the investor under-reaction, stock prices react less than they should do according to the EMH. In contrast, overreaction causes stock prices to react much stronger than they should be according to the EMH. Therefore, both of the two biases reflect in models as the stock prices move gradually to the equilibrium point.

In this chapter, the author aims to investigate both the behavioural explanations of investors' expectations and the risk-side explanations on liquidity risks, by examining how market liquidity affects momentum payoffs. To do so, this study revisits the definition of momentum in classical mechanics. Linear momentum is

defined as the product of the mass and velocity of an object (Callister and Rethwisch, 2007), where mass is equal to volume times density. In other words, linear momentum is equal to volume times density times velocity. Analogously, stock momentum is affected by market volume (volume), market liquidity (density) and the holding horizons (velocity) of momentum portfolios. At the investment level, this chapter finds that more market liquidity exhibit higher momentum profitability. The intuition behind this result is that under a liquid market condition (when density is high), given the size of stock market remains unchanged (assuming volume to be constant), the overall momentum yields and shows higher profits.

The assumption that market liquidity affects momentum payoffs, however, does not necessarily specify their linear relationship. In fact, if the actual relationship deviates from the model's specification, the estimates and inferences based on the linear regression will be highly misleading. To alleviate any potential specification error and capture partial nonlinearity, this study applies semi-varying coefficient models that allow for the coefficients propensity to change over time. This chapter's results indicate a clear heterogeneity in the UK sample, and the models exhibit a significant illiquidity bounce during the financial crisis from 2007 to 2009. This study exploits the sudden bank run event of Northern Rock in 2007 as an exogenous liquidity shock. The choice of shock is inspired by the semi-parametric coefficients, which show a dramatic drop in late 2007. This chapter's identification strategy relies on the hypothesis that this event affected more to relatively illiquid stocks prior to the bank run.

This study thus goes to the heart of the ongoing debate on the profitability of momentum strategies. The study contributes to the seemingly contradictory impacts of illiquidity on momentum returns in several ways. First, this study provides empirical evidence that is consistent with recent theoretical work on the behavioural-side of explanations about momentum phenomenon, helping bolster a fairly thin research base. Avramov et al. (2014) show that periods of high market

illiquidity are followed by low and negative momentum returns. They argue that during market recession, overconfident investors decide to opt out of the market due to short-sale constraints and this reduces market liquidity and the momentum effect thereby becomes less powerful. This study's measure of illiquidity, on the other hand, combines not only liquidity impact features but also liquidity risk features. In addition to the behavioural-side of explanations, this study provides new evidence suggesting that liquidity risk provides momentum profits. Second, this chapter contributes to the emerging body of empirical literature on applying varying coefficient models. For momentum payoffs, the existing literature has to date not yet considered the effect during financial crisis. The semi-parametric approach is different from existing literature that mostly assumes linearity and constant beta coefficients. The results present a high heterogeneity, and as such this study increases the accuracy and flexibility of estimations. Third, this chapter contributes specifically to the UK empirical literature by exploiting local shock in 2007. The sudden bank run event of Northern Rock is market specific. This study uses the 'difference-in-differences' estimation method, as well as both the in sample and out-of-sample experiments so as to find the predictive power of market illiquidity on momentum profits.

The remainder of the chapter is structured as follows: Section 3.2 provides a review of some of the key literature. Section 3.3 provides details of the data, models and methodology. Section 3.4 presents the empirical findings and section 3.5 concludes and draws together the main contributions of this chapter's data to the literature on momentum payoffs and suggests avenues for future research.

3.2 Literature Review

This section provides a detailed review of the momentum and liquidity literature. It first discusses the momentum profits found by using various momentum strategies and in many financial markets. These are followed by a detailed review of the existing explanations regarding the abnormal profits. Furthermore, it presents the possible link between momentum returns and liquidity risk. This is followed by a review of different liquidity measures. Finally, the gap in existing literature is discussed and highlighted.

Momentum trading was first brought to the attention to finance literature by Jegadeesh and Titman (1993), indicating that individual stocks with high past medium-term returns will continue to earn high average percentage returns over the following three to twelve months. Following the seminal work of Jegadeesh and Titman (1993), numerous studies in different markets around the world have provided evidence for the profitability of momentum trading. For example, significant momentum profits are discovered by Foerster, Prihar, and Schmitz (1996) and Korkie and Plas (1995) in the Canadian stock market; by Rouwenhorst (1998) in 12 European markets; by Chui, Wei, and Titman (2000) in 8 Asian stock markets except Japan and Korea; by Hameed and Mian (2015) in international stocks indices; by Chordia and Shivakumar (2002) in NYSE and AMEX stocks; by Hameed and Kusnadi (2002) in 6 emerging Asian stock markets; by Demir, Muthuswamy, and Walter (2004) in Australian market; and by Gunasekarage and Wan Kot (2007) in the New Zealand stocks market. Further, Moskowitz and Grinblatt (1999) suggested a strong medium-term momentum payoff in industry selected momentum portfolios. Lewellen (2002) found similar profits in size and book-to-market portfolios. George and Hwang (2004) proposed an investing strategy that ranks stocks based on their nearness to past 52-week high and find momentum profits in both individual and industry portfolios.

Although the return continuation phenomenon has been well documented, the sources of these profits and the interpretation of the evidence are widely debated in literature. Researchers present different explanations about the source of the momentum returns. These explanations are generally divided into the risk-related explanations and the explanations based on behavioural finance.

For macroeconomic risk model of explanations, there has been a long running debate on the relationship among macroeconomic variables, industry returns and stock momentum payoffs. For example, Hutchinson and O'Brien (2015) claim that the industry momentum trading profits and individual stocks both contribute to the common prediction factors. Also, the individual stock momentum profits and the industry-based momentum returns are proven to be separate and distinct (Hutchinson and O'Brien, 2015). Similarly Brunnermeier and Sannikov (2012) argue that different credit market situations have a significant impact on risks and expected returns for small and big corporations. Further, they suggest that time variation in expected returns depends on the context of the economy's development. In another study, Burganova, Novak, and Salahieva (2014) indicate that the number of active projects, systematic risk of existing assets and the current interest rates can determine the expected stock returns. Elsewhere, Perez-Quiros and Timmermann (2000) found the change in interest rates has a different impact on expected returns and that small companies have larger discrepancies between risk characteristics across business cycles than large companies. In this line of research, the profitability of momentum trading is simply interpreted as the compensation for risk. For example, Conrad and Kaul (1998) argued that momentum profit is attributable to the cross-sectional dispersion in unconditional expected returns. In another study, Lewellen (2002) found that the negative cross-serial correlation among stocks, not under-reaction, is the main source of momentum profits. Also, Yao (2008) used the frequency domain component method and decomposed stock returns that suggest momentum is rather a systematic phenomenon. Similarly,

Berk, Green, and Naik (1999) illustrated that momentum profits arise because of persistent systematic risk in a firm's project portfolios. In another study, Johnson (2002) posited that momentum comes from a positive relation between expected returns and firm growth rates.

Another body of research focuses on explaining momentum returns based on irrational financial investor behaviours. Recent development in behavioural finance provides with many possible explanations for the observed return continuation effect through psychological models. These models are developed based on the way how investors behave. Some of these models are based on the fact that investors are subject to some psychological biases, for example, the cognitive bias, that enable them to make systematic errors in forming their beliefs and preferences. Some models, on the other hand, purely build on the interaction among different investor types. For the behavioural arguments, the return continuation phenomenon is often interpreted as evidences that investors under-react to new information. For example, Barberis et al. (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong et al. (2000) have developed behavioural models to explain momentum phenomenon and demonstrated that momentum profits are related to several characteristics not typically associated with the priced risk in standard asset pricing models. Furthermore, a large part of the literature concurs with behavioural and information-based explanations. In this vein, momentum in stock returns is interpreted as the result of investors having a tendency to herd, under-react to information, trade securities too infrequently, or pay too much attention to recent stock performance (e.g.(Barberis et al., 1998; Daniel et al., 1998; Grinblatt and Han, 2005)).

There is other strand of literature that places emphasis on momentum profits and stocks characteristics. For example, momentum returns are observed to be higher for stocks that are small, have relatively low analyst coverage (Hong et al., 2000), have high analyst forecast dispersion (Verardo, 2009), demonstrate low

return R2 (information efficiency) (Hou, Xiong, and Peng, 2006), and present high market-to-book ratios (Daniel and Titman, 1999). Since these characteristics are often used to proxy for information efficiency and limits to arbitrage, these findings are often interpreted as evidences to support the behavioural explanations of momentum phenomenon. Other studies document elevated momentum returns for stocks with low-grade credit ratings (Avramov et al., 2007) and high turnover (Lee and Swaminathan, 2000). For the market state variables, Cooper, Gutierrez, and Hameed (2004) argued that the momentum strategy cannot produce profitable earnings following periods of declines of market returns. Similarly, Wang and Xu (2010) found that high market volatility periods are followed by lower momentum payoffs. In addition, Daniel and Moskowitz (2013) documented huge momentum crashes following market recessions and high market volatility states.

It is thus necessary to further understand which explanation is more reliable in generating the momentum returns in order to gauge the relevance of the two prospectives. However, recent publications offer contradictory evidence on the relative importance of these two explanations. The behavioural approach assumes that short-term momentum profits are rather a delayed overreaction to positive news or historical return, resulting in an upward buying pressure on previous winner shares. Similarly, with negative news, there will be a downward selling pressure on previous loser shares. For instance, Barberis et al. (1998) attempted to explain behavioural under-reaction patterns by relying on psychological evidence, for example, self-attributive overconfidence. Similarly, Hong et al. (2000) argue that momentum profits arise from gradual information diffusion. However, these psychological explanations ignore the risks that drive momentum patterns. Indeed, it is challenging to give rational risk-based explanation because it is difficult to ascertain precisely why it is that a recent stock price increase has a greater risk. Much research has failed to present direct evidence to suggest risk would

drive momentum. For example, Fama and French (1996) reported that their three-factor model cannot explain momentum. Avramov and Chordia (2006) found that momentum profits are not affected by the time-varying common risk factors. Also Griffin et al. (2003) showed that there is no evidence that macro economic risk variables can explain momentum. Yet, Liu and Zhang (2008) changed test designs and by doing so found very different results. They concluded that risk explains more than half of momentum profits. In another study, Conrad and Kaul (1998) found that cross-sectional variations in mean returns can drive momentum, and Pástor and Stambaugh (2003) argued that liquidity risk factor explains half of momentum. In addition, Bansal et al. (2005) documented that aggregate consumption risks in cash flows can explain mean return differences in momentum portfolios. To conclude, the risk academy argued that short-term momentum profits can be wholly attributed to the cross-sectional variations in mean returns, implying that stocks with high (low) unconditional expected rates of return in adjacent time periods are expected to have high (low) realized rates of returns in both periods.

With regard to liquidity, the literature and findings on the effects of illiquidity on momentum profits is mixed. Chan, Hameed, and Tong (2000) applied momentum strategies to equity indices and found persistent momentum profits across the world market. They found that return continuation is more pronounced after an increased extent of trading volume over previous periods. Their findings point to the possibility that momentum profits are in some way related to the aggregate liquidity of the underlying market. Similarly, Sadka (2006) presented data and indicated that high liquidity equates to a high level of portfolio turnover and transaction costs. These variations in liquidity, however, may help to explain a component of the excess returns earned by momentum strategies. Sadka (2006) also argued that both strategies appear to perform better with positive liquidity shocks but that they under-performed when there were negative liquidity

shocks. In another study, Korajczyk and Sadka (2004) found that conventional momentum trading tend to be unprofitable for large investment funds. However, momentum trading may still generate considerable returns if one considers liquidity when constructing portfolios. In the same vein, Pástor and Stambaugh (2003) found that the addition of liquidity spreads can explain nearly half of the return anomaly achieved from momentum portfolios. Further, Lee and Swaminathan (2000) found that the momentum return premium was much higher in stocks with high volumes. This is consistent with the findings of Sadka (2006). The authors hypothesised that trading volume serves as an indicator of demand for a stock, implying that there is a contemporaneous and structural connection between overreaction and high trading volumes. Similarly, Chen, Ibbotson, and Hu (2010) considered liquidity as an investment style and found that portfolios constructed of low turnover shares outperformed their highly turnover counterparts. The authors considered the effects of combining liquidity and momentum strategies and found that the high momentum together with low liquidity portfolios achieved the highest returns over the sample period, implying that investors are compensated for liquidity risk even when engaging in momentum strategies. The above shows that further research is needed to clarify the contradictions in existing documents regarding the determinants of momentum. This current chapter seeks a rational explanation of price momentum by looking at its relationship with market illiquidity. Liquidity as a factor has to date been widely documented for explaining cross sectional stock returns. Amihud and Mendelson (1986) used bid-ask spread as a liquidity measure and found a positive relationship between illiquidity and portfolio returns. In another study, Brennan, Chordia, and Subrahmanyam (1998) used trading volume to measure liquidity and found that illiquid stocks produce higher returns. Elsewhere, Amihud (2002) proposed a liquidity measure, which is defined as the absolute daily return divided by daily trading volume and found evidence to support liquidity and return model from 1962 to

1999 in the US market. Similar findings have been documented using different liquidity proxies such as reversal measures, number of zero return days, and effective tick (e.g. (Corwin and Schultz, 2012; Goyenko et al., 2009; Lesmond et al., 1999; Liu, 2006; Pástor and Stambaugh, 2003)).

Despite the fact that the literature to date has not reached consensus on which proxy measures liquidity, most of the measures are highly correlated. This chapter follows Lesmond (2005) and adopts their ‘zero-return days’ measure to proxy illiquidity. Intuitively, when trading cost is higher than the benefit of trading, rational investors would choose not to trade (Lesmond et al., 1999). Therefore, zero return would be observed for such days. This measure is reported to be popular in international finance research, especially when high-quality daily trading volume data are not available. In another study, Goyenko et al. (2009) compared almost all existing proxies and develop three new spread measures and nine new price impact measures. They provided answers to which measure researchers are supposed to use. It is suggested that the dominant and simplest measure for relatively lower frequency estimations is the analytic ‘effective tick’. Other measures that are widely used in the literature such as ‘the return to value’ measure proposed by Amihud (2002), the ‘reversal measure’ developed by Pástor and Stambaugh (2003) are not appropriate to use as proxies for effective or realized spreads. Since this chapter applies monthly observations in the estimations, the author uses the ‘effective tick’ as an alternative to the ‘zero-return days’ measure for robustness check. As they are shown below, the results shed light on the relationship of liquidity proxy inclusion to weakening the explanatory power of momentum.

In another research, Daniel et al. (1998) suggest that investors overreact to private information because of overconfidence and that this triggers return momentum. The model shows that when overconfidence is high, there is excessive liquidity and momentum profits become high. Conversely, there is a reduced momentum payoff when the market illiquidity is high. Avramov et al. (2014)’s conditional

models suggest that the profitability of momentum trading varies with the overall market illiquidity. Nevertheless, there is one common limitation in financial empirical literature. It is often assumed that coefficients in linear estimations are constant. This could lead to the omission of significant bounce among various coefficients. What is more, there is time when less sufficient data are available when running time-series regressions. It is therefore problematic because there will be no estimation under certain time framework. To solve this problem, this study improves traditional linear regressions by applying semi-parametric tests, which to the best of the author's knowledge, has not been done in momentum-liquidity literature. In particular, the author modifies the varying coefficient models originally proposed by Zhang, Lee, and Song (2002) and applies various bandwidth in the estimations.

3.3 Data, Models and Methodology

3.3.1 Data and Variables

The author obtains raw data from Thomson DataStream of all stocks listed on the FTSE All-Share index. The sample spans the period 1990-2013. The author extracts datatype including daily market value (share price multiplied by the number of ordinary shares in issue); return index (a theoretical growth in value of a share-holding over a specified period); and unadjusted closing price. At the end of each month, the total number of shares outstanding, the return index, and the market value of each stock are obtained. Stocks are kept if they existed for at least three years prior to the year start.

The Fama-French factor data are downloaded directly from the University of Exeter database as described in Gregory, Tharyan, and Christidis (2013).²The data include market factor, which is the excess return on the value-weighted market

²While Kenneth French's US website provides data for the US market, there is currently

index over the one month T-bill rate; the size factor, which is the small minus big return premium; and the value factor, which is the high book-to-market minus low book-to-market return premium.

The momentum portfolio formation method closely follows the approach proposed by Jegadeesh and Titman (1993) and Daniel and Moskowitz (2013).³In particular, at the beginning of each month t , all shares are sorted into decile portfolios based on their lagged eleven-month returns. To avoid the bouncing effect, this study skips one month from the ranking period (as suggested by Jegadeesh and Titman (1993)) meaning that the holding period stock returns of month $t - 12$ to $t - 2$ are calculated. The top ten percent of stocks are identified as the winner portfolios while the bottom ten percent are loser portfolios. Since one year of data is lost in forming the momentum factors, the momentum returns in this study start from January 1991. This chapter only includes stocks that have valid share prices and number of shares outstanding at the beginning of formation date. This approach is similar to the screening method used by Daniel and Moskowitz (2013). Incidentally, the construction of the momentum portfolios is similar to the ones reported by Gregory et al. (2013).

This chapter employs the zero return days measure (ZR) and the effective tick (ET) measure advocated by Goyenko et al. (2009) to proxy illiquidity. The zero return days measure is identified as:

$$ZR_{i,t} = \frac{N_{i,t}}{T_t} \quad (3.3.1)$$

where T_t is the number of trading days at time t ; $N_{i,t}$ is the number of zero-return days of stock i in time t .

no equivalent for the UK market. The author thanks the University of Exeter for providing remedy and making the UK data freely downloadable at this website: <http://business-school.exeter.ac.uk/research/areas/centres/xfi/research/famafrench/>.

³To avoid survivor-ship bias, this analysis covers not only presently listed stocks but also dead stocks. Dead stocks refer to those of firms that were de-listed at some point during the sample period.

The effective tick is identified as:

$$ET = \frac{\sum_{j=1}^1 \gamma_j S_j}{\bar{P}_k} \quad (3.3.2)$$

This study obtains S_j by using the decimal grid, which is an approach similar to that of the dollar grid proposed by Hagströmer, Hansson, and Nilsson (2011). In this case, the possible spreads are at £0.01, £0.05, £0.1, £0.2, £0.5 and £1. \bar{P}_k is the average daily prices in month k , and γ_j is defined as:

$$\hat{\gamma}_j = \left\{ \begin{array}{ll} \text{Min}[\text{Max}\{U_j, 0\}, 1] & j = 1 \\ \text{Min}[\text{Max}\{U_j, 0\}, 1 - \sum_{k=1}^{j-1} \hat{\gamma}_k], & j = 2, 3, \dots, j \end{array} \right\} \quad (3.3.3)$$

Based on

$$U_j = \left\{ \begin{array}{ll} 2F_j, & j = 1 \\ 2F_j - F_{j-1}, & j = 2, 3, \dots, j-1 \\ F_j - F_{j-1}, & j = j \end{array} \right\} \quad (3.3.4)$$

where

$$F_j = \frac{N_j}{\sum_{j=1}^j N_j} \quad \text{for } j = 1, 2, J.$$

N_j is the number of trades on prices to the j spread using positive volume days.

3.4 Models and Methodology

3.4.1 Varying Coefficient Models

Despite its popularity in the empirical literature, multi-variate linear regression could lead to many problems. First, linear regression is fully parametric, and is consequently subject to a number of model assumptions such as linearity. For example, if the actual relationship between dependent and independent variables deviates from the model specification, the estimates and inference based on such

regression will be highly misleading. Furthermore, linear regression cannot accommodate heterogeneity, which means that the coefficients do not evolve along a time dimension. This scenario is unrealistic in financial estimations because the time-varying effects of certain variables cannot be captured. The non-parametric estimations, on the other hand, make no assumption on the model specifications. However, the non-parametric estimators are highly inaccurate and require fat data. In addition, non-parametric models are difficult to interpret because they do not provide the usual coefficient estimates (Chen and Sherif, 2016).

Due to the limitations of the parametric and non-parametric approaches, semi-parametric models are here introduced in order to achieve accuracy and flexibility. In particular, the varying coefficient models as one example of semi-parametric models are simulated by their need in practice. That is different from linear regression as it allows for one or more of the coefficients to change in line with variables, for example, time. First, varying coefficient models contain functional components which capture partial non-linearity and alleviate potential specification errors. Second, the idea of a time varying coefficient is especially appealing in this study because the author can capture the illiquidity bounce during certain periods by allowing for varying betas instead of constant coefficients. Finally, it is documented that semi-parametric models are usually more accurate in predictions. The models are identified in the next section.

3.4.2 Semi-varying Coefficient Models

This study uses the variant of the varying-coefficient model termed the semi-varying coefficient model proposed by Zhang et al. (2002). The model is defined as follows,

$$Y = \sum_{j=1}^{p_1} \beta_j(t)X_j + \sum_{j=1}^{p_2} \gamma_j Z_j + e \quad (3.4.5)$$

The dependent variables are divided into two groups, X_1, \dots, X_{p_1} whose coefficients change with time t and Z_1, \dots, Z_{p_2} whose coefficients do not vary.

To estimate the functional coefficient, this study uses local linear regression as described by Fan and Gijbels (1996).

For a given functional coefficient $\beta(\cdot)$ at point t , the author considers the neighbourhood U of t and apply a first order Taylor approximation,

$$\beta_j(t_i) = \beta_j(t) + \frac{\partial \beta(t)}{\partial t}(t_i - t) := \beta_{0,j} + \beta_{1,j}(t_i - t)$$

for all $t_i \in U$ and $j = 1, \dots, p$. Using Taylor approximation, $\beta_j(t)$ at arbitrary time is linked to $\beta_j(t_i)$ where data are observed. This study combines local least square with the kernel method to minimise the following objective function:

$$\sum_{i=1}^n \left\{ y_i - \sum_{j=1}^{p_1} [\beta_{0,j} X_{i,j} + \beta_{1,j}(t_i - t) X_{i,j}] - \sum_{j=1}^{p_2} \gamma_j Z_{i,j} \right\} K_h(t_i - t) \quad (3.4.6)$$

where $K_h(\cdot) = K(\cdot/h)h$ is a kernel function which assigns weights to local observations. Here, the author chooses the Epanechnikov kernel $K(u) = 0.75(1 - u^2)\mathbf{1}\{|u| \leq 1\}$. The author minimises the objective function with respect to $\beta_{0,j}$ will give (unfeasible) $\beta(\cdot)$ estimate at time t . To obtain both estimates for β and γ , the author shall work with matrix notations. Denote $\mathbf{Y} = (y_1, \dots, y_n)^T$, $\mathbf{Z} = (\mathbf{z}_1, \dots, \mathbf{z}_n)^T$, $\mathbf{X} = (\mathbf{x}_1, \dots, \mathbf{x}_n)^T$, $\mathbf{U}_t = (\mathbf{x}_1(t_1 - t), \dots, \mathbf{x}_n(t_n - t))^T$, $\mathbf{D}_t = [\mathbf{X}, \mathbf{U}_t]$, $\mathbf{W}_t = \text{diag}(K_h(t_1 - t), \dots, K_h(t_n - t))$, $\mathbf{e} = e_{2,1}^T(e_1, \dots, e_n)$. $\boldsymbol{\beta} = (\beta_{0,1}, \dots, \beta_{0,j})^T$.

For each t ,

$$\hat{\boldsymbol{\beta}}_{uf}(t) = (I_{p_1 \times p_1} \mathbf{0}_{p_1 \times p_1})(\mathbf{D}_t^T \mathbf{W}_t \mathbf{D}_t)^{-1} \mathbf{D}_t^T \mathbf{W}_t (\mathbf{Y} - \mathbf{Z} \boldsymbol{\gamma}) \quad (3.4.7)$$

where $I_{p_1 \times p_1}$ is a p_1 dimensional identity matrix and $\mathbf{0}_{p_1 \times p_1}$ is a $p_1 \times p_1$ zeros matrix.

The estimator, however, is not feasible for the moment, because it involves the unknown nonvarying coefficient γ . Once obtaining an estimate $\hat{\gamma}$ for γ , the author simply includes it into equation 3.4.7 and this study shall obtain a feasible one.

$$\hat{\beta}_f(t) = (I_{p_1 \times p_1} \mathbf{0}_{p_1 \times p_1})(\mathbf{D}_t^T \mathbf{W}_t \mathbf{D})^{-1} \mathbf{D}_t^T \mathbf{W}_t (\mathbf{Y} - \mathbf{Z}\hat{\gamma}) \quad (3.4.8)$$

For the purpose of estimating $\hat{\gamma}$, this study uses the profile least square method proposed by Fan and Huang (2005). The author first defines

$$\mathbf{M} = (\hat{\beta}_{uf}^T(t_1) \mathbf{x}_1, \dots, \hat{\beta}_{uf}^T(t_n) \mathbf{x}_n)^T$$

For each term in \mathbf{M} , it can be further expanded as

$$\hat{\beta}_{uf}^T(t_j) \mathbf{x}_j = (\mathbf{x}_j, \mathbf{0}_{p_1 \times p_1})(\mathbf{D}_{t_j}^T \mathbf{W}_{t_j} \mathbf{D})^{-1} \mathbf{D}_{t_j}^T \mathbf{W}_{t_j} (\mathbf{Y} - \mathbf{Z}\gamma)$$

This implies the study could rearrange $\mathbf{M} = \mathbf{S}(\mathbf{Y} - \mathbf{Z}\gamma)$, with

$$\mathbf{S} = \begin{pmatrix} (\mathbf{x}_1, \mathbf{0}_{p_1 \times p_1})(\mathbf{D}_{t_1}^T \mathbf{W}_{t_1} \mathbf{D})^{-1} \mathbf{D}_{t_1}^T \mathbf{W}_{t_1} \\ \vdots \\ (\mathbf{x}_n, \mathbf{0}_{p_1 \times p_1})(\mathbf{D}_{t_n}^T \mathbf{W}_{t_n} \mathbf{D})^{-1} \mathbf{D}_{t_n}^T \mathbf{W}_{t_n} \end{pmatrix} \quad (3.4.9)$$

Then semi-varying coefficient model (3.4.2) then can be written as

$$\mathbf{Y} - \mathbf{Z}\gamma = \mathbf{S}(\mathbf{Y} - \mathbf{Z}\gamma) + \mathbf{e} \quad (3.4.10)$$

or

$$(I - \mathbf{S})\mathbf{Y} = (I - \mathbf{S})\mathbf{Z}\gamma + \mathbf{e} \quad (3.4.11)$$

The last equation naturally gives rise to an OLS estimator for γ

$$\hat{\gamma} = (\mathbf{Z}'(I - \mathbf{S})'(I - \mathbf{S})\mathbf{Z})^{-1} \mathbf{Z}'(I - \mathbf{S})'(I - \mathbf{S})\mathbf{Y} \quad (3.4.12)$$

3.4.3 Choice of Bandwidth

A Semi-parametric regression estimator usually contains a tuning parameter that controls the level smoothness of the estimated function. For the semi-varying coefficient model, the tuning parameter is the bandwidth h , which controls the size of the neighbourhood for local estimation. If h is large, then more data points are included, which result in smoother function estimates.⁴ In contrast, a small h implies a small neighbourhood, which gives wiggly estimated curves. It is less biased, as only data very close to the point are used but the estimates are less accurate. Choice of Bandwidth is essentially the balance between bias and variance.

This chapter relies on *cross-validation* techniques to choose the bandwidth similar to the one applied by Wu, Chiang, and Hoover (1998). Let $\hat{\beta}_{-i}(t_i)$ and $\hat{\gamma}_{-i}$ be the estimate at t_i without using the i th data. Then the study could examine the performance of $\hat{\beta}_{-i}(t_i)$ by computing its prediction error,

$$\hat{PE}_i = (Y_i - \mathbf{x}_i^T \hat{\beta}_{-i}(t_i) - \mathbf{z}_i^T \hat{\gamma}_{-i})^2 \quad (3.4.13)$$

This study chooses h so as to minimise the sum of \hat{PE}_i for all i .

$$h^* = \arg \min_h \frac{1}{n} \sum_{i=1}^n (Y_i - \mathbf{x}_i^T \hat{\beta}_{-i}(t_i) - \mathbf{z}_i^T \hat{\gamma}_{-i})^2 \quad (3.4.14)$$

3.4.4 Time Variation Momentum Payoffs in Portfolios

The study examines the predictive role of market illiquidity in explaining the inter-temporal variation in momentum profits. The analysis is based on the following

⁴Smoother estimates are less volatile but may have more bias.

time-series regression:

$$WML_t = \alpha_0 + \beta_1 Mktchg_{t-1} + \beta_2 Mktilliq_{t-1} + \beta_3 DOWN_{t-1} + \beta_4 Mktvol_{t-1} + c'F_t + e_t, \quad (3.4.15)$$

where WML_t is the value-weighted return on the winner minus loser momentum deciles in month t . At the end of each month t , stocks are ranked based on returns from months $t - 12$ to $t - 2$. This study skips month $t - 1$ as suggested by Jegadeesh and Titman (1993). $Mktchg_{t-1}$ is the lagged market change in returns, $Mktilliq_{t-1}$ is the lagged aggregate market illiquidity proxied by ‘zero return days’ proposed by Lesmond (2005). It has been documented by Næs, Skjeltorp, and Ødegaard (2011) that stock market liquidity is pro-cyclical and worsens during bad economic states. Therefore, market state and volatility could possibly capture the market illiquidity effects. It is thus essential to control for these two variables. In this context, $DOWN_{t-1}$ is a dummy variable that takes the value of one only when the return on the value-weighted FTSE index during the past twenty-four months is negative or zero otherwise, and $Mktvol_{t-1}$ is the lagged market volatility of daily market returns. The F vectors are the Fama-French three factors which include the market factor (mkt), the size factor (smb), and the value factor (hml). It is important to gauge the ability of market illiquidity after controlling for risks on the momentum portfolio. For the purpose of comparison, this study also runs the predictive regressions excluding the three risk factors.

3.4.5 Price Momentum in Individual Stocks

It is suggested that to avoid data snooping bias, asset pricing models are better implemented using individual securities (Lo and MacKinlay, 1990). Indeed, Avramov and Chordia (2006) used returns on individual stocks in the conditional beta setup and found that the impact of momentum on the cross-section of individual stock returns was influenced by the business cycle. Further, this study

examines the impact of market illiquidity on momentum from the cross-section of individual stock returns. Inspired by the two frameworks proposed by Fama and MacBeth (1973), the varying coefficient adjusted two stage of regressions are implemented.

First, the author runs the monthly cross-sectional regressions in the following ways.

$$R_{i,t} = \alpha_0 + \beta_{0,t_i} R_{i,t-12:t-2} + \gamma_t ILLIQ_{i,t-1} + e_t \quad (3.4.16)$$

Where $R_{i,t}$ is the return of stock i in month t , $R_{i,t-12:t-2}$ is the cumulative stock return in the formation period from month $t - 12$ to $t - 2$, and $ILLIQ_{i,t-1}$ is the stock illiquidity in the previous one month. This study regresses a stock's returns on its past returns and illiquidity and obtain the varying coefficients β_{0,t_i} . This measures the individual stock level of momentum in month t for stock returns. The second stage is the time series regressions. The author uses the estimated betas arising from the above cross-sectional regressions as the dependent variable. The independent variables are the market illiquidity, market state, and the volatility. The regression is formulated as

$$\beta_{0,t_i} = \alpha_0 + \gamma_1 Mktilliqt_{-1} + \gamma_2 Mktchg_{t-1} + \gamma_3 Mktvol_{t-1} + e_t \quad (3.4.17)$$

3.4.6 Individual Stock Momentum and Variation with State Variables

To ascertain whether stock exposures to market state variables can drive momentum payoffs, this study follows Avramov et al. (2014) and run the two-pass regression method. In the first stage, the time-series regressions are implemented for each firm and the expected stock returns predicted by past market variables

and asset pricing factors are removed:

$$R_{i,t}^e = \alpha_0 + \beta_{i,1}Mktilliqt_{-1} + \beta_2Mktchg_{t-1} + \beta_3Mktvol_{t-1} + c'F_t + e_{i,t} \quad (3.4.18)$$

Where $R_{i,t}^e$ is the excess return of stock i on month t . $Mktilliqt_{-1}$, $Mktchg_{t-1}$ and $Mktvol_{t-1}$ are the market state variables on month $t-1$. The vector F is the Fama-French three factors. Consequently, by running the above equation, this study obtains the unexpected part of each individual stock returns, i.e.

$$R_{i,t}^* = \alpha_i + e_{i,t}.$$

For the second stage, this study measures the extent to which the market state variables account for the individual stock level momentum. The monthly cross-sectional regression is identified as:

$$R_{i,t}^* = \alpha_0 + \beta_1 R_{i,t-12:t-2} + u_{i,t}, \quad (3.4.19)$$

Where $R_{i,t-12:t-2}$ is the past eleven months return of stock i .

3.4.7 Robustness Test: Liquidity Shock Using the Difference in Differences (DID) Method

The difference in differences (DID) method is a technique used to examine the differential impact of a sudden event on a treatment group versus a control group (Ashenfelter and Card, 1985). In contrast to time-series and cross sectional estimates, DID uses panel data to measure the differences between the treatment and control groups of the changes in the outcome variable that occur over time (Abadie, 2005). The formula is described as follows:

$$Y(i, t) = \delta(t) + \alpha * D(i, t) + \eta(i) + v(i, t) \quad (3.4.20)$$

where $\delta(t)$ is the time specific component, $\eta(i)$ is the individual component, $v(i, t)$ is the control variable and α represents the impact of the treatment.

The DID approach is an important analysis to test the differing sensitivities on momentum crash when significant liquidity shock occurs. The 2007-2009 financial crisis is a natural liquidity shock. This study therefore performs the next regression to check whether stocks associated with high illiquidity are more sensitive to systemic shocks.

$$R_{i,t} = \beta_0 + \beta_1 Liquid_{i,t} + \beta_2 Crisis_{i,t} + \beta_3 Liquid * Crisis_{i,t} + \beta_4 Size_{i,t-1} + u \quad (3.4.21)$$

where $Liquid_{i,t}$ is the dummy variable that takes 1 if the stock is included in the high liquid portfolio⁵ and 0 otherwise. $Crisis_{i,t}$ is the dummy variable that takes the value 1 if the time is between September 2007 and December 2009 and 0 otherwise. Importantly, this study is interested in the value of β_3 , a difference in difference coefficient that measures the different explanatory powers of high liquid stocks following a sudden liquidity shock.

3.5 Empirical Findings

This study begins the analysis with the descriptive statistics of momentum predictors. Panel A of Table 3.1 reports the summary statistics of market state variables in evaluating momentum payoffs over the full sample period. As seen from Table 3.1 the momentum profit (WML) is negatively skewed with a skewness equal to -1.034. This pattern and characteristic is similar to the findings reported

⁵The author ranks stocks based on illiquidity in ascending orders. The top 20% stocks are grouped in the high liquid portfolio.

in Daniel and Moskowitz (2013) and Avramov et al. (2014), suggesting that momentum comes with occasional crashes. The change in market return (Mktchg) is measured by using the changes of market return from month $t - 1$ to month t . It is known at month t to predict momentum returns at month $t + 1$. Therefore, market return as a variable here is different from the contemporaneous market return of the Fama-French model, which is a risk factor. The author also reports the characteristics of aggregate market illiquidity proxied by ‘zero-return days’ (Lesmond, 2005). The individual illiquidity is defined as $ZR_{i,t} = \frac{N_{i,t}}{T_t}$, where T_t is the number of trading days at time t ; $N_{i,t}$ is the number of zero-return days of stock i in time t . Aggregate market illiquidity (Mktilliq) in month $t - 1$ is then defined as the value-weighted average of each stock’s monthly zero-return illiquidity. The high cross-sectional market level illiquidity (mean=3.755%) and high positive skewness (skewness=3.220) indicate that the performance of momentum is potentially linked to market level illiquidity and that illiquidity can be one possible explanation of momentum crash. ‘Down’ is a market dummy that takes the value of one only if a negative cumulative two-year return is calculated in month $t - 1$. Finally, the monthly time series market volatility (Mktvol) is constructed by taking the average daily volatility in each month.

Panel B of Table 3.1 shows the correlation matrix of the four aggregate market level variables and examines their time-series correlation with the momentum returns. Notably, the lagged change in market return is negatively correlated with momentum profits (correlation=-0.017), implying that momentum tends to make profits after a recent market decline. The study also reports a negative correlation between momentum and the market dummy Down (correlation=-0.024). Unlike the market change variable, the Down indicator specifies a long and persistent market recession over the previous two years. The negative correlation further suggests that momentum is negatively linked to market conditions. This is consistent with the findings of Cooper et al. (2004) and Avramov et al. (2014), who

Table 3.1: Summary Statistics and Correlations

Panel A presents the descriptive statistics of market state variables. WML is the momentum profits, Mktchg stands for market change, Mktilliq is the market aggregate illiquidity proxied by the ‘zero return days’ proposed by Lesmond (2005), Down is the market dummy for negative market returns over the previous two years, and Mktvol is the market return volatility. Panel B reports the correlation of momentum returns and the market state variables.

Panel A	WML	Mktchg	Mktilliq	Down	Mktvol
Mean	1.044%	-1.079	3.755%	0.900%	55.52%
Std.	4.776%	8.342	6.531%	0.520%	49.78%
Skew.	-1.034	0.053	3.220	2.538	-0.222
Kurt.	7.940	30.368	17.517	13.770	1.049
Min.	-25.03%	-62.7946	0	0	0
Max.	16.04%	62.9315	47.88%	4.539%	1

Panel B	WML_t	$Mktchg_{t-1}$	$Mktilliq_{t-1}$	$Down_{t-1}$	$Mktvol_{t-1}$
WML_t	1.000				
$Mktchg_{t-1}$	-0.017	1.000			
$Mktilliq_{t-1}$	-0.027	-0.042	1.000		
$Down_{t-1}$	-0.024	-0.041	0.123	1.000	
$Mktvol_{t-1}$	-0.050	-0.051	-0.057	-0.076	1.000

claim that the negative market states are associated with lower momentum returns. Also, the lagged market illiquidity is negatively correlated with momentum returns, with a correlation of -0.027, suggesting that momentum payoffs are low following periods of high aggregate illiquidity. In unreported results, the author considers an alternative illiquidity measure ‘effective tick’ proposed by Goyenko et al. (2009) to construct market aggregate illiquidity. This chapter’s results hold using this alternative measure. This is consistent with the existing literature. Finally, this study reports the correlation between momentum profits and the lagged market volatility. The evidence shows a negative correlation of -0.050, which confirms the findings of Wang and Xu (2010) that the aggregate market volatility predicts momentum profits.

Next, this study examines the predictive role of market state variables in explaining the variation in momentum profits. The examination is based on the time-series regression specification mentioned in Section 3.4. Table 3.2 reports the results of the monthly time-series regression of momentum profits. In particular, the study runs all seven regressions that take into consideration the combination of predictive variables.

Table 3.2: Momentum Payoffs and Market States

This table presents the results of the following monthly time-series regressions and their corresponding p-values, $WML_t = \alpha_0 + \beta_1 Mktchg_{t-1} + \beta_2 Mktilliq_{t-1} + \beta_3 DOWN_{t-1} + \beta_4 Mktvol_{t-1} + c'F_t + e_t$, where WML_t is the value-weighted return on the winner minus loser momentum deciles in month t , $Mktchg_{t-1}$ is the lagged market change in returns, $Mktilliq_{t-1}$ is the lagged aggregate market illiquidity proxied by ‘zero return days’ proposed by Lesmond (2005), $DOWN_{t-1}$ is a dummy variable that takes the value of one only when the return on the value-weighted FTSE index during the past twenty-four months is negative and zero otherwise, and $Mktvol_{t-1}$ is the lagged market volatility of daily market returns. The F vectors are the Fama-French three factors which include the market factor (mkt), the size factor (smb), and the value factor (hml). Numbers with “*”, “**”, and “***” are significant at the 10%, 5%, and 1% level respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept	0.011*** (0.000)	0.010*** (0.001)	0.007** (0.030)	0.015*** (0.001)	0.023*** (0.001)	0.022*** 0.003	0.026 *** (0.001)
Mktchg		-0.001** (0.044)				-0.001** 0.039	-0.001 ** (0.023)
Mktilliq			-0.091** (0.039)			-0.082* (0.063)	-0.091** (0.037)
Down				-0.007 (0.255)		-0.011* (0.067)	-0.010* (0.088)
Mktvol					-1.257** (0.043)	-1.021* (0.068)	-1.469** (0.018)
mkt	-0.049 (0.498)	-0.069 (0.343)	-0.062 (0.388)	-0.050 (0.491)	-0.107 (0.167)		-0.153 ** (0.049)
smb	0.064 (0.468)	0.070 (0.423)	0.066 (0.454)	0.064 (0.469)	0.020 (0.827)		0.020 (0.818)
hml	-0.230*** (0.007)	-0.220*** (0.010)	-0.233*** (0.006)	-0.220*** (0.010)	-0.228*** (0.007)		-0.206** (0.014)
R-square	0.034	0.048	0.049	0.038	0.048	0.048	0.089
Adj-Rsq	0.023	0.034	0.035	0.024	0.034	0.033	0.065

This study considers the regressions ranging from the simplest Model 1, which drops all predictors and retains the intercept and Fama-French three-factors only, to the all-inclusive Model 7, which consists of the variables of market change, market illiquidity, market conditions, market volatility, and the Fama-French three-factors. For all these regressions, the explained variable WML_t is the value-weighted return on the winner minus loser deciles that is formed based on the previous eleven-month stock returns.

With regard to explanatory variables, $Mktchg_{t-1}$ is the lagged market change in returns. $Mktilliq_{t-1}$ is the lagged aggregate market illiquidity proxied by ‘zero return days’ proposed by Lesmond (2005). $DOWN_{t-1}$ is a dummy variable that takes the value of one only when the return on the value-weighted FTSE index during the past twenty-four months is negative and zero otherwise, and $Mktvol_{t-1}$ is the lagged market volatility of daily market returns. The F vectors are the Fama-French three factors, which include the market factor (mkt), the size factor (smb), and the value factor (hml). For Model 6, the author excludes the F vectors for the purpose of comparison.

The evidence from Table 3.2 suggests a negative impact of the ‘zero-return days’ illiquidity on momentum profits. The slope coefficients are negative across the board from -0.091 to -0.082. This implies that momentum profits will decline after the illiquid periods. This further suggests that momentum could crash following the illiquid market conditions. This is consistent with the findings of Avramov et al. (2014) who investigated this relationship in the US market. Meanwhile, this study finds a significant negative impact of market volatility on momentum payoffs. As seen from Table 3.2, the slope coefficient is -1.469 for the all-inclusive model. However, conversely to Cooper et al. (2004) and Wang and Xu (2010), this chapter’s analysis indicates only weak evidence to capture meaningful connections between momentum payoffs and the market long-term condition. Notably, the coefficient is insignificant for the Down-only predictive model (Model 4). Therefore,

this study applies the proxy for short-term market change (*Mktchg*). Subsequently, the study finds that the slope coefficients are negative and significant. To illustrate, market change, market illiquidity and market volatility are statistically significant at the 5% level. The market condition dummy, however, is significant only at the 10% level of significance in the all-inclusive models. Overall, the main evidence from Table 3.2 confirms the important predictive role of illiquidity either on a stand-alone basis or on a joint-basis with volatility and the overall market conditions.

Next, the author performs the estimations from portfolio level to individual level. This is especially important when the sample size is not large enough to form meaningful portfolios. In fact, it is argued by Lo and MacKinlay (1990) that portfolio estimation could result in potential data snooping bias. Therefore, this study further investigates the relationship between momentum and illiquidity by performing asset pricing tests on individual securities. Moreover, to bring new insights regarding the validity of various models and account for anomalies, the study applies the semi-parametric tests to allow for varying betas. This approach allows us to capture the impact of momentum on the cross-section of stock returns influenced by the economic cycle.

Figure 3.1 plots the time series momentum portfolio payoffs over the period between February 1991 and December 2013. It reports the average monthly value-weighted price momentum profits. As seen in Figure 3.1 the momentum profits tend to bounce dramatically in the early 2000s and during the 2007-2009 financial crisis time. Considering these illiquidity events, this study further investigates such patterns of findings by applying the varying coefficient models.

Figure 3.1: Time Series Momentum Portfolio

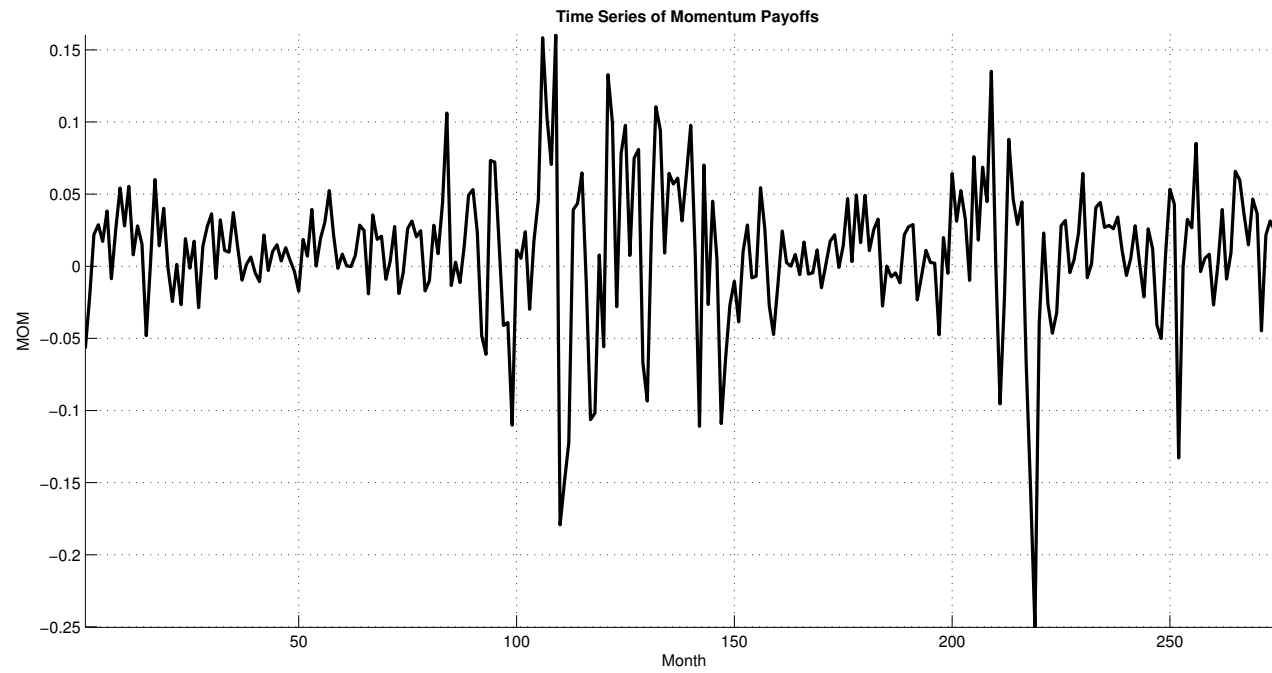


Figure 3.2 presents the results from the varying coefficient models. On the left hand side, the three graphs are generated based on relatively low bandwidth settings. The graph presents a clear heterogeneity existing in the sample. The horizontal axis represents the monthly observations from the sample pool. The varying coefficient models clearly suggest a significant bounce after the financial crisis, which happened during periods between 2007 and 2009. The three graphs on the right hand side are varying betas along months based on wider bandwidth settings. In the extreme cases when bandwidth is enormously high, the beta coefficient becomes constant.⁶

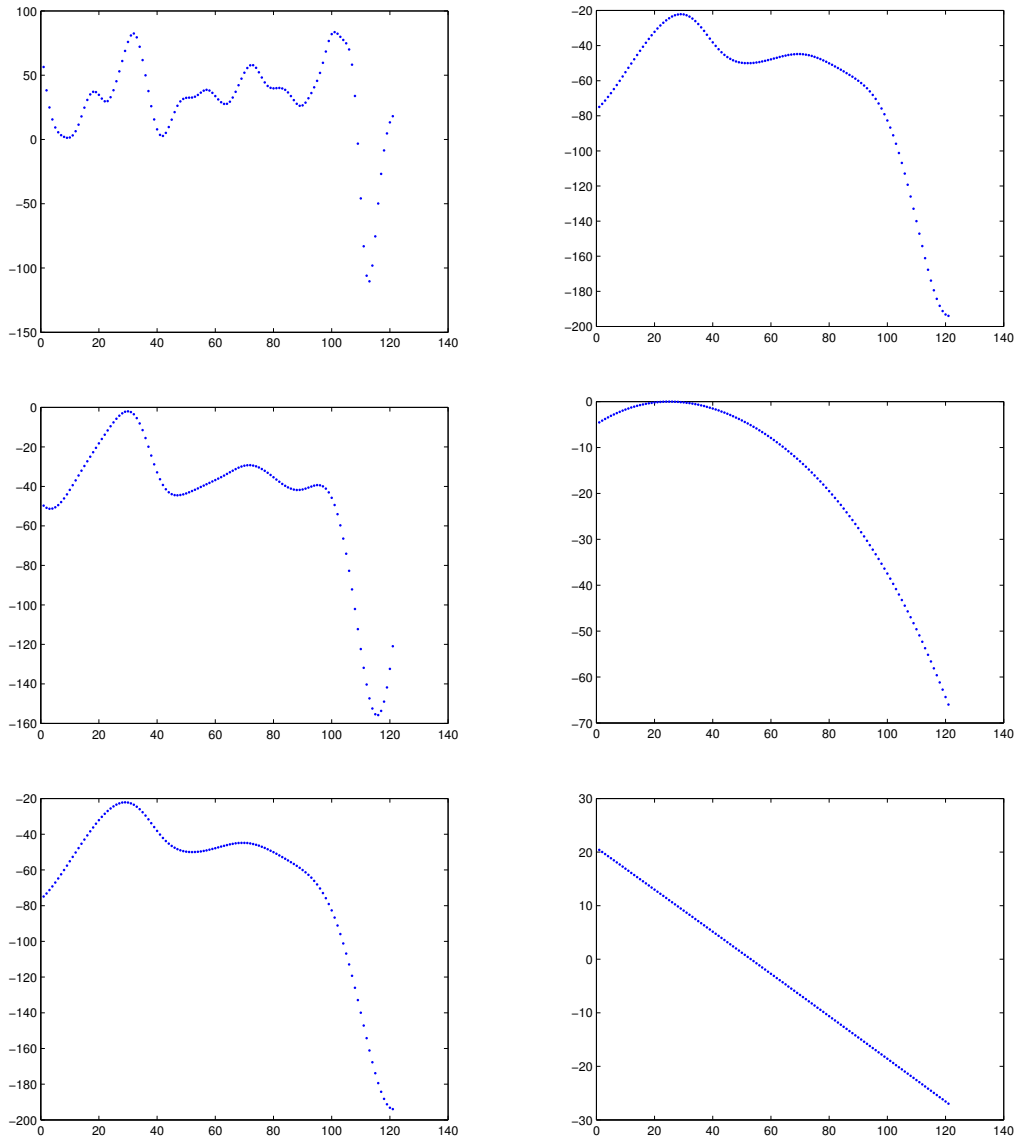
Table 3.3 shows the results of the varying coefficient models. In particular, this chapter is motivated by the Fama and MacBeth (1973)'s two-stage regressions in capturing the specific relationships between momentum and illiquidity. Both time series and cross-sectional regressions are applied in this chapter. In the first stage, the study runs the cross-sectional regressions of stock returns on its own past returns and past illiquidity, proxied by 'zero-return days'. In each month t , this study obtains varying stock momentum coefficients $\beta_0 t_i$. Panel A of Table 3.3 describes the cross-sectional first stage regression results.⁷ From the individual level of evidence, there is a strong continuation in stock returns in the cross-section. The optimal $\beta_0 t_i$ is significantly positive. The slope coefficient of the illiquidity has an average of 1.2746 suggesting that illiquid stocks earn higher future returns than relatively liquid stocks. This is in line with the findings from Chen and Sherif (2016) who applied the seven illiquidity proxies and reported significant illiquid premiums in the UK market.

Next is the second-stage estimations, i.e. the time-series regressions. Panel B in Table 3.3 presents the estimations associated with time series regressions of the

⁶This chapter contributes to literature by applying a narrow bandwidth setting and allow for varying betas to change along periods.

⁷To obtain more accuracy results, the author sets a narrow bandwidth in the varying coefficient models.

Figure 3.2: Choice of Bandwidth



(a) Low bandwidth varying coefficient models (b) High bandwidth varying coefficient models

Table 3.3: Individual stock momentum and market states with varying coefficients

Note: Panel A presents the coefficients of the following Fama-MacBeth regressions:

$$R_{i,t} = \alpha_0 + \beta_{0,t_i} R_{i,t-12:t-2} + \gamma_t ILLIQ_{i,t-1} + e_t,$$

where $R_{i,t}$ is the stock return i in month t , $R_{i,t-12:t-2}$ is the accumulated stock returns between month $t - 12$ and $t - 2$ and $ILLIQ_{i,t-1}$ is the ‘zero return days’ proposed by Lesmond (2005).

Panel B presents the second stage of regression which is described as:

$$\beta_{0,t_i} = \alpha_0 + \gamma_1 Mktilliq_{t-1} + \gamma_2 Mktchg_{t-1} + \gamma_3 Mktvol_{t-1} + e_t,$$

The coefficients are regressed on the time-series of lagged market state variables: $Mktilliq_{t-1}$ is the market illiquidity proxied by the ‘zero return days’ (Lesmond, 2005), $Mktchg_{t-1}$ is a dummy variable that takes the value of one if the return on stock market index is negative in the past twenty four months and zero otherwise, and $Mktvol_{t-1}$ is the standard deviation of daily market returns. Newey-West adjusted t-statistics are applied and ‘*’, ‘**’, and ‘***’ are significant at 10%, 5%, and 1% level.

Panel A: Varying coefficient regressions of stock returns	
	Average coefficient estimations
α_0	0.0406
$R_{t-12:t-2}$	0.0215***
$ILLIQ_{t-1}$	1.2746***
Panel B: Varying betas regressed on lagged state variables	
	Coefficient estimations on varying betas
α_0	-0.004
$Mktilliq$	-0.461***
$Mktchg$	-0.01
$Mktvol$	-1.964***

varying momentum coefficients β_{0,t_i} on the three market state variables, i.e. the market illiquidity, market condition ($Mktchg$), and market volatility. The analysis indicates a significant negative correlation between illiquidity and momentum in stock returns, with the estimated slope coefficient of -0.461 significant at the 1% level of significance. This study also reports the result of the all-inclusive regression in Table 3.3. Similar to the findings from portfolio level, this study fails to find a significant impact using the market conditions in the regression. The volatility, on the other hand, displays a significant negative effect on momentum profits, as the estimated slope coefficient for volatility is -1.964.

To conclude before moving onto the next stage of research, the study compares the results between Tables 3.2 and 3.3. The similarity in the effect of illiquidity on momentum in both portfolio and individual returns suggests that momentum strategies are largely dependent on the liquidity of stocks. The payoffs are weak or sometimes negative when the aggregate market is illiquid. Moreover, including the market illiquidity can eliminate the explanatory power of market state in the time series predictions. Notably, the varying coefficient estimations hold a similar pattern of results to those reported in the previous studies. For example, it is reported by Hameed, Kang, and Viswanathan (2010) that stock illiquidity is somehow related to market returns and volatility. Also, Næs et al. (2011) show that stock market liquidity is pro-cyclical and can be worsened during poor market conditions, which suggests that market illiquidity could cause momentum payoffs to vary over time.

Finally, the author was curious to see whether the stock exposures to market illiquidity drive the price momentum. Hence, Table 3.4 presents the cross-sectional and time series results.

Panel A of Table 3.4 presents the cross-sectional coefficients of the regression described in section 4.3 for firm i . The author includes the Fama-French three factors to control for the factor of risk exposure and report the all-inclusive model (Model 7) results in this table. This study reports high stock returns with high market illiquidity. The slope coefficient is reported to be 0.2108 and is statistically significant. The author also reports significant individual future stock returns implied by low market volatility (-0.4983). The effect of volatility is significantly negative, which is consistent with the findings of Avramov et al. (2014) who report a negative impact using US data. This chapter's findings, overall, suggest that following periods of high volatility in the market, stock returns tend to decline in the future. Panel B of Table 3.4 presents the second-stage regression results. Overall, this study finds that the individual stock momentum transpire to be insignificant after

Table 3.4: Individual stock momentum and market states

Panel A presents the cross-sectional coefficients of the following regression for firm i :

$$R_{i,t}^e = \alpha_0 + \beta_{i,1}Mktilliqt_{-1} + \beta_2Mktchg_{t-1} + \beta_3Mktvol_{t-1} + c'F_t + e_{i,t},$$

Where $R_{i,t}^e$ is the excess return of stock i on month t . $Mktilliqt_{-1}$, $Mktchg_{t-1}$ and $Mktvol_{t-1}$ are the market state variables on month $t-1$. The vector F is the Fama-French three factors.

Panel B presents the results of the following monthly regressions,

$$R_{i,t}^* = \alpha_0 + \beta_1R_{i,t-12:t-2} + u_{i,t},$$

Where $R_{i,t-12:t-2}$ is the past eleven months return of stock i . Newey-West adjusted t-statistics are applied and ‘*’, ‘**’, and ‘***’ are significant at 10%, 5%, and 1% level.

Panel A: First-stage regression coefficient estimations	
Average coefficient estimations	
α_0	0.068
$Mktilliq$	0.2108***
$Mktchg$	0.003
$Mktvol$	-0.4983***
$RM - RF$	0.039*
SMB	0.2197***
HML	0.056*
Panel B: Second-stage risk and market state adjusted regressions	
Coefficient estimations	
α_0	-0.05
$R_{i,t-12:t-2}$	-0.01

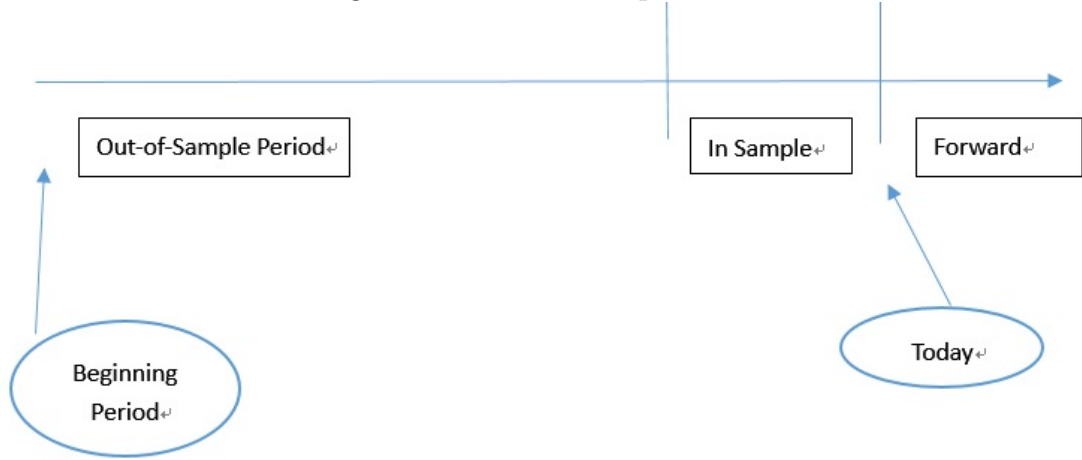
controlling for the predictive effect of the market states. Consequently, it can be concluded that the price momentum is driven by aggregate illiquidity and market volatility, but not market condition, either in a long-term or short-term specification. Furthermore, the overall results suggest that market illiquidity is related to momentum profits in both time series and cross-sectional analysis for the individual and portfolio-based stocks. Momentum strategy profits are significantly slashed after an illiquid market condition.

Next, this study examines the forecasting power of momentum profitability using out-of-sample performance. It is well documented that the empirical evidence based on in-sample performance is sensitive to outliers and data mining (White, 2000). According to Diebold and Rudebusch (1991), out-of-sample forecast performance is generally considered more trustworthy than evidence based on in-sample performance, and also reacts better to the information available to the forecaster in “real time”. This in fact has motivated the author to regard out-of-sample performance as the ‘ultimate test of a forecasting model’ (Stock, Watson, and Addison-Wesley, 2007). Table 3.5 reports the summary statistics of the forecast errors based on the time-series estimation of out-of-sample forecasts. The forecast of momentum profits in month $t + 1$ is obtained as follows:

$$W\hat{M}L_{t+1} = \hat{\alpha}_0 + \hat{\beta}_{1,t}Mktchg_t + \hat{\beta}_{2,t}Mktilliq_t + \hat{\beta}_{3,t}Down_t + \hat{\beta}_{4,t}Mktvol_t + c'_{t-1}F_t \quad (3.5.22)$$

where $W\hat{M}L_{t+1}$ is based on the lagged values of market state proxies. The data spans the period from February 1991 to December 2013. Following a common empirical approach of out-of-sample test literature (Hansen and Timmermann, 2012; Rapach, Strauss, and Zhou, 2010; Xie and Wang, 2015), the study performs out-of-sample tests using the latest 70%, 50%, 30% and 20% as split break-points of the full sample. The reason for adopting several different out-of-sample periods

Figure 3.3: Out-of-Sample Tests



are to minimize the concerns of data-mining. This study reserved multiple time periods of historical data. Figure 3.3 presents the illustrative time line representing the length of in and out-of-sample data used in the tests. Consequently, the four different out-of-sample periods applied in this study were 1997-2013, 2002-2013, 2007-2013, and 2009-2013.

Table 3.5: Out-of-sample Forecasting

This table presents the results of the root of mean squared error (RMSE) of the forecast error based on several out-of-sample forecasts. The momentum profits are regressed on an intercept, Fama-French three factors and a combination of the four market state variables (market change in returns, market aggregate illiquidity, down market dummy and the market volatility). The seven model specifications are the same as those presented in Table 3.2. The table reports out-of-sample test results in four different splits. The * represents the 10% level and ** represents the 5% level of Diebold-Mariano significance test.

RMSE	30% Breakpoint	50% Breakpoint	70% Breakpoint	80% Breakpoint
Model 1	0.0539	0.0488	0.0556	0.0527
Model 2	0.0537	0.0489	0.0554	0.0525
Model 3	0.0540**	0.0483*	0.0552*	0.0525**
Model 4	0.0537	0.0489	0.0555	0.0526
Model 5	0.0538	0.0490	0.0559**	0.0540
Model 6	0.0526**	0.0484*	0.0562*	0.0538**
Model 7	0.0530*	0.0480	0.0556*	0.0537*

For Table 3.5, the author follows the same sequence of model specifications as those used with Table 3.2. The forecast error is measured by reporting the difference

between the realised momentum profit and the predicted one. The out-of-sample analysis shows that the aggregate market illiquidity (Model 3) has the maximum effect and is statistically significant in reducing the root of mean squared forecast error (RMSE) compared with other models in the 50%, 70% and 80% splits. To conclude, the out-of-sample evidence supports the sample analysis that illiquid market states predict momentum payoffs.

This study presents the robustness check results in Table 3.6. The positive β_3 ($\beta_3=0.317$ and $t=3.93$) in Table 3.6 indicates that more liquid stocks yield returns higher than illiquid stocks in the post crisis period. This study includes time and stock fixed effects and size factor as the control variable.

Table 3.6: The Effect of Sudden Liquidity Shock

This study considers the 2007-2009 financial crisis as an exogenous liquidity shock to stock returns. This table presents regression results on the dependent variable *Return* for the full sample. This study considers liquid stocks as in the treatment group $Liquid_{i,t}$ and other stocks as control group. The dummy variable *Crisis* is one between September 2007 and December 2009, and zero otherwise. *DID* refers to the difference-in-differences beta coefficient which is $Liquid * Crisis$. The corresponding t-statistics are reported in parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% level.

	Return
DID	0.317*** (3.93)
$Size_{i,t}$	-0.247*** (-37.34)
Constant	-1.819 (-53.44)
Time fixed effects	Yes
Stock fixed effects	Yes
Number of observations	67,470
R^2	0.0224

This study finds that more liquid stocks, relative to illiquid stocks, exhibit significantly better performances after the sudden liquidity shock. This further proves that liquidity is an important variable in explaining return continuation effect.

3.6 Conclusion

Marketwide liquidity appears to be a state variable that is important for pricing common stocks and explaining momentum profits. This study investigated whether marketwide liquidity is a state variable important for momentum profits. Further, this chapter used the time varying coefficient models to analyze the ability of the state of market illiquidity to explain and predict momentum payoffs using out-of-sample performance at both the portfolio and individual levels. To correct heterogeneity in the sample, this chapter used semi-parametric estimations.

The author finds that the periods of high market illiquidity are followed by low momentum profits, and very often negative returns. In the presence of aggregate illiquidity, the power of the competing state variables (for example, the down market condition) disappears. This chapter finds significant bounce in varying beta coefficients changing over time. Consequently, the models capture more precise beta coefficients in the estimation compared to those linear parametric tests which assume linearity and smooth the line of slope coefficients. Furthermore, this study captures significant momentum crash and the increase of liquidity risks during the financial crisis. Regarding the endogeneity problem, the author investigates the change in return when sudden liquidity shocks hit the market. This chapter finds that stocks with high illiquidity are more sensitive to systemic shocks.

Overall, this chapter illustrates how illiquidity shocks predict both momentum and value investment returns. Thus, this study offers insights to policymakers interested in momentum profits and stock market liquidity. The results of this study, therefore, may be useful for investors and regulators who are continually adopting regulations in attempts to enhance understanding the factors that explain past and future stock price returns, or who are looking for additional ideas for profitable trading strategies.

Despite filling some of the gaps in current asset pricing and stock return literature, this study highlights a number of others for future research. One direction for future research is to explore whether liquidity risk plays a role in various pricing anomalies in financial markets. Future research could investigate whether expected returns are related to stocks' sensitivities to fluctuations in other aspects of aggregate liquidity. It would also be useful to explore whether some form of systematic liquidity risk is priced in other financial markets, such as fixed income markets.

Chapter 4

Momentum and Information

Uncertainty: the Case of

Institutional and Individual

Investors

4.1 Introduction

Testing stock trading strategies is one of the major topics in finance that has been the focus of financial scholars, investors and economists during the last two decades (Brock, Lakonishok, and LeBaron, 1992; Han, Yang, and Zhou, 2013; Jegadeesh and Titman, 1993; Kim and Shamsuddin, 2015). This is documented by the increasing number of studies, conferences and journals dedicated to stock trading perspectives. In particular, the robust momentum strategy of buying past winners and selling past losers has received significant attention and has had a significant impact on stock returns at short and intermediate horizons both in and out of sample across several markets around the world (e.g.(Jegadeesh and Titman, 1993; Rouwenhorst, 1998)).

Notably, this strategy and return pattern presents a real challenge and puzzle to the efficient market hypothesis (EMH) because the return continuation effect cannot be explained by the existing asset pricing models (Fama and French, 2015). Consequently, behavioural theories and their related studies have been introduced which claim that return continuation could be caused by irrational investors with biased expectations (Barberis et al., 1998; Hong et al., 2000). For example, Hvidkjaer (2006) present data to suggest that individual and institutional traders exhibit distinct trading behaviours. Hvidkjaer (2006)'s analysis shows that individual investors are more likely to suffer from initial under-reaction which is subsequently followed by delayed reactions. Institutional investors, however, have little evidence of initial under-reaction and this evidence is consistent with informed trading among large institutional traders. Hence, the momentum trading strategy is considered as a starting point in investigating individual and institutional investor behaviours due to its simplicity and its role in providing investors with key signals that are used by investors to gain momentum profits.

Previous studies on stock return momentum have paid significant attention to the JT momentum strategy presented in a seminal study by Jegadeesh and Titman (1993) (hereafter JT). JT found that returns on stocks exhibit continuation behaviour at intermediate periods. One of the alternative strategies to this, however, was advocated and proposed by George and Hwang (2004) (hereafter GH). GH examined the return predictability of the 52-week-high price in the US market with a strategy formed and based on the extent to which the current price of a stock is close to its past 52-week-highest price. When portfolios are sorted using current stock price divided by its past 52-week-high price, they found that companies with highest ratios performed better than those associated with low ratios over a subsequent period of 6 to 12 months subsequently. Consequently, GH claimed that investors are argued to form a psychological 'anchor' on the elevated price when stocks are traded near the 52-week-high price, resulting in an under-reaction

to new information on these stocks. When the information relating to the fundamental value of stocks continues to persist in the long term, the adjustment of investors' previous under-reaction leads to a price continuation effect. According to Burghof and Prothmann (2011), the existence of the GH momentum profits are attributable to information uncertainty in stocks, which results in an increase in the anchoring and adjustment biases (Tversky and Kahneman, 1974). Thus, the prevalence of the GH return anomaly provides a setting for examining the relationship between market efficiency and increasing information uncertainties. Further, previous studies have found that analysts facilitate market efficiency by processing information about firms. It is documented that analysts' recommendations are essential to reestablish stock prices back to fundamental values (e.g. (Barber, Lehavy, McNichols, and Trueman, 2001; Wieland, 2011)). However, there are also arguments in literature that analysts' forecasts are inefficient because they do not fully incorporate past information into their recommendations. Analysts are argued to place more weight on heuristic valuations than present valuation models (e.g. (Bradshaw, 2004)). Furthermore, the majority of previous studies are dominated by studies only considering institutional investors, who are arguably more sophisticated than individual investors (Amihud and Li, 2006; Cohen, Gompers, and Vuolteenaho, 2002; Gompers, Ishii, and Metrick, 2001; Sias, Starks, and Titman, 2006). For example, Campbell, Sharpe et al. (2009) and Feng and Seasholes (2005) indicate that experts' consensus forecasts of macroeconomic information are biased towards previous values, which in turn leads to a greater extent of forecast errors.

Several recent studies have documented that the 52-week high has predictive ability for stock returns (Amihud and Li, 2006; Cohen et al., 2002; George and Hwang, 2004; Gompers et al., 2001; Li and Yu, 2012; Liu, Liu, and Ma, 2011; Sias et al., 2006). However, most of the discussion and empirical work of the

previous studies is closely intertwined with institutional investors' trading. Inspired by the strong performance of the 52-week-high price momentum strategy, whether investor groups trade on stocks that exhibit price momentum is a question of importance. In addition, despite this large body of empirical research on anchoring (or reference points), there is as yet only limited literature on the effect of behavioural biases on informed trading. However, to the best of the author's knowledge, no prior study has examined the impact of both the momentum and contrarian trading of different investor groups in the UK.

Based on the existing literature, this study extends the literature on momentum return strategies by investigating both the individual and institutional investors' roles in the financial market. Thus, this chapter contributes toward filling a gap in the literature by differentiating the behavioural differences of institutional and individual investors in momentum trading. Indeed, the literature tends to ignore the fact that individual investors are inexperienced in terms of their financial knowledge. This study therefore examines the relationship between analysts' forecast revision ratios and stock future returns in order to determine the experience levels of institutional and individual investors. Further, in contrast to the existing literature, this study clearly classifies individual and institutional investors and investigates their different contributions to momentum crash when significant negative economic shock takes place.

In this study, the overall aim is therefore to study the role of institutional and individual investors in momentum tradings. This research is conducted by studying both anchored and unanchored momentum strategies for each type of investors. This study uses the 52-week-high momentum as a proxy for information uncertainty to study the behavioural differences of the two types of investors. Further, by applying 'difference in differences' methodology, This chapter aims to identify the causal link of momentum crash and negative economic shock and the corresponding selection bias for both institutional and individual investors.

Drawing upon time series UK data obtained from different sources coupled with a stock's current price and the 52-week high price over the period 1986 to 2014, this study finds that the 52-week-high measure is persistent and does not revert at short, intermediate and long horizons in the UK. The findings also show that during times of greater information uncertainty, individual investors tend to apply the 52-week-high price as a psychological anchor to assess the impact of new information about stocks more than institutional investors. This implies that momentum anomaly is partly driven by the behaviour of individual traders. This study also investigates the link between analysts' forecast revisions and the 52-week-high momentum strategy in various portfolio sorting and regression analyses. This study finds that analysts' forecast revisions have explanatory power for future stock returns especially for institutional investors. This is due to institutional investors having more expertise and access to analysts' recommendation information. Therefore, institutional investors can partly facilitate market efficiency by studying analysts' earnings forecasts that are closely related to momentum indicators.

Further, the time series momentum payoffs of both institutional and individual investors show that momentum tend to crash during negative event times. It is difficult to establish a causal link between investor reaction and momentum crashes and much remains regarding whether large systematic economic shocks translate into more pressure on institutional traders. This study exploits the sudden bank run event of local UK bank Northern Rock in September 2007 as a negative source of variation. This study's identification strategy relies on the hypothesis that a financial crisis affects institutional traders more than individual traders since institutions suffer from sudden liquidity constraints whereas individual investors are not much affected since they have limited cash flow in the first place. Empirically, this study identifies stocks included by institutional momentum investors but which were not selected by individual investors as the treatment group. This

study finds that large negative economic shock significantly affects institutional portfolio returns, for both winner and loser portfolios. The findings are consistent with the justification from Shleifer (2000) who argued that investors tend to use heuristics, leading them to hold particular models of risk and expected returns. When different models lead to similar predictions, investors will try to trade the same securities at the same time thus pushing prices far away from fundamentals. In this framework, the price ‘anchor’ does not apply to future stock returns. This chapter confirms such cognitive bias of institutional investors using an ‘unanchored’ robustness test proposed by Lou and Polk (2013). They proposed comomentum as the abnormal return correlation among momentum portfolios. They showed that during periods of low co-momentum, momentum strategies are profitable and stabilizing, whereas during periods of high comomentum, returns tend to crash and revert, reflecting previous overreaction resulting from crowded momentum tradings from institutional investors. This study confirms their findings in the UK market. This chapter concludes that both individual and institutional investors have a destabilising effect on stock market efficiency. Individual investors are largely subject to ‘anchoring biases’, reflecting initial under-reaction to new information. Institutional investors, on the other hand, absorb new information efficiently, especially with analysts’ earnings forecast revisions. However, they tend to have more ‘recognition biases’ when there are negative economic shocks. This chapter contributes to the momentum literature in the following ways. First, this study examines various holding horizons of GH momentum returns for both individual and institutional investors in the UK. Although momentum pattern has been documented to have generated significant returns for investors, existing studies mostly examine institutional investors. In fact, retail investors are often neglected because of barriers such as the relatively small amounts of capital they have invested, trading frictions and nonstandard trading horizons. However, momentum trading can be applicable to individual investors because it does

not require profound investing expertise and is easy to conduct. Therefore, in addition to conventional momentum strategies that applies to institutional investors, this chapter investigates the profitability of momentum trading when only small numbers of firms are selected to construct winner and loser portfolios. Second, this study examines the rolling holding horizons from 3 months to 5 years of momentum profits in a 26-year sample period. The author finds significant and positive GH momentum returns for both institutional and individual investors in the UK. In particular, individual investors can profit more from the sell side loser portfolios. This momentum profits do not revert even in the long run. Thirdly, this chapter links the 52-week-high momentum with information uncertainty and finds that price momentum is partly driven by individual traders who suffer from initial under-reaction to new information due to ‘anchoring biases’. During times of greater information uncertainty, individual investors tend to apply the 52-week-high price as an anchor more than institutional investors do, especially from the sell-side. Fourthly, this study links analysts’ forecasts with the 52-week-high momentum and finds that institutional investors who have access to analysts’ earnings forecasts revisions are more likely to facilitate market efficiency. This further demonstrates that stock market inefficiency is partly driven by individual investors. Fifthly, the author studies the causal link between investor behaviours and momentum crashes. This study exploits the sudden financial crisis as a negative shock. The difference-in-differences (DID) model suggests that large negative economic shock significantly affects institutional portfolio returns. Finally, this chapter confirms the presence of cognitive bias of institutional investors as evidenced by their use of ‘unanchored momentum strategy’.

The remainder of the chapter is organised as follows. Section 4.2 provides theoretical background that will guide us in the empirical investigation. Section 4.3 presents the full picture of research design. Section 4.4 provides information about the data and discusses the findings, while section 4.5 concludes the study.

4.2 Theoretical Background

4.2.1 Individual Investors Versus Institutional Investors

Individual investors were reported to hold 10.7% of shares listed on the London Stock Exchange by the end of 2012 (NationalStatistics, 2013). These investors are often criticised for their irrational investment decisions. For example, Barber and Odean (2011) reported that individual investors tend to excessively trade stocks, which resulting in higher transaction costs. It is also argued that due to their limited capital, individual investors are more likely to hold non-diversified portfolios (Statman, 2004). In fact, individual investors have been treated as noise traders because of their constant decision-making errors (De Bondt, 1998). This is in line with Barber et al. (2009), who documented that individual investors lost an annual average of 3.8 percentage points in portfolio performances in Taiwan in general.

Although individual investors are documented to be at a disadvantage in trading against professionals in terms of skills (Barber et al., 2009; Gao and Lin, 2015; Li et al., 2015; Tekçe et al., 2016), the literature tends to neglect the fact that individuals do indeed make profits. In addition, the distinct characteristics of individual investors suggest that momentum trading can benefit this group more because such strategies do not require extensive financial knowledge. Investors only need to buy and sell based on a typical strategy. Here, individual stocks are recommended for them to follow momentum trading patterns. The existing research mostly focuses on institutional traders who select a large amount of stocks in portfolios. Clearly, small investors are not in these financial positions for such big portfolios. In fact, Goetzmann and Kumar (2008) document that US individual investors hold an average of only three or four shares in each portfolio. Thus, individual investors in this study are investors who take a simplified momentum trading strategy that only exploits excess returns from top and bottom

side momentum for a small number of individual stocks. This definition of individual investors is consistent with the definitions of Siganos (2010) and Foltice and Langer (2015). Such a definition is contrasted with that of institutional investors, who can be defined as conventional momentum investors who manage portfolios that include a large number of stocks (Lou and Polk, 2013).

In terms of their approach to rationality, according to (Lou and Polk, 2013), investors are argued to be boundedly rational. There are a group of momentum investors acting as 'newswatchers'. This type of investors predict price movements based on market signals. These signals are essentially their private observations on future firm value. Given only newswatchers, market price exhibits pure under-reaction: prices slowly adjust to equilibrium. This study assumes individual investors tend to act as newswatchers. Additionally, Stein (2009) argues that momentum investors do not know how much other investors deploy in the same strategy. The failure of each investor to condition his trade on others' behaviour generates the controversial explanation of momentum investor behaviour: when there are too few participants in a strategy, the share mispricing is not fully corrected, sometimes exhibiting market under-reaction. However, when there are too many participants, the share mispricing is overcorrected as the market appears to overreact. This chapter assumes institutional rather than individual investors are more likely to have such behaviours.

4.2.2 Momentum and Information Uncertainty

Momentum profits are well documented in numerous studies. For example, Barberis et al. (1998) and Daniel et al. (1998) argue that momentum returns are the result of investor overreaction. However, both Hong et al. (2000) and Jegadeesh and Titman (1993) suggest that the abnormal returns come from investor under-reaction. Overall, this study believes that institutional investors and individual investors are distinct in their respective characteristics, and that they therefore

may reflect different trading behaviours.

George and Hwang (2004) propose a 52-week-high momentum strategy that buys stocks near this 52-week-high price and sells stocks far from 52-week-high price. This momentum strategy incorporates current price information rather than simply using past return changes as proposed by (Jegadeesh and Titman, 1993). Similarly, Liu et al. (2011) found this strategy generates significantly positive returns in 20 developed stock markets. In another study, Burghof and Prothmann (2011) defined the distance between the 52-week-high price and its 52-week-low price as a proxy for information uncertainty. They documented that the increase in anchoring biases resulted from information uncertainty in stocks. Furthermore, investors are slow to adjust their initial reactions to firm-specific information. Therefore, GH's momentum strategy provides us with a natural setting in examining the relationship between the effect of information uncertainty on stocks and the behavioural biases. This chapter evaluates the role of individual and institutional investors separately in facilitating market efficiency when there is increased information uncertainty.

4.2.3 Information Uncertainty and Analysts' Forecast Revision

In a seminal study, Jegadeesh, Kim, Krische, and Lee (2004) provided evidence that analysts' forecasts can reconnect stock prices back to their fundamental values. Indeed, analysts play a significant role in the financial market by professionally processing information on firms. Financial analysts have a number of informational advantages. First, they are reported to have greater expertise and access to information about companies. Therefore, their recommendations are more value-relevant. Moreover, analysts have the skill-sets to incorporate firm-specific strategies, industry review, and macroeconomic factors into their forecasts

(Wieland, 2011). In a key study, Barber et al. (2001) found empirical evidence of stock prices drift following the release of earnings forecast. It is argued elsewhere that such post-forecast revision drift is caused by a cumulative delayed response to new information since there is inefficiency in utilising analysts' forecast information (Gleason and Lee, 2003). These findings support Hoppe and Kusterer (2011)'s conservatism bias. Investors are criticised for not updating their expectations adequately, manifesting only slow adjustment of their under-reaction behaviour into stock prices. Elsewhere, Hou, Hung, and Gao (2014) found evidence using data on the Australian stock market that investors react more slowly to analysts' forecast revisions when there is increased information uncertainty regarding stocks. This implies that stock mispricing is contingent on the extent of uncertainty in information. Based on the existing literature, it can be argued that the mean of analysts' earnings forecast revision predict future stock returns.

4.2.4 Negative Economic Shock and Momentum Crashes

Despite the many documented high abnormal returns and Sharpe ratio, momentum payoffs are also reported to have negative skewness and excess kurtosis (Heidari, 2015). Notably, the abnormal returns are often wiped off during market recessions. In 1932, for example, during the Great Depression in the US, the momentum returns dropped by 92% in just two months. Echoing this, in 2009, momentum crashed around 73% in returns over three months in the US (Heidari, 2015). Grundy and Martin (2001) explain this pattern as the time-varying systematic risk of momentum strategy. They found significant negative beta following market recessions. Conversely, however, Daniel and Moskowitz (2011) empirically show that using betas does not avoid crashes taking place. Importantly, they found that loser stocks experience strong gains during extreme market environments, and it is these that result in the crashes. In behavioural literature, researchers argue that investor inexperience creates crashes. Caginalp, Porter,

and Smith (2000) observe investor behaviours in financial market under an experiment setting. They found that with inexperienced traders, crashes commonly occur and that this is a phenomenon that tends to disappear when traders become more experienced. To understand the price dynamics, they applied over 150 experiments, the results of which showed that inexperienced investors generated price bubbles. Due to the author's ability to distinguish between institutional investors who are more experienced than individual traders, this study is able to observe the role that different types of investors have, in particular when negative economic shock takes place.

Building on the previous different streams of studies, the author facilitate this research by studying the relationship between momentum crash and negative economic shock. Moreover, the author studies the difference between institutional and individual investors. In particular, this chapter studies the relationship between level of experience and momentum crashes.

4.3 Research Design

4.3.1 Momentum Variables

To construct the winner and loser portfolios of current (GH) and past (JT) information, this study ranks stocks based on each strategy's ranking criterion at the end of each month t .

GH's current price to the 52-week-high price ratio is given by:

$$GH_{i,t} = P_{i,t-1}/High_{i,t-1} \quad (4.3.1)$$

where $GH_{i,t}$ is the GH ratio of stock i on month t ; $P_{i,t-1}$ is the price of stock i at the end of month $t - 1$; $High_{i,t-1}$ is the highest price of stock i during the past 52 weeks that ends on month $t - 1$ (George and Hwang, 2004). In this study, GHH

(GHL) is the dummy variable that equals to 1 if stocks are in the winner (loser) portfolios based on the GH ratio and 0 otherwise.

Comparatively, JT's ranking criterion is based on past stock returns:

$$JT_{i,t} = P_{i,t-1}/P_{i,t-j} \quad (4.3.2)$$

where $JT_{i,t}$ is the JT ratio of stock i on month t ; $P_{i,t-1}$ is the price of stock i at the end of month $t - 1$; $P_{i,t-j}$ is the price of stock i at the end of month $t - j$, based on different ranking horizons j .

This study examines momentum strategies using UK data between January 1987 and December 2012. The data are obtained over the period 1986 to 2014 to construct meaningful momentum portfolios. Based on different ranking criteria, stocks are classified into three portfolios: loser portfolio (Pl), median portfolio (Pm), and winner portfolio (Pw). A filter rule of 30% is then applied for institutional investors: that is, the top 30% of stocks are classified as winners and the bottom 30% of stocks are included in the loser portfolios. As for individual investors' momentum portfolios, they contain more extreme performing stocks: the individual held winner (loser) portfolios contain best (worst) performing 1, 2, 3, 4, 5, 10, 15 and 20 shares. Stocks are equally weighted and are held for 3, 6, 9, and 12 months as suggested by the conventional momentum literature. This study extends the holding period up to 5 years after the construction of portfolios as doing so allows us to observe long term return reversal effects.¹ The mean return of each portfolio is identified as:

$$Pk = \frac{1}{T} \sum_t r_k(t) = \frac{1}{T} \sum_t \left[\frac{1}{Nk(t)} \sum_{i \in k} r(i, t) \right] \quad (4.3.3)$$

where $r(i, t)$ is the holding period return of stock i in period t , $Nk(t)$ is the number of stocks in portfolio k in period t , and T is the total number of periods in full

¹The author also checks the returns of value-weighted portfolios in robustness tests.

sample.

The portfolio selection and holding process follow a rolling pattern that takes place at the end of each month in the sample period. The analyses of momentum returns are based on the following Fama and French (1993) three-factor model:

$$R_t^p - R_t^f = \alpha_p + \beta_{p,MKT}MKT_t + \beta_{p,SMB}SMB_t + \beta_{p,HML}HML_t + \varepsilon_t^p \quad (4.3.4)$$

where SMB_t stands for size factor and HML_t is the value factor at the end of month t .

This study intends to demonstrate the unexplained alphas after stock momentum returns are controlled for market, size, and value factors. The author reports both gross and adjusted momentum returns of various horizons and corresponding t-statistics in section 4.4.

4.3.2 Analyst Forecast Revisions

This study defines an analyst as the financial professional that has the expertise to evaluate investments and make earnings forecasts of securities for I/B/E/S similar to the classification from (Low and Tan, 2016). The measurement of analysts' forecast revisions are important in facilitating market efficiency. Following Zhang (2008) and Chen, Narayanamoorthy, Sougiannis, and Zhou (2015), this study proxies the earnings forecast revision ratio as:

$$RE_{i,t} = (F_{i,t} - F_{i,t-1})/P_{i,t-1} \quad (4.3.5)$$

where $F_{i,t}$ is the monthly mean earnings forecast of stock i at month t and $P_{i,t-1}$ is the price of stock i at previous month. The forecast consensus revision is measured as the percentage change in monthly consensus mean forecasts. This is consistent with the measurement of momentum variables.

The sign of this forecast revision ratio acts as the signal in response to good and bad news. For example, a positive sign would signal good news about a particular stocks and suggests a favourable recommendation and *vice versa*. Consistent with momentum variables, the top stocks with the highest analysts' forecast revision ratio are included in the 'buy' portfolio, while the bottom stocks are included in the 'sell' portfolio.

In this study, the author follows momentum literature (e.g.(Jegadeesh and Titman, 1993)) and includes firm size and value as control variables. Firm size and value are common risk factors defined by Fama and French (1993). They are also the measures of information uncertainty. While firm size is measured as the log value of market capitalisation, firm value is measured as the book-to-market ratio. Further, this study controls for the previous month's stock returns since past returns include the information about future stock returns. Subsequently, the chapter controls for short-term price reversals (Grinblatt and Moskowitz, 2004) and behavioural biases (Jegadeesh and Titman, 1993).

4.3.3 Panel Regression with Forecast Revisions

This study applies the following regression model and examine the role of analysts as information intermediaries in the market. Then the study tests their contributions in explaining future stock returns after controlling for momentum and information uncertainty variables for both individual and institutional investors. Using a panel regression approach, future stock returns in month $t + 3$ is the dependent variable. The control variables are positioned at month $t + 2$, and momentum variables are taken at month $t - 1$.

$$\begin{aligned}
 R_{i,t+3} = & \beta_0 + \beta_1 Buy_{i,t} + \beta_2 Sell_{i,t} + \beta_3 GHH_{i,t-1} + \beta_4 GHL_{i,t-1} \\
 & + \beta_5 Size_{i,t+2} + \beta_6 Value_{i,t+2} + \beta_7 R_{i,t+2} + u
 \end{aligned}
 \tag{4.3.6}$$

where $Buy_{i,t}$ is the buy revision and $Sell_{i,t}$ is the sell revision.²

4.3.4 The Financial Crisis and Groups of Investors: the Difference in Differences (DID) Method

The difference in differences (DID) method is a technique used to examine the differential impact of a sudden event on a treatment group versus a control group (Ashenfelter and Card, 1985). In contrast to time-series and cross sectional estimates, DID uses panel data to measure the differences between the treatment and control groups of the changes in the outcome variable that occur over time (Abadie, 2005). The formula is described as follows:

$$Y(i, t) = \delta(t) + \alpha * D(i, t) + \eta(i) + v(i, t) \quad (4.3.7)$$

where $\delta(t)$ is the time specific component, $\eta(i)$ is the individual component, $v(i, t)$ is the control variable and α represents the impact of the treatment.

The DID approach is an important analysis to test the differing contributions of institutional and individual investors on momentum crash when significant negative economic shock occurs. To study different investor behaviours associated with negative economic shocks, this chapter considers the 2007-2009 financial crisis as a sudden liquidity shock and examine the causal effects of investor behaviours and momentum crash. Thus, this study performs the next regression using:

$$R_{i,t} = \beta_0 + \beta_1 WHHT_{i,t} + \beta_2 PostCrisis_{i,t} + \beta_3 WHHT * PostCrisis_{i,t} + \beta_4 R_{i,t-1} + \beta_5 Size_{i,t-1} + \beta_6 Value_{i,t-1} + u \quad (4.3.8)$$

where $WHHT_{i,t}$ is the dummy variable that takes 1 if the stock is included in the institutional winner portfolio but is not included in the individual portfolio,

²The detailed variable explanations are presented in Table 4.1.

and 0 otherwise. $PostCrisis_{i,t}$ is the dummy variable that takes the value 1 if the time is after September 2007 and 0 otherwise. Importantly, and in particular, the study is interested in the value of β_3 , a difference in difference coefficient that measures the different explanatory powers of individual and institutional selected stocks following a negative economic shock.

4.3.5 Unanchored Momentum Comovement

Following Lou and Polk (2013) the author further exploits investor behaviours of cognitive bias through a robustness test by removing the effect of return premiums generated by the Fama-French three-factor model. According to Lou and Polk (2013), the size of the momentum crowd is identified by the degree of past abnormal return correlations among momentum shares. This is undertaken and performed by sorting all stocks into decile portfolios based on their previous 6-month return.³ It is worth noting that the JT approach is different from the 52-week-high momentum strategy used in this analysis because the former is more of an unanchored strategy. This study controls for Fama-French asset pricing risk factors and compute pairwise partial correlations. The size of momentum crowd is then measured by the average correlation of the three-factor residual of every stock in a particular momentum decile. The size of loser ($MomCrowd^L$) and winner ($MomCrowd^W$) crowd are identified as:

$$MomCrowd^L = \frac{1}{N^L} \sum_{i=1}^{N^L} partialcorr(retrf_i^L, retrf_{-i}^L | mktrf, smb, hml) \quad (4.3.9)$$

$$MomCrowd^W = \frac{1}{N^W} \sum_{i=1}^{N^W} partialcorr(retrf_i^W, retrf_{-i}^W | mktrf, smb, hml) \quad (4.3.10)$$

³In unreported analyses, this study finds that momentum strategy is most profitable via a 6-month selection horizon in the UK using JT strategy.

where $retrf_i^L$ ($retrf_i^W$) is the daily return of stock i in the extreme loser (winner) decile, $retrf_{-i}^L$ ($retrf_{-i}^W$) is the daily return of equal-weight extreme loser (winner) decile excluding stock i and N^L (N^W) is the number of stocks in the extreme loser (winner) decile.

When momentum investment is not crowded, price must appear to be a continuation in the short-run and there is no return reversal in the long run. When momentum investing is crowded, however, the overreaction phenomenon will appear, as a result of the fact that prices overshoot the fundamentals and render return reversals in the long run.

4.4 Data and Empirical Findings

4.4.1 Data and Descriptive Statistics

The sample comprises all companies listed on FTSE All-Share from 1986 to 2014 obtained from Thomson DataStream.⁴ This study starts from the year 1986 because return index data for FTSE All-share firms are available as of January 1986. This study collects daily and monthly stock prices and their corresponding 52-week high prices, trading volume (turnover by volume), market value (share price multiplied by the number of ordinary shares in issue), return index (a theoretical growth in value of a share-holding over a specified period), market to book value (market value of common equity divided by the balance sheet value of common equity in the company), number of shares outstanding and the bid and ask prices of companies. Stocks are kept if they existed for at least three years prior to the year start.

The author obtains analysts' earnings forecast data from the I/B/E/S Thompson Reuters detailed forecast database. In particular, the mean forecasts of earnings

⁴To avoid survivor-ship bias, this analysis covers not only presently listed stocks but also dead stocks. Dead stocks refer to those of firms that were de-listed at some point of time during the sample period.

per share of each company data are obtained.

The size and value risk factors are obtained from the University of Exeter as described in Gregory et al. (2013).⁵The data obtained is market factor (the excess return on the value-weighted market index over the one month T-bill rate), the size factor (small minus big return premium) and the value factor (high book-to-market minus low book-to-market return premium).

⁵While Kenneth French's US website provides data for the US market, there is currently no equivalent for the UK market. The author thanks the University of Exeter for providing remedy and making the UK data freely downloadable at this website: <http://business-school.exeter.ac.uk/research/areas/centres/xfi/research/famafrench/>.

Table 4.1: Variables and Descriptive Statistics

This table reports descriptive statistics of the key variables in full sample. The sample consists of stocks listed on FTSE All-Share for the period January 1987 to December 2012.

Variables	Description	Obs.	Mean	Std.	Min	Max
Panel A: Dependent Variable						
Returns	monthly stock returns	199,680	0.0076	0.0810	-0.2162	0.2535
Panel B: Independent Variables						
GHH	Dummy variable that takes value 1 if stock i belongs to GH winner portfolio and value 0 otherwise	199,680	0.1803	0.3844	0	1
GHL	Dummy variable that takes value 1 if stock i belongs to GH loser portfolio and value 0 otherwise	199,680	0.1802	0.3844	0	1
WHH	Dummy variable that takes value 1 if stock i belongs to Institutional selected winner portfolio but not belongs to individual selected winner portfolio and value 0 otherwise	199,680	0.1513	0.3583	0	1
WHL	Dummy variable that takes value 1 if stock i belongs to Institutional selected loser portfolio but not belongs to individual selected loser portfolio and value 0 otherwise	199,680	0.1513	0.3583	0	1
Buy	Dummy variable that takes value 1 if stock i belongs to top forecast revision portfolio and value 0 otherwise	199,680	0.1675	0.3734	0	1
Sell	Dummy variable that takes value 1 if stock i belongs to bottom forecast revision portfolio and value 0 otherwise	199,680	0.1615	0.3680	0	1
Panel C: Control Variables						
Returns_lag	lag one month stock returns	199,680	0.0075	0.0810	-0.2161	0.2537
Size_lag	log of market capitalization at previous month	120,414	5.8080	1.7996	-0.3425	12.2315
BTMV_lag	lag book to market value	199,680	0.4659	0.7393	0	2.2727

Table 4.1 presents a summary of each variable and the descriptive statistics. Panel A reports the summary of monthly stock returns. As can be seen from Table 4.1 panel A, the returns tend to cluster around a mean value of 0.76%. Panel B shows the independent variables associated with information uncertainty. GHH (GHL) is a dummy variable that equals to 1 if stocks are in the top (bottom) portfolios based on the GH ratio and 0 otherwise. The mean of GHH which is 0.1803 is interpreted as around 18% of the stocks having a current price that close to their 52-week-high price. WHH (WHL) is a dummy variable that equals to 1 if stocks belong to institutional winner (loser) portfolios but are not included in individual winner (loser) portfolios and 0 otherwise. Variables Buy and Sell are analysts' forecast revision dummies. Similar to momentum variables, Buy (Sell) is a dummy variable that takes 1 if stocks are in the top (bottom) forecast revision portfolio. Panel C presents the control variables used in this study. The log mean size of firms is around 5.81, which is large in size. The book-to-market ratio is evenly distributed around the mean of 0.47.

The average monthly stock returns are close to those reported by Chen et al. (2015) in the US market. The author further studies the relationship among variables in the next section.

4.4.2 Empirical Findings

Individual Anchoring and Adjustment Bias

The author reports the GH momentum returns in Table 4.2 and 4.3 for institutional and individual portfolios.

Table 4.2: GH Momentum Returns in the UK: Institutional Investors

This table presents returns of winner and loser portfolios for institutional investors and the consequent momentum profits of various holding periods. The sample includes firms listed on FTSE All-Share from January 1987 to December 2012. Relevant portfolios are constructed by sorting all firms by the current price to the past 52 week high price ratio. This study sorts top 30% winning performing firms into winner portfolio and the bottom 30% firms into loser portfolio. Panel A reports monthly returns and Panel B presents the corresponding Fama-French three-factor alphas in each portfolios respectively. The corresponding t-statistics are reported in parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% level.

Panel A: Holding Period Returns								
Portfolios	3 months	6 months	9 months	12 months	2 years	3 years	4 years	5 years
Winner	1.43%*** (9.07)	1.38%*** (11.92)	1.33%*** (14.38)	1.29%*** (16.07)	1.09%*** (20.52)	1.00%*** (21.93)	0.93%*** (23.90)	0.86%*** (23.79)
Loser	-0.27% (-1.04)	-0.25% (-1.29)	-0.23% (-1.46)	-0.21% (-1.53)	-0.11% (-1.25)	-0.06% (-0.90)	-0.06% (-1.23)	-0.05% (-1.37)
Buy-Sell Strategy	1.68%*** (10.34)	1.62%*** (13.45)	1.56%*** (15.31)	1.50%*** (16.93)	1.19%*** (22.25)	1.06%*** (25.41)	0.98%*** (25.76)	0.91%*** (25.11)
Panel B: Fama-French 3-Factor Alpha								
Portfolios	3 months	6 months	9 months	12 months	2 years	3 years	4 years	5 years
Winner	0.945%*** (6.16)	0.932%*** (7.70)	0.905%*** (9.20)	0.890%*** (10.31)	0.753%*** (13.22)	0.700%*** (15.29)	0.685%*** (19.88)	0.688%*** (25.49)
Loser	0.074% (0.26)	0.050% (0.23)	0.011% (0.06)	-0.035% (-0.22)	-0.259%*** (-2.58)	-0.322%*** (-4.53)	-0.346%*** (-5.78)	-0.321%*** (-6.50)
Buy-Sell Strategy	1.388%*** (7.40)	1.384%*** (10.11)	1.320%*** (11.46)	1.258%*** (12.69)	0.895%*** (15.16)	0.780%*** (18.37)	0.740%*** (19.62)	0.735%*** (21.80)

Table 4.3: GH Momentum Returns in the UK: Retail Investors

This table presents returns of winner and loser portfolios for retail investors and the consequent momentum profits of various holding periods. The sample includes firms listed on FTSE All-Share from January 1987 to December 2012. Relevant portfolios are constructed by sorting all firms by the current price to the past 52 week high price ratio. This study sorts top winning performing firms into winner portfolio and the bottom firms into loser portfolio. *, **, *** indicate statistical significance at 10%, 5%, and 1% level.

	No. of stocks	3 months	6 months	9 months	12 months	2 years	3 years	4 years	5 years
W	<= 5	1.56%***	1.32%***	1.33%***	1.26%***	0.97%***	0.84%***	0.72%***	0.66%***
L	<= 5	-1.14%**	-0.70%*	-0.42%	-0.22%	0.15%	0.27%**	0.45%***	0.48%***
W-L	<= 5	2.70%***	2.02%***	1.74%***	1.47%***	0.82%***	0.57%***	0.27%***	0.17%**
W	<= 10	1.45%***	1.26%***	1.28%***	1.21%***	0.91%***	0.80%***	0.70%***	0.64%***
L	<= 10	-1.12%	-0.78%**	-0.53%**	-0.32%	0.18%	0.33%***	0.46%***	0.50%***
W-L	<= 10	2.57%***	2.04%***	1.81%***	1.53%***	0.72%***	0.47%***	0.24%***	0.14%***
W	<= 15	1.40%***	1.24%***	1.21%***	1.17%***	0.89%***	0.79%***	0.71%***	0.66%***
L	<= 15	-0.85%**	-0.64%**	-0.45%*	-0.23%	0.27%**	0.39%***	0.49%***	0.52%***
W-L	<= 15	2.25%***	1.88%***	1.66%***	1.39%***	0.62%***	0.40%***	0.22%***	0.14%***
W	<= 20	1.37%***	1.21%***	1.18%***	1.13%***	0.88%***	0.79%***	0.72%***	0.66%***
L	<= 20	-0.78%**	-0.58%**	-0.39%*	-0.18%	0.33%***	0.44%***	0.51%***	0.53%***
W-L	<= 20	2.14%***	1.78%***	1.56%***	1.30%***	0.55%***	0.35%***	0.20%***	0.13%***

Panel A of Table 4.2 presents the returns of winner and loser portfolios for institutional investors and the gross momentum returns (winner minus loser) following the GH momentum strategy that ranks stocks based on the current price divided by its 52-week-high price. In addition, the monthly holding period returns of each holding horizons are calculated and reported in Table 4.2. Interestingly, this study finds positive and significant returns all coming from winner portfolios. Although this study finds negative average returns from loser side, none of these is statistically significant. Moreover, momentum returns decrease uniformly when holding horizons increase (from 1.68% to 0.86% over 3 months to 5 years). The shorter the holding period, the larger magnitude of momentum profits that can be obtained. However, the positive and significant gross returns do not revert over 5 years, reflecting a clear under-reaction behaviour from investors.

Panel B of Table 4.2 reports the Fama-French three-factor alpha of winner and loser portfolios following the GH momentum strategy. After controlling for market, size and value factor, the abnormal returns slightly decrease. However, the unexplained alpha still persists from 3 months to 5 years holding horizons. Similarly as with the gross returns, this study finds significant positive momentum returns for all holding horizons. The adjusted returns decrease uniformly with the increase of holding period. The net buy and sell strategy yields average returns from 1.388% held for 3 months to 0.735% held for 5 years. Interestingly, the loser portfolio returns become large in value and have statistical significances when holding horizons increase above 2 years. This suggests that the sell side loser portfolios may be under performing even in the long run.

Table 4.3 presents the returns of winner and loser portfolios for individual investors and the gross momentum returns (winner minus loser) following GH momentum strategy. This chapter reports portfolios that contains less than 5 stocks, and those that contain from 6 to 10 stocks, 11 to 15 stocks, and 16 to 20 stocks in the table. The study finds significant high returns for almost all portfolios in all

holding horizons. Individual winner portfolios, similarly to institutional held winner portfolios, yield significant positive monthly returns. The fewer the number of stocks contained in the portfolios, the higher the momentum returns this study observes. The highest per month return from the winner side comes from the extreme portfolio that contains less than 5 stocks. It yields an average of 1.56% monthly return over a 3-month holding horizon. Meanwhile, the sell side loser portfolio yields similar returns. This study observes 1.14% returns if investors sell loser portfolios simultaneously when they purchase the winner portfolio, resulting in a 2.70% monthly profit through buy and sell strategy. This study finds that individual held portfolios yields higher momentum returns over short (3 to 6 months) and intermediate (6 to 12 months) horizons compared to institutional held portfolios. This implies that individual investors act as destabilisers in the financial market. Moreover, the anchoring and adjustment biases are more significant among individual investors. When portfolios are held over a long horizon (greater than 12 months), the author observes loser portfolio return reversion from individual held portfolios. Note that this study didn't observe such reversion from institutional held portfolios. Therefore, this chapter concludes that, when compared to institutional investors, individual investors are more sensitive to negative information, resulting in an initial overreaction from the sell side.

Information Uncertainty and Earnings Forecast Revisions

Table 4.4 reports the findings and estimates examining whether analysts' forecast revision consensus ratio is a strong predictor for future returns.

Table 4.4 shows that if analysts are able to recognise momentum signals and translate their forecast revisions as news, and the author would therefore expect forecast revisions to explain future stock returns after controlling for GH momentum variables. The study reports the regression results for 3 months ahead stock returns for both institutional held portfolios and individual held portfolios. The

Table 4.4: Panel Regression with Forecast Revision

This table reports the regression results for month $t + 3$ stock returns as the dependent variable for institutional held portfolios and individual held portfolios. For full description of the variables, please refer to Table 4.1. The sample is stocks listed on FTSE All-Share for the period 1987 to 2012. The corresponding t-statistics are in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels.

Variables	Predicted Sign	Institutional R_{t+3}	Individual R_{t+3}
Buy	+	0.0056*** (7.87)	0.0063*** (8.87)
Sell	-	-0.0028*** (-3.58)	-0.0043*** (-5.85)
GHH	+	0.0006 (0.78)	-0.0044 (-1.33)
GHL	-	-0.0046*** (-5.78)	0.0232*** (7.00)
<i>Size_{lag}</i>	+/-	-0.0110*** (-29.87)	-0.0104*** (-28.47)
<i>Value_{lag}</i>	+/-	0.0151*** (33.35)	0.0148*** (32.79)
<i>R_{lag}</i>	+	0.0255*** (8.75)	0.0271*** (9.21)
Cons	+/-	0.0650*** (28.58)	0.0609 (27.30)
N		555	555
R^2		0.0205	0.0268
Fixed Effects		Yes	Yes

detailed introduction of each variable are listed in Table 4.1.

This study finds significant positive (negative) coefficients for Buy and Sell variables for both regressions ($\beta_{InstBuy} = 0.0056$, $t = 7.87$; $\beta_{IndiBuy} = 0.0063$, $t = 8.87$; $\beta_{InstSell} = -0.0028$, $t = -3.58$; and $\beta_{IndiSell} = -0.0043$, $t = -5.85$). The findings demonstrate that the self-funded strategy that longs stocks in the Buy revision and short stocks in the Sell revision portfolios is profitable and significant. Therefore, this study observes a post-forecast revision drift in the UK market, and the data confirms the profitability of Buy-Sell revision method, which is consistent with existing literature (Chen et al., 2015).

However, after controlling for anchored momentum variables, individual held

portfolios yield the opposite signs of coefficients for winner and loser dummies ($\beta_{IndiGHH} = -0.0044$, $t = -1.33$; $\beta_{IndiGHL} = 0.0232$, $t = 7.00$). This contrasts with the findings from Low and Tan (2016) who adopt 20% cutoff point to construct momentum portfolios which is similar to the institutional held portfolios that used a 30% filter rule. On the other hand, the institutional held portfolio regression results are consistent with other prior literature ($\beta_{InstGHH} = 0.0006$, $t = 0.78$; $\beta_{InstGHL} = -0.0046$, $t = -5.78$). This implies that individual investors are more volatile investors while institutional investors tend to incorporate rational recommendations in their strategies.

Momentum Crash and Institutional Cognitive Bias

To date, this chapter's results show that individual investors are more volatile investors and suffer from significant anchoring and adjustment biases compared to institutional investors.

Figure 4.1 visually represents the time-series momentum payoffs in the sample period for both institutional investors and individual investors. As can be seen from Figure 4.1, institutional momentum portfolio returns move in the same direction as individual momentum portfolio returns, but in a much smoother way. The plot further confirms the previous findings that due to anchoring-and-adjustment bias, individual investors tend to destabilise the market by pushing returns far away from fundamentals.

In Figure 4.1, the author plots the returns of winner and loser portfolios held by each group. It is worth noting that institutional loser portfolio performance is significantly different from individual loser portfolio performance. Notably, individual loser portfolios tend to have a lagged effect after institutional loser portfolios. These findings further confirm that individual investors have a destabilising effect in the stock market by under-reacting to new information.

In most of the previous cases, momentum returns are positive for both individual

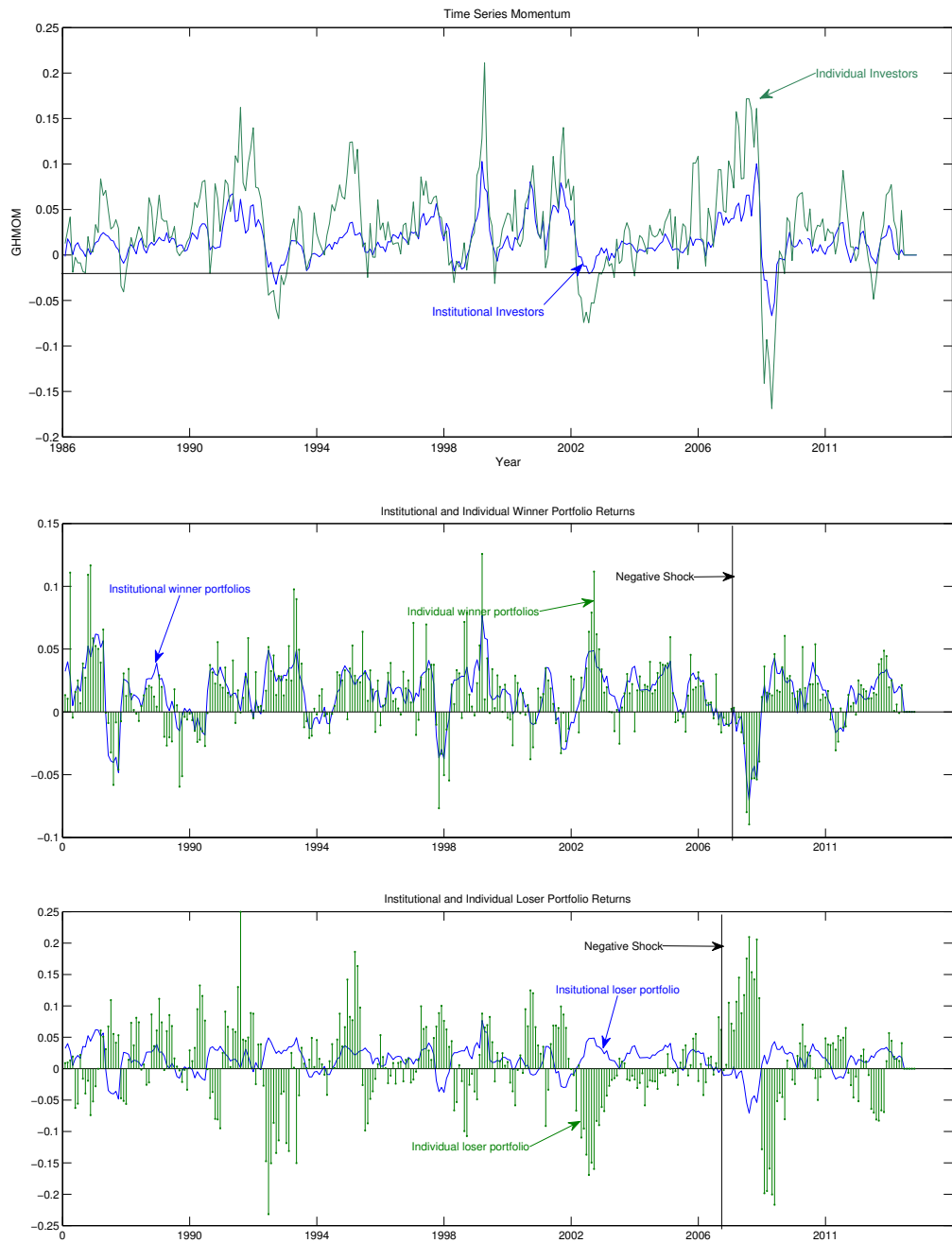


Figure 4.1: Time Series Momentum Returns

Table 4.5: Institutional Versus Retail Investors Around Financial Crisis

This study considers the 2007-2009 financial crisis as an exogenous shock to momentum investors to study the causal effects. This table presents regression results on the dependent variable *Return* for the full sample. The study considers stocks that are selected by institutional investors but are not included by retail investors in their winner (loser) portfolios as the treatment group *WHHT* (*WHLT*) and other stocks as control group. The dummy variable *PostCrisis* is one after September 2007, and zero otherwise. *DID* refers to the difference-in-differences beta coefficient which is $WHHT * PostCrisis$ ($WHLT * PostCrisis$). The corresponding t-statistics are reported in parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% level. The description of variables are listed in Table 4.1.

	WHHT	WHLT
DID	-0.147*** (-5.22)	0.171*** (4.67)
<i>Returns_{lag}</i>	0.118*** (21.69)	0.115*** (21.14)
<i>Size_{lag}</i>	-0.046*** (-12.61)	-0.045*** (-12.28)
<i>BTMV_{lag}</i>	-0.053*** (-6.88)	-0.053 (-6.88)
Constant	-2.509*** (-95.46)	-2.624*** (-100.44)
Time fixed effects	Yes	Yes
Stock fixed effects	Yes	Yes
Number of observations	36,478	36,478
R^2	0.0277	0.03

and institutional held portfolios, reflecting a significant return continuation effect. However, during the 2007 to 2009 global financial crisis, it can be observed that significant momentum crash exist for both types of investors. Indeed, the crisis appears as a huge negative shock and the author is eager to learn the impact of sudden liquidity shock on individual and institutional held stocks. Therefore, this study defines the time dummy of post crisis factor to be 1 if the observation time is after September 2007, when local UK bank Northern Rock was nationalized and 0 otherwise. The study defines the treatment group stocks as the stocks held by institutional investors, but not held by individual investors. Consequently, this study compares the difference between institutional held stocks and individual held stocks both before and after a large and negative economic event.

Table 4.5 reports the regression results after controlling for past return, size, and value factors. The study finds statistically significant evidence showing that after financial crisis, institutional held winning stocks revert in signs and have a negative impact over stock returns ($\beta_{DID} = -0.147$, $t = -5.22$) while previous losing stocks have a positive impact over stock returns ($\beta_{DID} = 0.171$, $t = 4.67$). The findings extend the existing momentum literature that suggests loser stocks reversion is the main reason of momentum crash. This study finds that not only losers, but also winners have the return reversal effect. Furthermore, the treatment group contains stocks that will only be selected by large traders. Therefore, the reversal effect is driven solely by the large amount of momentum trading activities. This is consistent with Hong et al. (2000)'s cognitive bias explanations. That is, stock mispricing appears when there are too many momentum participants. This mispricing is overcorrected as the market appears to overreact.

Further Analysis: Comomentum

To further examine the institutional investors' cognitive biases and their overreaction behaviour, this study adopts the methodology proposed by Lou and Polk

(2013) to observe institutional excessive tradings. This chapter designs the unanchored investigation of momentum investment in the UK by applying the 6*12 JT momentum strategy⁶, i.e. a six-month ranking period and a twelve-month holding period. Table 4.6 presents the summary statistics of the momentum crowd over the period 1987 to 2012 in the UK. Following a conventional momentum strategy, all stocks are sorted into decile portfolios based on previous 6-month returns at the end of each month, whilst skipping the most recent month. After controlling for the Fama-French three factors, this study computes pairwise partial return correlations for all stocks in both winner and loser momentum deciles. $MomCrowd^L$ ($MomCrowd^W$) is the average pairwise partial return correlation in the loser (winner) decile. $mktret36$ is the three-year return on market portfolio from year $t - 2$ to t , and $mktvol36$ is the monthly return volatility of the market portfolios in year $t - 2$ to t .

⁶In the unreported results, the author observes the highest JT momentum return comes from 6 * 12 strategy.

Table 4.6: Summary Statistics of the size of momentum crowd

This table presents summary statistics of momentum crowd over the period 1987 to 2012 in the UK. All stocks are sorted into decile portfolios based on momentum strategy. After controlling for the Fama-French three factors, this study computes pairwise partial return correlations for all stocks in both winner and loser momentum deciles. Stocks with prices below £5 a share are excluded from our sample. $MomCrowd^L$ ($MomCrowd^W$) is the average pairwise partial return correlation in the loser (winner) decile. $mktret36$ is the three-year return on market portfolio from year $t - 2$ to t , and $mktvol36$ is the monthly return volatility of the market portfolios in year $t - 2$ to t . Panel A reports summary statistics of the above variables while Panel B presents the time-series correlations among these variables.

Panel A: Summary Statistics of Momentum Crowd					
Variable	N	Mean	Std. Dev.	Min	Max
$MomCrowd^L$	288	0.121	0.093	-0.004	0.649
$MomCrowd^W$	288	0.107	0.092	-0.015	0.488
mktret36	288	0.329	0.327	-0.376	1.046
mktvol36	288	0.044	0.012	0.022	0.071
Panel B: Time-series Correlations					
	$MomCrowd^L$	$MomCrowd^W$	mktret36	mktvol36	
$MomCrowd^L$	1	0.580	-0.122	-0.024	
$MomCrowd^W$	0.580	1	-0.008	0.058	
mktret36	-0.122	-0.008	1	-0.565	
mktvol36	-0.024	0.058	-0.565	1	

Panel A shows the summary statistics of the above variables. It indicates that momentum crowd varies over time. The average loser portfolio has an abnormal correlation of 0.121 during the portfolio selection period throughout the 26-year UK sample. The results are similar to those documented by Lou and Polk (2013), who find an average correlation of 0.118 in loser portfolio in the US market. The abnormal correlation in the loser portfolio ranges from -0.004 to 0.649. The range is wider compared to those reported in the US market, exhibiting a higher volatility within the market. A similar pattern can be found from the winner portfolio. The average partial correlation in the winner portfolio is 0.107, also showing a wide range from -0.015 to 0.488.

Panel B presents the time-series correlations among these variables. It indicates that loser and winner momentum crowd are highly correlated over time (the correlation is 0.580). This corresponds with previous literature that has documented that momentum profits depend on general market state and market volatility (Cooper et al., 2004). This study also includes the past three-year return of the market and the monthly market return volatility over the past three years in the tests. Table 4.6 shows the loser momentum crowd is negatively correlated with both the average past market return (-0.122) and past market volatility (-0.024). The winner momentum crowd is also negatively correlated with past market return (-0.008), but positively correlated with past market volatility (0.058).

Figure 4.2 plots the momentum crowd for both the winner and loser portfolios. It shows that the momentum crowd is persistent over time. There is a spike in the momentum crowd in the early 1990s, the time when the Iraq invasion of Kuwait was taking place. Thereafter, momentum strategies started to attract popularity. Figure 4.2 also shows an increase of the momentum crowd during major financial shocks such as the Asian crisis in 1997, the long term capital management crisis in 1998, the tech boom in 2000 and the financial crisis from 2007 to 2010.

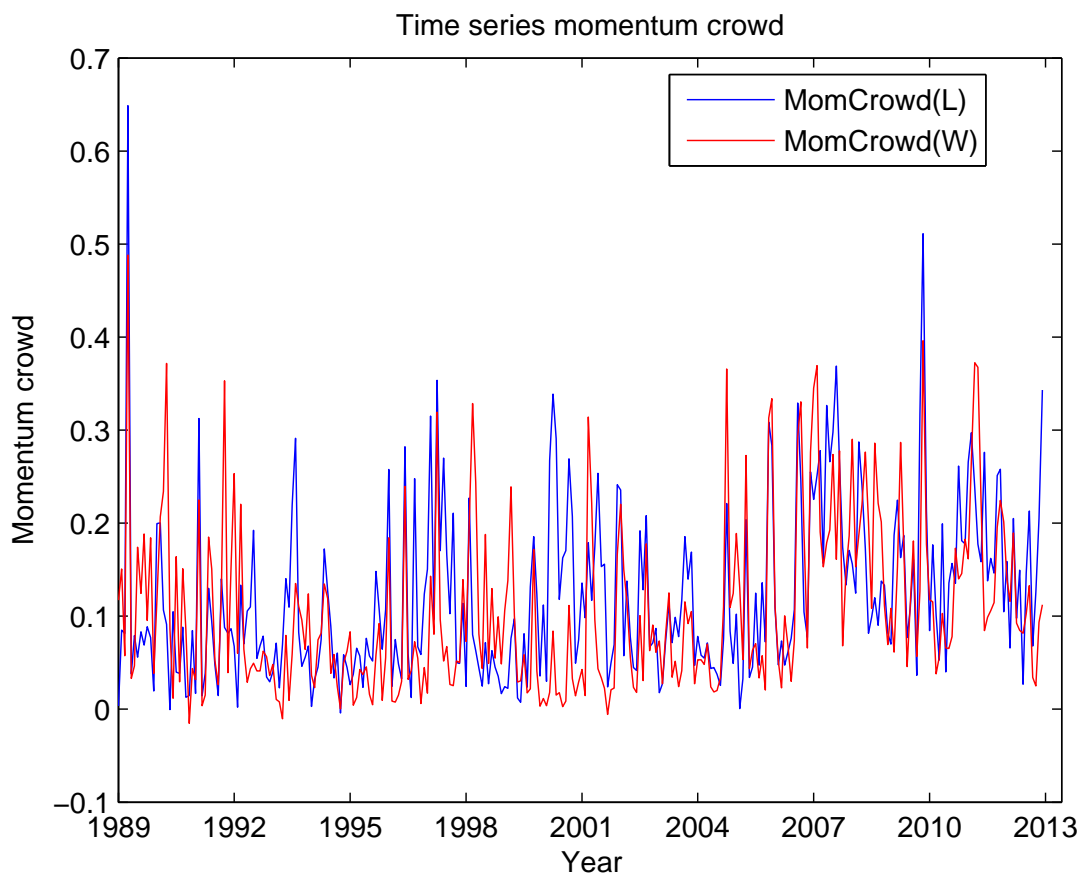


Figure 4.2: Momentum Crowd and Momentum Returns

Table 4.7 shows returns to the conventional Jegadeesh and Titman (1993) momentum strategy as a function of a lagged momentum crowd. All stocks are sorted into decile portfolios based on previous 6-month returns at the end of each month, whilst skipping the most recent month. Stocks with prices below £5 a share are excluded from sample. This study classifies all months into five groups based on $MomCrowd^L$, the average pairwise partial return correlation in the loser decile. The table reports returns to the momentum strategy in each of the three years after portfolio formation during 1987 to 2012, following low to high $MomCrowd^L$. Year zero is the portfolio selection period. This study presents the average monthly returns of the momentum strategy in Table 4.7.

Table 4.7: Momentum Returns with the size of momentum

This table presents returns to momentum as a function of lagged momentum crowd. Stocks with prices below £5 a share are excluded from our sample. This study classifies all months into five groups based on $MomCrowd^L$ (Panel A) and $mkt36$ (Panel B), the average pairwise partial return correlation in the loser decile. The table below reports returns to the momentum strategy in each of the three years after portfolio formation during 1987 to 2012, following low to high $MomCrowd^L$. Year zero is the portfolio ranking period. This chapter presents the average monthly returns of momentum strategy. $5 - 1$ is the difference between the highest and lowest $MomCrowd^L$ and OLS is the slope coefficient from the regression of monthly momentum returns on ranks of $MomCrowd^L$. T -statistics are presented in the parentheses.

Panel A: Momentum Returns Ranked by Momentum Crowd									
		Year 0		Year 1		Year 2		Year 3	
Rank	No. Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	52	10.54%	(11.23)	-0.26%	(-3.83)	-0.89%	(-27.74)	-0.84%	(-40.21)
2	52	11.49%	(11.73)	-0.35%	(-5.31)	-0.89%	(-29.85)	-0.82%	(-47.09)
3	52	14.42%	(13.06)	-0.53%	(-7.04)	-1.00%	(-28.41)	-0.83%	(-73.62)
4	52	15.54%	(15.27)	-0.57%	(-8.21)	-1.03%	(-29.66)	-0.83%	(-62.11)
5	52	18.01%	(22.23)	-0.74%	(-13.84)	-1.12%	(-36.58)	-0.86%	(-56.75)
$5 - 1$		7.47%	(6.07)	-0.47%	(-5.67)	-0.23%	(-5.38)	-0.03%	(-1.03)
OLS		0.03%	(5.70)	0.00%	(-5.29)	0.00%	(-3.09)	0.00%	(-1.33)
Panel B: Momentum Returns Ranked by $mkt36$									
		Year 0		Year 1		Year 2		Year 3	
Rank	No. Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	52	9.49%	(29.62)	-0.51%	(-1.93)	0.39%	(1.92)	0.52%	(1.94)
2	52	8.35%	(27.74)	1.59%	(3.35)	-0.60%	(-2.35)	0.00%	(0.01)
3	52	7.15%	(26.85)	0.24%	(0.59)	-1.26%	(-3.76)	0.36%	(1.35)
4	52	7.29%	(19.86)	-0.42%	(-0.90)	-1.70%	(-3.98)	-0.12%	(-0.38)
5	52	7.89%	(27.46)	0.36%	(1.02)	-1.71%	(-3.82)	-0.92%	(-2.82)
$5 - 1$		-1.60%	(-3.90)	0.87%	(2.03)	-2.10%	(-4.12)	-1.45%	(-3.51)
OLS		-0.01%	(-3.96)	0.00%	(0.62)	0.00%	(1.18)	0.00%	(-0.21)

This chapter finds that returns in portfolio formation year are consistently increasing with the momentum crowd. Group 1 contains months whose momentum crowd is low, whereas Group 5 has the highest momentum crowd months. The larger the momentum crowd, the higher the momentum returns that are generated. The study reports the momentum differential being 7.47% per month ($t = 6.07$) between Group 5 and Group 1. However, this study finds that post-formation returns are decreasing in the level of momentum crowd. Moreover, all returns become negative in Year 1, 2 and 3. In Year 1, the monthly momentum return is 0.47% per month lower (estimate=-0.47%, $t = -5.67$) when the momentum crowd is in Group 5 compared to the return in Group 1. Similar patterns are identifiable in Year 2 and 3. The momentum returns are marked and consistently decreasing in the momentum crowd. In Year 2, the post-formation monthly return gap between Group 5 and 1 on momentum stocks is 0.23% lower (estimate=-0.23%, $t = -5.38$). In Year 3, the gap becomes 0.03% lower (estimate=-0.03%, $t = -1.03$).

This study also reports returns to momentum strategy as a function of a lagged momentum crowd. The study classifies all months into five groups based on *mktret36*, the three-year return on market portfolio from year $t - 2$ to t . The results exhibit no clear pattern in the post-formation returns and there are no long-run reversal patterns. These findings are consistent with Lou and Polk (2013), who suggest that such measure of momentum crowd is unique.

The upper section of Figure 4.3 plots the cumulative returns from the momentum strategy in the past three years after the portfolio formation period. It shows that a cumulative buy-and-hold strategy return is positive when the momentum crowd is low, and negative when the momentum crowd is high. The bottom section of Figure 4.3 plots the momentum strategy from the beginning of the formation year to the three years after the portfolio's formation. It shows that when the momentum crowd is low, the cumulative momentum returns gradually increase and the pattern of under-reaction appears. Conversely, the scenario is the opposite

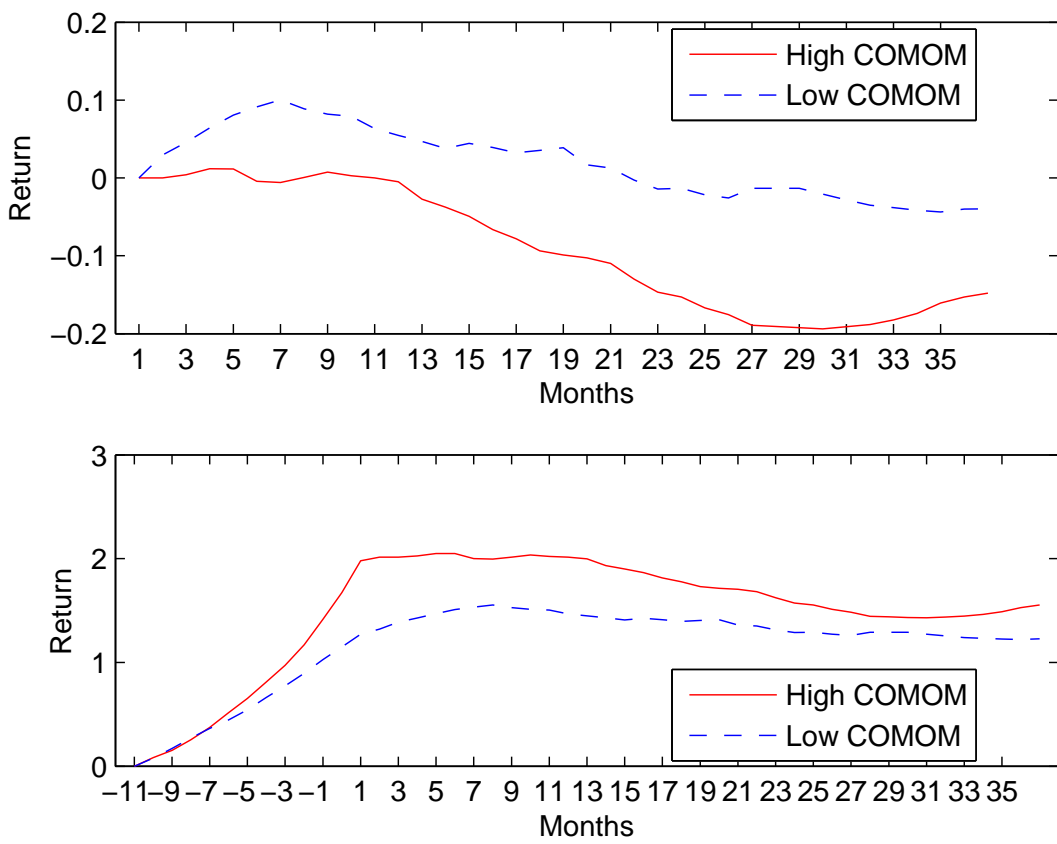


Figure 4.3: Momentum Crowd and Momentum Returns

with regard to the high momentum crowd. The corresponding momentum return exhibits overreaction as returns decline from the peak from Year 1 to Year 3. This further confirms Lou and Polk (2013)'s unanchored comomentum strategy of the cognitive bias effect among institutional investors.

Table 4.8: Forecasting Momentum Return Skewness

This table reports skewness of momentum returns as a function of lagged momentum crowd. Stocks with prices below £5 a share are excluded from our sample. This study classifies all months into five groups based on $MomCrowd^L$, the average pairwise partial return correlation in the loser decile. This table below reports the skewness in daily returns to the value-weight winner minus loser portfolio in month 1 to 3 (1 to 6 and 1 to 12) after portfolio formation during 1987 to 2012, following low to high $MomCrowd^L$. $5 - 1$ is the difference between the highest and lowest $MomCrowd^L$ and OLS is the slope coefficient from the regression of monthly momentum returns on ranks of $MomCrowd^L$. T -statistics are presented in the parentheses.

RankNo.	Obs.	Month1		Months 1-3		Months 1-6		Months 1-12	
		Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
1	52	0.054	(0.44)	0.015	(0.09)	-0.126	(-0.70)	-0.159	(-0.89)
2	52	-0.018	(-0.13)	-0.220	(-1.79)	-0.404	(-3.32)	-0.485	(-4.41)
3	52	-0.090	(-0.73)	-0.219	(-1.47)	-0.052	(-0.31)	-0.216	(-1.21)
4	52	0.048	(0.35)	-0.124	(-0.77)	-0.541	(-3.06)	-0.736	(-4.92)
5	52	-0.180	(-1.74)	-0.327	(-2.52)	-0.231	(-1.45)	-0.197	(-1.02)
$5 - 1$		-0.234	(-1.60)	-0.343	(-1.52)	-0.105	(-0.47)	-0.039	(-0.15)
OLS		0.000	(0.66)	0.000	(0.01)	-0.001	(-1.17)	-0.001	(-0.91)

There are a number of studies that point out that momentum crashes can be predicted when the market declines and when it is volatile. For example, Daniel and Moskowitz (2011) and Daniel, Jagannathan, and Kim (2012) focus on the non-normality feature of momentum returns. In Table 4.8 the study presents data to show the extent to which momentum crowd forecasts time-series variation in the momentum return skewness. The author examines the skewness of daily returns. Table 4.8 reports the skewness in daily returns to the value-weighted momentum portfolio in month 1, month 1 to 3, month 1 to 5 and month 1 to 12 after the formation of the portfolio. When the momentum crowd is high, the skewness becomes low. As can be seen from Table 4.8. In the first three months of the holding period, the months whose momentum crowd are the lowest have an

average return skewness of 0.015 ($t = 0.09$). Importantly, however, group 5, that contains the highest momentum crowd months, exhibits an estimate of skewness of -0.327 ($t = -2.52$). These results hold when the study examines daily return skewness over a longer holding period.

4.5 Conclusion

This chapter examined the 52-week high anchored momentum strategy (George and Hwang (2004)) for both institutional and individual investors of various holding horizons in the UK.

This chapter found that return continuation effect is high and robust with short holding horizons. The analysis also shows that individual investors appear to have more significant anchoring and adjustment biases over institutional investors. This chapter attributes such biases as being due to individual investors' inexperience. Using analysts' earnings forecast revision ratio, the findings suggest that experienced institutional investors are more likely to incorporate momentum signals and eventually translate their forecast revisions as news. Importantly, the analysis suggests significant coefficients for institutional held portfolios. Individual held portfolios, in contrast, do not yield similar results, demonstrating that individual investors are inexperienced. Thus, their strategies have a destabilising effect on the stock market efficiency.

Furthermore, momentum returns are mostly found to be significantly positive. However, there are certain moments when momentum crashes. For example, this study found significant momentum crash around 2007 when the global financial crisis occurred. Since the author is able to distinguish between individual held stocks and institutional held stocks, this study examined the difference between these two groups of stock returns both before and after financial crisis. This chapter found that momentum crash is caused not only by loser portfolios, but

also by winner portfolios. The study also finds that institutional investors tend to have cognitive biases that lead to momentum crash.

Following Lou and Polk (2013), this study further studied cognitive biases by applying the unanchored JT momentum strategy. This chapter quantified the momentum crowd in the UK market by sifting out the effect of other asset pricing anomalies. The results suggest that UK institutional momentum investors overreact when there are too many of them in momentum trading (i.e. when the momentum crowd is high).

Overall, this study concludes that individual investors are inexperienced and manifest anchoring and adjustment biases. Institutional investors, on the other hand, are more experienced. Even though they are still subject to cognitive biases, causing stock prices to move away from fundamentals. Their experience means that stock market is more efficient and stabilised.

Taken together, the findings of this study have a number of implications for practitioners, policy-makers, regulators and portfolio managers whose decisions depending on movements of stock prices. For individual investors, they can maximise their profits by holding portfolios at a short horizon. Compared to institutional investors, individual investors have more significant anchoring and adjustment biases. Policy makers are implied to distinguish the differences in the trading by institutions and individuals when making policies. It is generally argued that institutions are supposed to buy winners and sell losers in momentum trading. In contrast, the results imply that individuals tend to sell winners and buy losers and seem to engage in the contrarian behaviour even though the contrarian behaviour is not profitable at these horizons.

Chapter 5

Conclusion

5.1 Introduction

This chapter summarises the empirical findings of the thesis. It presents the limitations of the outcomes and then followed by a discussion of future research avenues.

5.2 Summary of the Main Findings

This thesis has three empirical dimensions including illiquidity premiums and expected stock returns, semi-varying momentum payoffs and illiquidity, and the 52-week high momentum strategy and information uncertainty in the UK. The main findings of each chapter is summarized in the next table.

Table 5.1: Main Findings From the Empirical Studies

Research Question	Methodology	Findings
Empirical Chapter 2		
1. Is there a single illiquidity proxy that can significantly outperform other proxies in asset pricing models?	Fama-MacBeth Regressions and HJ tests	No individual illiquidity proxy outperforms the others.
2. Does liquidity commonality exist in the UK?	Principal Component Analysis	There is a common illiquidity component.
3. Which liquidity-adjusted asset pricing model explains stock returns in the UK?	Fama-MacBeth Regressions and GMM	The inclusion of illiquidity with Fama-French model explains significant cross-sectional variations.
4. Do the results vary between parametric and non-parametric tests?	Fama-MacBeth Regressions and HJ tests	Parametrically Fama-French model outperforms while CAPM model yields a smaller HJ distance.
Empirical Chapter 3		
1. Why is there return continuation effect?	Time-series Regressions	Liquidity risk explains significant momentum effect.
2. Do UK data exhibit high heterogeneity?	Varying Coefficient Models	There is significant bounce in varying coefficients.
3. Does momentum persists at all times?	Out-of-Sample Tests	Momentum crashes during the financial crisis.
4. What happened when there is exogenous shock?	Diff-in-Diffs	High illiquid stocks are more sensitive to shocks.
Empirical Chapter 4		
1. How long is momentum strategy horizon?	Technical Analysis	From 3 months to 5 years.
2. Do individual investors trade differently from institutional investors?	Diff-in-Diffs and Technical Analysis	Yes. Individual investors significantly overreacted to economic shocks and destabilised efficient market.
3. How to explain momentum during times of greater information uncertainty?	52-Week High Anchor Diff-in-Diffs	Individual investors are more likely to have anchors, in particular from the sell-side.
4. Which type of investors help facilitate market efficiency?	Panel Regressions and Cross-sectional Regressions	Institutional investors who have access to analysts' earnings forecasts revisions do.

5.3 Limitations of the Study

The results of this thesis are considered in the context of the following limitations. Firstly, for the first empirical chapter, although the principal component analysis is a good approach to represent liquidity, it only captures linear correlations among liquidity measures. Therefore, the measure proposed in this chapter is subject to limitations of linearity.

Secondly, for the second empirical chapter, it illustrates how illiquidity shocks predict both momentum and value investment returns. Momentum anomaly is rather a complex puzzle. There are other factors that may contribute to momentum returns, for example volatility.

Thirdly, for the third empirical chapter, the way of distinguishing between individual and institutional investors assume individual to hold small numbers of stocks whereas institutional investors to hold larger numbers of stocks. This assumption may not be working in the real world.

Overall, liquidity and momentum puzzles are broad topics and may be market specific issues. Therefore, the results reported in this thesis may only be limited to similar developed markets and they may differ from developing countries.

5.4 Suggestions for Future Research

Despite filling some of the gaps in current asset pricing and stock return literature, this study highlights a number of others for future research.

Firstly, this thesis attempts to investigate asset pricing anomalies in the context of the UK stock market. Future research could be extended to investigate whether expected returns are related to stocks' sensitivities to fluctuations in other aspects of liquidity and in other markets, for example, the emerging markets.

Another direction for future research is to explore whether liquidity risk and momentum play a role in various pricing anomalies in financial markets. It would

also be useful to explore whether some form of systematic liquidity risk is priced in other financial markets, such as fixed income markets.

Thirdly, with regard to return continuation anomaly, future research could focus on studying the quality of governance that could be a potential explanation for continuing profits.

Appendix A

Unreported Results

A.1 Individual Parametric Illiquidity Results

Table A.1: Fama-MacBeth Estimates–CS

Note: λ_i is the mean of risk premium coefficients λ_i using Fama and MacBeth (1973) method. The monthly cross-sectional regressions of ten equally-weighted portfolio return premiums are estimated using the risk factors of Fama and MacBeth (1973). *ILLIQ* is CS factor of the pricing models. T-statistics are reported in parentheses. The last column reports the increase in R-squared coefficient due to the addition of the illiquidity factor.

	λ_0	λ_{mkt}	λ_{smb}	λ_{hml}	λ_{mom}	λ_L	R^2	ΔR^2
Unrestricted Model								
<i>CAPM_{ILLIQ}</i>	-0.418 (-2.990)	1.118 (3.008)				3.126 (0.811)	0.951	0.011
<i>FF_{ILLIQ}</i>	-0.172 (-1.009)	0.773 (1.386)	-0.030 (-0.033)	0.596 (0.992)		-6.315 (-1.714)	0.956	0.020
<i>CARHART_{ILLIQ}</i>	-0.227 (-1.413)	0.642 (1.031)	0.360 (0.371)	0.912 (1.473)	-1.851 (-0.977)	-4.055 (-0.473)	0.958	0.014

Table A.2: Fama-MacBeth Estimates–ET

Note: λ_i is the mean of risk premium coefficients λ_i using Fama and MacBeth (1973) method. The monthly cross-sectional regressions of ten equally-weighted portfolio return premiums are estimated using the risk factors of Fama and MacBeth (1973). *ILLIQ* is ET factor of the pricing models. T-statistics are reported in parentheses. The last column reports the increase in R-squared coefficient due to the addition of the illiquidity factor.

	λ_0	λ_{mkt}	λ_{smb}	λ_{hml}	λ_{mom}	λ_L	R^2	ΔR^2
Unrestricted Model								
<i>CAPM_{ILLIQ}</i>	2.711 (2.832)	-2.354 (-2.435)				1.592 (3.982)	0.905	0.666
<i>FF_{ILLIQ}</i>	1.297 (0.875)	-0.994 (-0.677)	0.756 (-3.363)	-1.455 (-1.592)		1.190 (1.761)	0.923	-0.025
<i>CARHART_{ILLIQ}</i>	2.174 (1.641)	-2.025 (-1.508)	0.808 (3.556)	-1.106 (-1.134)	-1.434 (-0.547)	1.279 (2.277)	0.926	-0.031

Table A.3: Fama-MacBeth Estimates–LM

Note: λ_i is the mean of risk premium coefficients λ_i using Fama and MacBeth (1973) method. The monthly cross-sectional regressions of ten equally-weighted portfolio return premiums are estimated using the risk factors of Fama and MacBeth (1973). *ILLIQ* is LM factor of the pricing models. T-statistics are reported in parentheses. The last column reports the increase in R-squared coefficient due to the addition of the illiquidity factor.

	λ_0	λ_{mkt}	λ_{smb}	λ_{hml}	λ_{mom}	λ_L	R^2	ΔR^2
Unrestricted Model								
<i>CAPM_{ILLIQ}</i>	0.959 (1.316)	-0.186 (-0.257)				0.923 (1.703)	0.581	0.089
<i>FF_{ILLIQ}</i>	0.906 (1.178)	-0.186 (-0.244)	0.099 (0.379)	-0.747 (-1.219)		0.334 (0.568)	0.834	0.013
<i>CARHART_{ILLIQ}</i>	0.036 (0.033)	1.070 (0.758)	0.262 (0.917)	-0.282 (-0.399)	3.999 (1.116)	-0.610 (-3.992)	0.914	0.066

Table A.4: Fama-MacBeth Estimates–PS

Note: λ_i is the mean of risk premium coefficients λ_i using Fama and MacBeth (1973) method. The monthly cross-sectional regressions of ten equally-weighted portfolio return premiums are estimated using the risk factors of Fama and MacBeth (1973). *ILLIQ* is PS factor of the pricing models. T-statistics are reported in parentheses. The last column reports the increase in R-squared coefficient due to the addition of the illiquidity factor.

	λ_0	λ_{mkt}	λ_{smb}	λ_{hml}	λ_{mom}	λ_L	R^2	ΔR^2
Unrestricted Model								
<i>CAPM_{ILLIQ}</i>	-0.221 (-1.576)	0.926 (3.195)				0.783 (1.574)	0.869	0.048
<i>FF_{ILLIQ}</i>	-0.287 (-1.605)	0.813 (2.588)	0.388 (1.743)	0.970 (0.704)		-0.184 (-0.263)	0.909	-0.004
<i>CARHART_{ILLIQ}</i>	-0.089 (-0.479)	0.772 (2.519)	0.547 (2.559)	3.694 (3.191)	-0.414 (-0.174)	-1.341 (-0.638)	0.957	0.027

Table A.5: Fama-MacBeth Estimates–RO

Note: λ_i is the mean of risk premium coefficients λ_i using Fama and MacBeth (1973) method. The monthly cross-sectional regressions of ten equally-weighted portfolio return premiums are estimated using the risk factors of Fama and MacBeth (1973). *ILLIQ* is RO factor of the pricing models. T-statistics are reported in parentheses. The last column reports the increase in R-squared coefficient due to the addition of the illiquidity factor.

	λ_0	λ_{mkt}	λ_{smb}	λ_{hml}	λ_{mom}	λ_L	R^2	ΔR^2
Unrestricted Model								
<i>CAPM_{ILLIQ}</i>	0.068 (0.095)	0.687 (0.872)				1.011 (1.263)	0.781	0.004
<i>FF_{ILLIQ}</i>	1.055 (1.061)	-0.183 (-0.193)	-0.124 (-0.470)	0.155 (0.201)		2.143 (1.710)	0.824	0.046
<i>CARHART_{ILLIQ}</i>	2.066 (1.823)	-0.931 (-0.896)	-0.566 (-1.855)	-1.248 (-1.418)	4.744 (2.094)	4.045 (2.968)	0.931	0.133

Table A.6: Fama-MacBeth Estimates–RV

Note: λ_i is the mean of risk premium coefficients λ_i using Fama and MacBeth (1973) method. The monthly cross-sectional regressions of ten equally-weighted portfolio return premiums are estimated using the risk factors of Fama and MacBeth (1973). *ILLIQ* is RV factor of the pricing models. T-statistics are reported in parentheses. The last column reports the increase in R-squared coefficient due to the addition of the illiquidity factor.

	λ_0	λ_{mkt}	λ_{smb}	λ_{hml}	λ_{mom}	λ_L	R^2	ΔR^2
Unrestricted Model								
<i>CAPM_{ILLIQ}</i>	1.065 (1.608)	-0.514 (-0.756)				0.738 (2.381)	0.900	0.698
<i>FF_{ILLIQ}</i>	0.799 (1.120)	-0.230 (-0.309)	0.290 (1.852)	-0.275 (-0.611)		0.665 (2.077)	0.914	0.019
<i>CARHART_{ILLIQ}</i>	0.761 (0.990)	-0.274 (-0.340)	0.342 (2.164)	-0.089 (-0.169)	-3.247 (-1.578)	0.626 (10.116)	0.991	0.002

Table A.7: Fama-MacBeth Estimates–ZR

Note: λ_i is the mean of risk premium coefficients λ_i using Fama and MacBeth (1973) method. The monthly cross-sectional regressions of ten equally-weighted portfolio return premiums are estimated using the risk factors of Fama and MacBeth (1973). *ILLIQ* is ZR factor of the pricing models. T-statistics are reported in parentheses. The last column reports the increase in R-squared coefficient due to the addition of the illiquidity factor.

	λ_0	λ_{mkt}	λ_{smb}	λ_{hml}	λ_{mom}	λ_L	R^2	ΔR^2
Unrestricted Model								
<i>CAPM_{ILLIQ}</i>	-0.478 (-1.149)	0.626 (0.522)				-0.267 (-0.757)	0.138	0.054
<i>FF_{ILLIQ}</i>	-0.297 (-0.634)	0.272 (0.215)	-0.195 (-0.227)	0.470 (0.842)		-0.290 (-0.808)	0.364	0.112
<i>CARHART_{ILLIQ}</i>	-0.618 (-1.039)	1.474 (0.979)	-0.390 (-0.463)	0.622 (1.147)	-2.201 (-1.027)	-0.157 (-6.168)	0.594	0.114

Appendix B

Program Codes

This section provides with some of the MATLAB codes this thesis uses.

B.1 Portfolio formation

1. Find the market value at the beginning of the year.

```
MVF=zeros(totalyears,totalstocks);  
MVF(1,:)=MV(1,:);  
for i=1:totalstocks  
for y=1:totalyears-1  
for j=1:totaldays  
if ta(j)-ta(1)+1==yta(j+1)-ta(1)+1==y+1  
MVF(y+1,i)=MV(j,i);  
end end end end
```

2. Form the portfolio.

```
[ ,id]=sort(MVF,2,'ascend');  
for y=1:totalyears  
nstocks(y)=length(find(MVF(y,:) =0));  
ncandidates(y)=floor(nstocks(y)*0.1);
```



```

for i=1:10 for j=1:ncandidates(y)
PMV(y,i,j)=id(y,totalstocks+1-
ncandidates(y)*(10-i)-j);
end end end

```

```

NMV=ncandidates;

```

3. Equal-weighted illiquidity and other characteristics by size portfolios.

```

PCAP=zeros(totalyears,10);

```

```

PMTBV=zeros(totalyears,10);

```

```

PRETURN=zeros(totalmonths,10);

```

```

PRV=zeros(totalmonths,10);

```

```

PPS=zeros(totalmonths,10);

```

```

PZR=zeros(totalmonths,10);

```

```

PLM=zeros(totalmonths,10);

```

```

PRO=zeros(totalmonths,10);

```

```

PCS=zeros(totalmonths,10);

```

```

PET=zeros(totalmonths,10);

```

```

for k=1:totalmonths

```

```

illiquidity average portfolio

```

```

for j=1:10 for i=1:NMV(ceil(k/12))

```

```

PRETURN(k,j)=

```

```

PRETURN(k,j)+RM(k,PMV(ceil(k/12),j,i))

```

```

/NMV(ceil(k/12)); PRV(k,j)=

```

```

PRV(k,j)+RV(k,PMV(ceil(k/12),j,i))/NMV(ceil(k/12));

```

```

PPS(k,j)=

```

```

PPS(k,j)+PS(k,PMV(ceil(k/12),j,i))/NMV(ceil(k/12));

```

```

PZR(k,j)=PZR(k,j)+ZR(k,PMV(ceil(k/12),j,i))/NMV(ceil(k/12));

```

```

PLM(k,j)=PLM(k,j)+LM(k,PMV(ceil(k/12),j,i))/NMV(ceil(k/12));

```

```

PRO(k,j)=PRO(k,j)+RO(k,PMV(ceil(k/12),j,i))/NMV(ceil(k/12));
PCS(k,j)=PCS(k,j)+CS(k,PMV(ceil(k/12),j,i))/NMV(ceil(k/12));
PET(k,j)=PET(k,j)+ET(k,PMV(ceil(k/12),j,i))/NMV(ceil(k/12));
end end end

for k=1:totalyears
for j=1:10
for i=1:NMV(k)
PCAP(k,j)=PCAP(k,j)+MVF(k,PMV(k,j,i));
PMTBV(k,j)=PMTBV(k,j)+MTBV(k,PMV(k,j,i))/
NMV(k);
end end end

tabel1_equal_weighted=[mean(PRETURN);
mean(PRV);mean(PPS);mean(PZR);
mean(PLM);mean(PRO);mean(PCS);mean(PET);
mean(PCAP);mean(PMTBV);std(PRETURN)]';

```

4. Value-weighted illiquidity and other characteristics by size portfolios.

```

VPRETURN=zeros(totalmonths,10);
VPRV=zeros(totalmonths,10);
VPPS=zeros(totalmonths,10);
VPZR=zeros(totalmonths,10);
VPLM=zeros(totalmonths,10);
VPRO=zeros(totalmonths,10);
VPCS=zeros(totalmonths,10);
VPET=zeros(totalmonths,10);
SPRETURN=zeros(totalmonths,10);
SPRV=zeros(totalmonths,10);
SPPS=zeros(totalmonths,10);
SPZR=zeros(totalmonths,10);

```

```

SPLM=zeros(totalmonths,10);
SPRO=zeros(totalmonths,10);
SPCS=zeros(totalmonths,10);
SPET=zeros(totalmonths,10);
for k=1:totalmonths
illiquidity average portfolio
MVsize=zeros(1,10);
for j=1:10 for i=1:NMV(ceil(k/12))
MVsize(1,j)=MVsize(1,j)+MVM(k,PMV(ceil(k/12),j,i));
SPRETURN(k,j)=SPRETURN(k,j)
+RM(k,PMV(ceil(k/12),j,i))*MVM(k,PMV(ceil(k/12),j,i));
SPRV(k,j)=SPRV(k,j)+RV(k,PMV(ceil(k/12),j,i))
*MVM(k,PMV(ceil(k/12),j,i));
SPPS(k,j)=SPPS(k,j)+PS(k,PMV(ceil(k/12),j,i))
*MVM(k,PMV(ceil(k/12),j,i));
SPZR(k,j)=SPZR(k,j)+ZR(k,PMV(ceil(k/12),j,i))
*MVM(k,PMV(ceil(k/12),j,i));
SPLM(k,j)=SPLM(k,j)+LM(k,PMV(ceil(k/12),j,i))
*MVM(k,PMV(ceil(k/12),j,i));
SPRO(k,j)=SPRO(k,j)+RO(k,PMV(ceil(k/12),j,i))
*MVM(k,PMV(ceil(k/12),j,i));
SPCS(k,j)=SPCS(k,j)+CS(k,PMV(ceil(k/12),j,i))
*MVM(k,PMV(ceil(k/12),j,i));
SPET(k,j)=SPET(k,j)+ET(k,PMV(ceil(k/12),j,i))
*MVM(k,PMV(ceil(k/12),j,i));
end
VPRETURN(k,j)=SPRETURN(k,j)/MVsize(1,j);
VPRV(k,j)=SPRV(k,j)/MVsize(1,j);

```

```

VPPS(k,j)=SPPS(k,j)/MVsize(1,j);
VPZR(k,j)=SPZR(k,j)/MVsize(1,j);
VPLM(k,j)=SPLM(k,j)/MVsize(1,j);
VPRO(k,j)=SPRO(k,j)/MVsize(1,j);
VPCS(k,j)=SPCS(k,j)/MVsize(1,j);
VPET(k,j)=SPET(k,j)/MVsize(1,j);
end end

tabel1_value_weighted=[mean(VPRETURN);
mean(VPRV);mean(VPPS);mean(VPZR);
mean(VPLM);mean(VPRO);mean(VPCS);
mean(VPET);mean(PCAP);mean(PMTBV)
;std(VPRETURN)]';
xlswrite('..tabel1_value_weighted.xlsx',
tabel1_value_weighted);

5. Momentum Crowd

clear;clc;

load secondchapterdata.mat;

for k=1:totalmonths n=1;

while (ty(n)-1986)*12+tm(n)>k

n=n+1;

end

tmf(k)=n;

end

[B,id]=sort(mvdaily,2,'ascend'); sumR=0;

summvdaily=0;

SMB=zeros(totaldays,1);

nstockssmb=zeros(totaldays,1);

ncandidatesmb=zeros(totaldays,1);

```

```

for i=1:totaldays
smallsum=0;
bigsum=0;
for j=1:(totalstocks*0.5)
smallsum=smallsum+R(i,id(i,j));
end
for j=(totalstocks*0.5+1):totalstocks
bigsum=bigsum+R(i,id(i,j));
end
SMB(i)=smallsum-bigsum;
end
[C,hmlid]=sort(btmv,2,'descend'); sumR=0;
sumbtmv=0;
HML=zeros(totaldays,1);
nstockshml=zeros(totaldays,1);
for i=1:totaldays
highsum=0;
lowsum=0;
for j=1:(floor(totalstocks*0.3))
highsum=highsum+R(i,hmlid(i,j));
end
for j=(floor(totalstocks*0.7)+1):totalstocks
lowsum=lowsum+R(i,hmlid(i,j));
end
HML(i)=highsum-lowsum;
end
MKT=Rmarket-RFD;
RMonthly=zeros(totalmonths,totalstocks);

```

```

for i=1:totalstocks;
for j=1:totalmonths-1
RMonthly(j,i)=monthlyRI(j+1,i)/monthlyRI(j,i)-1;
end
end
RMonthly(isnan(RMonthly))=0;
RMonthly(isinf(RMonthly))=0;
Rmarketmonthly=zeros(totalmonths,1);
for i=1:totalmonths-1
Rmarketmonthly(i,1)=marketRImonthly(i+1,1)
/marketRImonthly(i,1)-1;
end
Rmarketmonthly(isnan(Rmarketmonthly))=0;
Rmarketmonthly(isinf(Rmarketmonthly))=0;
for m=13:totalmonths;
for i=1:totalstocks;
Rmom(m,i)=monthlyRI(m,i)/monthlyRI(m-12,i)-1;
end;
end;
Rmom(isnan(Rmom))=0;
Rmom(isinf(Rmom))=0;
[D,momid]=sort(Rmom,2,'descend');
WML=zeros(totalmonths,1);
RPw=zeros(totalmonths,totalstocks);
RPl=zeros(totalmonths,totalstocks);
for i=13:totalmonths;
for j=1:(floor(totalstocks*0.1))
Pw(i,j)=momid(i,j);

```

```

end
for j=1:(floor(totalstocks*0.1))
Pl(i,j)=momid(i,j+floor(totalstocks*0.9));
end
RPw(:,i)=RPw(:,i)+RMonthly(:,Pw(i,j));
RPl(:,i)=RPl(:,i)+RMonthly(:,Pl(i,j));
end
daytomonth=zeros(totaldays,totalstocks);
for i=13:totalmonths-1
for j=tmf(1,i):(tmf(1,i+1)-1)
for k=1:totalstocks
daytomonth(j,k)=RPw(i,k);
end
end
end
for i=13:totalmonths;
for j=1:(floor(totalstocks*0.1));
for tradingday=1:(tmf(i)-tmf(i-12));
X1(tradingday,1)=R(tradingday-1+tmf(i-12),Pw(i,j));
X1(tradingday,2)=(daytomonth(tradingday-1+tmf(i-12),Pw(i,j)))/63;
Z1(tradingday,1)=MKT(tradingday-1+tmf(i-12),1);
Z1(tradingday,2)=SMB(tradingday-1+tmf(i-12),1);
Z1(tradingday,3)=HML(tradingday-1+tmf(i-12),1);
end
partial(j)=nonzeros(tril(partialcorr(X1,Z1),-1));
clear X1 Z1;
end
partial(isnan(partial))=0;

```

```

pcw(i)=mean(partial);
end
for i=13:totalmonths; for j=1:(floor(totalstocks*0.1));
Pl(i,j)=momid(i,j+floor(totalstocks*0.9));
for tradingday=1:(tmf(i)-tmf(i-12));
X1(tradingday,1)=R(tradingday-1+tmf(i-12),Pl(i,j));
X1(tradingday,2)=(daytomonth(tradingday-1+tmf(i-12),Pl(i,j)))/63;
Z1(tradingday,1)=MKT(tradingday-1+tmf(i-12),1);
Z1(tradingday,2)=SMB(tradingday-1+tmf(i-12),1);
Z1(tradingday,3)=HML(tradingday-1+tmf(i-12),1);
end
partial(j)=nonzeros(tril(partialcorr(X1,Z1),-1));
clear X1 Z1;
end
partial(isnan(partial))=0;
pcl(i)=mean(partial);
end
for t=37:totalmonths;
mkt36(t)=marketRImonthly(t)/marketRImonthly(t-36)-1;
mktvol36(t)=std(Rmarketmonthly(t-36:t,:));
end
panelA(1,1)=size(pcl(37:end),2);panelA(1,2)=mean(pcl(37:end));
panelA(1,3)=std(pcl(37:end));panelA(1,4)=min(nonzeros(pcl(37:end)));
panelA(1,5)=max(pcl(37:end));
panelA(2,1)=size(pcw(37:end),2);
panelA(2,2)=mean(pcw(37:end));
panelA(2,3)=std(pcw(37:end));panelA(2,4)=min(nonzeros(pcw(37:end)));
panelA(2,5)=max(pcw(37:end));

```



```

panelA(3,1)=size(mkt36(37:end),2);
panelA(3,2)=mean(mkt36(37:end));panelA(3,3)=std(mkt36(37:end));
panelA(3,4)=min(mkt36(37:end));panelA(3,5)=max(mkt36(37:end));
panelA(4,1)=size(mktvol36(37:end),2);panelA(4,2)=mean(mktvol36(37:end));
panelA(4,3)=std(mktvol36(37:end));panelA(4,4)=min(mktvol36(37:end));
panelA(4,5)=max(mktvol36(37:end));
panelB=corrcoef([pcl(37:end)' pcw(37:end)'
mkt36(37:end)' mktvol36(37:end)']);
panelC=corrcoef([pcl(37:end-1)' pcw(37:end-1)'
pcl(38:end)' pcw(38:end)']);

```

6. Class the months in to five groups based on commoml.

```

[C,id]=sort(pcl(37:end-37),2,'ascend');
for m=1:5
nmonths(m)=floor(size(C,2)*0.2);
for i=1:nmonths(m)
pd(m,i)=id(i+(m-1)*nmonths(m))+36;
X0(m,i)=MOM(pd(m,i),1);
X1(m,i)=MOM(pd(m,i),2);
X2(m,i)=MOM(pd(m,i),3);
X3(m,i)=MOM(pd(m,i),4);
end
end

```

7. Calculate portfolio in month k return in the following period.

```

for m=13:totalmonths-37
nstocks(m)=length(find(RMom(m,:) ==-1));
ncandidates(m)=floor(nstocks(m)*0.1);
for k=1:49
for j=1:ncandidates(m)

```

```

Ml(m,j,k)=RM(m+k-13,Pl(m,j));
weighted_Ml(m,j,k)=monthlvmv(m+k-13,Pl(m,j));
Mw(m,j,k)=RM(m+k-13,Pw(m,j));
weighted_Mw(m,j,k)=monthlvmv(m+k-13,Pw(m,j));
end
tempal=Ml(m,:,k);tempbl=weighted_Ml(m,:,k);
tempaw=Mw(m,:,k);tempbw=weighted_Mw(m,:,k);
Rpl(m,k)=tempal*tempbl'/sum(tempbl);
Rpw(m,k)=tempaw*tempbw'/sum(tempbw);
end
Rpmom=Rpw-Rpl;
end
8. regression
for m=13:totalmonths-37
Y=Rpmom(m,1:12)'-RF(m-12:m-1);
X1=RMARKETM(m-12:m-1)-RF(m-12:m-1);
X2=SMBM(m-12:m-1);
X3=HML(m-12:m-1);
X=[ones(12,1),X1,X2,X3];
beta=regress(Y,X);
FF0(m)=beta(1);
Y=Rpmom(m,14:25)'-RF(m+1:m+12);
X1=RMARKETM(m+1:m+12)-RF(m+1:m+12);
X2=SMBM(m+1:m+12);
X3=HML(m+1:m+12);
X=[ones(12,1),X1,X2,X3];
beta=regress(Y,X);
FF1(m)=beta(1);

```

```

Y=Rpmom(m,26:37)'-RF(m+13:m+24);
X1=RMARKETM(m+13:m+24)-RF(m+13:m+24);
X2=SMBM(m+13:m+24);
X3=HML(m+13:m+24);
X=[ones(12,1),X1,X2,X3];
beta=regress(Y,X);
FF2(m)=beta(1);
Y=Rpmom(m,38:49)'-RF(m+25:m+36);
X1=RMARKETM(m+25:m+36)-RF(m+25:m+36);
X2=SMBM(m+25:m+36);
X3=HML(m+25:m+36);
X=[ones(12,1),X1,X2,X3];
beta=regress(Y,X);
FF3(m)=beta(1);
end
FF=[FF0' FF1' FF2' FF3'];
[C,id]=sort(pcl(37:end-37),2,'ascend'); for m=1:5
nmonths(m)=floor(size(C,2)*0.2); for i=1:nmonths(m)
pd(m,i)=id(i+(m-1)*nmonths(m))+36;
X0(m,i)=FF(pd(m,i),1);
X1(m,i)=FF(pd(m,i),2);
X2(m,i)=FF(pd(m,i),3);
X3(m,i)=FF(pd(m,i),4);
for j=1:49
X4(m,i,j)=Rpmom(pd(m,i),j);
end
end
end
end

```

```

Rpm=squeeze(mean(X4,2));
for i=1:5
panelb(i,1)=i;
panelb(i,2)=nmonths(i);
panelb(i,3)=mean(X0(i,:));
[ , , ,stat]=ttest(X0(i,:));
panelb(i,4)=stat.tstat;
panelb(i,5)=mean(X1(i,:));
[ , , ,stat]=ttest(X1(i,:));
panelb(i,6)=stat.tstat;
panelb(i,7)=mean(X2(i,:));
[ , , ,stat]=ttest(X2(i,:));
panelb(i,8)=stat.tstat;
panelb(i,9)=mean(X3(i,:));
[ , , ,stat]=ttest(X3(i,:));
panelb(i,10)=stat.tstat;
end

panelb(6,3)=panelb(5,3)-panelb(1,3);
panelb(6,5)=panelb(5,5)-panelb(1,5);
panelb(6,7)=panelb(5,7)-panelb(1,7);
panelb(6,9)=panelb(5,9)-panelb(1,9);
[ , , ,stat]=ttest(X0(5,:)-X0(1,:));
panelb(6,4)=stat.tstat;
[ , , ,stat]=ttest(X1(5,:)-X1(1,:));
panelb(6,6)=stat.tstat;
[ , , ,stat]=ttest(X2(5,:)-X2(1,:));
panelb(6,8)=stat.tstat;
[ , , ,stat]=ttest(X3(5,:)-X3(1,:));

```

```

panelb(6,10)=stat.tstat;
whichstats = 'beta','tstat';
stats = regstats(FF0(37:end),'id','linear',whichstats);
panelb(7,3)=stats.beta(2);
panelb(7,4)=stats.tstat.t(2);
stats1 = regstats(FF1(37:end),'id','linear',whichstats);
panelb(7,5)=stats1.beta(2);
panelb(7,6)=stats1.tstat.t(2);
stats2 = regstats(FF2(37:end),'id','linear',whichstats);
panelb(7,7)=stats2.beta(2);
panelb(7,8)=stats2.tstat.t(2);
stats3 = regstats(FF3(37:end),'id','linear',whichstats);
panelb(7,9)=stats3.beta(2);
panelb(7,10)=stats3.tstat.t(2);

```

B.2 Liquidity measures

```

load stockdata;
clear
clc;
load uk.mat;
load t.mat;
1.RV Days=0;
Sum=0;
RV=zeros(totalmonths,totalstocks);
D=zeros(totalmonths,totalstocks);
for i=1:totalstocks for k=1:totalmonths for j=1:length(t) if tm(j)+12*(ta(j)-ta(1))==
kR(j,i)VO(j,i)P(j,i)

```

```

Days=Days+1;
Sum=Sum+1000*abs(R(j,i))/(VO(j,i)*P(j,i));
end
end
RV(k,i)=Sum/Days; D(k,i)=Days; Days=0;
Sum=0;
end end
RV(isnan(RV))=0;
RV(isinf(RV))=0;
2 PS
clear X1 X2 X3 Y;
for i=1:totalstocks
for k=1:totalmonths
if NTRADAY(k,i)>1
for d=1:NTRADAY(k,i)-1
Y(d)=R(TRADAY(k,i,d+1),i)-RMARKET
(TRADAY(k,i,d+1));
X1(d)=1;
X2(d)=R(TRADAY(k,i,d),i);
X3(d)=sign(R(TRADAY(k,i,d),i)-RMARKET
(TRADAY(k,i,d)))*VA(TRADAY(k,i,d+1),i);
end
X=[X1',X2',X3'];
beta=regress(Y',X);
PS(k,i)=-beta(3);
clear X1 X2 X3 Y;
else PS(k,i)=0;
end

```

```

end
end
PS(isnan(PS))=0;
PS(isinf(PS))=0;
3. ZR
Days=0;
for i=1:totalstocks
for k=1:totalmonths
if NTRADAY(k,i) > 1
for d=1:NTRADAY(k,i)-1
if RI(TRADAY(k,i,d),i) ==
RI(TRADAY(k,i,d+1),i)
Days=Days+1;
end
end
end
ZERODAY(k,i)=Days;
Days=0;
end
end ZR=ZERODAY./repmat(GENNTRADAY',1,totalstocks);
ZR=ZR.*100;
4. LM12 NZ=zeros(totalmonths,totalstocks);
for i=1:totalstocks
for k=13:totalmonths
for d=1:12
NZ(k,i)=NZ(k,i)+ZERODAY(k-d,i);
end
end end TVX=zeros(totalmonths,totalstocks);

```

```

for i=1:totalstocks
for k=13:totalmonths
for d=1:12
for dd=1:NTRADAY(k-d,i)
TVX(k,i)=TVX(k,i)+TRN(TRADAY(k-d,i,dd),i);
end
end
end
end DF=11000;
NX=zeros(totalmonths,1);
for k=13:totalmonths
for d=1:12
NX(k)=NX(k)+GENNTRADAY(k-d);
end
end LM=zeros(totalmonths,totalstocks);
for i=1:totalstocks
for k=13:totalmonths
if TVX(k,i)
LM(k,i)=(NZ(k,i)+(1/TVX(k,i))/DF)*21*12/NX(k);
end
end
end
LM(isnan(LM))=0;
LM(isinf(LM))=0;
Days=1;
clear Y X;
for i=1:totalstocks
for j=1:totaldays

```



```

if R(j,i)
Y(Days)=R(j,i);
X(Days,:)= [1,RMARKET(j)];
Days=Days+1;
end
end;
if Days<1
[b, ,r, ,stats]=regress(Y',X);
beta(i)=b(2);
theta(i)=std(r);
r2(i)=stats(1);
end
Days=1;
clear Y X;
end
6. RO clear TEMPRO;
R=R./100;
for i=1:totalstocks
for k=1:totalmonths
if NTRADAY(k,i)<1
for d=1:NTRADAY(k,i)
TEMPRO(d)=R(TRADAY(k,i,d),i);
end
RO(k,i)=2*sqrt(abs(cov(TEMPRO)));
clear TEMPRO;
end
end end
R=R.*100;

```

```

7. CS clear beta;
alpha=zeros(totaldays,totalstocks);
beta=zeros(totaldays,totalstocks);
gama=zeros(totaldays,totalstocks);
SCS=zeros(totaldays,totalstocks);
CS=zeros(totalmonths,totalstocks);
for i=1:totalstocks
for j=1:totaldays-1
if H(j,i)L(j,i)H(j+1,i)L(j+1,i)
beta(j,i)=1/2*((log(H(j+1,i)/L(j+1,i)))^2
+(log(H(j,i)/L(j,i)))^2);
gama(j,i)=(log((max(H(j+1,i),H(j,i)))/
(min(L(j+1,i),L(j,i)))))^2;
alpha(j,i)=(((sqrt(2)-1)*(beta(j,i)))
/(3-2*sqrt(2)))-sqrt((gama(j,i))/(3-2*sqrt(2)))));
SCS(j,i)=2*(exp(alpha(j,i))-1)/(1+exp(alpha(j,i)));
end end end
Days=0;
for i=1:totalstocks
for k=1:totalmonths
for j=1:totaldays
if tm(j)+12*(ta(j)-ta(1))==kSCS(j,i)
Days=Days+1;
CS(k,i)=CS(k,i)+SCS(j,i);
end
end
CS(k,i)=CS(k,i)/Days;
Days=0;

```

```

end
end
CS(isnan(CS))=0;
CS(isinf(CS))=0;
8. ET Days=0;sumP=0;
for i=1:totalstocks
for k=1:totalmonths
for j=1:length(t)
if tm(j)+12*(ta(j)-ta(1))==kP(j,i)
Days=Days+1;
sumP=sumP+P(j,i);
PDAY(k,i,Days)=j;
end
end
AP(k,i)=sumP/Days;
NPDAY(k,i)=Days; Days=0;
sumP=0;
end
end
AP(isnan(AP))=0;
N=zeros(totalmonths,totalstocks,6);
for i=1:totalstocks
for k=1:totalmonths
if NPDAY(k,i)
for d=1:NPDAY(k,i)
x=P(PDAY(k,i,d),i);
if x==floor(x) N(k,i,1)=N(k,i,1)+1;
elseif x-floor(x)==0.5 N(k,i,2)=N(k,i,2)+1;

```

```

elseif 5*x==floor(5*x) N(k,i,3)=N(k,i,3)+1;
elseif 5*x-floor(5*x)==0.5 N(k,i,4)=N(k,i,4)+1;
elseif 10*x-floor(10*x)==0.5 N(k,i,5)=N(k,i,5)+1;
else N(k,i,6)=N(k,i,6)+1; end
end
end
end
end
sumN=sum(N,3);
clear gamaET;
for i=1:totalstocks
for k=1:totalmonths
for n=1:6
F(n)=N(k,i,7-n)/sumN(k,i);
end
U(1)=2*F(1);
for n=2:5
U(n)=2*F(n)-F(n-1);
end
U(6)=F(6)-F(5);
gamaET(1)=min((max(U(1),0)),1);
for n=2:6
gamaET(n)=min((max(U(n),0)),1-sum(gamaET));
end
ET(k,i)=(gamaET(1)*0.01+gamaET(2)*0.05+
gamaET(3)*0.1+gamaET(4)*0.2+gamaET(5)*0.5+
gamaET(6))/AP(k,i);
clear gamaET;

```

```

end
end
ET(isnan(ET))=0;

```

B.3 Forecasting

```

[totalmonths,totalstocks]=size(monthlymv);
R1=zeros(totalmonths,totalstocks);
for i=1:totalstocks
for j=1:totalmonths-2
R1(j,i)=monthlyRI(j+2,i)/monthlyRI(j,i)-1;
end
end
R2=zeros(totalmonths,totalstocks);
for i=1:totalstocks
for j=1:totalmonths-2
R2(j,i)=monthlyRI(j,i)/monthlyRI(j+2,i)-1;
end
end
Revision=zeros(totalmonths,totalstocks);
for i=1:totalstocks
for j=1:totalmonths-1
Revision(j,i)=(monthlyfeps(j+1,i)
-monthlyfeps(j,i))/monthlp(j,i);
end
end
Revision(isnan(Revision))=0;
Revision(isinf(Revision))=0;

```

```

Revision(find(Revision==0))=-1;
monthlvmv(isnan(monthlvmv))=0;
[B,id]=sort(Revision,2,'descend');
MOM=zeros(totalmonths,1);
SumR=0;
SumMV=0;
MOM=zeros(totalmonths,1);
for m=1:totalmonths-1
nstocks(m)=length(find(Revision(m,:) ==-1));
ncandidates(m)=floor(nstocks(m)*0.3);
for j=1:ncandidates(m)
Pl(m,j)=id(m,nstocks(m)+1-j);
SumR=SumR+R2(m,Pl(m,j));
end Rl(m)=SumR/ncandidates(m);
Rl(m)=Rl(m)+1;
Rl(m)=Rl(m)';
Rl(m)=Rl(m).^(1/2);
Rl(m)=Rl(m)-1;
SumR=0;
SumMV=0;
for j=1:ncandidates(m)
Pw(m,j)=id(m,j);
SumR=SumR+R1(m,Pw(m,j));
end
Rw(m)=SumR/ncandidates(m);
Rw(m)=Rw(m)';
Rw(m)=Rw(m)+1;
Rw(m)=Rw(m).^(1/2);

```

```

Rw(m)=Rw(m)-1;
SumR=0;
SumMV=0;
MOM(m)=Rw(m)+Rl(m);
end
MOM(isnan(MOM))=0;
MOM(isinf(MOM))=0;
Rw(isnan(Rw))=0;
Rw(isinf(Rw))=0;
Rl(isnan(Rl))=0;
Rl(isinf(Rl))=0;
for n=1:335;
for m=1:640;
kl1(n,m)=ismember(m,Pl(n,:));
end
end
for n=1:335;
for m=1:640;
kw1(n,m)=ismember(m,Pw(n,:));
end
end
kl1=kl1(13:324,:);
kw1=kw1(13:324,:);
kw1=reshape(kw1,199680,1);
kl1=reshape(kl1,199680,1);

```

B.4 Data Preparation

```
clear;clc;

[TEMPG, , ]=xlsread('DATA.xlsx',2);
[TEMPV, , ]=xlsread('DATA.xlsx',3);
[TEMPRF, , ]=xlsread('risk-free rate.xlsx',2);
[TEMPMOM, , ]=xlsread('data.xlsx',2);
[TEMP2, , ]=xlsread('second paper.xlsx',2);
[TEMP4, , ]=xlsread('uk.xlsx',2);
[TEMP3, , ]=xlsread('second paper.xlsx',3);
[TEMP5, , ]=xlsread('return index monthly and yearly.xlsx',2);
[TEMP6, , ]=xlsread('return index monthly and yearly.xlsx',3);
TEMPMOM(isnan(TEMPMOM))=0;
TEMP2(isnan(TEMP2))=0;
TEMP3(isnan(TEMP3))=0;
TEMP4(isnan(TEMP4))=0;
TEMP5(isnan(TEMP5))=0;
TEMP6(isnan(TEMP6))=0;
TEMPG(isnan(TEMPG))=0;
TEMPV(isnan(TEMPV))=0;
TEMPRF(isnan(TEMPRF))=0;
TEMPMOM(isinf(TEMPMOM))=0;
TEMP2(isinf(TEMP2))=0;
TEMP3(isinf(TEMP3))=0;
TEMP4(isinf(TEMP4))=0;
TEMP5(isinf(TEMP5))=0;
TEMP6(isinf(TEMP6))=0;
TEMPG(isinf(TEMPG))=0;
```



```

TEMPV(isinf(TEMPV))=0;
TEMPRF(isinf(TEMPRF))=0;
MV=TEMP2(:,1:3:end);
MTBV=TEMP2(:,2:3:end);
BTMV=1./MTBV;
BTMV(isnan(BTMV))=0;
BTMV(isinf(BTMV))=0;
VO=TEMP2(:,3:3:end);
P=TEMPMOM(:,1:3:end);
RI=TEMPMOM(:,2:3:end);
MAX52=TEMPMOM(:,3:3:end);
RIM=TEMP4;
RIMARKETM=TEMP5;
RIMARKETA=TEMP6;
load t.mat;
[totaldays,totalstocks]=size(RI);
ta=year(t);tm=month(t);td=day(t);
totalmonths=(ta(end)-ta(1)+1)*12;
totalyears=(ta(end)-ta(1)+1);
RF=((TEMPRF./100+1).^(1/12) - 1);
RFD=(TEMPRF./100+1).^(1/365) - 1;
VA=P.*VO/1000;
R=zeros(totaldays,totalstocks);
RM=zeros(totalmonths,totalstocks);
for i=1:totalstocks
for j=1:totaldays-1
R(j,i)=RI(j+1,i)/RI(j,i)-1;
end
end

```

```

for j=1:totalmonths-1
RM(j,i)=RIM(j+1,i)/RIM(j,i)-1;
end
end RMARKET=zeros(totaldays,1);
RMARKETM=zeros(totalmonths,1);
for i=1:totaldays-1
RMARKET(i,1)=TEMP3(i+1,1)/TEMP3(i,1)-1;
end
for i=1:totalmonths-1
RMARKETM(i,1)=RIMARKETM(i+1,1)/RIMARKETM(i,1)-1;
end
R(isnan(R))=0;
RM(isnan(RM))=0;
RMARKET(isnan(RMARKET))=0;
RMARKETM(isnan(RMARKETM))=0;
R(isinf(R))=0;
RM(isinf(RM))=0;
RMARKET(isinf(RMARKET))=0;
RMARKETM(isinf(RMARKETM))=0;
RLOW=zeros(totalmonths,1);
RHIGH=zeros(totalmonths,1);
for i=1:totalmonths-1
RLOW(i,1)=TEMPG(i+1,1)/TEMPG(i,1)-1;
RHIGH(i,1)=TEMPV(i+1,1)/TEMPV(i,1)-1;
end
RLOW(isnan(RLOW))=0;
RHIGH(isinf(RHIGH))=0;
Days=0;

```

```

for i=1:totalstocks
for k=1:totalmonths
for j=1:length(t)
if tm(j)+12*(ta(j)-ta(1))
==kR(j,i)VO(j,i)P(j,i)
Days=Days+1;
TRADAY(k,i,Days)=j;
end
end
NTRADAY(k,i)=Days;
Days=0;
end
end Days=0;
for k=1:totalmonths
for j=1:length(t)
if tm(j)+12*(ta(j)-ta(1))==k
Days=Days+1;
end end
GENNTRADAY(k)=Days;
Days=0;
end
save('uk.mat');

```

Appendix C

Publications and Conference

Presentations

C.1 Publications and Working Papers

- Chen, J., Sherif, M., 2016. Illiquidity Premium and Expected Stock Returns in the UK: A New Approach. *Physica A: Statistical Mechanics and its Applications*. DOI: 10.1016/j.physa.2016.03.035. (**Published**)
- Chen, J., Sherif, M., Yu, Y., Governance and Stock Return Continuations: Evidence From G7 Countries. (**Targeting Journal of Banking and Finance**)
- Chen, J., Sherif, M., The 52-Week High Strategy and Information Uncertainty: the Case of UK Institutional and Individual Investors. (**Targeting Journal of Financial Stability**)
- Chen, J., Sherif, M., Semi-varying Momentum Payoffs and Illiquidity: Evidence from the UK. (**Targeting European Financial Management**)

C.2 International Conference Presentations

- 2013 SIRE Conference at the University of St. Andrews on Finance and Commodities sponsored by Scottish Institute for Research in Economics.
- 2014 Recent Developments in Money, Macroeconomics & Finance Workshop sponsored by Bank of England at the University of Warwick.
- 2014 British Accounting & Finance Association 50th Annual Conference at London School of Economics.
- 7th International Finance & Banking Society 2015 China Conference at Zhejiang University.
- Paper accepted by 2015 Midwest Finance Association Annual Conference in Chicago.
- Paper accepted by IFABS 2016 in Barcelona.
- Asset Pricing and Corporate Finance Workshop 2013, 2014, 2015 and 2016 at the University of Glasgow.

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