Three essays of Empirical Asset Pricing in the UK

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Declarations

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Abstract

The first empirical chapter examines the existence of a “net equity issuance” (NEI) effect in the UK stock market. Net Equity Issuance (NEI) refers to the change in a firm’s shares outstanding due to events such as SEOs, acquisitions financed by share issues, issues to staff and share repurchases. The NEI effect is the ability of share issuance by firms to predict their subsequent stock returns. My results mainly suggest that there is an NEI effect in the UK. However, a discrepancy exists between the UK results and those found in the US. In the UK market, negative-NEI stocks tend to show negative subsequent returns while zero-NEI stocks have the highest subsequent returns. I also find that the abnormal returns from the NEI effect disappear when transaction costs are taken into account. Furthermore, the asset pricing test results suggest that the new factor models partially explain the NEI effect in the UK.

The second empirical chapter evaluates the information content of new asset pricing factors in the UK. I find that two new risk factors, the investment factor and the profitability factor, improve the factor model’s performance in the UK while both the size factor “small minus big” (SMB) and the value factor “high minus low” (HML) are redundant. There is also evidence that factor construction methods matter to the information content of the profitability factor. The most informative profitability factor in the UK among the possible candidates is constructed using income before extraordinary items scaled by book equity.

The third empirical chapter explores the information content of the two new factors by linking them to the state variables which predict future investment opportunities. By doing this, I find confirmative evidence that the two new risk factors may proxy for state variables that capture time variations in the investment opportunity set. I find empirical evidence which confirms that the investment factor predicts future economic growth, proxied by GDP growth, investment growth and consumption

growth. In addition, the investment factor is found to be related to dividend yield shocks, whereas the profitability factor is related to inflation shocks. In addition, the pricing significance of macroeconomic variable shocks disappears when loadings on the two new factors are presented in the model. The evidence therefore provides economic interpretation to the information content of the new asset pricing factors in the UK market.

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CHAPTER 1

Introduction

Asset pricing studies attempt to address two of the most central issues in finance: how assets are priced and why some assets deliver higher average returns than others. Since the proposing of the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965; Mossin, 1966), the focus of empirical asset pricing researchers has been to investigate the stock return patterns from different perspectives. On the one hand, a large stream of academic literature has documented capital market anomalies that cannot be explained by asset pricing models. Harvey, Liu and Zhu (2015) document that 313 papers have been published in leading finance journals that study factors explaining the cross-section of expected returns since 1976. On the other hand, based on the assumption that higher returns are compensating investors who hold assets with higher systematic risks, asset pricing factor models have been proposed to capture the cross-section of expected returns (Fama and French, 1993; 2015a; Hou, Xue and Zhang, 2015). As the Fama-French three-factor model has become the benchmark of risk adjustment in the finance literature, their economic interpretation has become the subject of debate. Fama and French (1993) claim that other than the market factor, there are two additional factors that act as proxies for risk: one is "small minus big", based on size (market capitalization), and the other is "high minus low", based on book-to-market value. These factors may also represent state variables that capture time-variation in the investment opportunity set. A considerable literature has therefore investigated the risk-based interpretations (Lewellen, 1999; Liew and Vassalou, 2000; Vassalou, 2003, Vassalou and Xing, 2004; Zhang, 2005; Petkova, 2006).

While the mainstream asset pricing studies are conducted on the US stock market, it is important to provide out-sample analysis using a non-US sample, as asset pricing anomalies and risk factors may be sensitive to the economic and institutional backgrounds of different stock markets. For instance, a number of papers report an insignificant size effect in the UK stock market after controlling for other pronounced market effects (Chan and Chui, 1996; Miles and Timmermann, 1996; Strong and Xu, 1997). Moreover, Griffin (2002) and Hou, Karolyi and Kho (2011) suggest that asset pricing models are best constructed at country level as country-specific factors outperform global and regional factors.

Furthermore, several studies suggest that the performance of the asset pricing factor models in the UK does not fully resemble the US results (Fletcher, 2001; Gregory, Harris and Michou 2001; Fletcher and Forbes, 2002; Hung, Shackleton and Xu, 2004; Fletcher and Kihanda, 2005; Michou, Mouselli and Stark 2014). My thesis contributes to the existing empirical asset pricing literature by providing out-sample tests to complement the US studies by focusing on the UK market, one of the most influential stock markets globally.

The first empirical chapter (Chapter 2) examines the existence of a "net equity issuance" (NEI) effect in the UK stock market. Net Equity Issuance (NEI) refers to the change in a firm's shares outstanding due to events such as SEOs, acquisitions financed by share issues, issues to staff, and share repurchases. NEI has predictive power for cross-sectional stock returns in the US and other international markets (Daniel and Titman, 2006; Fama and French, 2008; Pontiff and Woodgate, 2008; McLean, Pontiff and Watanabe, 2009). The economic importance of the NEI effect is comparable with that of other leading capital market anomalies, including the momentum and accruals anomalies. However, the UK evidence suggests that the NEI effect might be small in the UK. Studies of LRARs (long-term abnormal returns) following SEOs report mixed results, with debates about both the impact of research design on the results and whether LRARs are different following rights issues compared with open offers or placings. There is no consensus that LRARs are negative following UK SEOs, as there is for US SEOs. The evidence is also inconclusive regarding returns following repurchases. Rau and Vermaelen (2002) report negative LRARs following repurchases by UK companies, which is the opposite of the US evidence. Overall, the existing evidence on returns following SEOs and repurchases casts doubt on the existence of a NEI effect in the UK stock market.

The main contribution of the first empirical chapter is that it offers a thorough investigation of the NEI effect using UK data. There is little existing evidence on the NEI effect that is specific to the UK. The international study by McLean *et al*. (2009) presents few results for individual countries. The negative coefficients on NEI they report for the UK, from regressions on future returns, are closer to zero than the coefficients for the USA. Secondly, all previous studies measure returns gross of transaction costs. It is therefore not known whether the NEI effect can underpin an investment strategy which would yield abnormal returns after transaction costs, and my study fills this gap in our knowledge. Finally, I present a thorough assessment of the NEI effect (before transaction costs) in the context of several existing asset pricing models. The original Fama-French three factors are augmented by momentum, investment, profitability and liquidity factors.

The empirical results from both Fama-Macbeth regressions and sorted portfolio analysis confirm that higher NEI is associated with lower subsequent returns in the UK. However, negative-NEI stocks tend to show negative subsequent returns while zero-NEI stocks have the highest subsequent returns, which differs from the US evidence. In addition, I also find that the abnormal returns from the NEI effect disappear when transaction costs are subtracted. Finally, the asset pricing test results suggest that although the new factors are able to explain much of the NEI effect, they fail to explain all of it. The overall results show the existence of the NEI effect in the UK market, which is not captured by the existing asset pricing models.

The second empirical chapter (Chapter 3) examines the information content of new asset pricing factors in the UK as a way of controlling for risk in UK asset pricing research. In the empirical asset pricing literature, numerous researchers have investigated the properties of three-factor models mainly using US data. However, the performance of the most widely used models such as the Fama-French three-factor model (Fama and French, 1993) have been subject to criticism. New factor models are therefore proposed, aiming to improve the description of the cross-section of expected returns (Fama and French, 2015a; Hou, Xue and Zhang, 2015). It is important to provide out-sample analysis of the US-based asset pricing results as studies show that regional models out-perform global-level asset pricing models (Griffin, 2002; Hou, Karolyi and Kho, 2011). Therefore, I specifically focus on the two new factors that have been used in the five-factor model (Fama and French, 2015a) and the q-theory model (Hou, Xue and Zhang, 2015). In addition, empirical evidence suggests that the performance of factor models is sensitive to the choice of factor construction (Novy-Marx, 2013; Ball *et al.*, 2015; Fama and French, 2015b). I construct alternative forms of the new factors with the general objective of evaluating the performance of the new linear factor models in the UK.

The first contribution of the second empirical chapter is to provide comprehensive evidence of the information content of new asset pricing factors in the UK. There is very limited evidence of how five-factor models perform in the UK market and most previous literature focuses on the performance of the Fama-French three-factor model (Gregory, Tharyan and Christidis, 2013; Michou, Mouselli and Stark, 2014). In addition, the second empirical chapter also contributes to the literature with regard to how factor choices influence the performance of factor models. I examine various versions of profitability factors with regard to their relative informativeness in explaining the cross-section of expected returns. Based on the empirical evidence, my results provide guidance to future UK researchers and investors regarding the choice of effective asset pricing factor models.

The empirical results suggest that both the size factor "small minus big" (SMB) and the value factor "high minus low" (HML) are redundant in the UK, as their information is spanned by other factors. UK researchers should consider using a new three-factor model by replacing the size factor and the value factor with a profitability factor and an investment factor to control for time-series variation among stocks. Amongst all the factor models tested, my results show that the choice of profitability factor affects model performance. The most informative profitability factor in the UK among the possible candidates is constructed using income before extraordinary items scaled by book equity.

While the second empirical chapter confirms the significant role of the two new risk factors in the UK, the third empirical chapter (Chapter 4) investigates the rational explanation for the new factors by linking them to the state variables and investigates whether they can predict future investment opportunities. Fama and French (1993) state that HML and SMB may represent state variables that capture time-variation of the investment opportunity set. This hypothesis is supported by a number of studies which provide supportive evidence that HML and SMB is related to future macroeconomic activities or shocks to macroeconomic state variables

(Liew and Vassalou, 2000; Vassalou, 2003; Petkova, 2006). For the two recently proposed factors, little attempt has been made to examine their links to the macroeconomic state variables, especially in the UK stock market. Although the two new factors are justified by models such as q-theory, the partial-equilibrium nature of the theoretical model may not justify the risk interpretation of the factors (Cooper and Priestley, 2011). The third empirical chapter therefore examines whether the two new risk factors are linked to future macroeconomic activities and to shocks to macroeconomic state variables.

The third empirical chapter mainly contributes to the literature by providing an economic interpretation for the information content of the new factors. As pointed out by Cochrane (2009), macroeconomic factor models are constructed not to outperform the Fama-French factors in asset pricing performance, but to understand why they work better and provide better justification. Previous studies use US data and show that the investment factor "conservative minus aggressive" (CMA) is related to future economic activities (Cooper and Priestley, 2011). My research extends the evidence to the performance of both the investment factor and the profitability factor using a UK data sample.

The results are, to some extent, consistent with the risk-based economic interpretations of the new factors. Firstly, the results confirm that the investment factor predicts future economic growth, proxied by GDP growth, investment growth and consumption growth. In addition, both the investment factor and the profitability factor have significant relation with shocks to macroeconomic state variables. The investment factor is related to dividend yield shocks, whereas the profitability factor is related to inflation. Furthermore, the two new factors provide incremental information to the macroeconomic factors in the UK market. The pricing significance of macroeconomic variable shocks disappear when loadings on the two new factors are presented into the model. The UK evidence therefore suggests that the two new risk factors are consistent with economic interpretations.

The conclusion chapter of the thesis further discusses the implications of my empirical results for investors, fund managers and policy-makers. In addition, limitations and potential directions for future research have also been identified.

CHAPTER 2

Net Equity Issuance Effect in the UK

2.1 INTRODUCTION

This empirical chapter examines the existence of a ‘net equity issuance’ (NEI) effect in the UK stock market. The NEI effect is the ability of share issuance by firms to predict their subsequent stock returns. Evidence in Daniel and Titman (2006), Fama and French (2008) and Pontiff and Woodgate (2008) indicates that both raw and abnormal returns, for up to three years following the measurement period for NEI, are negatively related to the change in shares outstanding measured over one year, or over five years.[1] Post-NEI returns are most positive for firms with the largest net repurchases as a proportion of existing shares, and most negative for firms with the largest positive net issues. International evidence is largely consistent with the findings for U.S. firms (McLean, Pontiff and Watanabe, 2009). The economic importance of the NEI effect is comparable with that of other leading anomalies, including the momentum and accruals anomalies. The NEI effect is not a smallcap phenomeneon – it holds across stocks of all sizes – and its explanatory power remains economically and statistically significant when NEI is included in a variety of factor models to explain subsequent returns.

To some extent – perhaps to a large extent – the NEI effect can be explained by earlier findings that the long-run average abnormal returns (LRARs) over on year or more are negative following seasoned equity offers (SEOs) and following acquisitions financed by share issues, whereas LRARs are positive following repurchases. However, the papers using an NEI variable extend this earlier evidence. The NEI effect applies to future returns measured over periods as short as one month, and it does not appear to be a manifestation of some other asset pricing anomaly. In addition, Pontiff and Woodgate (2008) find that the effect still exists even when changes in shares are removed due to SEOs, acquisitions financed by shares, and repurchases. On the other hand, there are caveats about the support for the NEI effect. Fama and French (2008) report that the relation between NEI and future returns is very weak once repurchases larger than the median repurchase

[1] The ‘composite issuance variable’ used by Daniel and Titman (2006) also includes cash dividends paid, and stock options awarded to staff.

at one end, and the largest quintile of positive net issuance at the other end, are excluded. In fact future returns are positive, not negative, following small-scale positive net issuance, found in firms in the first three or four quintiles by positive NEI. Second, Pontiff and Woodgate (2008) find that the NEI effect is largely absent in data before 1970. Finally, all the studies to date measure returns gross of transaction costs. So it is not known whether the NEI effect can underpin an investment strategy which would yield abnormal returns after transaction costs.

The existence of an NEI effect could be due in part to timing by managers of SEOs and stock-financed acquisitions for when shares are overvalued, and timing of repurchases for when shares are undervalued. However, the effect persists even when SEOs, shares issued to fund acquisitions, and repurchases are removed. Fama and French (2008) emphasise that the NEI variable, along with other 'anomaly variables', is a rough proxy for expected cash flows.

The main contribution of this study is that it offers a thorough investigation of the NEI effect using UK data. The UK is a major stock market, and it is of interest to see the extent to which findings from US data generalise to other markets. There is little existing evidence on the NEI effect that is specific to the UK. The international study by McLean et al. (2009) presents few results for individual countries. They find that the impact of positive NEI on future returns tends to be greater internationally than in the US, and that the impact is 'stronger in countries where it is less costly for firms to issue and repurchase shares' (p. 2). However, the negative coefficients on NEI they report for the UK, from regressions on future returns, are closer to zero than the coefficients for the USA.

Other evidence suggests that the NEI effect might be small in UK. Studies of LRARs following SEOs report mixed results, with debates both about the impact of research design on the results, and about whether LRARs are different following rights issues compared with open offers or placings.[2] There is no consensus that LRARs are negative following UK SEOs, as there is for US SEOs. The evidence is

[2] See Levis (1995), Ho (2005), Armitage (2007), Ngatuni, Capstaff and Marshall (2007), Iqbal, Espenlaub and Strong (2009), Armitage and Capstaff (2009), and Capstaff and Fletcher (2011).

also inconclusive about returns following repurchases. Rau and Vermaelen (2002) report negative LRARs following repurchases by UK companies, which is the opposite sign compared with the US evidence. Overall, the existing evidence on returns following SEOs and repurchases casts doubt on the existence of a NEI effect in the UK market.

I present three sets of findings, using data from 1980-2013 where I report results for a NEI variable. First I conduct Fama-MacBeth (1973) cross-sectional regressions, where the dependent variable is one-, six- or 12-month returns after month *t*. For returns measured over all these periods, and for all portfolios of stocks sorted by size, the NEI variable has a significant negative coefficient. This continues to apply when proxies for the size, book-to-market, and momentum factors are included, and the coefficients on NEI comparable with the coefficients on the other anomaly variables. To allay concerns about the assessment of the significance of the coefficients, the *t*-statistics are calculated using five different methods. These results establish that there is indeed a robust NEI effect in the UK.

Second, I report 12-month returns and abnormal returns for portfolios sorted by size and NEI. We find that future abnormal returns are positive for portfolios with zero NEI and for the first two quintiles of positive NEI, before turning negative for the third quintile and beyond. The results do not differ greatly across stocks sorted by size. These findings are qualitatively similar to those in Fama and French (2008) for US firms. But 12-month abnormal returns for the negative-NEI (repurchase) portfolios are mostly negative, consistent with the previous studies which find negative abnormal returns following repurchases in the UK. The largest (positive) raw and abnormal returns follow stocks with zero, not negative, NEI. This is an important difference from the US picture, because it indicates that the relation between NEI and future returns is not approximately monotonic in the UK, as it is in the US, considering stocks with negative and zero NEI as well as positive NEI.

I also calculate returns on ‘hedge portfolios’ which are long in zero-NEI stocks, with the highest raw and abnormal 12-month returns, and short in quintile-five positive-NEI stocks, with the lowest returns. These hedge portfolios produce average annual returns of 7.6% (value-weighted) or 16.4% (equally weighted), for the full sample of stocks. The hedge returns are larger for portfolios of small stocks. To assess whether such a trading strategy offers positive returns available to investors, I estimate the returns on the hedge portfolios after transaction costs. This is new evidence in relation to previous studies. Transaction costs make a huge difference. For the full sample, the hedge returns are 1.5% (value-weighted; not statistically significant) or -8.4% (equally weighted). For small stocks the returns after transactions costs are strongly negative. We conclude that, although there is a robust NEI effect in the UK which is similar in scale to the effect found in the US, it is not exploitable after transaction costs. This finding helps explains the existence of the effect itself.

Finally, another contribution of this study is that I present a thorough assessment of the NEI effect (before transaction costs) in the context of several existing asset pricing models. The original Fama-French three factors are augmented by momentum, investment, profitability and liquidity factors. The results vary across the models, but although the new factors are able to explain much of the NEI effect, they fail to explain all of it. We therefore support the findings of US studies that the NEI effect exists independently of other asset pricing anomalies.

The chapter proceeds as follows. Section 2 provides a detailed overview of the academic literature. Section 3 describes the variable definitions and data. Section 4 discusses the methodology, including the Fama-MacBeth regression and *t*-tests, sorting of portfolios, construction of the asset pricing factors, and an outline of the various asset pricing models I deploy. Section 5 reports the empirical results, and Section 6 concludes.

2.2 LITERATURE REVIEW

In general, the research of post equity issuance activities effect may be categorised into three levels: The narrowest level examines the single type of financial decisions e.g. SEO, stock repurchases, public debt issue (Loughran and Ritter, 1995; Spiess and Affleck-Graves, 1995; Peyer and Vermaelen, 2009). The middle level employs a broader measure of equity financing (Net Equity issuance) which comprises of both SEOs and repurchases (Daniel and Titman, 2006; Pontiff and Woodgate, 2008 and Mclean, Pontiff and Watanabe, 2009). The third level holds the broadest view whose measure comprises of both equity and debt financing (Billett, Flannery and Garfinkel, 2011).

The three levels of research have different but overlapping purposes. The *first level* of research mainly contributes to the following aspects: a) examines the motivations behind corporate financing decisions such as investment needs (Kim and Weisbach, 2008), timing the market under/over-valuation(Chan, Ikenberry and Lee, 2007; Bradford, 2008; Yook, 2010, Campello and Graham, 2013), cash saving (McLean, 2011); b) provides interpretations to the long-term abnormal return following issuance/repurchase activities by linking the phenomena to mispricing or risk factors such as liquidity risk and investment risk. The *second level* mainly contributes to the asset pricing literature by generalizing the explanatory power of equity issuance activities in cross-sectional difference in stock return. (Daniel and Titman, 2006; Pontiff and Woodgate, 2008 and McLean, Pontiff and Watanabe, 2009) The *third level* of research has recently proposed and tries to reconcile the conflicting first level research outcomes and generates further implication in the future. (Billett, Flannery and Garfinkel, 2011)

The existence on net equity issuance effect can be viewed as a generalization of the long-term abnormal return research for the first level of studies. The net equity issuance effect is consistent with the abnormal stock outperformance after repurchases and underperformance after SEOs in the US market. The possibility of managers' opportunistic timing of the market mispricing is also consistent with both levels of research. Therefore the studies associated with the motivation and the long-term stock return effect for single issuance activities are relevant for the net equity issuance stream of academic literature . In the following sub-sections, both an analysis of the motivation and the long term post-announcement return studies will be reviewed for SEOs and stock repurchases in the US and UK markets.

2.2.1 Seasoned equity offerings

2.2.1.1 Long-term abnormal return

Loughran and Ritter (1995) and Spiess and Affleck-Graves (1995) are among the first to document negative post-SEOs long-run returns. Both papers apply buy-and-hold-return (BHAR) method for post-SEO performance measurement. Loughran and Ritter (1995) uses size matching to illustrate the existence of abnormal underperformance after SEOs. Spiess and Affleck-Graves (1995), in contrast, use a matching approach on industry and size. They further show that the underperformance remains significant after controlling for trading system, offer size, issue firm's age and book-to-market ratio.

As stated by Fama (1998), long-run anomalies returns are sensitive to the choice of methodologies and tend to diminish when calendar-time portfolio return is used. Inspired by Fama's view, Mitchell and Stafford (2000) argue that BHAR approach may generate problematic results because of its flawed assumption that multiyear abnormal returns for event firms are independent of each other, which would overestimate the test statistics. In contrast, the calendar-time portfolio method serves as a better measurement. Their results on long-term performance show insignificant abnormal return after SEO using both calendar-time approach and revised BHAR approach. However, their results remain refutable due to variation in different benchmarks for BHAR approach and calendar-time approach.

The follow-up research has report a downward trend in the underperformance and the results are generally sensitive to the methodology. For BHAR results, Jegadeesh (2000) reports 34.3% abnormal loss for five year post-SEO period over 1970 to 1993; Alti and Sulaeman (2012), uses a sample from 1985 to 2005 and report 4% abnormal loss for five years post-SEO period; Fu, Huang and Lin (2012) report abnormal loss from 23.26% over 1984-2002 to 6.18% over 2003-2012 for three year post-SEO period. They attribute this decline to the improvement of market efficiency in the US market. In contrast, calender-based results are ambiguous. Jegadeesh (2000) find 0.31% abnormal loss; Alti and Sulaeman (2012) report 43%

abnormal loss. They use the sample from 1985 to 2005 and suggest that the low figure of BHAR approach stems from good post-SEO performance in late 1990s. Fu, Huang and Lin (2012) find economically insignificant result using calendar-based approach over 1984 to 2012.

2.2.1.2 Explanations for abnormal performance after SEOs

Liquidity explanation

Some recent papers explain the observed underperformance by “bad model” and propose a liquidity factor to be the omitted control variable. Compared with other explanations, liquidity risk seems to offer a better risk-based explanation for the long-run underperformance after SEOs.

Eckbo, Masulis and Norli (2000) employ stock turnover as proxy for liquidity and report an improvement after SEO. They attribute the abnormal stock performance after SEOs to the change of liquidity and thus the failure of matching. Later, Eckbo and Norli (2005) use the same measure of liquidity for liquidity-augmented Carhart (1997) model to explain long-term post-SEO returns. The result indicates that abnormal loss is insignificant under this model.

Bilinski, Liu and Strong (2012) extend the literature by testing of SEO firms’ improvement in post-issue stock liquidity and the source of liquidity gain and examining whether liquidity change explains post-SEO underperformance of stock return. They differ from previous studies as they employ four different measures of liquidity and illustrate that SEO firms experience significant post-issue liquidity improvement, which is mainly attributable to increase in institutional investors’ holdings. Using liquidity-augmented CAPM and turnover-based liquidity factor, they show that SEO firms have normal long-term performance.

Investment explanation

Another stream of academic literature attempts to explain post-SEO underperformance by increase in investment after SEO. Cochrane (1991) is among the first to document the negative relation between investment and average stock returns in time series analysis. Titman, Wei and Xie (2004) report confirmative result in cross-sectional context. Their follow-up research explains the post-SEO underperformance by either mispricing or risk-based view.

Titman, Wei, Xie (2004) and Cooper, Gulen, Schill (2008) interpret their results as evidence of investors' overreaction to overinvestment. Cooper, Gulen and Schill (2008) document that asset growth has significant influence on stock returns. They illustrate an economic and statistical significance of 19.5% per year on the spread between low and high asset growth stocks after controlling for risks. The authors show that the anomalous effect stems from the ability of asset growth to capture common return effects across firm's total investment activities. The post-SEO underperformance is partially explained by asset growth effect.

In contrast, Carlson, Fisher and Giammarino (2006), Li, Livdan and Zhang (2009) and Lyandres, Sun and Zhang (2008) provide a *rational-risk-based explanation* based on various models. Carlson, Fisher and Giammarino (2006) propose a rational real option theory. Their model is based on the intuition that firms' realised real investment becomes less risky than investment options. The authors argue that investment after SEO leads to a fundamental risk change on firms and therefore reduces stock return. Their quantitative model replicates the underperformance result observed by Ritter (2003), and thus confirm their argument that rational explanation may underpin the observed figures. Li, Livdan and Zhang (2009) employ a q-*theory model* and also replicate the long-term underperformance after SEO. They use their model to reproduce the result from Loughran and Ritter (1995) and report a confirmative result which indicates that q-theory model also explains the phenomenon.

Inspired by the papers above, Lyandres, Sun and Zhang (2008) propose an *investment-based asset pricing model* by adding an investment factor to the Fama-French model by long low investment-to-asset stocks and short high investment-to-asset stocks. They interpret the investment factor as another common factor for stock returns in addition to the original three factors. The abnormal loss after SEO partially (75%) explained by the new four-factor model. However, the result does not rule out the mispricing explanation for the investment-related anomalous return. Though most of the investment-based explanations are not able to fully explain post-SEO underperformance, they provide indirect evidence that that various motivations exist for the SEO decision.

Earning management explanation

Another group of recent papers explains the post-SEO underperformance as the consequence of misleading earning information manipulated by managers. Early research such as Rangan (1998) and Teoh, Welch and Wong (1998) report poor stock return returns after SEOs are accompanied by poor earning performance, which inspire a follow-up research of earnings management to examine the phenomenon. Papers such as Shivakumar (2000) and DuCharme, Malatesta and Sefcik (2004) provide confirmative evidence that accrual earnings management are around SEOs. However, controversy exists as whether the stock market is misled by the earnings management. Survey conduct by Graham, Harvey and Rajgopal (2006) reveals that managers prefer to conduct earnings management via real activities than accrual manipulation. Inspired by them, recent papers re-examine the explanatory power of both types of earnings management on post-SEO underperformance.

Cohen and Zarowin (2010) examine the underperformance of post-SEO operating figures. Their paper reports that more severe decline in operating performance is caused by real activity management rather than by accrual management. However, the relation between earnings management and the poor post-SEO stock return is not examined. Kothari, Mizik and Roychowdhury (2015) fill the gap by finding that stock return underperformance after SEO tend to exists among firms engaging real activities management rather than accrual management. The authors infer that managers' attempt to manage earning with real actions is the primarily driver of SEO overvaluation. Due to the fact that real activity management measure is based on hindsight data, the market overreaction surrounding SEO period is likely to be caused by asymmetric information as the price reflect public information available.

2.2.1.3 Motivations of SEO decisions

This stream of literature focuses more on exploring the motivation of the SEO decisions. The most documented perspective is the timing of market overvaluation. It should be noted that research on timing of overvaluation simultaneously provide both the motivation of SEO and offer explanations for the post-SEO return underperformance since the deterioration of return can be interpreted as correction of mispricing.

According to Graham and Harvey (2001)'s survey results, two thirds of the CFOs claim that the decision of making SEO is determined mostly by the managers' view of mispricing of shares of their companies. In other words, managers time the capital market overvaluation to exploit benefit for existing shareholders at the cost of new share purchasers. Empirical analysis illustrate that stocks with low book-to-market tend to issue equity, which is interpreted as timing the overvaluation (Marsh, 1982; Jalilvand and Harris, 1984; Rajan and Zingales, 1995; Jung, Kim and Stulz, 1996). The early papers on long-term abnormal underperformance after SEO are also supporting the undervaluation argument (Loughran and Ritter, 1995; Spiess and Affleck-Graves, 1995). Baker and Wurgler (2002) provide extra evidence that managers time the market for equity offers by analysing the influence of equity offers on capital structure in the long run.

Although the undervaluation results are questioned based on the "bad model" problem as mentioned earlier, some recent papers provide new evidence that managers have the capability to time the market overvaluation. Khan, Kogan and Serafeim (2012) contribute to the literature by using mutual funds purchase pressure to proxy for the overvaluation indicator. Their results illustrate that mutual fund demand generates significant price pressure, and both SEO and insider sales are driven by mutual fund pressure, which indicate that managers have capacity to exploit equity overvaluation. Alti and Sulaeman (2012) document that high stock returns firms accompanied by strong demand from institutional investors tend to trigger SEO decisions. They further demonstrate that high institutional demand lead to higher price for new issued shares, which is interpreted as the outcome of reduced adverse selection. The researchers explain timing motivation as to reduce market adverse selection rather than timing overvaluation.

Another stream of literature provides more comprehensive analysis for alternative motivations for SEO decisions. Kim and Weisbach (2008) use an international sample over 1990 to 2003. Their results indicate that firms tend to increase investment in R&D and capital expenditure using SEO proceeds, which is consistent with the investment financing explanation. On the other side, evidence consistent with mispricing is reported: high book-to-market firms are more likely to issue more secondary shares and save more cash than low book-to-market firms. Their evidence therefore supports both investment financing and market mispricing motivations. DeAngelo, DeAngelo and Stulz (2010) report that market-timing for mispricing and corporate lifecycle have some but inadequate explanatory power for SEO decisions. The authors further observe similar incremental cash saving as Kim and Weisbach (2008)'s research. However, they interpret the raw cash saving figures as the outcome of increased cash demand from the asset growth adjusting for which would render majority of the issuers to have subnormal cash balances without the proceeds from SEOs. The authors therefore argue that timing and lifecycle play ancillary roles while near-term cash demand is the primary motive for SEO decisions. The ambiguity in explaining similar result requires further investigation.

2.2.2 Share repurchase

2.2.2.1 Long-term abnormal return

Various academic papers show that share repurchases lead to abnormal long-run performance improvement. Lakonishok and Vermaelen (1990) investigate the tender offers' anomalous price behaviour around repurchase as well as their long term performance. They provide evidence that post-repurchase stocks outperform their size and beta matching firms by about 20% in 24 months after the expiration of the offer. Ikenberry, Lakonishok and Vermaelen (1995) extend Lakonishok and Vermaelen (1990) research. They use size and book-to-market matching benchmark and report abnormal BHAR for 12.1% over the four years after the repurchase announcement date. Further, they use the book-to-market ratio as under/overvaluation proxy and find that "value" stocks outperform their matching group by 42.3% over the same period. This result implies that US stock repurchases decisions are mainly driven by undervaluation. The follow-up paper by Ikenberry, Lakonishok and Vermaelen (2000) extends the research to the Canadian stock market and reports 7% annual abnormal return over three years following the repurchase.

However, Mitchell and Stafford (2000) and Bradford (2008) provide different results about the long-term stock performance. They attribute the abnormal return results to methodological issues. Their results are questioned by a follow-up research such as Chan, Ikenberry and Lee (2004) and Peyer and Vermaelen (2009) who confirm the existence of the outperformance after repurchase announcement using both approaches. Recent research by Fu, Huang and Lin (2012) reports an economically significant abnormal return using BHAR but insignificant result from calendar-time approach over the period of 1984-2012. Therefore, the debate about "bad model" problem remains controversial.

Yook (2010) offers another re-examination of the long-term performance after repurchases. His paper contributes to the literature by measuring actual repurchase activities rather than announcement regardless whether or not the actual activities follow. The previous research mainly focuses on repurchase announcement and thus may subject to sampling method error. This is important since the motivation for repurchase and merely repurchase announcement without real activity might be different. Using calendar-portfolio approach, the author find confirmative evidence that firms conduct real repurchase are followed by abnormal returns while the whole sample of firms with repurchase announcement are not. This result provides a potential explanation to the previous conflicting results of the long-term abnormal return.

2.2.2.2 Explanations for abnormal performance after Repurchases

Earnings management

Lie (2005) finds significant post-announcement improvement in operating performance for firms announce open-market repurchase. He postulates that managers may decide to initiate repurchase when they expect significant improve in operating performance in the future. Gong, Louis and Sun (2008), however, propose an earning management explanation to Lie's result. They conjecture that the post-repurchase improvement may be attributable to pre-repurchase downward earning management. Their result from open-market repurchase is consistent with the conjecture: significant deflation in earnings is observed for firms actually repurchase shares. Further, they find positive relation between extent of earnings downward and proportion of shares repurchased and also positive relation between extent of earnings downward and equity holdings of CEO. This evidence strengthen the argument of pre-repurchase earnings management. From earnings management point of view, the market price reflects the downward earnings management and thus the pre-repurchase undervaluation is misled by discretionary decisions of the managers who pursue private interest.

In addition to accrual-based earnings management, recent paper by Downes, Gorman and Rao (2013) provide evidence that firms attempt to reduce income by under-producing inventory and increasing discretionary expenditures around their repurchases. Further evidence shows that those income-decreasing real earning management are followed by abnormal return in post-repurchase period. Though evidence shows that both types of earning management are employed to mislead the investors, future research may emphasis on their joint effects, as studies conducted for SEO.

Motivation of Share Repurchases decisions

Various explanatory models are proposed to explain both initial market reaction and long-term performance following repurchases. The mainstream view is the mispricing theory suggested by Vermaelen (1981) and Ikenberry and Vermaelen (1996). They argue that repurchases can be used as signalling mechanism and transfer value from short-term to long-term investors. It should be noted that these papers are based on the premise that public information reflect the mispricing and thus “value” stocks could outperform “growth” stocks in the long run for repurchase firms.

Chan, Ikenberry and Lee (2004) test alternative motivations of repurchase announcement. Their employ both annual BHAR and calendar approach and reveal the existence of long-term post-repurchase abnormal return. Further, both evidence of initial reaction of the market and long term performance of the repurchase stocks are consistent with mispricing theory based on public information. In their follow-up paper, Chan, Ikenberry and Lee (2007) rule out the pseudo-market timing hypothesis for repurchase anomaly and support the notion that managers possess the ability to timing market under-pricing in the context of stock repurchases.

Peyer and Vermaelen (2009) re-examine the existence of long-term post-repurchase abnormal return using Fama-French three factor model with Return Across Securities and Times (RATS) methodology by Ibbotson (1975). They find a cumulative average abnormal return of 24.3% over 48 months after the repurchase announcement. Their paper further contributes to the analysis of underpinning reasons of the persistence of the repurchase anomaly. It tests alternatively three hypotheses: “risk-change hypothesis”, “liquidity change hypothesis” and “overreaction hypothesis”. The risk-based hypothesis is rejected since abnormal return is generated after control for Fama-French risk factors. The liquidity change hypothesis is also rejected because the abnormal returns are unaffected after adding a liquidity control factor to the Fama-French model. The overreaction hypothesis is supported by the evidence since most significant long-term abnormal return is triggered by severe decline of stock price before repurchase announcement. This overreaction hypothesis is consistent with the early mispricing theory by Ikenberry and Vermaelen (1996), except here the authors find prior stock return performance serves as better proxy than book-to-market-ratio for undervaluation.

Yook (2010) also examines amispricing story. Their sample of repurchase announcement firms shows contradictory evidence from the previous research. “Value” firms do not show higher undervaluation than “growth” firms in terms of long-run performance. The author thus postulates that there might have been a shift in the primary motivation for repurchase announcement. One alternative explanation is that there is the difference in motivation between subgroup of firms with actual repurchase and firms without actual activity after announcement. Therefore future research on the analysis of the motivation may differentiate these two subgroups of overall repurchase announcement sample.

The mispricing explanation is further confirmed by Huang and Thakor (2013) using real repurchase samples. They employ various proxies for investor-management disagreement and postulate that repurchases are used to change investor base so as to reduce investor-management disagreement. Their evidence further shows that high investor-management disagreement tends to trigger repurchase decisions which reduce the disagreement afterwards.

Another extension from mispricing hypothesis is proposed by Babenko, Tserlukevich and Vedrashko (2012). This paper employs past insider trading information as proxy for signal of mispricing based on private information. The authors find that past insider trading leads to higher probability of real repurchase activities and have predicting power for post-announcement stock returns.

Therefore, their results indicate that repurchases are also motivated by private mispricing information. However, they do not rule out the past evidence from public information mispricing. Therefore it is likely that mispricing based on both types of information are incentives for manager to make repurchase decisions, though they may serve for different purposes.

2.2.3 Broader views on Net Issuance Effect (NEI)

2.2.3.1 Net Equity Issuance effect (NEI)

The findings above have inspired the research on the "net stock issue effect" proposed by Daniel and Titman (2006); Pontiff and Woodgate (2008), who document that net stock issue has negative cross-sectional relation with the future return for U.S. Pontiff and Woodgate (2008) also show that the explanatory power of net equity issuance remains significant when major events such as SEOs and repurchases are excluded. Mclean, Pontiff and Watanabe (2009) further test the predicting power of net share issuance effect in the global market and find confirmative evidence. They further document that market factors such as aggregated frequency of issuance activity, investor protection have influence on the return predictability. These results suggest that institutional difference among stock markets have impact on the net equity issuance effect. Fama and French (2008) applies both sorting of returns on net equity and Fama-Macbeth (1973) regression and finds that net stock issuance effect is pervasive across all size groups. The monthly abnormal return for net stock issue effect is 0.66% with long bottom 20% decile firms and short top 20% decile firms in the US market.

McLean (2011) provides a motivation analysis for net equity issuance. The author use variables such as R&D spending and cash flow volatility as proxies for precautionary motives, which reflect financial constraints. His results shows that precautionary motives lead to higher cash savings from issuance. In addition, the author employs stock illiquidity measures to proxy cost of issuance and provides evidence that managers time the issuance cost for share issuance-cash saving purpose.

Several interpretations are suggested by Daniel and Titman (2006). Firstly, it is possible that managers opportunistically time the issuance decision and take advantage of the market mispricing. Another possibility is that managers time the market before favourable growth options. Alternatively, rational-risk difference may explain the effect using additional risk factors. These hypotheses are overlapping with mispricing explanations of both SEO and repurchase. However, as mentioned earlier, various papers have implied that mispricing may be one of the motivations behind major finance events, the same should apply to net equity issuance effect. The existence of net equity issuance effect may have similar additional explanations such as liquidity risk and investment risk change.

2.2.3.2 External financing events effect

Billett, Flannery and Garfinkel (2011) examine the long-term post-issue stock performance of five types of external financing events: IPO, SEO, Public debt issue (PD), Bank Loans (BL) and private equity issues (PVEQ). The evidence suggests that underperformance tends to follow high variety and function of external finance rather than any single type of them. This research provides a broader perspective upon post-issuance stock performance analysis since it simultaneously use equity issuance and debt issuance as explanatory variables to explore their influences. Therefore the post-issuance effect may be part of the overall issuance effects rather than a single channel of equity finance.

2.2.4 The UK evidence

2.2.4.1 Seasoned Equity Offerings(SEO)

The UK stock market differs from US market in terms of the issuance choices. In the US market, open offering has been the dominant method of SEOs. SEOs in the UK were dominated by right issues until 1990s (Armitage, 1998). London Stock Exchange began to relax the rules and the choice of SEOs become effectively unconstrained after January 1996 (Capstaff and Fletcher, 2011).

There is a stream of academic literature in the UK stock market which focuses on the post-issue stock performance of SEO. The early stage papers report stock price underperformance after right issues. Levis (1995) examines a sample of 158 UK firms which made rights issues over five years after their IPO from 1980 to 1988 and reports significant 18-month post-issue stock price underperformance using size-matched benchmark. Michailides (2000) uses UK right issuance sample from 1975 to 1996 and finds significant 36-month post-issue underperformance against FTA Share Price Index return. Similarly, Suzuki (2000) employs a sample of right issuance of period from 1991 to 1996. He also documents a negative BHAR over 24 month after right issuance, using size-matched portfolio.

More recent papers have reported inconclusive results for different choices of SEOs. Ho (2005) examines both rights issuance and placings for the period between1989-1997. Although there is significant negative BHAR for right issues over 3-year post-issue period, no evidence is found for placings. Further, he reports limited evidence of underperformance for both types of issue method against Fama-French (1993) and Carhart (1997) model. Armitage (2007) finds no evidence for post-issue underperformance with 186 pre-renounced right issues cases over period 1987-2001 using BHAR. Ngatuni, Capstaff and Marshall (2007) employ BHAR and CAR and reports underperformance over 5-year-period following the right issues from 1986 to 1995, but positive abnormal return following open offers during 1991 to 1995. Iqbal, Espenlaub and Strong (2009), in contrast, provide opposite result as they find significant underperformance in 48 months post-issue period for open offers during 1991 to 1995. Capstaff and Fletcher (2011) use larger sample from 1996 to 2007 and find no evidence for underperformance following rights issues but significant negative abnormal returns for placings and placing/open offer combinations over 36-month post-issue period. In general, since the regulatory relax of SEC, research has been generating conflicting results for post-issue stock price performance.

Potential explanations for the conflicting result have been proposed. Existing research such as Iqbal, Espenlaub and Strong (2009) proposes that the difference in test results might be caused by the survivorship bias in paper of Ngatuni, Capstaff and Marshall (2007). Armitage and Capstaff (2009) confirm this suspicion by correcting the bias and generating closer post-issue underperformance result. Alternatively, “bad model” might underlie the problem. As mentioned earlier, additional factors such as liquidity risk and investment risk factor may provide additional explanation for the abnormal return.

It seems that there is a research gap for future UK SEO study on the motivation analysis, as no previous paper has drawn attention to the motivations of UK SEO decisions. As the choice and institutional environment being different from US stock market, a UK SEO motivation study would provide evidence underlying the financing decision and thus deepen our understanding of the information included. In addition, the role of real earnings management and accrual earnings management remains unclear in explaining post-SEO underperformance. It might shed more light on the conflicting results of post-SEO stock return performance.

2.2.4.2 Share Repurchase

The institutional differences between US and UK repurchases exist in disclosure requirement and tax treatment. In the US market, the real shares repurchased are not disclosed after the repurchase announcement. In contrast, London Stock Exchange requires listed firms to publish actual repurchases on the regulatory news services (RNS) which is available to the public. On the other hand, US tax treatment for pension funds is indifferent between capital gain and dividends, while the UK tax regulation has been through a dynamic process.

According to Rau and Vermaelen (2002), the tax efficiency made the repurchase an unattractive choice for firms before 1994. Investment banks invented “agency buyback” in 1994, which increased the efficiency and make open repurchase attractive. The tax authorities abolished this loophole in 1996 but made repurchase and dividend indifferent again in 1997.

Previous research has investigated some characteristics of the repurchase activities in UK. Erwin and Miller (1998) report that 90% of the repurchases are conduct through open market repurchases. Rees (1996) examines the market reaction of actual repurchases over 1981 to 1990. He reports 3% abnormal return around the announcement.

The long run abnormal return results are controversial. Rau and Vermaelen (2002) conduct the first research over the horizon between1985 to 1998. They report that open market repurchase are not followed by significant abnormal return, therefore rejecting the undervaluation explanation. The authors attribute this finding to the tax difference between the UK and US market. Oswald and Young (2004) update the result of Rau and Vermaelen (2002) using several databases over the period between 1995 to 2000 and report statistically significant positive abnormal stock returns in the following year of repurchases announcements. The difference between these two academic studies might be a reflection of the dynamic regulatory change of UK tax rules or the consequence of sample bias in Rau and Vermaelen (2002)'s database. A follow-up research paper by Lee, Ejara, Gleason (2010), however, report insignificant long-term stock outperformance using sample from 1990 to 2005. Crawford and Wang (2012) extend the literature using data from 1999 to 2005 and generate evidence that firms announcing repurchases are followed by significantly two-year abnormal stock return. It should be noted that the ignorance of regulatory change in UK tax rules might be the underpinning reason for the conflicting results. Therefore more detailed analysis with consideration on the tax factors in UK market might shed more light on the repurchase studies in UK market.

Motivation analysis of repurchases has been conducted by Oswald and Young (2008) and Wang, Strong, Tang and Lin (2009) from the cash distribution perspective. They employ different methods to examine the market reaction and probability of repurchase decisions respectively. From corporate governance and market reaction perspectives respectively, the conclusion is consistent with cash distribution hypothesis. However, Wang, Strong, Tang and Lin (2009) report that the choices of repurchase announcement especially by frequent repurchases are not explained by cash distribution theory. Therefore the motivation underlying UK repurchases calls for further explanations.

2.3 DEFINITIONS AND SAMPLE

2.3.1 Variables for Fama-MacBeth regressions and sorted portfolios

My sample of UK stocks is obtained from the London Share Price Database (LSPD) and Datastream. LSPD is used to collect information about stock returns and capital adjustments for companies listed on the London Stock Exchange (LSE). Datastream is the source of all accounting information. SEDOL numbers are used to match these two databases. Before describing the sample, I define the main variables.

Return: the natural logarithm of monthly return from LSPD is used as the dependent variable in Fama-Macbeth regression, which is calculated as:

$$R_t^i = ln(\frac{p_t^i + d_t^i}{p_{t-1}^i}) \tag{1}$$

where:

R_t^i	is the log-return of asset i in month t
p_t^i	is the last traded price of asset i in month t
d_t^i	is the dividend of asset i during month t and the dividend is adjusted to a month-end basis.
p_{t-1}^i	is the last traded price of asset i in month t-1

Based on monthly returns available, 6 month and 12 month returns are created as the sum future log-return in 6 and 12 months:

$$R_{6}{}_t^i = \prod_{j=1}^{6}(R_{t+j-1}^i); \tag{2}$$

$$R_{12}{}_t^i = \prod_{j=1}^{12}(R_{t+j-1}^i). \tag{3}$$

where:

${R_6}_t^i$	is the is the log-return of asset i in 6 month begin with month t
${R_{12}}_t^i$	is the is the log-return of asset i in 12 month begin with month t

LSPD uses `-10' to represent unavailable stock returns due to suspension or delisting. In terms of delisting, following Liu, Strong and Xu (1999), Stocks with LSPD death type 7, 14, 16, 20, or 21 [3]are set to -1 log return in the delisting month; stocks with other death types is are assigned returns of 0.

Net equity issuance (NEI):

The main variable of interest in this paper is the change of share capital, i.e. net equity issuance factor. Since the number of shares of listed firms may change due to distributional activities such as stock splitting, the number of shares outstanding needs to be adjusted to reflect any change in share capital. The adjustment for distributional activities is captured by both a capital adjustment Index (CAI) in Datastream and the LSPD capital adjustment factor (C2). CAI_t is the cumulative product of the inverse of the individual-period capital adjustment factor (AX_t) while the LSPD capital adjustment factor equals AX_t. These two measures should be equivalent after aggregation of LSPD measure. However, through a manual cross-check with the annual financial reports, the capital adjustment information from LSPD has shown relatively higher accuracy than the Datastream index. A group of 32 random-chosen companies' capital change actions after 1980 are used as an accuracy examination. Among the total 141 actions, Datastream has 32 inaccurate data points (22.7%) with 14 missing and 18 inaccurate, while LSPD has 2 missing records (1.4%). From the stock level, Datastream's inaccurate records include 21 stocks (65.6%) while LSPD's records include 2 stocks (6.25%). Although the problem of Datastream data may not have significant effect on the

[3] LSPD type of death: 7: liquidation; 14: Quotation cancelled for reason unknown with dealings ceased; 16: Receiver appointed/liquidation; 20: In administration/Administrative receivership; 21: Cancelled and assumed valueless or suspended but assumed valueless

final results, LSPD data is more appropriate due to higher reliability. Therefore I construct my CAI by aggregating the LSPD capital adjustment factor.

The capital adjustment index is calculated by:

$$CAI_t^i = \prod_{i=1}^{t}(1000/C2_t^i) \tag{4}$$

where:

CAI_t^i	is the capital adjustment index of asset i in month t
$C2_t^i$	is the LSPD factor of asset i in month t by which the old share price is adjusted to allow for capital changes.

where:

$C2_t^i = true\ factor * 1000$

e.g. A scrip issue of 1 of 2.[4]

Adjustment factor = 0.667 * 1000 = 667

Therefore the number of adjusted shares is calculated by the share outstanding figure divided by capital adjustment factor:

$$adjusted\ shares_t^i = \frac{Shares\ outstanding_t^i}{CAI_t^i} \tag{5}$$

where:

$adjusted\ shares_t^i$	is the number of adjusted shares outstanding of asset i at month t
$Shares\ outstanding_t^i$	is the number of ordinary shares outstanding of asset i at month t from Datastream `NOSH' which measures total number of ordinary shares of the company

[4] The sample is from LSPD 2014 reference manual

Based on the number of adjusted shares, the Net equity issuance (NEI) is measured as the change of log adjusted shares outstanding:

$$Short\ term\ NEI\ (NEIS)_t^i$$
$$= ln(adjusted\ shares\ outstanding_{t-6}^i) - ln(adjusted\ shares\ outstanding_{t-17}^i) \quad (6)$$

$$Long\ term\ NEI\ (NEIL)_t^i$$
$$= ln(adjusted\ shares\ outstanding_{t-6}^i) - ln(adjusted\ shares\ outstanding_{t-65}^i) \quad (7)$$

where:

$Short\ term\ NEI\ (NEIS)_t^i$	is the natural logarithm of short term (11 months) change of number of shares outstanding of asset i at month t
$Long\ term\ NEI\ (NEIL)_t^i$	is the natural logarithm of long term (59 months) change of number of shares outstanding of asset i at month t
$adjusted\ shares_t^i$	is the number of adjusted shares outstanding of asset i at month t

The short-term NEI measures the aggregated change of adjusted shares outstanding for the 11 months period ending six months before. It is designed to reflect the short term share capital change for stocks. The long-term NEI measures the change in the last 5 years. The reason for having a six months gap is to ensure the information availability of share capital changes. The same measures for net equity issuance have been applied in the study of the US market (Pontiff and Woodgate, 2008) and international evidence (Mclean, et al. 2009).

In addition, due to the fact that a considerable number of observations (41.9%) for short-term net equity issuance activities is zero, a dummy variable `NEISzero' is created for the Fama-Macbeth regression. NEISzero equals one when NEIS is zero and equals zero otherwise. For NEIL, a dummy is also created to measure its availability. NEIL_DUM equals one when shares outstanding exists at t-65, otherwise it equals to zero. Accordingly, NEIL_ DUM is set to zero when it is missing due to data unavailability. The use of two dummy variables aims at capturing the potential impact on future stock returns from the existence of stock issuance activities.

Book-to-market ratio: the book-to-market ratio is important indicator of future stock return and is commonly used as controlling variable for capital anomalous effect test. The book-to-market (BM) value is the inverse of market-to-book value (MTBV) from Datastream collected in December the previous year, which measures market value of the ordinary equity divided by the balance sheet value of the ordinary equity in the firm. Agarwal and Taffler (2008) state that 22% of UK firms' fiscal year ends in March and 37% at December, using previous year end's BM value ensures the availability of information for market participants. The natural logarithm of book-to-market value is used in regressions. As a consequence, negative BM value and missing BM is set to have zero log value. A dummy variable BM_dum is thus created, which equals zero when raw BM is missing or has a negative value.

$$BM_t^i = ln\left(\frac{1}{MTBV_{Dec,Y-1}^i}\right) \tag{8}$$

where:

BM_t^i is the book to market value ratio of asset i at month t

$MTBV_{Dec,Y-1}^i = \frac{MV_{Dec,Y-1}^i}{BV_{Dec,Y-1}^i}$ is the market to book value of asset i at the end of December one year before collected from Datastream and defined as market value of the ordinary equity divided by the balance sheet value of the ordinary equity in the firm.

where:

MV_t^i is the product of number of shares outstanding and share price for asset i at month t

BV_t^i is the represents common shareholders' investment in a company i at month t, which include Common stock value; Retained earnings; Capital surplus; Capital stock premium; Cumulative gain or loss of foreign currency translation; Goodwill written off; preference stock which participates with the common shares in the profits of the company

Momentum: following the literature, the momentum factor used in Fama-Macbeth regression is measured as the last six months log stock return. The log-return from LSPD is used as it is more accurate and comprehensive for UK listed stocks compared with the Datastream data. The Momentum variable is calculated as:

$$Mom_t^i = \sum_{i=t-7}^{t-1} R_t \quad (9)$$

where:

Mom_t^i is the momentum factor of asset i at month t

R_t^i is the one month log-return of asset i at month t

Market value: the size vlue is also commonly used as controlling variable for stock return prediction. Although size effect has been insignificant in the recent studies using UK data (Michou et al. 2014; Gregory, et al. 2013), it remains a crucial factor as anomalies effects are usually criticized because of the influence of a large quantity of small-size stocks. Both LSPD and Datastream provide monthly data for Market Value of total ordinary shares outstanding. The Datastream value is more accurate as it is measured in thousand while LSPD in million, which makes the market value of small-size stocks relatively inaccurate. Therefore the Market Value (MV) variable from Datastream is used. To ensure the availability of this variable, the data from the same month in the previous year is used in my regressions. For the Fama-Macbeth regressions, the natural logarithm of market value is used.

$$MV_t^i = ln(MV_{t-12}^i) \quad (10)$$

where:

MV_{t-12}^i	is the market value of asset i one year before month t, collected from Datastream, which equals share price multiplied by the number of ordinary shares in issue

2.3.2 Sample

The sample of UK stocks is obtained from LSPD and Datastream equity data. LSPD provides reliable information about the stock return and capital adjustment for companies listed in the London Stock Exchange (LSE). Datastream is used as a source for accounting information such as Book to Market Value and market value. LSPD 2014 contains 9929 unique listed companies' information while there are 10115 companies available from Datastream UK equity database. Both sources consist of firms listed in main market and AIM of LSE. The sample data is obtained by matching these two databases.

Two methods are used to finalize the sample data. Firstly, as both databases include SEDOL information for companies, it can be used as a common identifier to match the source codes from both databases: `DS code' for Datastream and `g1' for LSPD. Using the Stata `joinby' command, 5266 pairs of firms are identified share common SEDOL numbers, which offers 5266 listed firms in the sample. However, there is a mismatch between the timing of SEDOL information between both databases. Datastream provides the latest SEDOL number for each company as of July 2014. The LSPD, on the other hand, contains all historical SEDOL information up to December 2013. This mismatch may restrain the availability of SEDOL number matches. Therefore, a name match is used as a complement to maximize the sample data size. The firm names provided by both databases also differ in format: e.g. Datastream tends to use `group' while LSPD tend to use `grp' instead; Datastream AIM firms are usually ended with ` (London)' while LSPD do not. Name match mainly is performed in two steps. The first word of each company's name is extracted from both databases, and they are processed in the same way as the SEDOL to find possible matches. Only a one to one match is recognised as a correct match. The first word of name match generates 3448 pairs of matches. The same method is then applied using first two words extracted of the firm name, which results in 3816 matches. Putting the matching results for SEDOL and name together gives a total sample of 6434 matched stocks from all industries. Eight of the matched pairs have conflict results between the name match and SEDOL match, which is resolved through a manual check of the time-series data of Market Value of shares outstanding from both databases.

Among the 6434 firms, 5455 belong to the non-financial sector according to Datastream industrial classification and the Industry Classification Benchmark (ICB). The sample of 5455 stocks is used for data collection. Using the sample of 5455 matched companies, LSPD data is extracted for monthly log-return, and Capital Adjustment Factor (C2). Datastream data on `capital adjustment index', market to book value (MTBV), market value (MV) and number of shares outstanding (NOSH) are collected for net equity issuance research. Due to data unavailability in Datastream, 21 stocks are lacking relevant accounting information and therefore are excluded from the sample, which means the final sample size become 5434.

The sample period is from January 1980 December 2013. Both live and delisted companies are included, to avoid survivorship bias (Shumway, 1997). Financial-sector companies are excluded, because their high leverage and the radically different nature of their assets makes comparison with non-financial companies problematic (Fama and French, 1992).

Table 2-1

Sample Observations by Year	
Year	**Sample size**
1981	1032
1982	1018
1983	1033
1984	1044
1985	1061
1986	1092
1987	1119
1988	1168
1989	1210
1990	1218
1991	1047
1992	1051
1993	1008
1994	1013
1995	1047
1996	1122
1997	1147
1998	1165
1999	1143
2000	1141
2001	1079
2002	1080
2003	1138
2004	1111
2005	1075
2006	1181
2007	1326
2008	1300
2009	1251
2010	1196
2011	1153
2012	1123
2013	1093

Notes:

The year column represents the year in which returns data are available (e.g., 2000 represents the returns data used in that year to construct portfolios from July 2000 to April 2001).

Table 2-1 illustrates the availability of my sample at the end of June every year from 1981 to 2013. The sample includes companies listed on both the main market and alternative investment market of the London Stock Exchange. The number of companies with data is more than one thousand each year.

Table 2-2

Descriptive Statistics of Variables

BM: the natural logarithm of the book to market ratio measured at December the previous year; MV: the natural logarithm of the market value measured at 12 months ago, t-12; Mom: the past six months aggregated log-return as a proxy of momentum factor; NEIS: change of the logarithm of the number of adjusted number of shares outstanding, NEIS for short term = log(adjusted shares outstanding, t-6) – log(adjusted shares outstanding, t-17); NEIL for long term = log(adjusted shares outstanding, t-6) – log (adjusted shares outstanding, t-65); Return: the aggregated log-return of the next 12 months, from t+1 to t+12

Variables	Mean	25th percentile	median	75th percentile	standard deviation
Return	-0.037	-0.266	0.048	0.316	0.750
BM	-0.558	-1.099	-0.501	0.073	0.980
MV	3.477	1.943	3.245	4.812	2.170
MOM	-0.013	-0.174	0.015	0.201	0.420
NEIS	0.090	0.000	0.000	0.032	0.334
NEIL	0.433	0.001	0.117	0.561	0.827

Correlation table

	Return	BM	MV	MOM	NEIS
BM	0.0789				
MV	0.0102	-0.3457			
MOM	0.0806	0.1125	-0.0264		
NEIS	-0.0802	0.0261	-0.1142	-0.0486	
NEIL	-0.1412	-0.0611	-0.1282	-0.1125	0.4917

For NEIS, there are 514,980 observations in total, 6.4% of which are negative, 42.9% have no issuance and 50.7% positive, indicating that more than half of the sample have positive NEI. The correlation table indicates a high correlation between short-term and longer-term issuance activities (0.483). The correlation between the 12-month future return and the other variables is consistent with expectations: higher book-to-market ratio stocks tend to have higher returns, which is the value-glamour effect; higher market value is correlated with lower returns, but the correlation is relatively insignificant; higher momentum shares also tend to offer higher future returns; both short- and long-term NEI are negatively correlated with future returns, consistent with the NEI effect.

2.4 METHODOLOGY

The methods I use to test for the existence of a NEI effect are Fama-MacBeth cross-sectional regressions, and sorted portfolio analysis. These two approaches are chosen following the literature on the NEI effect. Fama and French (2008) argue that they have different advantages and disadvantages in identifying capital market anomalies. Fama-MacBeth regressions provide direct information about the marginal effect that an anomaly variable has on the average return. However, the regression results could be driven by influential observations such as extreme individual stock returns or numerically dominant small-size stocks. Sorted portfolio analysis provides an explicit picture of the differences in average returns across different levels of the variable, and is recommended as a complementary approach to examine the robustness of the Fama-MacBeth regression results. As the regression results could be driven by small cap stocks with high trading costs, a natural robustness check is to split the sample into different size groups, to observe the pervasiveness of any anomalies.

On the choice of controlling variables for Fama-MacBeth regressions, I follow Daniel and Titman (2006) and Pontiff and Woodgate (2008) to use the book-to-market ratio, the market value and the momentum factor. Although empirical studies in the UK market have proposed other firm characteristics such as earnings-to-price ratio, cash flow to total asset (Gregory et al. 2001; Soares and Stark, 2011), dividend yield (Chan et al, 1996), Research and development to market value (Al-Horani et al. 2003) and leverage ratio (Muradoglu and Sivaprasad, 2012), I construct my cross sectional regression models using three controlling variables for parsimonious purpose. I choose this specification because additional controlling variables is unlikely capture the information contained in the NEI variables. Fama and French (2008) report empirical evidence with their US sample that the explanatory power of NEI variables remains significant after controlling for additional firm characteristics, which is robust across all size groups. Their results suggest that the mechanism underlying the explanatory power of NEI variables may differ from those variables capturing expected growth or cost of capital effects. Accord to that, Daniel and Titman (2006) propose that managerial timing of the share-overvaluation may be the source of the net equity issuance effect. Therefore the explanatory power of NEI variables is unlikely to be sensitive to the choice of additional controlling variables in this scenario. Moreover, to provide further robustness, I employ time-series regressions as the third set of empirical tests using various factor models to further mitigate the concern of the lack of sufficient control of systematic risks. Time-series regressions are able to show whether the NEI premium can be explained by the other risk factors.

2.4.1 Fama-MacBeth regressions

The method has two steps. In the first step, cross-sectional regressions are conducted for every month from January 1981 to December 2013,[5] which generates a time series of beta estimates for each explanatory variable. We do this for the whole sample and also for three samples grouped by size of stock. In the second step, averages of the beta estimates across time are obtained for each of the explanatory variables and a *t*-test is conducted to test the statistical significance of each average.

Step 1: Each month the cross-section of stock returns is regressed on the explanatory variables using OLS:

$$R_t^i = \alpha_t + \boldsymbol{\beta_t}'\boldsymbol{\gamma_t^i} + \varepsilon_t^i, \qquad (11)$$

where:

R_t^i: is the one-, six- or 12-month returns of share *i* from the end of month *t*;

[5] The regression periods are adjusted by availability of variables such as NEIS which requires 11 month ex ante data. The same adjustments apply to portfolio sorting analysis.

α_t: is the intercept term, one for each return interval;

$\boldsymbol{\beta_t}$: is the vector of the regression coefficients for month t on each explanatory variable, representing the factor loadings;

$\boldsymbol{\gamma_t^i}$: is the vector of values of the explanatory variables;

ε_t^i: is the error term.

Step 2: take averages across the months of the coefficients $\boldsymbol{\beta_t}$ and the intercepts α_t:

$$\widehat{\boldsymbol{\beta}} = \frac{1}{T}\sum_{t=1}^{t}\boldsymbol{\beta_t}\ , \qquad \hat{\alpha} = \frac{1}{T}\sum_{t=1}^{t}\alpha_t \tag{12}$$

where:

$\widehat{\boldsymbol{\beta}}$**:** is the vector of the averages of the coefficients across the total number of sample months T;

$\hat{\alpha}$: is the average of the intercepts.

The time-series standard deviation of $\boldsymbol{\beta_t}$ and α_t are used to obtain the standard error for a *t*-test of each explanatory variable and the intercept term. However, the overlap of the holding period for the shares, for returns of more than one month, induces potential autocorrelation of the error term. Therefore *N*-1 orders of autocorrelation should be adjusted for, where *N* refers to the length of the holding period in months (Pontiff and Woodgate, 2008). We apply the Newey-West autocorrelation-robust standard errors to the *t*-test on the averages of the coefficients and intercepts. Specifically, the cross-sectional coefficients $\boldsymbol{\beta_t}$ and intercept α_t are regressed on an intercept term. The intercepts of the regressions would amount to the time-series average of the estimators $\widehat{\boldsymbol{\beta}}$ and the intercept $\hat{\alpha}$. The regressions are as follows:

$$\beta_{tk} = \widehat{\beta_k} + \epsilon_t, \quad t = 1,2,\dots\dots T\ , \quad \text{for each explanatory variable } k \tag{13}$$

$$\alpha_t = \hat{\alpha} + \epsilon_t, \quad t = 1,2,\dots\dots T \tag{14}$$

where:

β_{tk}: is the regression coefficient on explanatory variable k for month t;

$\widehat{\beta_k}$: is the time-series average value for the coefficients on k;

ϵ_t: is the auto-correlated error term assuming N-1 lag autocorrelation, where N is the number of months of return holding period.

For each of the cross-sectional regression estimators, the test statistic for the t-test is:

$$t_k = \frac{\beta_k}{\frac{\widehat{\sigma_k}}{\sqrt{T}}} \tag{15}$$

And the same applies to the intercept term α_t :

$$t_\alpha = \frac{\alpha}{\frac{\widehat{\sigma_\alpha}}{\sqrt{T}}} \tag{16}$$

where:

$\frac{\widehat{\sigma_k}}{\sqrt{T}}$: is the Newey-West autocorrelation-robust standard error assuming N-1 lags for the error term. See, for example, Wooldridge (2006, pp. 432-5) for the calculation of $\widehat{\sigma_k}$ and $\widehat{\alpha_\alpha}$.

All the explanatory variables are winsorized to eliminate the potential influence of extreme observations on regression results: following Pontiff and Woodgate (2008), the smallest and largest 1% observations are set to equal to the value at the respective 1% tail.

Standard errors in panel data analysis are subject to potential biases. Petersen (2009) supports the use of Fama-MacBeth regressions when there might be a ‘time effect’, i.e. correlation across firms of the residuals for a given period, as in studies of equity returns. The unadjusted Fama-MacBeth standard error, however, is biased downwards if there is also a ‘firm effect’, i.e. time-series correlation of the residuals for a given firm. Therefore I follow Petersen’s advice and test for time and firm effects in my data, to examine the robustness of my adjusted Fama-MacBeth standard errors. We calculate four more standard errors: 1) the White standard error, which is robust to heteroscedasticity but not to time or firm effects; 2) the firm-clustered standard error; 3) the time-clustered standard error; 4) the two-way clustering standard error (Thompson, 2011; Cameron et al., 2008). The difference between the White standard error and the firm-clustered standard error measures the firm effect, while the difference between the White standard error and the time-clustered standard error measures the time effect. The two-way clustering standard error provides unbiased estimation if both time and firm effects exist, and thus it can be used as benchmark for my adjusted Fama-MacBeth standard errors.

2.4.2 Sorted portfolio analysis

My second test of the NEI effect is based on abnormal returns on portfolios sorted by NEIS and size. The abnormal return on a stock is the net return after deducting the return from a matching benchmark portfolio, using BM and MV, as in Fama and French (2008). At the end of June each year, stocks are allocated into four groups using quartiles of their BM values measured at the end of December in the previous year. Then another four groups are formed each year using quartile break points of MV measured at the end of June. The intersections of these two independently sorted groups create 16 portfolios each year, representing 16 different intersections of spectrums of BM and MV. Every year a 12-month value-weighted return is calculated for each of the 16 portfolios. These returns are the benchmarks for the abnormal returns. 4×4 matching is used rather than 5×5 due to the limited number of observations. With 5×5 sorting, some portfolios have fewer than 20 observations on average, which may reduce the reliability of their returns.

Each June the positive values of NEIS are allocated into quintiles by percentile of NEIS. Group zero consists of stocks with zero NEIS, and group -1 includes stocks with a negative NEIS. The subsequent value- and equally weighted 12-month returns are calculated, along with other attributes of the portfolios, for each year of the sample period. Independently sorted portfolios in terms of both NEIS and size are constructed to diagnose the role of small-size stocks in the effect. [6] Twenty-one new portfolios are constructed at the end of June every year, based on the seven NEIS levels, three for MV. The MV break points are the 30th and 70th percentiles.

We also calculate returns on sorted portfolios after transaction costs. Following Soares and Stark (2009), I estimate three types of cost: bid-ask spread, commissions, and stamp duty (a tax on trading). The requisite data are available for the period 1991 to 2013. The costs relate to normal trading rather short-selling, which is likely to be at least as costly. For bid-ask spread, I employ the proportional spread measure, Pspread, calculated using the daily bid price (Datastream datatype PB) and daily ask price (PA) over the 12 months preceding the end of June each year:

$$Pspread_i = \frac{1}{T}\sum_{\tau=1}^{T}\frac{Ask_{i,\tau} - Bid_{i,\tau}}{(Ask_{i,\tau} + Bid_{i,\tau})/2} \quad (17)$$

where:

$Ask_{i,\tau}$: is the ask price for stock *i* on day τ;

$Bid_{i,\tau}$: is the bid price;

T: is the number of trading days over the relevant 12 months.

For commissions paid by investors, I follow Agyei-Ampomah, (2007) and Soares and Stark (2009), and use a rate of 0.13% of the midpoint price. The rate of stamp duty, on purchases only, was 0.5% during 1991-2013. Based on the above costs mentioned above, the roundtrip costs (RC) for share *i* are:

[6] We also conduct the analysis using consecutive portfolio sorting approach as a robustness test. The results are similar. See Berk (2000) for more on consecutive sorting.

$$RC_{i,t} = Pspread_i + (2 * commission) + stamp\ duty \quad (18)$$

The total transaction costs (TC) for a hedge portfolio p of n stocks for a given holding period starting at the end of month *t* is:

$$TC_{p,t} = 2 \times \sum_{i=1}^{n} (W_{i,t} \times RC_{i,t}) \quad (19)$$

where:

$W_{i,t}$: is the weight of stock *i* in the portfolio;

$RC_{i,t}$: is the roundtrip cost for stock *i*.

The cost involves two roundtrip costs, one for the long and one for the short position.

2.4.3 Asset pricing tests

My third set of tests explore the NEI effect in the context of various asset pricing models. We use Fama-French three factor model (1993) as well as augmented Fama-French models including the five-factor model (Fama and French, 2015a), four-factor model (Hou et al., 2015), and other models involving a liquidity factor. For my asset pricing tests the sample period is restricted to 1992-2013, due to a lack of certain data for earlier years.

2.4.3.1 Factor measures

The size (MV), book-to-market (BM), and momentum (Mom) factors are defined above. Following Hou et al. (2015), the *investment factor* is measured using the change in total assets from year *Y*-2 to *Y*-1, divided by total asset for year *Y*-2, where *Y*-1 is the financial year ending in the calendar year before month *t*. We use Datastream total assets **(**WC02999) to calculate the investment measure, denoted by I/A.

Profitability factor. Two approaches are used to measure profitability. Fama and French (2015a) define profitability as the ratio of net income over book value of equity from the prior year. Net income is calculated as net income before extra items and preferred dividends (Datastream WC01551) minus preferred dividends (WC01701). We denote the Fama-French profitability measure as OP/B, which is $Net\ income_{Y-1}/Book\ value_{Y-1}$. Hou et al. (2015) instead use the book value from two years ago as the denominator. Their measure is denoted by ROE: $Net\ income_{Y-1}/Book\ value_{Y-2}$.

Liquidity factor. We report results using the bid-ask spread over the past 12 months, *Pspread*, defined above.

There are various approaches to proxy stock liquidity focusing on different dimensions. According to Liu (2006), there are four major dimensions of stock liquidity: trading quantity, trading speed, trading cost and price impact. The major viable liquidity proxies include Share turnover (Datar, Naik and Radcliffe, 1998; Brennan, Chordia and Subrahmanyam, 1998), illiquidity measure by Amihud (2002), illiquidity measure by Liu (2006) and Amihud and Mendelson(1986)'s relative bid-ask spread measure. Based on the previous research, several major stock liquidity proxies are used to construct liquidity factor.

The first measure is the relative bid-ask spread over the past 12 months (Liu, 2006), reflecting the transaction cost of liquidity characteristics.

$$Pspread_i = \frac{1}{T}\sum_{t=1}^{T}\frac{Ask_{i,l} - Bid_{i,l}}{Ask_{i,l}} \tag{20}$$

where:

$Ask_{i,l}$ is the daily ask price for stock i at day l (Datastream PA)

$Bid_{i,l}$ is the daily bid price for stock i at day l (Datastream PB)

T is the number of available days recorded in Datastream over the previous 12 months

The second measure is share turnover (TR) (Datar, Naik and Radcliffe, 1998; Brennan, Chordia and Subrahmanyam, 1998), which focus on the trading quantity of liquidity characteristics. TR is measured as the average ratio of daily trading volume over share outstanding over the trading days of prior 12 months.

$$TR_i = \frac{1}{n}\sum_{i=1}^{n}\frac{volume_{it}}{shares_{it}} \tag{21}$$

$volume_{it}$ is the daily number of traded shares for stock i at day t (Datastream VO)

$shares_{it}$ is number of shares outstanding for stock i at day t (Datastream NOSH)

n is the number of trading days the prior 12 months at day t

The third measure is the illiquidity measure of Amihud (2002), return to volume metric (RtoV), which tries to capture the price impact of trading. Goyenko, Holden and Trzcinka (2009) report that RtoV is the best measure of price impact among a group of other candidates. RtoV is measured as the average ratio of daily absolute return over daily trading volume across the trading days of the prior 12 months.

$$RtoV_i = \frac{1}{n}\sum_{i=1}^{n}\frac{|R_{it}|}{volume_{it}} \tag{22}$$

$|R_{it}|$ is the absolute daily return for stock I at day t, derived from Datastream price (P)

$volume_{it}$ is the daily number of traded shares for stock i at day t (Datastream VO)

n is the number of trading days the prior 12 months at day t

The fourth measure is the LM12 proposed by Liu (2006). Liu (2006) states that LM12 proxies multiple dimensions of liquidity including trading speed, trading quantity and trading cost with particular emphasis on trading speed. LM12 is calculated as standardized turnover-adjusted number of zero-trading volume days in the prior 12 months.

$$LM12_i = \left(N_0 + \frac{1/TR12_i}{Deflator_{it}} \right) \times \frac{21 \times 12}{NoTD} \tag{23}$$

N_0	is the number of zero trading volume days over the prior 12 months
$TR12_i$	is the sum of daily turnovers for stock i over the prior 12 months
$Deflator_{it}$	is 5,000,000 to ensure 0< $\frac{1/TR12_i}{Deflator_{it}}$ <1
$NoTD$	is the number of trading days the prior 12 months at day t for stock i
$\frac{21\times12}{NoTD}$	is the term to standardize number of trading days in a month of 21

In unreported analysis I also use all the three alternative measures: share turnover (Datar et al., 1998; Brennan et al.,1998); the return-to-volume metric of Amihud (2002), and the LM12 measure of Liu (2006). The results using these measures are qualitatively similar to those using Pspread.

2.4.3.2 Construction of the factors

Following Gregory et al. (2001) and Gregory et al. (2013), I use the break points from largest 350 stocks. At the end of June each year, stocks are allocated into two size groups of unequal numbers, based on the median size of the largest 350 stocks at the end of year Y-1. Stocks are also sorted independently into three groups of other variables: BM, MOM, ROE, OP/B and I/A, using the 30th and 70th percentile from the largest 350 stocks as the breakpoints. The size, B/M, ROE, OP/B and I/A groups are reformed annually, as are the corresponding factors. The momentum, portfolios are reformed monthly.

These portfolios are labelled using letters: for size category, small (S) or big (B); for BM, high (H), neutral (N), or low (L); for ROE, High (H), weak (W), or low (L); for OP/B, robust (R), neutral (N), or weak (W); for I/A group, conservative (C), neutral (N), or aggressive (A); for momentum, up (U), neutral (N) or down (D). Intersection portfolios are created to build the factors, and value-weighted returns are obtained for each portfolio. For example, SL stands for the monthly value-weighted return of the portfolio with small size and low BM. The factors are obtained using the formulas stated in Table 2-10. For instance, each month the momentum factor is defined as the difference between the simple average of the returns on two winning-stock portfolios, SU and BU, and the simple average of the returns on two losing-stock portfolios, SD and BD.

For the liquidity factor, stocks are sorted into two size groups; the largest 350 stocks, and the remaining stocks. Each group is then sorted in terms of liquidity. The low-liquidity portfolio (LL) is constructed using the 15% lowest liquidity stocks from the large-size group and the 35% lowest liquidity stocks from the small-size group. The high-liquidity portfolio (HL) is constructed using the 35% highest liquidity stocks from large-size group and the 15% highest liquidity stocks from the small-size group.

2.4.3.3 Review of asset pricing models used

Liquidity-based model. Equity issuance potentially affects expected returns because it increases the liquidity of the shares. Eckbo and Norli (2005) document that firms that conduct IPOs and SEOs tend subsequently to be more liquid than their matched firms, which reduces their expected returns. Bilinski et al.(2012) confirm that SEOs increase liquidity and thus reduce liquidity risk, which could explain the negative long-run abnormal returns following SEOs. We follow Eckbo and Norli (2005) and add momentum and liquidity factors to the Fama-French three-factor model:

$$r_{pt} - r_{ft} = \alpha_p + \beta_1 RM_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \beta_5 Liquidity_t + e_t \quad (24)$$

where:

α_p	is the regression intercept;
r_{pt}	is the return on portfolio p in month t;
r_{ft}	is the risk-free rate;
RM_t	is the excess return on the market index over risk free rate;
SMB_t	is the return on small stocks minus the return on large stocks;
HML_t	is the return on high BM stocks minus the return on low BM stocks;
UMD_t	is the return on up-performance stocks minus the return on down-performance stocks;
$Liquidity_t$	is the return on low-liquidity stocks minus the return on high-liquidity stocks;
e_t	is the error term.

On the other hand, Liu (2006) proposes a two-factor model which captures the liquidity premium and outperforms the Fama-French three-factor model, accounting for anomalies associated with size, book-to-market and other possible factors:

$$r_{pt} - r_{ft} = \alpha_p + \beta_1 RM_t + \beta_2 Liquidity_t + e_t \quad (25)$$

Investment-based model. The investment characteristics of firms have been used to predict the cross-section of expected stock returns (Titman et al., 2004; Cooper et al., 2008; Polk and Sapienza, 2009). There is also evidence that an investment factor can explain the puzzling abnormal returns after new issues such as IPOs, SEOs and convertible debt offerings. These findings are supported by two main theories.

Carlson et al. (2006) employ a real option model and argue that equity-financed investment will decrease risk and expected return, because investment extinguishes some risky options. On the other hand, following the derivation of a negative relation between real investment and expected return (Cochrane, 1991), Li et al.(2009) argue that Q theory suggests that low returns following equity issues are likely to be driven by real investment. Lyandres et al. (2008) use an investment-augmented Fama-French three-factor model and partially explain the negative abnormal returns after SEO (75% explained), IPO (80%), convertible debt offerings (50%), and net equity issuance in general (40%).

$$r_{pt} - r_{ft} = \alpha_p + \beta_1 RM_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 I/A_t + e_t \qquad (26)$$

where:

I/A_t	is the return on low investment-to-asset stocks minus the return on high investment-to-asset stocks.

Profitability and momentum. The profitability of firms has also been found to explain the cross-section of stock returns. For instance, Haugen and Baker (1996) and Cohen et al. (2002) find a positive relation between profitability and future stock return after controlling for book-to-market. Fama and French (2006) use the dividend discount model to articulate the theory behind the positive relation between profitability and expected return. However, their portfolio test using current earnings as a proxy for profitability produces insignificant results. Novy-Marx (2013) refines the proxy and finds that gross profitability has roughly the equivalent predictive power as book-to-market value for the cross-section of returns. He proposes a four-factor model, including profitability and momentum factors, which subsumes various anomalies including the NEI effect:

$$r_{pt} - r_{ft} = \alpha_p + \beta_1 RM_t + \beta_2 HML_t + \beta_3 UMD_t + \beta_4 PMU_t + e_t \qquad (27)$$

where:

PMU_t is the return on high gross profit-to-asset stocks minus return on low gross profit-to-asset stocks.

Novy-Marx's model uses factors that are adjusted by industry, which means each stock position is net of an equal position in the corresponding value-weighted industry portfolio.

Profitability and investment. Hou et al. (2015) propose a four-factor model which employs the profitability, investment, size and market factors. Their empirical results indicate that the significant hedge portfolio return on NEI is subsumed by their four-factor model. The hedge portfolio return remains significant under Fama-French three-factor model and the Carhart (1997) four-factor model. The model of Hou et al. (2015) is:

$$r_{pt} - r_{ft} = \alpha_p + \beta_1 RM_t + \beta_2 SMB_t + \beta_3 ROE_t + \beta_4 I/A_t + e_t \quad (28)$$

where:

ROE is: is the return on high income before extraordinary items/total asset minus return on low income before extraordinary items/total asset stocks.

I/A is: is the return on low investment-to-asset stocks minus the return on high investment-to-asset stocks.

Five-factor model. Following from their dividend discount model analysis (Fama and French, 2006), Fama and French (2015a) augment their three-factor model with the profitability factor and investment factor. Their evidence suggests that most capital market anomalies, including NEI effect, shrink using these five factors compared with three factors. Their five-factor model is:

$$r_{pt} - r_{ft} = \alpha_p + \beta_1 RM_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 OP/B_t + \beta_5 I/A_t + e_t \quad (29)$$

where:

OP/B is: is the return on high operating profit/book equity stocks minus the return on low operating profit/book equity stocks.

2.5 RESULTS

2.5.1 Fama-MacBeth regressions

My first set of results is from Fama-MacBeth regressions, using panel data from January 1980 to December 2013 (Table 2-3). For the natural log of one-month, six-month and twelve-month returns, the cross-sectional differences are related to book-to-market (BM), size (MV), momentum (MOM), one-year issuance (NEIS) and five-year issuance (NEIL). Different combinations of factors are used for regression tests. The coefficients for BM and MOM are consistent with previous research in UK. The slope coefficient for BM is positive and statistically significant. The MOM coefficient is also positive and statistically significant. The size effect, however, is statistically insignificant in most cases.

For NEI, the slope coefficient is negative for both NEIS and NEIL, confirming the existence of a NEI effect. A one-standard-deviation increase (0.334) in NEIS change would on average reduce the one-month future return by 0.37%, the six-month return by 2.2%, and the 12-month return by 3.7%. NEIL also has a significant negative impact on future stock returns. A one-standard-deviation increase in NEIL (0.827) would on average reduce the one-month, six-month and 12-month future returns by 0.5%, 2.4% and 4.5% respectively. The autocorrelation-robust *t*-statistics for both NEI measures are significant in all the regressions except for NEIS with one-month returns. Their significance is similar to the *t*-statistics for the momentum factor and book-to-market ratio, which suggests that NEI is a considerable determinant of future stock returns. Therefore, the results from the Fama-MacBeth regressions show that higher share issuance leads to lower future stock returns in the UK stock market.

However, the relationship between share issuance and returns is not simply linear, from net repurchase to positive net issuance. The dummy variable for NEIS_zeros is significantly positive in all the regressions. On average, zero issuance leads to a 1.3% and 2.9% increase in the six-month and 12-month return, respectively. This result is different from the US studies where Fama and French (2008) find an insignificant impact for the no-issuance dummy in their Fama-MacBeth regressions.

Table 2-3

Fama-MacBeth Cross-sectional Regressions, 1980-2013

Fama-MacBeth monthly cross-sectional regressions are conducted on the sample period on the following variables: the natural logarithm of the book to market value measured at the end of December year-1, BM; Book to market dummy variable which equals to zero when BM is missing, BMdum; the natural logarithm of equity market value measured at year-1, MV ; the log stock return of past 6 months as proxy for momentum, Momentum; the change of the natural logarithm of the number of shares outstanding adjusted for distributional activities. NEIS for short term change in net equity issuance: NEIS = Ln (shares outstanding, t-6) – Ln (shares outstanding, t-17); NEIL for long term change in net equity issuance: NEIL = Ln (shares outstanding, t-6) – Ln (shares outstanding, t-65); dummy variable which equals to one when NEIS is zero, and zero otherwise, NEISzero; dummy variable which equals to one when shares outstanding exists at t-65, and zero otherwise, NEILdum. The R_square is the average adjusted-R^2 from the cross-sectional regressions. The regressions are obtained for 396 months from January 1980 to December 2013.

Dependent variable: one month log-return

Constant	0.000	-0.001	-0.007**	-0.031***	-0.007***	-0.029***	-0.021***	-0.021***
	(0.06)	(-0.39)	(-2.36)	(-7.48)	(-2.75)	(-7.49)	(-5.92)	(-4.74)
BM				0.002***			0.002***	0.001*
				(2.96)			(3.32)	(1.86)
BM_Dum				0.013***			0.013***	0.011***
				(5.84)			(7.80)	(4.77)
MV				0.004***		0.004***		0.002***
				(8.67)		(8.67)		(4.93)
MOM				0.064***	0.065***			0.062***
				(14.7)	(15.2)			(14.1)
NEIS	-0.019***		-0.035***					-0.011***
	(-5.56)		(-10.0)					(-3.08)
NEIS_Zero	-0.004***		-0.004***					-0.001
	(-3.14)		(-3.35)					(-1.02)
NEIL	-0.011***	-0.015***						-0.006***
	(-8.90)	(-11.3)						(-5.13)
NEIL_Dum	-0.018***	-0.017***						-0.008***
	(-9.12)	(-10.2)						(-4.56)
R_square	0.006	0.003	0.002	0.018	0.011	0.004	0.002	0.022
observation	441506	515892	441506	426000	472067	448908	413240	413240

Table 2-3 (cont.)

Dependent variable: six month log-return								
Constant	0.014	0.020	-0.012	-0.078***	-0.015	-0.051*	-0.043*	-0.036
	(0.83)	(1.18)	(-0.60)	(-2.71)	(-0.78)	(-1.87)	(-1.84)	(-1.43)
BM				0.024***			0.025***	0.018***
				(5.30)			(5.38)	(4.36)
BM_Dum				0.051***			0.044***	0.041***
				(5.53)			(5.91)	(4.89)
MV				0.007***		0.007***		0.004*
				(2.82)		(2.82)		(1.77)
MOM				0.136***	0.152***			0.124***
				(8.62)	(8.80)			(8.43)
NEIS	-0.073***		-0.129***					-0.065***
	(-6.55)		(-7.94)					(-7.04)
NEIS_Zero	0.013***		0.012***					0.013***
	(3.08)		(2.68)					(4.31)
NEIL	-0.042***	-0.056***						-0.029***
	(-9.34)	(-9.88)						(-8.15)
NEIL_Dum	-0.069***	-0.076***						-0.047***
	(-6.34)	(-6.11)						(-5.25)
R_square	0.019	0.015	0.009	0.041	0.023	0.011	0.009	0.051
observation	410212	478245	410212	401490	444950	416779	389590	389590
Dependent variable: twelve month log-return								
Constant	0.028	0.042	-0.015	-0.122**	-0.022	-0.075	-0.059	-0.053
	(0.86)	(1.22)	(-0.41)	(-2.02)	(-0.58)	(-1.34)	(-1.30)	(-0.99)
BM				0.042***			0.044***	0.030***
				(4.47)			(4.05)	(3.52)
BM_Dum				0.077***			0.067***	0.062***
				(4.05)			(4.44)	(3.67)
MV				0.011*		0.011*		0.007
				(1.96)		(1.96)		(1.38)
MOM				0.178***	0.204***			0.158***
				(6.49)	(6.51)			(6.28)
NEIS	-0.120***		-0.215***					-0.112***
	(-4.83)		(-6.18)					(-5.80)
NEIS_Zero	0.029***		0.026***					0.028***
	(3.57)		(3.06)					(4.68)
NEIL	-0.075***	-0.099***						-0.055***
	(-8.75)	(-8.81)						(-8.09)
NEIL_Dum	-0.114***	-0.132***						-0.081***
	(-5.27)	(-4.81)						(-4.91)
R Square	0.028	0.023	0.014	0.051	0.026	0.015	0.013	0.066
observation	374934	437317	374934	368961	409232	380967	358229	358229

According to Fama and French (2008), the explanatory power of certain anomaly variables is driven by smallcap stocks. Therefore I follow their approach and conduct Fama-MacBeth regressions across small, middle and big size groups using MV percentiles of 30% and 70% as break points. We find that the regression coefficients are in general consistent across three size groups (Table 2-4). Rather than being driven by small-size stocks, the predictive power of NEI remains persistent across different sizes of stocks in UK.

Table 2-5 presents coefficients and their *t*-statistics from four methods of estimating standard errors in panel regressions, and from Fama-MacBeth regressions using the autocorrelation-robust standard error explained in Section 2.4.1. The dependent variable is the one-month, six-month, or 12-month log returns. When using one-month returns, I observe a significant time effect, indicated by the fact that the *t*-statistics from time-clustered standard errors are significantly smaller than when White standard errors are used. Fama-MacBeth regression provides unbiased standard errors and *t*-statistics in this scenario, and two-way clustered standard errors provide similar results as my sample has sufficient time and cross-sectional scale.

For six-month and 12-month returns, both time and firm effects are present, as both time-clustered and firm-clustered *t*-statistics are much smaller than the White *t*-statistic. This shows that both directions of residual dependence need to be controlled for in the regression. My adjusted Fama-MacBeth *t*-statistics are close to those using two-way clustered standard errors, and are not inflated by the existence of a firm effect. This is due to my use of the Newey-West standard error in the second stage of the regression. Overall, the results in Table 2-5 indicate that Fama-MacBeth regression with adjusted standard errors is robust with respect to problems of residual dependence in panel data analysis.

Table 2-4

Fama-MacBeth Cross-sectional Regressions across all size groups, 1980-2013

Fama-MacBeth monthly cross-sectional regressions are conducted on the sample period across three size groups on the following variables: the natural logarithm of the book to market value measured at the end of December year-1, BM; Book to market dummy variable which equals to zero when BM is missing, BMdum; the natural logarithm of equity market value measured at year-1, MV ; the log stock return of past 6 months as proxy for momentum, Momentum; the change of the natural logarithm of the number of shares outstanding adjusted for distributional activities. NEIS for short term change in net equity issuance: NEIS = Ln (shares outstanding, t-6) – Ln (shares outstanding, t-17); NEIL for long term change in net equity issuance: NEIL = Ln (shares outstanding, t-6) – Ln (shares outstanding, t-65); dummy variable which equals to one when NEIS is zero, and zero otherwise, NEISzero; dummy variable which equals to one when shares outstanding exists at t-65, and zero otherwise, NEILdum. Dependent variable return1; return6 and return12 represents natural log of futhre stock returns for 1 month; 6 month and 12 month respectively. At the end of June each year, MV percentile of 30% and 70% are used as breaking points for 'small', 'middle' and 'big' groups. The R_square is the average adjusted-R^2 from the cross-sectional regressions. The regressions are obtained for 396 months from January 1980 to December 2013.

dependent variable	**return1**	**return6**	**return12**	**return1**	**return6**	**return12**	**return1**	**return6**	**return12**
	small			middle			large		
Constant	-0.015*	-0.013	-0.005	0.007	-0.011	-0.076	-0.002	-0.022	-0.068
	(-1.80)	(-0.50)	(-0.14)	(1.48)	(-0.44)	(-1.62)	(-0.42)	(-0.70)	(-1.31)
BM	-0.004*	0.003	0.010	0.003***	0.024***	0.038***	0.002***	0.013**	0.024***
	(-1.80)	(0.61)	(1.29)	(3.26)	(5.88)	(5.39)	(3.81)	(2.57)	(2.88)
BM DUMMY	0.019***	0.080***	0.123***	0.010***	0.046***	0.072***	0.003*	0.011	0.023
	(3.61)	(6.58)	(6.79)	(4.00)	(5.35)	(5.17)	(1.89)	(1.16)	(1.29)
MV	-0.008***	-0.037***	-0.054***	-0.003***	-0.003	0.008	0.000	0.006**	0.015***
	(-3.26)	(-8.01)	(-7.05)	(-3.28)	(-0.89)	(1.20)	(1.38)	(2.35)	(3.59)
MOM	0.079***	0.079***	0.093***	0.040***	0.137***	0.192***	0.031***	0.137***	0.201***
	(10.2)	(5.20)	(4.25)	(9.48)	(8.95)	(8.66)	(6.39)	(6.61)	(6.78)
NEIS	-0.010	-0.074***	-0.109***	-0.021***	-0.092***	-0.138***	-0.006**	-0.041***	-0.115***
	(-1.22)	(-5.20)	(-5.04)	(-4.52)	(-6.36)	(-5.73)	(-2.22)	(-3.34)	(-4.94)
NEISZERO	-0.001	0.019***	0.027***	-0.002	0.011**	0.029***	0.001	0.008**	0.018**
	(-0.31)	(3.45)	(3.14)	(-1.55)	(2.57)	(3.91)	(1.61)	(2.23)	(2.47)
NEIL	-0.007**	-0.021***	-0.043***	-0.006***	-0.027***	-0.054***	-0.003***	-0.031***	-0.051***
	(-2.21)	(-3.11)	(-4.94)	(-4.09)	(-5.65)	(-7.90)	(-4.01)	(-5.30)	(-5.08)
NEIL DUMMY	-0.006	-0.026**	-0.033**	-0.010***	-0.055***	-0.097***	-0.004***	-0.037***	-0.067***
	(-1.37)	(-2.52)	(-2.26)	(-5.90)	(-6.18)	(-6.92)	(-2.60)	(-3.82)	(-4.84)
R square	0.020	0.034	0.048	0.031	0.060	0.068	0.055	0.077	0.085
observation	126323	111830	97982	188235	176866	164138	157041	151022	144134

Table 2-5

Comparison of multiple regression approaches, 1980-2013

Variables definition: natural log of stock returns for 1 month; 6 month and 12 month; the natural logarithm of the book to market value measured at the end of December year-1, BM; Book to market dummy variable which equals to zero when BM is missing, BMdum; the natural logarithm of equity market value measured at year-1, MV ; the log stock return of past 6 months as proxy for momentum, Momentum; the change of the natural logarithm of the number of shares outstanding adjusted for distributional activities. NEIS for short term change in net equity issuance: NEIS = Ln (shares outstanding, t-6) – Ln (shares outstanding, t-17); NEIL for long term change in net equity issuance: NEIL = Ln (shares outstanding, t-6) – Ln (shares outstanding, t-65); dummy variable which equals to one when NEIS is zero, and zero otherwise, NEISzero; dummy variable which equals to one when shares outstanding exists at t-65, and zero otherwise, NEILdum. The R_square is the average adjusted-R^2. The regressions are obtained for 396 months from January 1980 to December 2013. Regression coefficients and t-statistics are obtained based on White-robust standard error; firm-clustered standard error; time-clustered standard error; two-way clustered standard error and Fama-MacBeth cross-sectional regression.

1 month log return

VARIABLES	White robust	firm clustered	time clustered	Two-way clustered	Fama-MacBeth
Constant	-0.023***	-0.023***	-0.023***	-0.023***	-0.021***
	(-8.25)	(-8.09)	(-4.84)	(-4.81)	(-4.74)
bm	0.002**	0.002**	0.002	0.002	0.001*
	(2.84)	(2.77)	(1.90)	(1.88)	(1.86)
bmdum	0.013***	0.013***	0.013***	0.013***	0.011***
	(5.62)	(5.38)	(4.74)	(4.60)	(4.77)
mv	0.003***	0.003***	0.003***	0.003***	0.002***
	(8.93)	(8.80)	(4.26)	(4.25)	(4.93)
momentum	0.060***	0.060***	0.060***	0.060***	0.062***
	(17.97)	(17.28)	(8.42)	(8.35)	(14.1)
neis	-0.011**	-0.011**	-0.011**	-0.011**	-0.011***
	(-3.06)	(-2.89)	(-2.77)	(-2.64)	(-3.08)
neiszero	0.003*	0.003*	0.003	0.003	-0.001
	(2.36)	(2.30)	(1.48)	(1.47)	(-1.02)
neil	-0.010***	-0.010***	-0.010***	-0.010***	-0.006***
	(-7.75)	(-7.59)	(-6.79)	(-6.69)	(-5.13)
neildum	-0.015***	-0.015***	-0.015***	-0.015***	-0.008***
	(-10.24)	(-9.64)	(-5.72)	(-5.61)	(-4.56)
Observations	413,240	413,240	413,240	413,240	413,240
Adjusted R-squared	0.007	0.007	0.007	0.007	0.007

Table 2-5 (cont.)

6 month log return					
VARIABLES	**White robust**	**firm clustered**	**time clustered**	**Two way clustered**	**Fama-MacBeth**
Constant	-0.028***	-0.028***	-0.028*	-0.028	-0.036
	(-6.79)	(-3.69)	(-2.12)	(-1.91)	(-1.43)
bm	0.030***	0.030***	0.030***	0.030***	0.018***
	(24.70)	(12.76)	(8.77)	(7.56)	(4.36)
bmdum	0.045***	0.045***	0.045***	0.045***	0.041***
	(14.19)	(7.57)	(9.74)	(6.59)	(4.89)
mv	0.003***	0.003**	0.003	0.003	0.004*
	(6.09)	(2.97)	(1.58)	(1.43)	(1.77)
momentum	0.080***	0.080***	0.080***	0.080***	0.124***
	(22.35)	(14.24)	(3.61)	(3.55)	(8.43)
neis	-0.067***	-0.067***	-0.067***	-0.067***	-0.065***
	(-12.72)	(-7.42)	(-9.19)	(-6.48)	(-7.04)
neiszero	0.034***	0.034***	0.034***	0.034***	0.013***
	(17.88)	(9.77)	(6.69)	(5.80)	(4.31)
neil	-0.044***	-0.044***	-0.044***	-0.044***	-0.029***
	(-23.79)	(-12.98)	(-14.52)	(-10.59)	(-8.15)
neildum	-0.072***	-0.072***	-0.072***	-0.072***	-0.047***
	(-30.75)	(-15.41)	(-8.76)	(-7.86)	(-5.25)
Observations	389,590	389,590	389,590	389,590	389,590
Adjusted R-squared	0.019	0.019	0.019	0.019	0.019
12 month log return					
VARIABLES	**White robust**	**firm clustered**	**time clustered**	**Two way clustered**	**Fama-MacBeth**
Constant	-0.035***	-0.035**	-0.035	-0.035	-0.053
	(-6.74)	(-2.60)	(-1.84)	(-1.54)	(-0.99)
bm	0.056***	0.056***	0.056***	0.056***	0.030***
	(35.75)	(12.89)	(11.60)	(8.88)	(3.52)
bmdum	0.069***	0.069***	0.069***	0.069***	0.062***
	(17.10)	(6.39)	(12.87)	(6.08)	(3.67)
mv	0.005***	0.005**	0.005	0.005	0.007
	(8.02)	(2.78)	(1.86)	(1.58)	(1.38)
momentum	0.080***	0.080***	0.080**	0.080**	0.158***
	(19.51)	(10.62)	(2.65)	(2.60)	(6.28)
neis	-0.120***	-0.120***	-0.120***	-0.120***	-0.112***
	(-18.74)	(-8.03)	(-12.26)	(-7.20)	(-5.80)
neiszero	0.069***	0.069***	0.069***	0.069***	0.028***
	(27.40)	(11.33)	(9.29)	(7.45)	(4.68)
neil	-0.077***	-0.077***	-0.077***	-0.077***	-0.055***
	(-31.81)	(-12.18)	(-18.64)	(-10.76)	(-8.09)
neildum	-0.121***	-0.121***	-0.121***	-0.121***	-0.081***
	(-38.71)	(-14.09)	(-11.22)	(-9.01)	(-4.91)
Observations	358,229	358,229	358,229	358,229	358,229
Adjusted R-squared	0.030	0.030	0.030	0.030	0.030

2.5.2 Sorted portfolio analysis

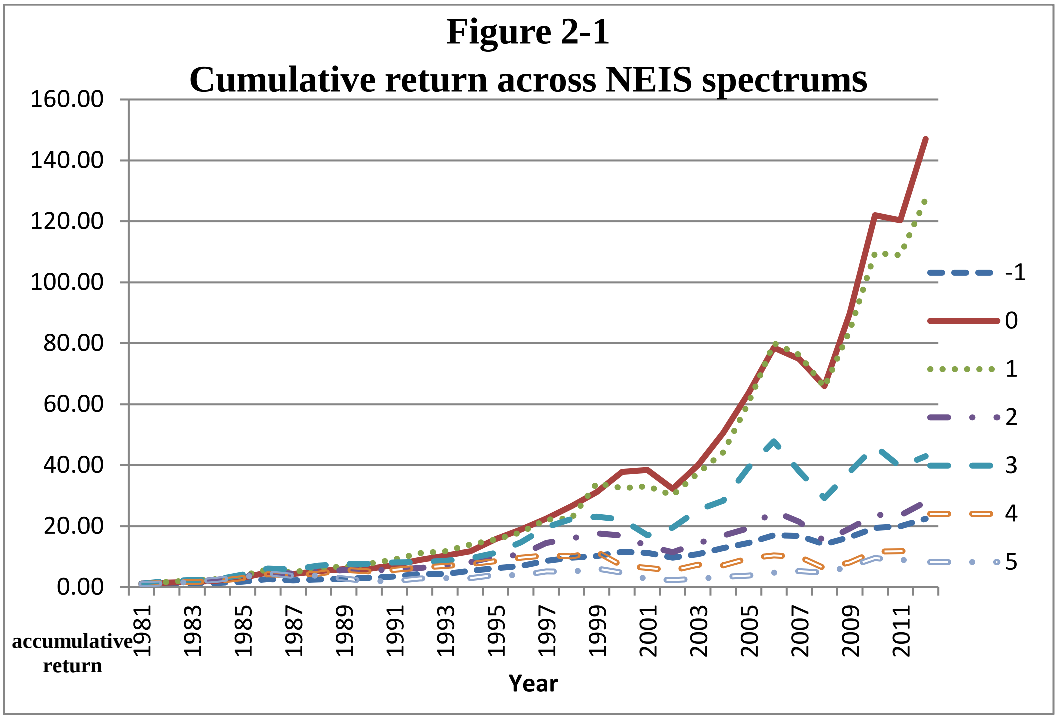
Table 2-6

Descriptive statistics for the independently sorted portfolio on MV and BM for period 1981-2013

The table reports the descriptive statistics of the portfolios sorted independently on MV and book-to-market value. At the end of June each year, 16 value weighted portfolios are formed based on the intersection between these two sorted groups. MV is measured as the product of number of shares outstanding and stock price at the end of June. Book-to-market is measured at the end of December of previous year.

MV quartile	**BM quartile**			
	Low	2	3	High
	Average monthly value-weighted return (%)			
Small	1.13	1.51	1.58	1.71
2	0.74	0.85	1.20	1.84
3	0.83	1.25	1.46	1.77
Big	1.02	1.18	1.41	1.60
	Average book-to-market			
Small	0.24	0.56	0.93	2.34
2	0.25	0.56	0.92	1.94
3	0.25	0.55	0.90	1.98
Big	0.25	0.55	0.89	1.66
	Average firm MV (mil)			
Small	5	6	5	5
2	22	21	21	20
3	84	84	79	74
Big	2535	2327	1848	1771
	Average of number of firms in each portfolio			
Small	42	44	66	127
2	58	63	77	81
3	78	80	72	48
Big	100	90	63	27

We next present results from sorted portfolios. First, Table 2-6 shows descriptive statistics for 4×4 matching portfolios used to calculate abnormal returns. We see that monthly average return increases with the BM value. Meanwhile, although the smallest size groups tend to have higher returns, the relation between size and return is not monotonic. This is consistent with the results from the Fama-MacBeth regressions, and with previous literature (Gregory et al., 2013; Michou et al., 2014).



Notes:

This figure shows the cumulative return for each NEIS level from June 1981 to December 2013. At the end of June each year, 7 portfolios are formed based on the short term net equity issuance: negative NEIS stocks are included in level '-1'; zero NEIS stocks are grouped into level '0'; positive NEIS stocks are categorised into five quintile groups from lowest level'1' to highest level '5'. NEIS is measured as the change of the logarithm of the number of adjusted number of shares outstanding: NEIS = log(adjusted shares outstanding, t-6) – log(adjusted shares outstanding, t-17). The cumulative return is calculated as the product of annual value weighted return for each NEIS group.

Next, Table 2-7 presents descriptive statistics for portfolios independently sorted by seven NEIS and three size groups. The evidence includes the raw 12-month future returns, values for BM and MV, and the average number of firms in each portfolio. The 'hedge portfolio return' column reports the average (raw) return from a long position in the zero-NEIS and short in the quintile-5 portfolio. It is evident that from level 0 to level 5 of NEIS, the raw value- and equally weighted returns have a decreasing trend. Figure 1 shows the impact of these differences in returns over time. Consistent with the yearly averages in Table 2-7, the zero-NEIS portfolio has the highest cumulative value-weighted return, and the cumulative return becomes lower as the NEIS level increases. But the level -1, negative-NEIS portfolio provides a lower cumulative return than the other categories except quintiles 4 and 5. My comparison of raw returns confirms a negative relation between short-term NEI and future return, setting aside the negative-NEIS portfolio.

The pattern of results for the NEIS portfolios is similar across all three size categories, though the drop in return as one moves from zero NEIS and quintile 1 to quintile 5 is especially pronounced for the small-stock category. There is a hint that the NEI effect could be linked to book-to-market value, which falls monotonically from 0.94 for zero-NEIS to 0.60 for quintile 5. The data on size show that the repurchase portfolio has largest stocks on average, with average size decreasing from quintile 1 to 5. In other words, positive issuance is greater among smallcap firms. The zero-NEIS group turns out to have the lowest average size, indicating that firms with no issuance activity tend to be small.

Table 2-7

Descriptive statistics of independent-sorted portfolios on NEIS and MV for the period 1981 – 2012

The table reports the descriptive statistics of value-weighted (VW) and equally-weighted (EW) portfolios sorted independently on MV and short term net equity issuance (NEIS). At the end of June each year, all stocks are categorised into seven groups by the short term net equity issuance: negative NEIS stocks are included in level '-1'; zero NEIS stocks are grouped into level '0'; positive NEIS stocks are categorised into five quintile groups from lowest level'1' to highest level '5'. NEIS is measured as the change of the logarithm of the number of adjusted number of shares outstanding: NEIS = log(adjusted shares outstanding, t-6) – log(adjusted shares outstanding, t-17). Independently, all stocks are categorised into three MV groups where MV is measured as the product of number of shares outstanding and stock price at the end of June. MV percentile of 30% and 70% are used as breaking points for 'small', 'middle' and 'big' groups. The 'Full Sample' group combines all three size groups. At the end of June each year, 21 portfolios are formed based on the intersection between these two sorted groups. Book-to-Market is measured at the end of December of previous year.

MV level	**NEIS level**							**Hedge Portfolio Return**
VW average annual return	**-1**	**0**	**1**	**2**	**3**	**4**	**5**	**0-5**
Small	13.2%	19.0%	19.1%	13.8%	14.8%	6.6%	-0.9%	19.8%
Middle	15.0%	17.7%	18.1%	14.7%	10.6%	7.8%	3.9%	13.8%
Big	11.0%	18.2%	17.8%	12.5%	14.8%	10.9%	11.9%	6.3%
Full Sample	11.3%	18.2%	17.7%	12.5%	14.6%	10.4%	10.5%	7.6%

Table 2-7 (cont.)

EW average annual return	-1	0	1	2	3	4	5	0-5
Small	14.5%	20.4%	36.5%	15.0%	14.5%	9.0%	1.4%	19.0%
Middle	15.3%	17.7%	17.3%	14.5%	10.2%	7.3%	3.2%	14.5%
Big	12.9%	17.4%	17.2%	15.5%	11.6%	7.3%	10.5%	6.9%
Full Sample	15.1%	18.8%	18.4%	15.4%	11.1%	6.5%	2.4%	16.4%
Book-to-Market	**-1**	**0**	**1**	**2**	**3**	**4**	**5**	
Small	0.99	1.01	0.97	1.13	0.74	1.02	0.63	
Middle	0.84	0.99	0.91	0.82	0.66	0.62	0.70	
Big	0.63	0.68	0.66	0.59	0.65	0.56	0.61	
Full Sample	0.76	0.94	0.77	0.72	0.66	0.62	0.60	
MV(millions)	**-1**	**0**	**1**	**2**	**3**	**4**	**5**	
Small	5	5	6	6	6	5	5	
Middle	39	35	44	44	42	39	36	
Big	3472	1229	1794	1818	1369	1029	1143	
Full Sample	1734	216	1015	990	544	332	248	
Sample size	**-1**	0	1	2	3	4	5	
1	16	254	15	16	26	34	46	
2	30	238	46	47	59	62	62	
3	37	104	75	72	51	40	27	

Table 2-8 presents results using abnormal 12-month returns, where the benchmark return for each stock is the return on a portfolio matched by size and BM. The results in Table 2-8 again show that a NEI effect exists in the UK market, for both value-weighted and equally weighted returns. The value-weighted abnormal return across NEIS levels decreases monotonically from 3.3% (t = 3.66) for zero-NEIS, to -3.0% (t = -1.07) for quintile 5, for the full sample. Within each size category, the abnormal returns are also consistent with a NEI effect. But the effect is much stronger among small stocks. The value-weighted abnormal return for the small category is 1.0% (t = 0.92) for zero-NEIS, and -14.4% (t = 4.65) for quintile 5. The equivalent results for 'big' stocks are 3.6% (t = 3.47), falling to -2.0% (t = -0.61) for quintile 5. The results are similar for equally weighted returns. For portfolios with negative-NEIS stocks, the abnormal returns are mostly negative, and are more negative using value weighting.

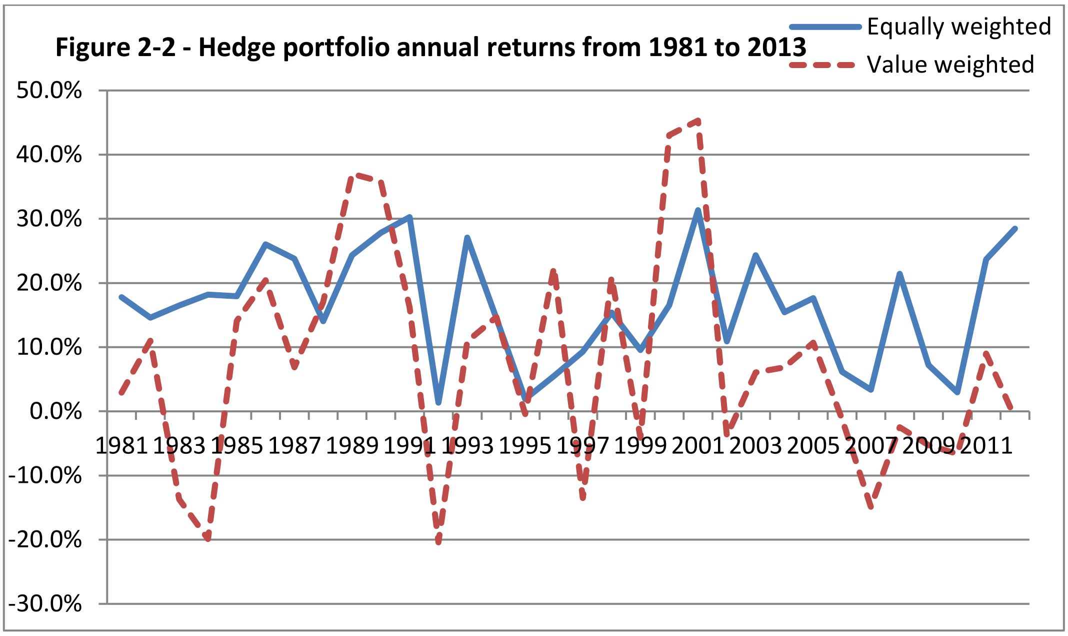
Table 2-8

Abnormal return on portfolios independent-sorted on NEIS and MV for the period 1981 - 2012

The table reports the abnormal returns of value-weighted (VW) and equally-weighted (EW) portfolios sorted independently on MV and short term net equity issuance (NEIS). At the end of June each year, all stocks are categorised into seven groups by the short term net equity issuance: negative NEIS stocks are included in level '-1'; zero NEIS stocks are grouped into level '0'; positive NEIS stocks are categorised into five quintile groups from lowest level'1' to highest level '5'. NEIS is measured as the change of the logarithm of the number of adjusted number of shares outstanding: NEIS = log(adjusted shares outstanding, t-6) – log(adjusted shares outstanding, t-17). Independently, all stocks are categorised into three MV groups where MV is measured as the product of number of shares outstanding and stock price at the end of June. MV percentile of 30% and 70% are used as breaking points for 'small', 'middle' and 'big' groups. The 'Full Sample' group combines all three size groups. At the end of June each year, 21 portfolios are formed based on the intersection between these two sorted groups. t statistics are adjusted for heteroscedasticity and autocorrelation, bolded when statistically significant.

MV level	**NEIS level**							**Hedge Portfolio Return**
VW abnormal annual return	**-1**	**0**	**1**	**2**	**3**	**4**	**5**	**0-5**
Small	-4.7%	1.0%	3.3%	0.3%	0.3%	**-8.1%**	**-14.4%**	**19.8%**
t	-1.32	0.92	0.67	0.07	0.10	**-3.44**	**-4.65**	**7.19**
Middle	1.0%	**2.0%**	2.0%	0.7%	-2.8%	**-5.9%**	**-10.0%**	**13.8%**
t	0.47	**2.56**	1.07	0.53	-1.34	**-2.82**	**-4.47**	**5.67**
Big	**-3.4%**	**3.6%**	**3.1%**	-0.8%	0.0%	-2.1%	-2.0%	6.3%
t	**-2.17**	**3.47**	**2.14**	-0.82	0.00	-1.05	-0.61	1.73
Full Sample	**-3.3%**	**3.3%**	**3.1%**	-0.8%	-0.1%	-2.6%	-3.0%	**7.6%**
t	**-2.25**	**3.66**	**2.19**	-0.80	-0.03	-1.48	-1.07	**2.31**
EW abnormal annual return	**-1**	**0**	**1**	**2**	**3**	**4**	**5**	**0-5**
Small	-0.9%	2.4%	21.4%	1.9%	-0.4%	-5.4%	**-13.1%**	**19.0%**
t	-0.21	1.53	1.20	0.30	-0.10	-1.55	**-4.27**	**9.86**
Middle	1.0%	**2.1%**	1.7%	1.0%	-2.8%	**-6.1%**	**-10.3%**	**14.5%**
t	0.48	**3.71**	0.87	0.64	-1.72	**-2.75**	**-4.90**	**5.82**
Big	-2.1%	2.7%	2.3%	1.4%	-2.4%	**-6.6%**	-4.6%	**6.9%**
t	-0.88	1.75	1.91	1.16	-1.77	**-3.80**	-1.92	**2.73**
Full Sample	-0.3%	**2.2%**	3.3%	1.3%	-2.0%	**-6.4%**	**-10.6%**	**16.4%**
t	-0.17	**3.54**	1.76	1.05	-1.77	**-3.46**	**-6.87**	**10.19**

The hedge portfolios generate abnormal returns that are positive across all size groups, and most are statistically significant. The hedge portfolio returns are much higher for the small and middle portfolios than for the large-size portfolio. For example, the average value-weighted hedge return is 19.8% for small stocks, and 6.3% for large stocks. Figure 2 shows the performance of the hedge portfolios constructed from the full sample. The equally weighted hedge portfolio provides positive annual returns for all 32 years of sample period, while the value-weighted portfolio has a less consistent performance with 19 positive returns. Overall, the results suggest a potential opportunity for making additional raw or abnormal returns from a trading strategy using information on short-term NEI.



Notes:

This figure shows the hedge portfolio returns from June 1981 to December 2013. At the end of June each year, 7 portfolios are formed based on the short term net equity issuance: negative NEIS stocks are included in level '-1'; zero NEIS stocks are grouped into level '0'; positive NEIS stocks are categorised into five quintile groups from lowest level'1' to highest level '5'. Hedge portfolio is constructed by long portfolio '0' and short portfolio '5'. NEIS is measured as the change of the logarithm of the number of adjusted number of shares outstanding: NEIS = log(adjusted shares outstanding, t-6) – log(adjusted shares outstanding, t-17).

To assess whether the NEI effect can be exploited in practice by investors, I estimate the returns from hedge portfolios after transaction costs (Section 2.4.2). The results are in Table 2-9. Data on transaction costs are limited to the period 1991 to 2013. The results before transaction costs for this sub-period are similar to those presented above for the full sample period. Twelve-month returns from hedge portfolios long in zero-NEIS stocks and short quintile 5 stocks are positive across all size categories, and similar in value and statistical significance as the results for 1981-2013. But the estimated transaction costs of implementing the hedge strategy are enormous, at over 30% per year for small-size and around 15% per year for middle-size portfolios. Table 2-9 shows that after deduction of transaction costs, the hedge returns become negative for almost all value and equally weighted portfolios. In particular, the large and significant positive hedge return for small stocks becomes a large and significant negative return after costs. The only positive return after costs is the value-weighted return for the largest stocks, which is 1% per year (t = 0.30). We conclude that the NEI effect cannot be exploited allowing for transaction costs.

Table 2-9

Transaction cost adjusted low-minus-high hedge return from 1991 - 2013

The table reports the with/without transaction cost low-minus-high hedge returns of value-weighted (VW) and equally-weighted (EW) portfolios sorted independently on MV and short term net equity issuance (NEIS). At the end of June each year, all stocks are categorised into seven groups by the short term net equity issuance: negative NEIS stocks are included in level '-1'; zero NEIS stocks are grouped into level '0'; positive NEIS stocks are categorised into five quintile groups from lowest level'1' to highest level '5'. NEIS is measured as the change of the logarithm of the number of adjusted number of shares outstanding: NEIS = log(adjusted shares outstanding, t-6) – log(adjusted shares outstanding, t-17). Independently, all stocks are categorised into three MV groups where MV is measured as the product of number of shares outstanding and stock price at the end of June. MV percentile of 30% and 70% are used as breaking points for 'small', 'middle' and 'big' groups. The 'Full Sample' group combines all three size groups. At the end of June each year, 21 portfolios are formed based on the intersection between these two sorted groups. Low-minus-high hedge portfolio is formed by long one unit zero NEIS portfolio and short one unit level five NEIS portfolio across all size groups. T statistics are adjusted for heteroscedasticity and autocorrelation, bolded when statistically significant.

	Equally weighted			**Value weighted**		
Size	**before adjustment**	**transaction cost**	**after transaction cost**	**before adjustment**	**transaction cost**	**after transaction cost**
Small	**19.0%**	36.0%	**-17.1%**	**18.5%**	30.3%	**-11.9%**
	(9.04)		**(-5.30)**	**(5.86)**		**(-2.77)**
Middle	**12.9%**	15.7%	-2.8%	**12.6%**	13.4%	-0.8%
	(4.06)		(-0.87)	**(4.21)**		(-0.28)
Big	3.5%	7.1%	-3.6%	5.5%	4.5%	1.0%
	(1.29)		(-1.19)	(1.79)		(0.30)
Full Sample	**14.2%**	22.7%	**-8.4%**	**7.4%**	5.8%	1.5%
	(8.06)		**-(3.76)**	**(2.56)**		(0.52)

2.5.3 Asset pricing tests

In this section I examine the NEI effect (before transaction costs) in the context of the asset pricing models outlined in Section 2.4.3. We find that the investment and profitability factors are able to provide extra explanatory power compared with the three-factor model, which is consistent with the results of Fama and French (2015b). However, none of the asset pricing models is able to fully capture the NEI effect. Table 2-10 summarises how the factors are constructed.

Table 2-10

Factor construction methods

Factor	**Sort**	**Breakpoints**	**Factors and their components**
Size	2×3 sorts on Size and BM	Size: largest 350 stocks median BM: largest 350 stocks 30th & 70th percentile	$\mathrm{SMB} = (\mathrm{SL}+\mathrm{SM}+\mathrm{SH})/3-(\mathrm{BL}+\mathrm{BM}+\mathrm{BH})/3$
BM	2×3 sorts on Size and BM	Size: largest 350 stocks median BM: largest 350 stocks 30th & 70th percentile	$\mathrm{HML} = (\mathrm{SH}+\mathrm{BH})/2-(\mathrm{SL}+\mathrm{BL})/2$ $\mathrm{UMD} = (\mathrm{SU}+\mathrm{BU})/2-(\mathrm{SD}+\mathrm{BD})/2$
Momentum	2×3 sorts on Size and Momentum	Size: largest 350 stocks median Momentum: largest 350 stocks 30th & 70th percentile	$\mathrm{UMD} = (\mathrm{SU}+\mathrm{BU})/2-(\mathrm{SD}+\mathrm{BD})/2$
Profitability	2×3 sorts on Size and ROE or OP/B	Size: largest 350 stocks median ROE or OP/B: largest 350 stocks 30th & 70th percentile	$\mathrm{ROE} = (\mathrm{SH}+\mathrm{BH})/2-(\mathrm{SL}+\mathrm{BL})/2$ $\mathrm{OP/B} = (\mathrm{SR}+\mathrm{BR})/2-(\mathrm{SW}+\mathrm{BW})/2$
Investment	2×3 sorts on Size and I/A	Size: largest 350 stocks median I/A: largest 350 stocks 30th & 70th percentile	$\frac{\mathrm{I}}{\mathrm{A}} = (\mathrm{SC}+\mathrm{BC})/2-(\mathrm{SA}+\mathrm{BA})/2$
Liquidity	2×4 subsequent sorts on size and liquidity	Size: threshold of largest 350 stocks liquidity: 15th , 35th , 65th , 85th percentile for large-size/small-size group	$\mathrm{liquidity} = \mathrm{LL}-\mathrm{HL}$

Table 2-11 provides descriptive statistics about the time series of the asset pricing factors. The average market premium is 0.46% per month (t = 1.67). The size premium in the UK market is -0.03% (t = -0.11), which is consistent with previous findings about the insignificance of the size effect in the UK (Gregory et al., 2001). The book-to-market factor (HML) has an average monthly premium of 0.48% (t = 2.01), and the momentum factor (MOM) has a similar monthly premium of 0.47% (t = 1.12). Both profitability factors have positive monthly premium: 0.32% for OP/B and 0.16% for ROE. The investment factor (I/A) has the largest monthly premium, of 0.53 (t = 2.73).

Regressions are run for each of the 21 portfolios sorted by NEIS and size at the end of June each year. The dependent variable is the monthly value-weighted portfolio return in excess of the Treasury-bill rate. If a model is successful in explaining the monthly excess returns, the alpha (intercept) terms should each be approximately equal to zero across the 21 regressions. A test statistic is calculated to test the null hypothesis that $\alpha_p = 0$ for all portfolios p, using the method of Gibbon et al. (1989) – GRS test.

The time series test:

$$\boldsymbol{r_i} = \alpha_i + \boldsymbol{\beta}_i'\boldsymbol{f}_t + \boldsymbol{\varepsilon_t^i} \qquad \text{for i = 1, 2, 3 … N (N asset in total)} \tag{30}$$

where:

$\boldsymbol{r_i}$	is the vector of excess return of investment portfolio over treasury bill rate for asset i.
$\boldsymbol{f}_t$	is the vector of asset pricing model factor return at period t: e.g. smb, hml, cma, etc.
$\boldsymbol{\beta}_i'$	is the vector of OLS time series regression coefficients on model factors
$\boldsymbol{\varepsilon_t^i}$	is the vector of residual values of OLS time series regression for asset i

Null hypothesis:

α_i for all N asset is jointly equal to zero.

Test statistic:

$$\frac{T-N-K}{N}\left(1+\boldsymbol{E_T}(\boldsymbol{f})'\,\widehat{\boldsymbol{\Omega}}^{-1}\boldsymbol{E_T}\,(\boldsymbol{f})\right)\widehat{\boldsymbol{\alpha}}'\widehat{\boldsymbol{\Sigma}}\,\widehat{\boldsymbol{\alpha}} \sim F_{N,\ T-N-K} \tag{31}$$

where:

T	is the number of time period
N	is the number of assets (portfolios)
K	is the number of asset pricing model factors
$\boldsymbol{E_T}(\boldsymbol{f})$	is the vector of expected value of asset pricing model factors
$\widehat{\boldsymbol{\alpha}}$	is the vector of estimated intercepts of N assets(portfolios)

$$\widehat{\boldsymbol{\Omega}} = \frac{1}{T}\sum_{t=1}^{T}\,[\boldsymbol{f}_t - \boldsymbol{E_T}(\boldsymbol{f})\,]\;[\boldsymbol{f}_t - \boldsymbol{E_T}(\boldsymbol{f})\,]',$$

$$\widehat{\boldsymbol{\Sigma}} = \frac{\boldsymbol{1}}{\boldsymbol{T}}\sum_{\boldsymbol{t=1}}^{\boldsymbol{T}}(\widehat{\boldsymbol{\varepsilon}}\;\widehat{\boldsymbol{\varepsilon}}')$$

where:

$\widehat{\boldsymbol{\varepsilon}}$	is the matrix of OLS time series residuals of N assets across T periods

P-value of GRS statistic were calculated.

Table 2-11

Descriptive Statistics of Factors

The table reports the descriptive statistics of the factors. RMRF: excess return of market index over risk Treasury bill rate; SMB: size factor; HM: book-to-market factor; UMD: momentum factor; I/A: investment factor; OP/B: profitability factor; ROEe: profitability factor; TR: liquidity factor Turnover; Ppread: relative bid-ask spread liquidity factor.

	RMRF	SMB	HML	UMD	I/A	OP/B	ROE	Pspread
Mean	0.46	-0.03	0.48	0.47	0.53	0.32	0.16	0.70
Median	0.90	-0.18	0.33	0.71	0.13	0.29	0.13	0.39
Maximum	9.90	17.43	11.62	24.38	12.35	12.78	11.90	21.24
Minimum	-13.61	-14.54	-13.53	-27.41	-8.76	-12.64	-9.08	-7.51
Sdt. Dev.	0.04	0.04	0.03	0.05	0.03	0.03	0.02	0.03
Newey-west t	1.67	-0.11	2.01	1.12	2.73	1.25	0.97	2.54
Observations	258	258	258	258	258	258	258	258

Table 2-12 shows the various factor models with their corresponding GRS test results. The GRS results reject all the models as explanations of the observed excess returns on the 21 size-NEIS portfolios: the intercepts are not jointly equal to zero for any model. However, by including the investment factor, profitability factor and bid-ask spread liquidity factor, a six-factor model provides the best description of the excess returns of size-NEIS portfolios, as its GRS test statistic is the lowest among the models. The results indicate that the additional three factors are able to provide explanatory power for the NEI effect beyond that of the three-factor model, but NEIS retains some explanatory power that is independent of the six factors.

The same table (Table 2-12) also shows the intercepts of the 21 regressions for a selection of the models[7]. We choose the CAPM, the Fama-French three-factor model, and two augmented models. The results are consistent with the GRS test. Both investment factors, and the profitability factor, improve explanatory power, as shown by reduced variation in the intercepts. The negative intercepts in high-NEIS portfolios are partially explained by the five-factor model. But the variation in the excess returns across the 21 portfolios is not fully explained by any of the models.

Table 2-13 illustrates the regression coefficients of the 21 portfolios using the Fama-French three- factor model augmented by the investment factor I/A, profitability factor ROE and the bid-ask spread. From the factor loadings, I can observe the exposure of the portfolios to the investment and profitability factors. The portfolios with negative NEIS in general have the positive exposure to the investment factor, and portfolios with higher NEIS tend to have negative exposure. Therefore low-NEIS portfolio returns tend to covary positively with low-investment stock returns while high-NEIS portfolios returns tend to covary positively with high-investment stock returns. Similarly, the exposure to ROE indicates that high-NEIS portfolio returns tend to be positively correlated with low profitability stock returns. According to the statistics for the investment and

[7] For the profitability factor, I report the results of the ROE factor only, the results for OP/B are similar they are available upon request.

profitability factors, low-investment firms and high-profitability firms tend to have larger return. The higher return of lower investment stocks and higher profitability stocks could therefore partially explain the monotonic change of NEIS portfolio returns and the positive intercepts of zero-NEIS portfolios.

Table 2-12

Time series Regression intercepts for multiple asset pricing models

This table reports the regression intercepts with the corresponding t-statistics for alternative factor models for monthly 21 size-neis portfolios July 1992-December 2013. It also compares GRS results. Factor definition: rmrf: excess return of market index over risk Treasury bill rate; SMB: size factor; HM: book-to-market factor; UMD: momentum factor; I/A: investment factor; OP/B: profitability factor; ROEe: profitability factor; TR: liquidity factor Turnover; Ppread: relative bid-ask spread liquidity factor. The LHS variables are monthly portfolios excess returns. The RHS asset pricing models are, CAPM model, Fama-French 3 factor model and augmented Fama-French factor models using investment factor, profitability factor and liquidity factor. Average monthly portfolio excess returns are presented under 'Excess return'. The last column reports F-statistics with the corresponding p-value from GRS-F tests for the joint significance of the intercepts.

Size quintile	**Neis quintile**														**GRS F Test**
	a							**t(a)**							
	-1	**0**	**1**	**2**	**3**	**4**	**5**	**-1**	**0**	**1**	**2**	**3**	**4**	**5**	
	Excess return														
1	0.49	1.11	0.84	1.64	0.76	0.41	0.05	1.11	**3.71**	1.67	**2.87**	1.58	0.91	0.11	
2	0.84	0.66	0.83	0.48	0.42	-0.10	-0.38	**2.62**	**2.17**	**2.41**	1.35	1.14	-0.25	-0.80	
3	0.46	0.91	0.83	0.43	0.29	0.41	0.50	1.64	**3.18**	**2.90**	1.75	0.84	1.05	1.24	
	CAPM														
1	0.23	0.85	0.43	1.28	0.35	0.08	-0.27	0.55	**3.22**	0.95	**2.37**	0.81	0.19	-0.65	4.86
2	0.54	0.30	0.43	0.06	0.00	-0.57	-0.89	**1.96**	1.29	1.62	0.22	0.00	-1.79	**-2.35**	<0.01
3	0.05	0.49	0.36	0.04	-0.21	-0.11	0.00	0.31	**2.96**	**2.94**	0.37	-0.98	-0.40	-0.01	
	Fama-French 3 factor model														
1	0.26	0.90	0.38	1.29	0.33	0.19	-0.19	0.69	**5.04**	0.95	**2.72**	0.94	0.53	-0.52	4.61
2	0.47	0.26	0.38	-0.02	0.04	-0.48	-0.84	**2.26**	**2.19**	**2.33**	-0.11	0.21	**-2.41**	**-3.14**	<0.01
3	-0.06	0.47	0.39	0.03	-0.27	-0.12	-0.08	-0.34	**2.79**	**3.19**	0.24	-1.37	-0.47	-0.27	
	Three factor plus I/A and ROE														
1	0.18	0.93	0.47	1.57	0.37	0.37	0.07	0.47	**5.06**	1.14	3.23	1.04	1.00	0.18	4.21
2	0.46	0.28	0.48	-0.07	0.12	-0.21	-0.65	**2.11**	**2.26**	**2.89**	-0.38	0.66	-1.07	-2.37	<0.01
3	-0.16	0.42	0.42	0.02	-0.03	0.09	0.27	-0.94	**2.46**	**3.32**	0.13	-0.16	0.33	0.98	
	Three factor plus I/A, ROE and pspread														
1	-0.13	0.34	0.00	0.96	-0.20	-0.60	-1.05	-0.32	**2.28**	-0.01	1.94	-0.55	-1.80	**-3.37**	3.54
2	0.47	0.14	0.42	-0.07	0.01	-0.32	-1.15	**2.06**	1.08	**2.42**	-0.35	0.07	-1.58	**-4.28**	<0.01
3	-0.13	0.32	0.40	0.09	0.10	0.16	0.30	-0.72	1.76	**2.96**	0.65	0.48	0.57	1.04	

Table 2-13

Time series regression results

This table reports the regression results for regressions for 21 size-neis portfolios July 1992-December 2013. $r_{pt} - r_{ft} = \alpha_p + \beta_1 RM_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 ROE_t + \beta_5 \frac{I}{A_t} + \beta_6 pspread$. This table shows the coefficients and their corresponding t-statistics for each of the RHS variable.

Size quintile	**Neis quintile**														
	Factor								***t***						
	-1	**0**	**1**	**2**	**3**	**4**	**5**		**-1**	**0**	**1**	**2**	**3**	**4**	**5**
	alpha														
1	-0.13	0.34	0.00	0.96	-0.20	-0.60	-1.05		-0.32	**2.28**	-0.01	1.94	-0.55	-1.80	**-3.37**
2	0.47	0.14	0.42	-0.07	0.01	-0.32	-1.15		**2.06**	1.08	**2.42**	-0.35	0.07	-1.58	**-4.28**
3	-0.13	0.32	0.40	0.09	0.10	0.16	0.30		-0.72	1.76	**2.96**	0.65	0.48	0.57	1.04
	RM-Rf														
1	0.58	0.66	0.88	0.75	0.94	0.87	0.85		**5.52**	**16.95**	**8.10**	**5.89**	**10.24**	**10.12**	**10.62**
2	0.56	0.74	0.76	0.82	0.81	0.85	1.08		**9.53**	**22.45**	**16.87**	**17.11**	**17.42**	**16.32**	**15.65**
3	0.91	0.96	1.01	0.82	0.94	1.02	0.95		**20.21**	**20.73**	**29.51**	**23.81**	**18.09**	**14.28**	**12.71**
	SMB														
1	0.79	0.70	0.83	0.93	0.98	0.69	0.58		**6.84**	**16.42**	**6.88**	**6.65**	**9.64**	**7.22**	**6.53**
2	0.80	0.84	0.87	0.93	0.97	0.96	1.03		**12.25**	**23.24**	**17.50**	**17.42**	**18.92**	**16.78**	**13.47**
3	-0.09	-0.02	0.11	0.01	0.38	0.33	0.36		-1.77	-0.36	**2.78**	0.33	**6.68**	**4.13**	**4.32**
	HML														
1	0.07	0.12	0.28	0.21	0.30	0.15	0.14		0.50	**2.22**	1.80	1.18	**2.33**	1.21	1.20
2	0.22	0.24	0.20	0.28	0.06	-0.06	0.21		**2.60**	**5.14**	**3.22**	**4.07**	0.85	-0.86	**2.17**
3	0.16	0.03	0.00	-0.01	0.25	0.16	0.40		**2.55**	0.52	0.04	-0.22	**3.38**	1.62	**3.78**
	I/A														
1	0.23	0.07	0.09	-0.12	0.08	-0.14	-0.07		1.43	1.14	0.55	-0.60	0.54	-1.07	-0.55
2	0.08	0.00	-0.02	0.11	0.00	-0.21	-0.20		0.87	-0.05	-0.28	1.53	-0.04	**-2.55**	-1.84
3	0.19	0.11	-0.09	0.05	-0.42	-0.39	-0.69		**2.70**	1.56	-1.75	0.99	**-5.17**	**-3.54**	**-5.95**
	ROE														
1	-0.01	-0.08	-0.29	-0.56	-0.13	-0.20	-0.48		-0.05	-1.18	-1.54	**-2.59**	-0.85	-1.35	**-3.46**
2	-0.05	-0.03	-0.25	0.01	-0.21	-0.53	-0.24		-0.54	-0.50	**-3.29**	0.07	**-2.61**	**-5.99**	**-2.00**
3	0.06	0.00	0.03	-0.04	-0.21	-0.15	-0.19		0.84	0.04	0.53	-0.63	**-2.30**	-1.22	-1.44
	Pspread														
1	0.31	0.57	0.46	0.60	0.56	0.96	1.10		**2.51**	**12.57**	**3.63**	**4.01**	**5.18**	**9.47**	**11.65**
2	-0.01	0.14	0.06	0.00	0.10	0.11	0.49		-0.19	**3.65**	1.09	-0.03	1.84	1.83	**6.09**
3	-0.03	0.10	0.03	-0.07	-0.13	-0.07	-0.03		-0.56	1.93	0.64	-1.70	**-2.05**	-0.82	-0.36

Exposure to the liquidity factor does not show a monotonic change across the levels of NEIS portfolios. This suggests that the liquidity factor does not explain the NEI effect. However, the liquidity loading does change monotonically across three size groups. Portfolios of small stocks tend to be more positively correlated with the low-liquidity stock returns. The improvement in the GRS test statistics from the liquidity factor would appear to be because bid-ask spread helps explain expected return across the three size groups, rather than across NEIS categories.

2.6 Conclusion

Net equity issuance is one of a number of ‘anomaly variables’ that have been discovered, in recent years, to have predictive power regarding future stock returns. This paper examines the extent to which there is a NEI effect in the UK stock market. Results from Fama-MacBeth regressions show that higher NEI is associated with lower subsequent returns, that this relation persists when size, book-to-market, and momentum variables are introduced, and that it is pervasive across stocks of different size. We then study abnormal returns on portfolios independently sorted by NEI and size. For zero and positive NEI, higher NEI is associated with lower future abnormal returns, again across all size categories. The highest abnormal returns are for zero-NEI portfolios. However, negative-NEI portfolios (firms with net repurchases) tend to show negative subsequent abnormal returns. These last two findings differ from the US evidence, in which repurchase portfolios have large positive abnormal returns, and zero-issuance portfolios have abnormal returns close to zero. My evidence for the UK is that the simple negative relation between NEI and future returns, or abnormal returns, applies across the spectrum of zero and positive NEI firms, but does not apply when negative-NEI firms are considered as well.

We also find that there is no NEI effect allowing for transaction costs. We estimate the transaction costs of implementing a hedge portfolio consisting of a long positive in zero-NEI shares and short positive in shares with the highest quintile of NEI. The gains from the hedge portfolio more than disappear when transaction costs are subtracted.

Finally, I explore whether the NEI effect persists in the context of a variety of asset pricing models, with up to six factors. We form a number of portfolios based on independent sorts by NEI and size, and regress the excess returns (above the risk-free rate) over time on the factors in the relevant model. If a model is doing a good job of explaining the excess returns across the NEI-size portfolios, the intercept terms should all be approximately zero. A model using the Fama-French three-factors, augmented by investment, profitability and liquidity factors, has the greatest explanatory power for the NEI-size portfolio returns. But the GRS test, of the hypothesis that the intercepts are jointly equal to zero, rejects the hypothesis for all the models. Thus, I conclude that the NEI effect is not fully explained by existing asset pricing models.

Questions for further research include why the findings for repurchase and zero-issuance portfolio differ from the US evidence. McLean et al. (2009) also find evidence that returns can be negative following repurchases. Another question is whether the NEI effect for positive issuance in the UK is due to SEOs and share issues to fund takeovers, or whether it persists when these events are removed, as Pontiff and Woodgate (2008) find in US data.

CHAPTER 3

On the Information Content of New Asset Pricing Factors in the UK

3.1 INTRODUCTION

Asset pricing models have been widely employed in the academic literature to capture variations in stock returns. Due to their influence in the finance literature, the properties of three-factor models have been investigated by numerous researchers, mainly using US and international data. However, the performance of the most widely used models such as the Fama-French (FF) three-factor model has been subject to criticism. When the FF three-factor model was employed as the baseline model, many paper s have shown a relationship between additional factors and the cross-section of stock returns (Harvey, Liu and Zhu, 2016). Empirical asset pricing researchers have therefore proposed new factor models aimed at improving on the three-factor model. Fama and French (2015a) propose a new five-factor model which extends the FF three-factor model, using profitability and investment factors. Hou, Xue and Zhang (2015), by contrast, use a four-factor model with a different formation of profitability factors and making the value factor redundant. Both Fama and French (2015a) and Hou, Xue and Zhang (2015) demonstrate the performance of their new factor models by using various sorted portfolios on the left-hand side. Although both new papers justify the economic interpretation of their factor models, the new factor models are believed to be empirically motivated. They use US data and show that the new factor models outperform the Fama-French three-factor model and that the majority of capital market anomalies are subsumed by the new models.

For the newly proposed US factor models, out-sample testing is desirable from a practical perspective. Fama and French (2012) test and find inconsistent the performance of their three-factor model in describing international stock return cross-sections. Fama and French (2017), in a follow-up paper, examine the power of their five-factor model using international regional data. Interestingly, they report significant differences in model performance between North America, Europe, Asia Pacific and Japan. For instance, the value factors are found to be redundant in North America while in Europe investment factors and size factors hardly provide any information. These differences between regions therefore suggest that researchers need to keep abreast of the use of new factor models outside the US markets. Moreover, Fama and French (2012; 2017) suggest in both papers that regionally constructed factor models out-perform global models. Griffin (2002) compares the performance of the FF three-factor model between regional level and country level and concludes that country-level factor models have a better performance. In the UK, past literature has followed Griffin (2002) and focused on local FF three-factor model performance. Discernible differences from the US results have been reported (Gregory, Tharyan and Christidis, 2013; Michou, Mouselli and Stark, 2014). However, there is limited evidence regarding the performance of the new factor models in the UK. The first contribution of this study is to fill this gap by testing the performance of the new factor models using a UK sample during the period from July 1990 to December 2013.

Another crucial issue for the new empirical asset pricing models is the choice of factors. Evidence suggests that the information content of new asset pricing factors is sensitive to factor variable definition and methods of factor construction (Fama and French, 2015b). Different choices of factor variable definition have been proposed for the five-factor models, especially with respect to profitability factors. For instance, Fama and French (2015a) follow Novy-Marx (2013) and construct their profitability factor using operating profitability scaled by book value. Hou, Xue and Zhang (2015) instead use income before extraordinary items as the numerator of their profitability measure. Fama and French (2015b) compare alternative factor forms such as cash profitability (Ball *et al.*, 2015) and quality minus junk (Asness *et al.*, 2013). Their results suggest that using cash profitability measures and the small-end construction method improve the performance of the five-factor model. The arbitrary nature of factor construction is more pervasive outside the US market. For instance, Michou, Mouselli and Stark (2014) find that researchers using UK data construct SMB and HML in nine different ways. It is therefore reasonable, in the early stages of development of a new model, to test the sensitivity of the new factor model’s performance to the choices of factor construction. The second object of this chapter is to provide an insight into the choice of factor construction method in the UK.

Given the discussion above, the main aim of the chapter is to cast light on the efficiency of new asset pricing factors in the UK as a way of controlling for risk in the UK asset pricing literature. This paper contributes to the literature in the following ways:

- It is the first to illustrate how profitability and investment influence stock return patterns in the UK stock market;
- Secondly, the chapter provides evidence for the information content of new asset pricing factors in the UK, as there is very limited evidence on how new factor models perform on UK data specifically;
- In addition, the chapter contributes to the stream of literature related to the sensitivity of factor choices, as it employs alternative profitability measures in seeking to find the most effective profitability factors in the UK market.

I attempt a number of tasks within the overall objective of this chapter in evaluating the performance of a five-factor model in the UK. First, I seek to establish whether there are profitability and investment patterns across the UK stock returns. Secondly, I construct various versions of new asset pricing factors and test whether they are statistically different from zero. Thirdly, I use factor-spanning tests to examine the relative informativeness of all versions of the asset pricing factors, especially the profitability factors. Finally, I employ time-series asset pricing tests to compare the performance of the new asset pricing models, seeking to find effective forms of new factor models for the UK.

Based on the sorted portfolio approach used, returns suggest that the size effect does not exist while the value effect is significant in the UK market, which is consistent with previous academic evidence (Gregory, Tharyan and Christidis, 2013; Michou, Mouselli and Stark, 2014). For my new profitability factor and investment factor, distinguishable stock return effects are evident in the UK market.

Spanning tests produce initial results for the choice of new factor models. Firstly, I find consistent evidence that SMB does not provide additional information uncaptured by the other factors, which suggests that SMB is a redundant factor in the UK. Secondly, I find that the value factor HML is spanned by the new factors and when used the small end does not save the value factor. This result is consistent with the findings in the US market (Fama and French, 2015a). Thirdly, the investment factor provides information uncaptured by the other factors. The use of the small-end factor construction method further improves its information content. For profitability factors, my evidence suggests that using total asset as the denominator does provide extra information compared with those scaled by book-to-equity. Between the three versions of profitability measures used, operating income and income before extraordinary items outperform gross profit. However, the interaction between choice of construction methods and scaler makes it difficult to decide on the best profitability factor.

GRS tests results are in general consistent with factor-spanning tests. I use sorting combinations of size and book-to-market (BM), size and profitability, and size and investment (I/A). I compare more than twenty versions of factor models in terms of their asset pricing test performance. GRS tests confirm that SMB and HML are redundant factors in the UK. The results further show that using operating profit or income before extraordinary items produces the best profitability factors. However, the choice of scaler and small/normal end factor is sensitive to portfolio sorting methods. Instead of a five-factor model, a three-factor model including a market factor (RM-RF), an investment factor (CMA_S) and a profitability factor (RMW) explains most of the variations across sorted portfolio returns in the UK.

The structure of this chapter is as follows: Section 2 discusses the empirical evidence; Section 3 explains the data and sample; Section 4 describes the methodology used; Section 5 explain the factor construction procedure; Section 6 presents the results; and Section 7 draws conclusions.

3.2 LITERATURE REVIEW

One of the key questions that finance researchers seek to answer is why assets have heterogeneous returns, especially the return cross-sections among stock prices. The mainstream literature on both theoretical and empirical asset pricing for the stock market is based on the assumption that higher average returns are compensating investors who hold assets with higher systematic risks. So far, the most widely employed asset pricing models are the linear factor models proposed by Fama and French. The Fama and French three-factor model (Fama and French, 1993) has had such a large impact that the paper has become one of the most cited papers in the finance literature. The history of asset pricing factor models research starts from the Capital Asset Pricing Model (CAPM). The inadequacy of the CAPM in explaining many of the market “anomalies” was what drove the proposing of the Fama-French three-factor model and most recently the Fama-French five-factor model.

The following literature review is mainly constructed following chronological order. The first section reviews the proposing and development of the CAPM. Then I review studies on price-based anomalies that explain stock return cross-sections, especially those that inspired the Fama-French factor models. The third section reviews papers on the Fama-French three-factor model. The follow-up section covers return-based studies that have inspired the momentum factor in Carhart’s (1997) model. Then I present the major accounting-based anomalies, followed by the new Fama-French-type models. The final section presents the relevant literature regarding the UK stock market.

3.2.1 The Capital Asset Pricing Model

Earlier researchers (Sharpe, 1964; Lintner, 1965; Mossin, 1966) develop the Capital Asset Pricing Model (CAPM) based on the mean-variance portfolio theorem proposed by Harry Markowitz (1959). His model assumes that investors are risk-averse and only care about their single-period portfolio returns and variance. Hence, rational investors would choose to hold portfolios that are "mean-variance-efficient", which has the minimum variance at a given level of expected return and maximum return at a given level of variance.

Sharpe (1964) and Lintner (1965) extend the mean-variance portfolio theory with two additional assumptions. The first assumption is that all investors have the same perception regarding the joint distribution of the asset returns. The second assumption is that all investors can borrow and lend at the same risk-free rate without constraints. As a result, the CAPM argues that all investors face the same investment opportunity set and would only hold a combination of market portfolio and risk-free assets, with weights depending on the investors' personal risk preferences. Furthermore, the CAPM implies that the expected return of an asset should be the risk-free interest rate plus the asset's market beta times the risk premium of the market portfolio:

$$r_i = r_f + \beta_{im}(R_m - r_f)$$

The empirical performance of the CAPM model has been unsatisfactory. Papers such as Douglas (1968), Black, Jensen and Scholes (1972), Miller and Scholes (1972), Blume and Friend (1973) and Fama and MacBeth (1973) report evidence that although average returns are positively correlated with market beta, the monotonic changes in betas are too "flat" to explain the return cross-sections. As a result, the cross-sectional regression intercepts are consistently over treasury-bill rates in the US market. The time-series regressions reported by Friend and Blume (1970), Jensen, Black and Scholes (1972) and Stambaugh (1982) show positive intercepts for low-beta portfolios and negative intercepts for high-beta portfolios. Fama and French (2004) extend the earlier research and reject the empirical assumptions implied by the CAPM using a US sample from 1928 to 2003.

The poor performance of the CAPM may be attributable to the problems imbedded in the model's empirical tests. As argued by Fama and French (2004), one could argue that the CAPM can never be tested accurately. The first reason is that left-hand-side portfolios used in the research do not include all marketable assets for investors in the market. The second reason is related to the difficulty in measuring the true "market portfolio". The commonly used proxy for market portfolio is the aggregated US stock market return. Roll (1977) argues that the market portfolio should consist of all risky assets, which should include real estate, bonds, human capital and other non-equities. He shows that the incompleteness of the market portfolio will result in estimation errors in beta, which invalidates the CAPM empirical test results.

The CAPM model is also criticized for its potential misspecification problem. Ross (1976) proposes an alternative pricing theory, Arbitrage Pricing Theory (APT), where he assumes that investors believe asset returns follow a factor structure. In addition, investors try to maximize certain types of utility function. Furthermore, Ross (1976) assumes that the market equilibrium drives away arbitrage opportunities, and thus the expected returns of assets should be described by a linear model of factor loadings. Both the CAPM and APT models imply that expected returns of assets are described by a linear relationship between assets' expected returns and their covariances with other variables. APT suggests that factors apart from the market portfolio could serve as factors in the model.

The intertemporal CAPM (ICAPM) developed by Merton (1973) expands the CAPM model into a multi-period model. ICAPM suggests that an asset's expected return stems from its covariance with the market portfolio return and its covariance with future available returns. The change in investment opportunity set should be represented by a group of state variables that capture the conditional distribution of future available returns. Campbell and Vuolteenaho (2004) propose a two-factor ICAPM model by decomposing the market portfolio beta of a stock into two constituents, one capturing news about the market's future cash flow and one representing news about the market's discount rates. The paper uses VAR to implement the decomposition. As ICAPM suggests that investors care more about permanent cash-flow-led volatilities than about impermanent discount-factor-driven changes in the aggregated market, cash-flow beta should have a higher risk price than discount-rate beta. The authors provide consistent results that small stocks and value stocks tend to have higher cash-flow beta, which mitigates the inadequate explanatory power of the CAPM.

3.2.2 Price-based anomalies

Starting from the late 1970s, a number of papers reveal empirical evidence that challenge the CAPM model. This stream of academic literature provides new evidence that variables other than market beta predict future stock returns. The early work focuses on price-based ratios that provide further information on the future stock returns (Basu, 1977; Banz, 1981; Rosenberg, Reid and Lanstein, 1985; Bhandari, 1988; Fama and French, 1992). The evidence has two implications: the anomalous results could either mean inefficiencies of the stock market, or it could be that the CAPM model is misspecified and more risk factors should be included in the asset pricing model. Fama and French (2004) corroborate the latter view and state that as stock price depends on both expected cash flows and expected returns, it is no surprise to find the linkage between price cross-section and expected return cross-section.

Basu (1977) examines the relation between stock returns and their price to equity (P/E) ratios. He sorts US common stocks into five portfolios using their P/E ratios, with a sample period from 1957 to 1971. He finds that portfolios with low P/E ratios tend to have higher future stock returns. The five portfolios have a similar level of CAPM betas, suggesting that the monotonic change in returns is not explained by the CAPM. The results are also consistent for CAPM alphas: portfolios with lower P/E ratios have higher CAPM alphas and vice versa. The author argues that the CAPM model could have been misspecified and P/E ratios could be a proxy for some omitted risk factor.

Banz (1981) uses common stocks from 1936 to 1975 and quantifies the relationship between size and returns. He sorts the sample into 25 size and CAPM market beta portfolios. The empirical results of Fama-Macbeth (1973) regressions show that small stocks earn excessive returns compared with larger stocks after controlling for CAPM risks. The results also reveal that the size effect is not linear, and the main anomalous part is obtained from the smallest portfolios. The profit of small-minus-big strategy is volatile across different sub-periods. The author also suggests that CAPM may have been misspecified. Conjectures are made by the author, suggesting that size could be the proxy of omitted variables such as the P/E ratio, or that smaller firms are subject to higher information asymmetry and thus assigned higher systematic risks.

Rosenberg, Reid and Lanstein (1985) use a trading portfolio perspective and find that book-to-market ratio can be used to predict future stock returns. They use a sample from 1973 to 1980 and construct hedge portfolios based on book-to-market ratios. The strategy is designed so that weights on the long and short portfolios have one standard deviation above and below the cross-sectional mean of book-to-market ratios across the sample period. The strategy generates positive returns for 102 out of 141 months tested and its positive monthly profit is highly significant with 36 basis points of risk-adjusted alpha and a 5.7 *t*-statistic. The authors also illustrate that there is seasonality in the book-to-market trading strategy. Consistent with the January effect, the most pronounced profits cluster in January.

Bhandari (1988) establishes the link between debt/equity ratio and future stock returns. He employs the Fama-Macbeth (1973) regression for a sample period 1948–1979. The regression results suggest that both debt/equity ratio and size predict future stock returns after controlling for market beta. Debt/equity ratio has a statistically significant coefficient of 0.13 percent monthly returns. The author further tests the seasonality of both explanatory variables. The results indicate that the size effect is concentrated in January whereas the debt/equity effect is significant after excluding January from the sample. Therefore the author argues that debt/equity ratio should proxy a risk factor, which captures systematic risks beyond market beta.

Fama and French (1992) use both a double-sorted portfolio returns analysis and the Fama-Macbeth (1973) cross-sectional regression analysis to re-examine the explanatory power of variables such as book-to-market ratio, size, P/E ratio, asset-to-book ratio and asset-to-market ratio. The sorted portfolio returns confirm that there is a significant correlation between book-to-market ratio, size and future returns. The formal tests of cross-sectional regressions using US stocks from 1963 to 1990 shed light on the relative information content of the variables. The explanatory power of asset-to-book ratio and asset-to-market ratio is captured by book-to-market ratio. The market beta does not play a significant role once size is controlled for in the regression. The predictive power of the P/E ratio is spanned by both size and the book-to-market ratio. The authors suggest that the ratios tested represent different ways of extracting information from price cross-sections about the expected returns cross-section. They conclude that, amongst the group of possible candidates, size and book-to-market capture the most information.

To reconcile the strong information contained in size and book-to-market ratio, papers propose different models to explore their potential economic explanation. Berk (1995) suggests that the size effect exist because smaller firms are riskier. Assuming all firms have identical expected cash flow and the same size, riskier firms tend to have a relatively smaller market value and thus higher expected return. Therefore, he argues that size and size-related ratios such as book-to-market ratio should be related to the systematic risks.

Berk, Green and Naik (1999) use a dynamic model of firm assets and growth options to validate the predictability of book-to-market and size. In their model, an attractive investment made by a firm increases its current value and decreases its systematic risk and average future return. They show that book-to-market therefore proxies for a state variable that measures risk per unit of asset. The model also implies that firms with higher market values tend to have a larger proportion of current asset and cash flows. Therefore, size reflects the relative importance of existing asset-to-growth options. The authors further provide simulation results that corroborate both size and the book-to-market effect.

Daniel and Titman (1997) argue that size and book-to-market effects are caused by mispricing rather than systematic risks, which is supported by their characteristics-based theory. They present evidence using a sample period from 1973 to 1993 and show that average returns are related to characteristics. They disentangle the predictive power of characteristics from the factor loadings by sorting stocks using rankings of book-to-market ratio and factor loadings. The results show that the predictive power of Fama-French factor loadings is subsumed by the corresponding characteristics, which is consistent with a mispricing explanation.

Lewellen (1999) focuses on the time-series relations among size, book-to-market and expected returns of the stock market. He firstly reports evidence from time-series regressions that the book-to-market ratio predicts future stock returns, which suggests that either risk or mispricing is not consistent through time. Furthermore, he provides evidence that characteristics contain much information about portfolio riskiness, but limited information regarding future stock returns. Finally, the author constructs an "industry-neutral" book-to-market factor and shows that empirical results favour the risk-based explanation for the book-to-market effect.

Davis, Fama and French (2000) address the debate between characteristic-based and factor-based explanations by extending Daniel and Titman (1997)'s tests into a 68-year sample period. They find that Daniel and Titman (1997)'s results are specific to their 20·5-year sample period. The long-run tests show that there are monotonic changes in average returns across three levels of pre-formation HML loading within each book-to-market sub-group. The formal regression test also accords with the return evidence. The authors therefore argue that value effect is driven by systematic risks instead of a characteristics model.

Campbell and Vuolteenaho (2004) suggest that size effect and book-to-market are proxies for systematic risks. Their proposed theory breaks the market portfolio beta of a stock into two constituents, one capturing news about the market's future cash flow and one representing news about the market's discount rates. The paper uses VAR to implement the decomposition of the market portfolio beta. As ICAPM suggests that investors care more about permanent cash-flow-led volatilities than about impermanent discount-factor-driven changes in the aggregated market, cash-flow beta should have a higher risk price than discount-rate beta. The authors provide consistent results that small stocks and value stocks tend to have higher cash-flow beta, which is consistent with the empirical evidence.

3.2.3 The Fama-French three-factor model

Two main perspectives emerge among those who believe that the well-documented price-based anomalies indicate the failure of the CAPM. The first group of researchers use a behavioural explanation (Lakonishok, Shleifer and Vishny, 1994; Haugen, 1995). Lakonishok, Shleifer and Vishny (1994) suggest that value (high book-to-market) stocks outperform growth (low book-to-market) stocks because of investor overreaction. Investors over-extrapolate past performance and therefore value stocks are undervalued and growth stocks become overvalued. The correction of misvaluation leads to the differences in future expected returns. Lakonishok, Shleifer and Vishny (1994) use double-sorted portfolio returns to support their argument. Among the value stocks, low past sales growth stocks outperform high past sales growth stocks by 4% over the subsequent year. The cross-sectional regressions corroborate the statements by showing that book-to-market ratio lost explanatory power when the previous five years' sales growth is included in the model.

On the other hand, Fama and French (1995) provide evidence against the behavioural explanation and support their rational-pricing model. They firstly document that high book-to-market stocks have persistently lower profitability relative to low book-to-market stocks, suggesting that value stocks are more distressed ones. In a consistent manner, smaller stocks have sustained lower profitability compared with larger stocks. Furthermore, the authors test the time-series patterns of earnings/price ratios across value and growth stocks. The relatively stable pattern contradicts the investor over-extrapolation theory, which predicts dramatic variations in earnings–price ratio after portfolio formation. The authors also show that earnings of different size–book-to-market groups load on market factor, size factor and value factor's earnings in the same way as their returns, suggesting that profitability difference may be the source of the rational-pricing explanation.

In an earlier paper, Fama and French (1993), inspired by the empirical performance of size and book-to-market ratio in explaining stock return cross-sections, propose a three-factor model to address the potential misspecification of the CAPM. They augment the CAPM with the size factor SMB to capture the return difference between small and large stocks, with the value factor HML capturing the return difference between value and growth stocks:

$$r_{it} - r_{ft} = \alpha_i + \beta_{im} RM_t + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \varepsilon_t$$

They suggest that the stock returns are determined by their sensitivity to the three factors. Using a US sample from 1963 to 1991, empirical evidence shows that the value factor and size factor provide incremental information to the market factor. The three-factor model does a better job of explaining the size effect and the book-to-market effect. Despite the fact that the GRS test still rejects the three-factor model, it later becomes extremely influential in the financial and accounting area.

Fama and French (1996) focus on time-series regressions to test the explanatory power of their Fama-French three-factor model (1993). A number of sorted portfolio returns are used as left-hand-side portfolios to represent "anomaly" patterns in the stock market that are not captured by the CAPM. The authors test the performance of their three-factor model's performance using the GRS test (Gibbons, Ross and Shanken, 1989), which illustrates whether time-series regressions across all left-hand-side variables are jointly equal to zero. The empirical results show that the Fama-French three-factor model captures portfolio return patterns that stem from P/E ratio, sales growth, cash flow/price ratio (Lakonishok, Shleifer, and Vishny, 1994) and the long-term return reversal effect (Debondt and Thaler, 1985). However, the variations from double-sorted portfolios by size and book-to-market effect and the momentum effect (Jegadeesh and Titman, 1993) are not fully explained by the three-factor model.

3.2.4 Return-based anomaly

Another category of papers mainly uses return-based information to predict future stock returns (Debondt and Thaler, 1985; 1987; Jagadeesh, 1990; Jegadeesh and Titman, 1993; 2001). The proposing of the Fama and French three-factor model does not resolve the puzzle, especially because it fails to capture the momentum effect (Fama and French, 1996; 2008). As a result, a momentum factor is widely employed in addition to the Fama-French three-factor model to better explain the stock return cross-sections.

Debondt and Thaler (1985) extract information on past returns on future stock returns by examining the overreaction hypothesis. The authors firstly rank stocks using the past three or more years of their return performance. Hedge portfolio strategies are formulated by long past losing stocks and short past winning stocks in a sample period from 1926 to 1982. The authors find that past losers outperform past winners based on the previous three years' returns by 25% in the subsequent three-year returns. The 50 extreme losers outperform the 50 extreme winners based on the previous five years' returns by 31.9%. The results are interpreted by the authors using the investor overreaction hypothesis and challenge the existing asset pricing model specifications.

Debondt and Thaler (1987) explore alternative explanations to the overreaction phenomenon that they discovered in the previous paper. They document that the past losing stocks in general have higher market beta than past winning stocks; however, the difference remains insufficient to compensate for the large abnormal return of the long-short strategy. Furthermore, past losing stocks do not have smaller size compared with winning stocks, while there seems to be a correlation between market-to-book value and the long-term past performance of stocks.

Jegadeesh (1990) documents that there are robust serial correlations among stock returns. He uses a sample period from 1929 to 1982 and obtains results of significant negative one-month serial correlation and positive serial correlations from three-month lag returns to up to 14-month lag returns. Based on the cross-sectional regression results, the author further tests the profitability of portfolio strategies based on the serial correlation. The abnormal returns obtained from long-short extreme decile portfolio strategy are 2.49%, 2.20% and 4.37% using an autoregressive predictive model, one-month-lag return ranking and 12-month-lag return ranking respectively. The author suggests that the evidence strongly contradicts the efficient market hypothesis.

Jegadeesh and Titman (1993) examine the profitability of portfolio strategies based on momentum effect. They use a sample from 1965 to 1989 and rank US common shares into 10 decile groups based on lag returns from one to four quarters. The momentum strategy that long past winning group and short past losing group is able to generate significant profit. The authors also test various versions of momentum strategies by choosing different holding periods. The most successful portfolio strategy is formulated based on past one-year returns with a holding period of one year, which generates a 1.31% monthly return. The source of abnormal profits is mainly attributed to the long side of the strategy.

Jegadeesh and Titman (2001) respond to the criticism of the data-snooping problem with regard to the momentum strategy. The authors extend their previous study with a sample period of 1965 to 1998 and conduct further analysis. The empirical results are consistent with Jegadeesh and Titman (1993) in terms of the profitability of the momentum strategies. The authors also examine the sub-period performance of the strategies and obtain consistent results. The authors further address potential concern about liquidity by excluding micro-value stocks, and the result remains robust. The momentum strategy profit is more pronounced among small-cap stocks, as small-cap portfolios generate momentum profit of 1.47% per month whereas the large-cap momentum profit is 0.72%.

The momentum effect is not well captured by the Fama-French three-factor model. Carhart (1997), in his study of mutual fund performance, reports that continuation of past performance in a mutual fund is attributable to the momentum effect in the stock market. He therefore proposes a four-factor model. In addition to the Fama-

French three factors, a momentum factor is added, using returns difference between past-winner and past-loser stocks:

$$r_{it} - r_{ft} = \alpha_i + \beta_{iM} RM_t + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \beta_{iUMD} UMD_t + e\varepsilon_t$$

However, it remains controversial as to whether the momentum factor accounts for systematic risks.

3.2.5 Accounting-based anomalies

After the propounding of the Fama-French three-factor model, the literature continued to expand with new factors to explain the cross-section of expected returns. Harvey, Liu and Zhu (2016) document 313 papers published in selected journals that study factors explaining the stock return cross-section since 1976. They argue that the cut-off thresholds should be tougher over time as data-mining of factors continues. This argument is underpinned by three reasons. Firstly, the likelihood of spotting effective factors decreases as the obvious ones have already been discovered. Secondly, there is a scarcity of information available for data-mining in the stock market. Thirdly, the cost of data-mining decreases with technological development. Therefore the authors suggest using 3.0 as the hurdle of significant *t*-statistic for newly proposed explanatory factors affecting the stock return cross-section.

Harvey, Liu and Zhu (2016) summarize 316 factors in total, which are classified into common factors and characteristics factors. The factors that are most relevant to the Fama-French factor models are accounting factors. There is a large stream of literature that links accounting-based measures to future stock returns such as the analyst's expected earning effect (La Porta, 1996); the profitability-related effect (Haugen and Baker, 1996); the capital investment effect (Titman, Wei and Xie, 2004), the total asset effect (Cooper, Gulen and Schill, 2008), the accrual effect (Sloan, 1996), and the others (Ikenberry *et al.*, 1995; Loughran and Ritter, 1995;

Frankel and Lee, 1998; Daniel and Titman, 2006; Pontiff and Woodgate, 2008). The documented effects challenge the Fama-French three-factor model as the anomaly variables provide incremental explanatory power to the stock return cross-section.

3.2.5.1 Methodology

For the attempts to challenge the Fama-French three-factor model, it is common to start by documenting anomalies with a sorted portfolio analysis. The regressions are then used to formally identify the marginal explanatory power of the anomaly variables over stock return cross-sections. The two frequently used approaches are the cross-sectional regression based on the Fama-Macbeth (1973) approach and the time-series regressions with the GRS test (Gibbons, Ross and Shanken, 1989). As argued by Fama (2015), the two methods complement each other. This is also consistent with the fact that factor models are inspired by firm-specific characteristics that explain stock return cross-sections.

Sorted portfolio returns analysis provides a simple and clear picture of average return variation across the level of anomaly variable. The stocks are commonly sorted by both market capitalization and the anomaly variable, which mainly addresses the anomalies returns among small-size stocks and ensures that the anomaly variable pattern is consistent across different size groups. However, as argued by Fama and French (2008), sorted portfolio analysis cannot examine the marginal explanatory power of the anomaly variable over stock return cross-sections. In contrast, multiple regressions provide direct information regarding this. Therefore, most empirical studies use both methods to illustrate the robustness of the anomaly.

The Fama-Macbeth (1973) regression is carried out in two stages. In the first stage, one needs to estimate risk factor betas for each left-hand-side portfolio using time-series regression. The betas obtained are then used in the second stage as explanatory variables for cross-sectional regressions. For each period, cross-sectional regression is conducted and factor premia are obtained. The *t*-statistics for each factor premium will then be interpreted with regard to whether the factor is significantly priced by the market. The main attraction of the Fama-Macbeth (1973) methodology is that the monthly cross-sectional regressions allow for covariance in the regression residuals without the need for estimating the covariance matrix (Fama, 2015). This is important when the left-hand-side assets involve thousands of individual assets. However, the downside is that when individual stocks are used as test assets, there tend to be higher measurement errors in beta estimates. To mitigate the error-in-variable issue, Shanken (1992) derives a corrected version of standard error for *t*-statistics, which is employed in the mainstream asset pricing literature.

On the other hand, the time-series regression mainly centres on the GRS test (Gibbons, Ross and Shaken, 1989). The main hypothesis of the GRS test is that time-series regression intercepts for all left-hand-side assets are jointly equal to zero, which means the asset pricing model captures all variations across the testing assets. According to Fama (2015), the main benefit of using the GRS test is that it takes into account the covariance matrix of residual values across all time-series regressions, the sampling errors of factor betas and the covariance matrix of factors. However, the power of the GRS test becomes worse when there are a large number of left-hand-side testing assets. When portfolios rather than individual assets are used as testing assets, something which has been widely accepted by the empirical studies, the patterns across individual assets may not be well presented. As a result, one has to make a trade-off between the precision of the GRS *t*-statistics and the cross-sections represented by the left-hand-side testing assets. One further issue concerning the GRS test is that it has specific results with regard to each set of left-hand-side assets. Therefore it is frequently seen that the asset pricing model used passes some sets of the testing assets and fails the others.

Lewellen, Nagel and Shanken (2010) criticize the empirical methods used in the empirical asset pricing literature and offer a number of suggestions. They argue that high explanatory power over size and book-to-market effects may be achieved by choosing factors that are correlated with SMB and HML instead of their residuals. Therefore they propose a few solutions to the empirical problems. Firstly, they suggest using different sets of left-hand-side portfolios as testing assets, such as industrial portfolios or portfolios sorted by beta, etc. Secondly, more restrictions could be imposed on the risk premia. For instance, zero-beta rates should not be different from risk-free rates. Thirdly, the authors suggest using GLS instead of OLS regression for the cross-sectional tests. The final solution is to provide estimates of confidence interval rather than relying on point estimates and p-values in the regressions.

3.2.5.2 Accounting-based anomalies

La Porta (1996) uses analyst earnings forecast data and shows that it has predictive power over the future stock return cross-sections in the period 1982–1991. Portfolios are constructed based on rankings of analysts' expected growth in earnings. The extreme low expectation portfolio outperforms the extreme high expectation portfolio by 20.9% for annual returns. The difference is robust for size-adjusted performance. The multivariate Fama-Macbeth regressions confirm that analysts' forecast of earnings growth negatively predicts one-year future return, while book-to-market and size become insignificant variables with the existence of the analyst forecast variable.

Haugen and Baker (1996) assess the predictive power of various firm profitability measures including net earnings to book value, operating income to total assets, operating income to total sales, total sales to total assets. They find that the profitability measures predict future stock returns after controlling for other risk factors using cross-sectional regressions. The authors propose a portfolio strategy based on rankings of predicted future stock returns and obtain significant profit using Russell 3000 stocks during the period 1979–1993.

Sloan (1996) investigates the relation between accrual and future stock returns using a sample from 1962 to 1991. Accrual is defined as the non-cash component of earnings. The author finds that accrual is less persistent relative to the cash component of earnings. The empirical results suggest that market participants may have failed to recognize the low persistence of accrual since higher (lower) accrual predict lower (higher) future stock returns. Results from both sorted portfolio adjusted returns and cross-sectional regressions suggest that accrual negatively predicts future stock returns after controlling for other firm characteristics. The author interprets the evidence as a consequence of investors' fixation on earnings, with a failure to recognize the low persistence of accrual earnings.

Frankel and Lee (1998) use a residual-income-based model to derive the intrinsic value of stocks based on analysts' forecasts and show that the estimated value-price ratio predicts future stock returns. The predictability of the value-price ratio is more pronounced than the book-to-market ratio for a future return period over 12 months for cross-sectional regressions in the period 1976 to 1993. The portfolio return analysis corroborates the regression results as the high value-price ratio quintile portfolio outperforms the low quintile portfolio by 32.9% in 36-month returns. The authors further show that errors in long-term prediction by analysts has an incremental explanatory power relative to value-price ratio.

Titman, Wei and Xie (2004) document a negative relation between abnormal capital investments and future stock returns. The authors employ both portfolio returns analysis and time-series regressions to address the relationship. Results from both methods suggest that future stock return is negatively related to abnormal capital investments after controlling for book-to-market effect, size effect and momentum effect. Furthermore, the effect is not subsumed by a return reversal effect or a seasonal equity issuance effect. The authors suggest underreaction of investors to managerial over-investment may be the underpinning reason. However, there are other possible explanations that the authors do not rule out. For instance, the managers may choose to invest more when cost of capital is relatively low. It is also possible that the investment factors represent systematic risks separate from the Fama-French three factors.

Cooper, Gulen and Schill (2008) use change in total asset as a measure of asset growth and find a significant negative relation to future stock returns. The authors firstly use portfolio return analysis to show that the lowest decile of asset growth firms has an average annual return of 18% while the highest decile portfolio has a lowest annual return of 5%. The outperformance of low asset growth stocks over high growth stocks goes beyond one year to up to three years. In addition, the Fama-Macbeth regression results indicate that total asset growth is the strongest indicator of future stock return compared with other controlling variables such as book-to-market ratio, size, short-term past return, long-term past return, accrual and other growth measures. The authors further reveal that asset growth factors partially explain the net equity issuance anomaly suggested by Daniel and Titman (2006).

Daniel and Titman (2006) and Pontiff and Woodgate (2008) document a net equity issuance effect which states that change in shares outstanding has a negative predictive power over future stock returns. Both sorted portfolio analysis and cross-sectional regression confirm the robust predictive power of net equity issuance after controlling for other risk characteristics. The predictive power is robust after partialling out major issuance events such as M&A, SEO and repurchases. The authors conjecture that the effect could be due to managerial timing of share over-valuation. Fama and French (2008) document that the net equity issuance provides incremental information to the stock return cross-section across all size groups.

3.2.6 The new Fama-French factor models

As argued by Harvey, Liu and Zhu (2016), when the Fama-French three-factor model is employed as the baseline model, hundreds of papers have shown relationships between additional factors and the cross-section of stock returns. Fama and French (2008) examine the pervasiveness of the anomalous effect of net equity issuance, accruals, momentum, profitability and asset growth. The cross-sectional regressions and sorted portfolio analysis show that momentum and net equity issuance are robust anomalies after controlling for size and book-to-market, which is robust across different size groups. As responses to the vast literature on new explanatory factors, empirical asset pricing researchers have proposed new factor models aiming to improve on the three-factor model (Fama and French, 2015a; Hou, Xue and Zhang, 2015).

Hou, Xue and Zhang (2015) propose a four-factor model to address the inadequacy of the Fama-French three-factor model and the Carhart four-factor model in explaining anomalies. They justify their four-factor model based on q- theory, which suggests that investment and profitability should predict future stock returns. They propose a four-factor model composed of market factor, size factor SMB, profitability factor RMW and investment factor CMA. The authors present evidence that the new four-factor model outperforms the Fama-French three-factor model and the Carhart four-factor model in explaining 35 significant anomalies. The GRS tests reject the new model in 20 sets of anomalies portfolios, while the Carhart model is rejected in 24 sets and the Fama-French three-factor model in 28 sets:

$$r_{it} - r_{ft} = \alpha_i + \beta_{iM} RM_t + \beta_{iSMB} SMB_t + \beta_{iRMW} RMW_t + \beta_{iCMA} CMA_t + \varepsilon_t$$

Fama and French (2015a) use a dividend discount model to justify their new five-factor model. They augment their three-factor model with two new factors, the investment factor CMA and the profitability factor RMW. The formation of RMW is different from the profitability factor proposed by Hou, Xue and Zhang (2015). The authors show that the new Fama-French five-factor model captures return cross-sections stemming from profitability, investment, size and book-to-market, as GRS statistics do not reject the new model. The two new factors bring incremental explanatory power to the Fama-French three-factor model and the new model also outperforms the Carhart model:

$$\begin{aligned} r_{it} - r_{ft} = \alpha_i + \beta_{iM} RM_t + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \beta_{iRMW} RMW_t \\ + \beta_{iCMA} CMA_t + \varepsilon_t \end{aligned}$$

The follow-up papers try to address the empirical performance of the new factor models. Fama and French (2015c) employ six sets of left-hand-side portfolios constructed by variables not used in new asset pricing models to test the new five-factor models. The GRS test statistics have consistent results that show that the two new factors provide incremental explanatory power and decrease the size of intercepts of time-series regressions. However, the GRS test shows that the new Fama-French five-factor model does not fully capture any of the six anomalous patterns.

Hou, Xue and Zhang (2017) use a larger set of left-hand-side variables and conduct a comparison of the performance of the two versions of the new factor models. The authors document 161 significant anomalies and report that their four-factor model outperforms both the Fama-French five-factor model and the Carhart model. Forty-eight out of 161 high-minus-low portfolio returns have significant alpha after controlling for the new four-factor model, whereas the numbers for the Fama-French five-factor model and the Carhart model are 84 and 94 respectively. Regarding the GRS test performance, 107 sets of anomalous portfolios reject the new four-factor models, which is slightly lower than the totals of 108 sets for the Fama-French five-factor model and 119 sets for the Carhart model.

3.2.7 More recent literature

As suggested by the comprehensive review of the performance of the new Fama-French factor models (Hou, Xue and Zhang, 2017), the cross-sections of stock returns are not fully captured. The results have different indications to those of the asset pricing literature. Factor-model researchers seek to establish better model performance by employing different factor measures or formations (Fama and French, 2015b; Ball *et al*., 2016; Stambaugh and Yuan, 2016). On the other hand, anomalies researchers examine the performance of anomaly strategies, augmenting their baseline control with the new factors (Green, Hand and Zhang, 2016; George, Hwang and Li, 2017; Yan and Zheng, 2017). It is notable that, as suggested by

Harvey, Liu and Zhu (2016), the cost of data-mining has dropped dramatically and thus it is common for recent research to test a large number of stock return characteristics simultaneously.

The choice of accounting measures used to construct return predictors also affects their performance. For instance, Ball *et al*. (2015) document that deflators affect the information content of profitability predictors. Although Novy-Marx (2013) suggests that gross profit has a greater predictive power than operating profit, Ball *et al*. (2015) find that the better performance is due to the choice of using total asset as the deflator. They further compare the information content of various profitability measures and suggest that operating profit provides greater predictive power than gross profit to the stock return cross-section.

Ball *et al*. (2016) further address the information content of the profitability factor measure. They suggest that the accrual anomaly exists because accrual-based profit is negatively correlated with the cash-based profit, which provides a strong indication for future stock returns. As a result, they propose to use a cash-based profitability measure in explaining the stock return cross-section. Fama-Macbeth regressions suggest that cash-based measurement captures the predictability of accrual and operating profitability. Time-series regressions corroborate the results. Profitability factors constructed using cash-based profitability measures provide incremental information in explaining the size-accrual sorted portfolio returns.

Fama and French (2015b) extend the comparison and investigate the differences in information content of profitability factors constructed with different profit measures and deflators. They compare the relative performance of profitability measures including operating profit scaled by book equity (Novy-Marx, 2013; Fama and French, 2015a; 2015b), cash profitability scaled by book equity (Ball *et al*., 2016) and quality minus junk (Asness *et al.*, 2013). The authors find that the cash profit measure outperforms the other specifications as it generates lower GRS *t*-statistics across different left-hand-side portfolios. Furthermore, using /the small-end construction method for the factors increases the explanatory power of both the profitability factor and the investment factor in their new five-factor model.

Stambaugh and Yuan (2016) take a different stance and construct their mispricing factors using aggregated information from 11 prominent anomaly factors. They construct their mispricing factor model by augmenting the market factor and the size factor with two additional mispricing factors using the average rankings of 11 anomalies variables. The authors believe that although the significant anomalies represent mispricing, their combined information could contribute to explaining the stock return cross-sections. The authors compare the model's performance with the q-theory model (Hou, Xue and Zhang, 2015) and the Fama-French five-factor model. The results show that the mispricing factor model outperforms both alternative models in explaining 73 anomalies used in Hou, Xue and Zhang (2015). The mispricing factor model explains more anomaly variable long-short spreads and the GRS statistics confirm its superior performance.

George, Hwang and Li (2017) examine whether the four-factor model of Hou, Xue and Zhang (2015) explains the PTH (price-to-52-week-high) anomaly. The PTH anomaly (George and Hwang, 2004) documents that stocks with current prices near to their 52-week highs have higher abnormal returns than those stocks whose current prices are farther from their 52-week highs. The authors suggest a rational explanation for the PTH anomaly. They show that PTH is positively linked to future profitability and future investment growth, which corroborates the predictions of q-theory. According to Liu and Zhang (2014), q-theory also suggests that expected returns are related to current investment, future profitability and future investment growth. The GRS statistics show that the PTH anomaly is best captured by the four-factor model, which outperforms the Fama-French three-factor model and five-factor model. Furthermore, a modified four-factor model that incorporates rankings of PTH into the profitability factor better captures the PTH anomaly.

Green, Hand and Zhang (2016) investigate the information concerning 94 characteristics over the stock return cross-section using Fama-Macbeth regressions for a sample period 1980–2014. They firstly show that Hou, Xue and Zhang (2015)'s four-factor model outperforms the other factor models. Using the q-theory model as a benchmark, only one of the stock characteristics provides significant incremental information to the stock return cross-section. Without the factor model controls, 12 characteristics provide predictive power over future stock returns. Furthermore, the return predictability of 12 characteristics deteriorates dramatically after 2003. This may be attributable to the increase in market efficiency, as the predictability fell more sharply among non-microcap stocks with lower arbitrage costs.

Yan and Zheng (2017) employ a data-mining approach to extend the fundamental signals from financial statements to predict future stock returns. Based on 240 accounting variables and 76 ratio configurations, they construct a universe of over 18,000 fundamental signals. Long-short portfolios are constructed and the authors report that top-ranked signals deliver high return performance that cannot be explained by sampling variation using bootstrapping methods. They further show that the superior performance of the top-ranked fundamental strategies are more pronounced among stocks with greater limits to arbitrage and during market expansion. Therefore, the evidence seems to be more consistent with mispricing-based explanations.

3.2.8 The UK evidence

In the UK literature, a number of papers also document different firm-characteristics explaining stock cross-sectional returns. The results obtained are not entirely consistent with the US results. It seems that different institutional backgrounds may have led to different stock mark representations. The UK stock market shares major risk characteristics that have been documented in the US literature, such as book-to-market and E/P ratio (Levis, 1989; Chan and Chui, 1996; Liu, Strong and Xu, 1999; Leledakis and Davidson, 2001). Anomalies such as accrual anomaly and momentum effect are also reported in the UK market (Liu, Strong and Xu, 1999; Soares and Stark, 2009). However, there are notable differences, such as the explanatory power of size.

Using a different data set but with more comprehensive accounting information, a number of papers do find an insignificant size effect in the UK stock market after controlling for other pronounced market effects (Chan and Chui, 1996; Miles and Timmermann, 1996; Strong and Xu, 1997). Moreover, as noted by Griffin (2002) and Hou, Karolyi and Kho (2011), asset pricing models are best constructed at country level as country-specific factors outperform global and regional factors. The performance of the asset pricing factor models does not fully match the US results (Fletcher, 2001; Fletcher and Forbes, 2002; Hung, Shackleton and Xu, 2004; Fletcher and Kihanda, 2005): the choice of factor formation also influences the performance (Gregory, Tharyan and Christidis, 2013; Michou, Mouselli and Stark, 2014).

Levis (1989) examines the predictive power of dividend yield, E/P ratio, size and share prices over future stock returns. He mainly employs sorted portfolio analysis and reports significant return premia of 5.2% from size, 10.0% from dividend yield, 5.2% from price rank in sample period 1955 to 1983 and 7.0% annual premium from E/P ratio. The author notes that the size effect is not robust across different groups of dividend yield and E/P ratio. There is also a close link between the size effect and the price-level effect, which means size may be a proxy for fundamental risks instead of an independent predictor in the UK market.

Chan and Chui (1996) extend Fama and French (1992) into a UK sample for the period 1973 to 1990. They examine the explanatory power of stock return cross-sections in size, market beta, book-to-market, asset-to-book, share price, and dividend yield. In contrast to Levis (1989), the authors use the Fama-Macbeth regression to compare the information content of the characteristics. Consistent with the US results, book-to-market ratio significantly influences future stock returns, and market beta does not have incremental information. However, size does not significantly predict future stock returns, which differs from the US results. Furthermore, the authors show that the information content gained from book-to-market mainly stems from the asset-to-book ratio.

Miles and Timmermann (1996) also examine the determinants of UK stock cross-sections with a sample period 1979 to 1991. Consistent with Chan and Chui (1996), Fama-Macbeth regressions reveal that book-to-market significantly influences future stock returns, whereas size, market beta, dividend yield, debt-to-book ratio and liquidity measured by trading volume do not have predictive power. In addition, the authors construct Fama-French three-factor models and investigate the factor loadings across size-book-to-market double-sorted portfolio returns. The observed patterns suggest that the market factor, size factor and book-to-market factor are priced in the UK market.

Strong and Xu (1997) test the relationship between expected returns and market beta, size, book-to-market ratio, asset-to-book ratio, asset-to-market ratio and E/P ratio in the UK. They use both portfolio return analysis and cross-sectional regressions with a sample period from 1973 to 1992. Although the one-dimension sorted portfolio returns suggest that each of the variables alone is correlated with future stock return, the multivariate Fama-Macbeth regressions reveal that one of the leverage ratios (asset-to-book, asset-to-market) and the book-to-market ratio consistently predict future stock returns in the UK market. The explanatory power of other variables seems to have been subsumed by these two factors.

Dimson and Marsh (1998) investigate the reverse of size premium in the UK market. They provide evidence that UK small-size stocks outperform the FTSE All-Share Index by 6.1 % during the period from 1955 to 1986, whereas in the period 1989 to 1997 the performance difference becomes -6.5%. The authors use the publication of the UK size effect (Dimson and Marsh, 1987) and the launch of Hoare Govett Smaller Companies Index (HGSC) as the cut-off point and show there is a reversal of size premium in the UK. The reverse may be attributable to two reasons. Firstly, the smaller stocks tend to be clustered in the underperforming sectors in the reversed sample period. And the second reason is the underperformance of small-size firms, which is illustrated by the reversal of dividend yield and dividend growth.

Liu, Strong and Xu (1999) document the momentum effect using a sorted portfolio analysis in the UK market. They test the profitability of various momentum strategies and find that the most profitable strategy in the UK is to use past 12 month returns to rank stocks and hold them for three months, which generates an annualized return of 23.3% in their sample from 1977 to 1998. The results corroborate the US findings. Furthermore, the authors show that the momentum effect is robust after adjusting for the Fama-French three factors and other characteristics such as the P/E ratio. The authors conjecture that the distinctive predictive power of momentum in the UK may stem from investor underreaction.

Bagella, Becchetti and Carpentieri (2000) examine the profitability of naïve-ranked portfolios using size, market-to-book, P/E ratio and return on equity (ROE). Using UK data from 1971 to 1997, they firstly document that all four characteristic-ranked portfolio groups show a monotonic trend in future stock returns. Then they further test the risk-adjusted return patterns using risk models including the Fama-French three-factor model. The adjusted returns show that the return premia related to size, book-to-market and ROE are reduced but not fully captured by the three-factor model. The monotonic return pattern of P/E remains apparent despite the fact that the high-minus-low strategy returns are not regressed on the risk factors as a formal test. The authors suggest that the uncaptured profit leaves room for further research.

Leledakis and Davidson (2001) use both portfolio return analysis and Fama-Macbeth regression to examine the determinants of UK stock cross-sections over the period 1980–1996. The one-dimension portfolio sorting confirms that future stock returns are linked to measures such as book-to-market ratio, size, sales-to-market ratio and debt-to-book ratio. The multivariate cross-sectional regressions reveal the relative informativeness of the factors. The authors provide evidence that size, book-to-market ratio and sales-to-market ratio significantly predict future stock returns. Debt-to-book ratio loses significance with the existence of the book-to-market ratio and sales-to-market ratio.

Dimson and Marsh (2001) use a comprehensive UK data set of stock returns from 1955 to 1999 to make a comparison with the US market in terms of return seasonality, dividend yield and the size effect. They document that the size effect, despite its existence in the UK, exhibits different seasonality that cannot be explained by the end-of-year effect. The dividend growth for UK was higher and more volatile than that of the US market. Moreover, the size effect in the UK experienced a reverse in its premium after its documentation by Dimson and Marsh (1987) and the follow-up media coverage. The annual size premium turned from 9.7% over the period 1955-1988 to -6.8% over the period 1989-1999. Although there seems to be a similar premium switch in the US market, the authors argue that the diminished size effect requires further research.

Fletcher (2001) tests the mean-variance efficiency of various linear asset pricing factor models in the UK. He uses GRS test statistics to examine factor models including the CAPM, the Fama-French three-factor model, the Carhart model and an APT model based on macroeconomic variables. The test statistics reject the null hypothesis of mean-variance efficiency for all four models using a sample period 1982–1996. The pricing errors are less severe for the Fama-French model and the Carhart model. Fletcher further shows that missing risk factors do not mitigate the pricing errors. As a result, he argues that the specified linear factor models may produce biased control for systematic risks in the UK.

Gregory, Harris and Michou (2001) document the profitability of value-minus-growth strategy in the UK during the period 1975–1998. They firstly report that long-value stocks and short-growth stocks generate significant abnormal returns in the UK. In addition, they provide evidence that poor past performance and low expected future performance lead to higher future returns, which is consistent with the contrarian model proposed by Lakonishok, Shleifer and Vishny (1994). Furthermore, the value-minus-growth profit from one-dimension sorted portfolios are broadly captured by the Fama-French three factors, whereas the double-sorted portfolio returns are not explained by the risk factors. The results corroborate Fletcher (2001)'s conclusion that the Fama-French three-factor model's performance in the UK is not as good as in the US market.

Fletcher and Forbes (2002) examine the sensitivity of UK unit trust fund performance to different specifications of linear factor models. They employ five linear factor models including the CAPM, the Fama-French three-factor model and the Carhart model. The empirical results suggest that all the factor models lead to some bias in performance evaluation. Using the Carhart model as a benchmark suggests that unit trust funds do not outperform passive strategies. With respect to explanatory power over the stock returns cross-section, Carhart has the least pricing error among all factor models for the UK sample from 1982 to 1996.

Dissanaike (2002) documents the UK size effect in a FT500 sample. During the sample period 1975–1990, small stocks outperform large stocks by 58.8% four years after the portfolio formation. The author also reports a return reversal effect. Past losing stocks outperform past winning stocks by 98.9% four years after the portfolio formation. The profits of both strategies seem correlated throughout the sample period. However, the regressions suggest that there is little evidence of a size effect subsuming the reversal effect.

Gregory, Harris and Michou (2003) examine the rational explanation with regard to the contrarian strategies in the UK market from 1980 to 1998. They firstly document that value-minus-growth profits do not perform worse during recessions. Besides, the long-short portfolio abnormal returns remain significant after controlling for the Fama-French three-factor model. Both results are inconsistent with a rational-pricing explanation, suggesting contrarian profits may be explained by mispricing or incomplete control of systematic risks. Furthermore, the authors report evidence that both HML and SMB are positively related to future GDP growth, future investment and consumption growth.

Dimson, Nagel and Quigley (2003) use a comprehensive UK data set from 1955 to 2001 to reveal the size and book-to-market effects in the UK. Consistent with the prior literature, they find that the size factor SMB is not significantly positive across the sample period, which has a mean return of 0.15% with 0.91 *t*-statistic. The value factor HML generates a monthly return of 0.49% with statistical significance. The authors further construct a factor based on dividend yield and it has a similar performance to that of HML. Moreover, the authors suggest that capturing the value premium among the small-size stocks requires particular caution due to the illiquidity issue.

Al-Horani, Pope and Stark (2003) document the predictive power of research and development (RD) activity for future stock returns in the UK, using a sample from 1990 to 2001. They firstly use the Fama-Macbeth regression and show that RD activity positively predicts the stock returns cross-section after controlling for size and book-to-market. The authors then construct an additional factor based on RD intensity. Time-series regression implies that the RD factor is related to the Fama-French three factors, but may provide incremental information. Further risk premia analysis shows that the RD factor has significant influence upon the market factor premia across various industries, especially zero-RD industries. The overall evidence suggests that the RD factor may provide incremental information to the UK stock returns cross-section.

Hung, Shackleton and Xu (2004) make a comparison between the CAPM, the Fama-French three-factor model and a higher order pricing factor model in the UK market regarding their factor-pricing significance. The left-hand-side stocks are grouped into beta-sorted, size-sorted and book-to-market-sorted portfolios. Firstly, Hung, Shackleton and Xu document that size premium and value premium remain significant after controlling for the factor models. Regarding the pricing significance, Fama-French factors are priced significantly when the market condition is used to divide the sample period into an up and down scenario. There is little evidence that a higher-order market factor provides incremental information to the linear factor model in the UK.

Fletcher and Kihanda (2005) examine the performance of a number of unconditional and conditional models in explaining the UK stock returns. They use the Hansen and Jagannathan (1997) distance measure to compare the relative performance among models estimated with GMM. They report that four-moment CAPM augmented with a proxy for labour income growth has the best performance among all unconditional models in explaining the industry portfolio returns cross-section. The conditional version of the model also has the best performance among all the alternatives. The authors also examine the time-series predictability of the models, which also suggests that a four-moment CAPM augmented with a proxy for labour income growth beats the other models. However, the out-sample analysis suggests that the best-performing model has the worst performance, which means the results are sensitive to left-hand-side portfolio selections and may not be generalized.

Clubb and Naffi (2007) follow the fundamental analysis perspective and show that expected book-to-market value and expected return-on-equity (ROE) provide incremental information in explaining stock return cross sections in the UK. The authors use a first-order autoregressive model to construct expected book-to-market and expected ROE measures. Cross-sectional regressions at both annual and monthly frequency show that both expected measures have significant explanatory power regarding the future stock returns in the UK stock market from 1991 to 2000. The results remain robust after controlling for variables such as book-to-market ratio, size, momentum and R&D.

Soares and Stark (2009) document the accrual anomaly in the UK market by forming a portfolio strategy and examining the profitability after transaction costs using a sample from 1990 to 2005. Following Sloan (1996), the portfolio returns are revealed and the results obtained corroborate the US evidence that higher accruals are linked with lower future stock returns. The abnormal returns remain significant after controlling for the Fama-French three-factor models. The authors extend the literature by exploring the profitability of naïve long-short strategy after taking into account the transaction costs. The results imply that the long-short abnormal returns are offset by the transaction costs across different size groups. The authors therefore argue that the results indicate that the UK stock market is of semi-strong form efficiency.

Petrovic, Manson and Coakley (2016) investigate the role that changes in non-current operating asset and property, plant and equipment play in the UK stock cross-sections. They employ portfolio returns analysis, time-series regression and cross-sectional regression to test their hypothesis. Using a sample from 1990 to 2012, the authors show that changes in both measures are negatively related to future stock returns and the results are consistent across different methods. The anomalous returns are not captured by illiquidity of the stocks, but are partially explained by the change in a composed measure of investment.

Two recent papers also examine the performance of the Fama-French factor models in the UK market. Gregory, Tharyan and Christidis (2013) test various versions of the Fama-French three-factor model and the Carhart model in the UK market. In addition to the basic Fama-French models, they further construct alternative specifications such as value-weighted factors and small-end factors. Using both the Fama-Macbeth regression and the time-series GRS test, the authors document some evidence that HML is priced while the other factors are not. Regarding the explanatory power of the models, the tested models well capture the pattern of size and book-to-market, but fail to explain momentum-related portfolio returns. Furthermore, the explanatory power is improved by excluding small-size firms on the left-hand-side portfolios, indicating that limits to arbitrage may have caused the poor performance of the factor models.

Michou, Mouselli and Stark (2014) address the performance of the Fama-French three-factor model in the UK with regard to its sensitivity to different methods of factor construction. They compare nine different Fama-French factor specifications that have been adopted in the UK literature. They use size-book-to-market portfolios and industry portfolios as testing assets. The asset pricing tests suggest that factor construction methods are important to the explanatory power of the models. The authors therefore argue that more work is required in the UK market to develop more reliable measures that better capture size and book-to-market effect in the UK, which corroborates the results of Gregory, Tharyan and Christidis (2013).

The Fama-French factor model evidence in the UK has a few implications for future academic research. Firstly, the explanatory power of factor models differs from the US evidence. Secondly, more evidence needs to be established to examine the power of Fama-French factor models using a larger set of left-hand-side test portfolios. Thirdly, the Fama-French three-factor models are not priced consistently in the UK, therefore further investigation is needed to find valid models to estimate the cost of equity.

3.3 DATA AND SAMPLE

3.3.1 Data and variables

The distribution of firms available across my sample period is illustrated in Table 3-1. My sample is used to construct time series asset pricing factors and left-hand-side portfolios for asset pricing tests.

The data in this sample is collected for the period from July 1990 to December 2013. My research uses both accounting and returns data, of which the annual accounting data are sourced from Datastream and monthly returns data from the London Share Price Database (LSPD). I used the SEDOL number to match the two databases. I also use the London Share Price Database Industrial classification (G17) and the FTSE Industrial Classification Benchmark (ICB) to construct the industry portfolios.

I use the following sample criteria:

- Firstly, I exclude stocks with negative book-to-market (BM) ratios to be consistent with the academic literature such as Fama and French (1992), Vassalou and Xing (2004), which advocate the exclusion of stocks with negative BM. Such stocks are omitted because negative values of BM have no clear interpretation. Fama and French (1993) also exclude negative BM with the only justification being that these firms are rare before 1980. Dichev (1998) also shows that firms with a high bankruptcy risk and consequently high relative financial distress have a high BM ratio.

- Secondly, I exclude stocks that belong to the financial sector. These include banking, real estate, insurance and financial services companies due to their different financial and accounting characteristics or due to high leverage. This exclusion also follows Fama and French (1992) and most academic papers who argue that high leverage is a characteristic feature of financial sector companies. They also argue that excluding financial and utility companies helps to alleviate any omitted variable problems caused by industry effects in financing decisions.

- Thirdly, I include in the sample companies that have been de-listed due to merger, bankruptcy, etc, in order to eliminate the survivorship bias problem (Banz and Breen, 1986; Kothari, Shanken and Sloan, 1995). Nagel (2001) also argues that survivorship bias is a serious problem in stock return predictability studies because portfolios constructed using accounting data with inherent *ex post* selection bias do not represent trading strategies that are replicable *ex ante*.

- I also exclude companies with more than one class of ordinary share.

The distribution of firms available across the sample period is illustrated in Table 3-1.[8] The sample is used to construct time series asset pricing factors and left-hand-side portfolios for asset pricing tests.

Table 3-1

Year	No. of stocks
1990	1218
1991	1047
1992	1051
1993	1008
1994	1013
1995	1047
1996	1122
1997	1147
1998	1165
1999	1143
2000	1141

[8] Details on the sample are included in the second chapter pages37-38.

2001	1079
2002	1080
2003	1138
2004	1111
2005	1075
2006	1181
2007	1326
2008	1300
2009	1251
2010	1196
2011	1153
2012	1123
2013	1093

As mentioned earlier I use monthly returns data from the London Share Price Database (LSPD). They are continuously compounded and they are calculated as follows:

$$r_t = In\frac{p_t + d_t}{p_{t-1}} \qquad (1)$$

where

p_t is the last traded price for month *t*;

p_{t-1} is the last traded price for month *t-1*;

d_t is the dividend when the ex-dividend date falls in month *t*.

The method for measuring returns can vary across several dimensions. Returns can be discrete or continuous. This choice should relate to the motivation for the study, which probably dictates in terms of discrete returns. In cross-sectional studies of asset returns, discrete returns are mostly used, i.e. Campbell, Lo and Mackinlay (1997). Therefore, in order to be consistent with the academic literature, I use discrete monthly returns where all LSPD returns are converted back into a discrete basis.

3.4 METHODOLOGY

3.4.1 CAPM

Built on the premise of the mean-variance framework (Markowitz, 1959), Sharpe (1964) and Lintner (1965) propose an equilibrium Capital Asset Pricing Model (CAPM). The model implies that the expected return on an asset should be risk-free interest plus the asset's market beta which measures the sensitivity of the excess return of the assets to the changes in the market excess returns times the risk premium of the market portfolio. This model is sufficient to capture the cross-section of expected returns:

$$R_{it} - R_{ft} = a_i + \beta_{iM}(R_{Mt} - R_{ft}) + \varepsilon_{it}, \forall i \qquad (2)$$

where

R_{it}	is the return for portfolio *i* for period *t*;
R_{ft}	is the risk-free return for period *t*;
a_i	is the intercept term for portfolio *i*;
R_{Mt}	is the return on the market for period *t*;
ε_{it}	is an error term for portfolio *i* for period *t*; and
β_{iM}	is the exposure of portfolio *i* to the market return R_M and is defined by the following equation:

$$\beta_{iM} = \mathrm{cov}(R_{it}, R_{Mt}) / \mathrm{var}(R_{Mt}) \qquad (3)$$

3.4.2 The Fama and French model

Despite its empirical contribution, the CAPM fails empirically to explain the cross-section of expected returns. Fama and French (1993; 1995) propose an alternative model which claims that there are two additional factors other than the market factor that can explain the cross-section of expected returns. The Fama-French three-factor model is an extension of the empirical CAPM to accommodate more risk factors. Just as $(r_{mt} - r_{ft})$ is a market (excess return) factor, SMB is a factor for size, and HML is a factor for book-to-market equity. To be more precise, SMB stands for "small minus big" and is the difference in average returns between portfolios of small and big stocks, controlling for book-to-market. Similarly, HML stands for "high minus low" and is the difference in average returns between portfolios of high and low book-to-market stocks, controlling for size:

$$R_{it} - R_{ft} = a_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{iHML} HML_t + \beta_{iSMB} SMB_t + \varepsilon_{it}, \forall i \tag{4}$$

where

a_i	is the intercept term for portfolio *i*;
R_{it}	is the return of portfolio *i* in month *t*;
R_{ft}	is the three-month T-bill rate in month *t*;
R_{Mt}	is the return on the market in the UK in month *t*;
SMB_t	is the size factor small minus big firms based on market capitalization;
HML_t	is the value factor high minus low of book-to-market equity;
β_{iM}, β_{iHML}, and β_{iSMB}	are the exposures of portfolio *i* to R_M, HML, and SMB respectively;
ε_{it}	is the error term for portfolio *i* for period *t*.

3.4.3 The five-factor model

Given that the Fama and French model cannot fully explain the cross-section of returns, I also introduce an alternative five-factor model which is designed to capture the common variations in the cross-section of returns by linking returns to the real economy using an investment factor.

The investment factor variable is defined following Hou, Xue and Zhang (2015), which is measured using change in total assets from year *t-2* to year *t-1*, divided by total asset (TA) at year *t-2*. I use Datastream total asset (WC02999) to calculate the investment measure, denoted by I/A.

I use three different measures for the profitability variable: firstly, I follow Fama and French (2015a) and Novy-Marx (2013) using $(operating\ income/BE)_{t-1}$ *w*here BE stands for book to equity. The second profitability measure is $(income\ before\ extraordinary\ items/BE)_{t-1}$ following Hou, Xue and Zhang (2015). I also follow Novy-Marx (2013) and use $(gross\ profit/BE)_{t-1}$ as the third measure. Finally, I follow Ball *et al*. (2015) to replace the denominator of the three profitability measures with Datastream total asset (TA) (WC02999). Altogether, I test six profitability measure formations.

Following Fama and French (2015a) and Hou, Xue and Zhang (2015), the general time-series regression model for the five-factor model is given in the equation below:

$$R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t + \beta_{iRMW}RMW_t + \beta_{iCMA}CMA_t + \varepsilon_{it} \quad (5)$$

where

a_i is the intercept term for portfolio *i*;

R_{it} is the return of portfolio *i* in month *t*;

R_{ft} is the three-month T-bill rate from the UK in month *t*;

R_{Mt} is the return on the market in the UK in month *t*;

SMB_t is size factor small minus big;

HML_t is value factor high minus low of book-to-market equity;

RMW_t is robust minus weak factor for profitability;

CMA_t is conservative minus aggressive for investment factor;

β_{iM} , β_{iHML}, β_{iSMB}, β_{iRMW} , β_{iCMA} are the exposures of portfolio *i* to R_M, *HML*, *SMB* , RMW and CMA respectively;

ε_{it} is the error term for portfolio *i* for period *t*.

Both Fama and French (2015a) and Hou, Xue and Zhang (2015) augment the FF three-factor model with an investment factor and profitability factor. Hou, Xue and Zhang (2015) make the value factor HML redundant and use a different definition of the profitability factor variable. Fama and French (2015a) also find empirical evidence of the redundancy of HML using US data. They suggest it could be specific to their sample selection. Fama and French (2017) confirm this point of view but further differences in the information content of new factors are reported across different regions. Under the general form of the five-factor model, I test various versions of the model above with respect to factor redundancy, variable formation, and construction methods with my UK sample.

In the CAPM context, Jensen *et al*. *(*1972) report N univariate *t*-statistics based on each equation in regression (Equations 2, 4 & 5) where *N* is the number of testing portfolios. However, the GRS F-test (it will be explained in details in a follow up sub-section) is used to test whether the intercepts are jointly zero across the N regressions of Equations 2, 4 and 5. This test takes into account the correlation in the estimation errors of a_i's. I test the following null hypothesis for the joint significance of the intercepts:

$$H_0 : all \quad a_i = 0 \tag{6}$$

This hypothesis applies to all factor models mentioned earlier. For instance, if a three factor model captures the systematic risks effectively, it is expected that the intercepts across all regressions will be zeros. The rejection of the null hypothesis would suggest that the variations of excess returns of the tested portfolios are not fully explained by the asset pricing factor model.

3.5 FACTOR CONSTRUCTION

The asset pricing factors are constructed in line with the Fama and French-style factors. I construct six independently sorted portfolios using size and the corresponding factor variable. Following Gregory, Tharyan and Christidis (2013), I use the break points from the largest 350 UK stocks each year simulating NYSE break points in the US market to sort factor construction portfolios. At the end of June each year from 1990 to 2013, stocks are allocated into two size groups based on the median size of the largest 350 stocks at the end of year *t-1*. Stocks are sorted independently into three groups of other variables such as book-to-market (BM), Investment (I/A) and six forms of profitability using the 30th and 70th percentiles from the largest 350 stocks as breakpoints based on data at the end of year *t-1*. The intersections of size sorting and the other variable sorting lead to six portfolios, which are used to produce corresponding factor return time-series.

These independently sorted portfolios are labelled using letters: for the size group, small (S) or big (B); for the BM group, high (H), neutral (N) or low (L); for the profitability group, robust (R), neutral (N) or weak (W); for the I/A group, conservative (C), neutral (N) or aggressive (A). Intersected portfolios are obtained to build the factors. Value-weighted (VW) returns are calculated for each portfolio. For example, SL stands for the monthly value weighted return of intercepted portfolio with small size and low BM.

The factors are obtained using the formula stated in Table 3-2. For instance, each month the normal value factor HML is defined as the difference between the simple average of the VW returns on two high-BM-stock portfolios (SH and BH) and the simple average of the VW returns on two losing-stock portfolios (SL and BL). In order to differentiate the profitability factors (RMW), I name its different versions as follows:

OP_B for factors obtained using $(\boldsymbol{operating\ income/BE})_{\boldsymbol{t-1}}$;
OP_A for factors obtained using$(\boldsymbol{operating\ income/TA})_{\boldsymbol{t-1}}$;
ROE_B for factors obtained using$(\boldsymbol{income\ before\ extraordinary\ items/BE})_{\boldsymbol{t-1}}$;
ROE_A for factors obtained using $(\boldsymbol{income\ before\ extraordinary\ items/TA})_{\boldsymbol{t-1}}$;
GRO_B for factors obtained using $(\boldsymbol{gross\ profit/BE})_{\boldsymbol{t-1}}$;
GRO_A for factors obtained using $(\boldsymbol{gross\ profit/TA})_{\boldsymbol{t-1}}$.

I choose different versions of profitability following the spirit of Ball et al. (2015) and Fama and French (2015b). Ball et al. (2015) examine the return predictability of various profitability components such as cost of goods sold and selling, general and administrative expenses and research and development expenses and find that in the US, the research and development expenses significantly influences return predictability of the profitability measure. They further find that deflators also play key roles in the return predictability. Consistent with that, Fama and French (2015b) reveal that, for factor models, profitability measures also matter to the information content of the profitability factor. Due to the lack of empirical implications from the asset pricing theory, the effective choice of profitability measure in the factor models is considered as an empirical question. As the covariance structure of different profitability components and returns remains unclear in the UK market, I attempt the above six versions. The research and development expenses are not included in the measure variation due to data limitation from Datastream.

In addition to the normal factor construction, I follow Fama and French (2015b) and calculate alternative value, profitability and investment factors using the small end of sorted portfolios to test whether they outperform their normal peers. For instance, the six portfolios used to produce investment factors are SC (small and conservative), SN (small and neutral), SA (small and aggressive), BC (big and conservative), BN (big and neutral) and BA (big and aggressive). The standard investment factor (CMA) is calculated using value-weighted returns (SC + BC – SA –BA)/2. The small end of the factor (CMA_S) is calculated by SC – SA. I use "_S" at the end of the corresponding factor name to denote its small-end version: for instance, ROE_A_S is the small-end factor of the profitability factor obtained using income before extraordinary items/total asset.

Table 3-2

Factor	**Variable definition**	**Factors and their components**
Mkt	FT all share index return; One month Treasury Bill return	$(R_m - R_f)$
Size	Market Capitalization	$\mathrm{SMB} = (\mathrm{SL} + \mathrm{SM} + \mathrm{SH})/3 - (\mathrm{BL} + \mathrm{BM} + \mathrm{BH})/3$
Value	Book-to-Market ratio	$\mathrm{HML} = (\mathrm{SH} + \mathrm{BH})/2 - (\mathrm{SL} + \mathrm{BL})/2$ $\mathrm{HML\_S} = (\mathrm{SH} - \mathrm{SL})$
Profitability	$operating\ income/BE$ $operating\ income/TA$ $income\ before\ extraordinary\ items/BE$ $income\ before\ extraordinary\ items/TA$ $gross\ profit/BE$ $gross\ profit/TA$	$\mathrm{RMW} = (\mathrm{SR} + \mathrm{BR})/2 - (\mathrm{SW} + \mathrm{BW})/2$ $\mathrm{RMW\_S} = (\mathrm{SR} - \mathrm{SW})$
Investment	Investment/TA	$\mathrm{CMA} = (\mathrm{SC} + \mathrm{BC})/2 - (\mathrm{SA} + \mathrm{BA})/2$ $\mathrm{CMA\_S} = (\mathrm{SC} - \mathrm{SA})$

3.5.1 Factor-spanning tests

In the spirit of Huberman and Kandel (1987), the factors in an asset pricing model should be constructed by portfolios that are close to multifactor minimum-variance (MMV). Fama (1998) proposes the foundations of factor-spanning regression under the premise of ICAPM. He suggests that if a state variable is of hedge concern, the premium of its mimicking portfolio should not be captured by excess market return and the excess returns on the other state variables. Thus, in a regression where one factor is regressed on the other factors, the intercepts cannot be zero. In the follow-up studies, the factor-spanning tests are used to compare the relative informativeness of the asset pricing factors (Fama and French, 2015a; 2015b; 2017)

I run a number of factor-spanning tests to compare the relative informativeness of the asset pricing factors. Each factor candidate is regressed against all the other factors in the five-factor model. A factor might be seen as redundant if the spanning test intercept is not significantly different from zero. For instance, the following regression is used to test whether information provided by HML is fully captured by other factors in the asset pricing model:

$$HML_t = \alpha_0 + \beta_{\mathrm{iM}}(R_{Mt} - R_{ft}) + \beta_{i\mathrm{SMB}}SMB_t + \beta_{i\mathrm{RMW}}RMW_t + \beta_{i\mathrm{CMA}}CMA_t + \varepsilon_{it} \tag{7}$$

The statistical significance of the regression intercepts indicate whether or not the HML factor provides additional information uncaptured by the right-hand-side factors. Factor spanning test results provide initial implication for the information content of asset pricing factor candidates. Along with the Gibbons, Ross and Shanken (1989) (GRS) test, I provide guidance on the choice of factors in new factor models in the UK.

3.5.2 GRS tests

The GRS tests are based on a time-series regression model. Firstly, I construct different test portfolios on the left-hand-side (LHS) and compare the performance of alternatives of factor models based on the GRS statistics. The investment- and profitability-based portfolios are also used to illustrate investment-related and profitability-related patterns of UK stock returns.

The left-hand-side (LHS) portfolios are mainly constructed using asset pricing factor measures. I construct various groups of independently sorted portfolios based on intersections of different pairs of factor measures. At the end of June each year I use accounting data from the end of the previous year and construct 25 size-BM portfolios; 25 size-Profitability portfolios and 25 Size-I/A portfolios. Fama and French (2012) suggest that appropriate breakpoints need to be employed for both factors and test portfolios for regional studies. I therefore follow Gregory, Tharyan and Christidis (2013) to use breakpoints based on the largest 350 stocks in the UK market. The largest four size groups are constructed using the quartiles of the largest 350 stocks and the smallest size group is formed from the rest of the sample. The five groups of other variables are sorted using quintile breakpoints of the largest 350 stocks. (In addition to the 25 annually rebalancing portfolios, I also follow Lewellen, Nagel and Shanken (2010)'s suggestion to construct industry-based portfolios for robustness test.)

The Gibbons, Ross and Shanken (1989) test, or GRS test, is used in the following steps. Each group of the LHS portfolios is regressed on the time series asset pricing factor returns:

$$R_{it} - R_{ft} = \alpha_i + \beta_i F_t + e_{it} \tag{8}$$

where

R_{it} is the return of portfolio *i* in month *t*, (i=1….N);

R_{ft} is the three-month T-bill rate from the UK in month *t*;

F_t is the vector of factor returns (K x 1)) of the corresponding asset pricing model tested in month *t*;

β_i is the vector of factor loadings (K x 1);

e_{it} is the error term.

To test whether the intercept estimates of the time-series regression in equation (8) are jointly different from zero, Gibbons, Ross and Shanken (1989) develop an F-test. If the given asset pricing model is well specified, the intercept estimates should not be different from zero. More specifically, the GRS F-test examines the overall performance of the asset pricing models by asking if the alphas across LHS portfolios are jointly equal to zero, in which case the return variations across LHS portfolios are fully captured by asset pricing factors. I report estimates of the intercepts computed in the first-stage time series regressions and their associated individual *t*-statistics, and present a joint test of the significance of the intercepts by applying the GRS F-test. Under the null hypothesis that all the $a_i = 0$, GRS uses the following test statistic, W_N, defined by the following equation:

$$W_N = \frac{T-N-K}{N}\left[1+E_T(\hat{f})'\hat{\Omega}^{-1}E_T(\hat{f})\right]^{-1}\hat{a}'\hat{\Sigma}^{-1}\hat{a} \sim F(N,T-N-K) \tag{9}$$

where

T is the number of time period;

K is the number of asset pricing risk factors;

$E_T(\hat{f})$ is the vector of expected value of the asset pricing risk factors with characteristic element $E_T(\hat{f}_i)$, i = 1, 2, 3;

N is the number of assets (portfolios);

$\hat{a}$ is the vector of estimated intercept terms of N assets (portfolios);

$\hat{\Sigma}$ is the variance-covariance matrix for the estimated error terms, with characteristic term in the *i*'th row and *j*'th column equal to $\frac{1}{T}\sum_{t=1}^{T}\hat{\varepsilon}_{it}\hat{\varepsilon}_{jt}$;

$\hat{\Omega}$ is the estimated variance-covariance matrix of monthly asset pricing risk factors with a characteristic term in the *i*'th row and *j*'th column equal to $\frac{1}{T}\sum_{t=1}^{T}(\hat{f}_{it} - E_T(\hat{f}_i))(\hat{f}_{jt} - E_T(\hat{f}_j))$,

where

$\hat{f}_t$ is the vector of estimated asset pricing risk factors for month *t* with characteristic element $\hat{f}_{it}$, i = 1, 2, 3.

Cochrane (2009) also suggests how the GRS F-test can be applied to multifactor asset pricing models.

3.5.3 Cross-sectional regressions

Cochrane (2009) argues that the main difference between time-series regressions and cross sectional regressions is that the times series regressions primarily focus on the explanatory power of returns on given factors on test asset (portfolio) returns and on the pricing error of the given asset pricing model. The cross sectional regressions primarily focus on the explanatory power of factor loadings for asset (portfolio) returns, and so examine whether the factor itself is priced. In this study, I use the Fama-MacBeth (1973) method to test the cross-sectional explanatory power of the asset pricing models. I follow the Fama-MacBeth (1973) cross-sectional regression methodology to examine in the first stage the performance of the CAPM model. In equation 2, I estimate the portfolios' exposure to the market factor by running time series regressions of portfolio excess returns against the excess market return over the sample period.

The beta $\hat{\beta}_{iM}$ estimates from the time series regressions above are then used as the independent variables in the cross sectional regressions. I run one regression for every month, where the portfolio excess returns are the dependent variables:

$$R_{it} - R_{ft} = \gamma_{0t} + \gamma_{1t}\hat{\beta}_{it} + \varepsilon_{it}, \forall t \tag{10}$$

where

γ_{0t}	is the constant;
γ_{1t}	is the vector of cross sectional regression coefficients;
β_{it}	is the vector of estimated asset pricing risk factor loadings from the first pass regression;
ε_{it}	is the pricing error of portfolio *i* for period *t*.

I repeated the previous two steps for each month, providing for each variable a time series of its associated risk premium $\hat{\gamma}_{1t}$. The time series averages of these estimates are then tested by a *t*-statistic for significant differences from zero.

As a follow up step, I calculate the average risk premium $\bar{\gamma}_1$ using the following equation:

$$\bar{\gamma}_1 = \frac{1}{T}\hat{\gamma}_{1t} \tag{11}$$

and also the standard deviation of $\hat{\gamma}_1$ in a following way:

$$\hat{\sigma}(\bar{\gamma}_1) = \sqrt{\frac{1}{(T-1)}\sum_{t=1}^{T}(\hat{\gamma}_{1t} - \bar{\gamma}_1)^2} \tag{12}$$

The *t*-statistic will be the average of the risk premium divided by its time series standard error given by the equation below:

$$\hat{t}(\bar{\gamma}_1) = \frac{\bar{\gamma}_1}{\hat{\sigma}(\bar{\gamma}_1)/\sqrt{T}} \tag{13}$$

I follow the same Fama-MacBeth cross sectional regression methodology for the other risk factors too.

In order to address issues with regard to time-varying betas and following Mouselli, Michou and Stark (2014), I re-estimate the exposures of the portfolio excess returns to risk factors in the time series stage using 60-month rolling multiple time series regressions. The procedure has as follows: I run the regression in equations 2, 4, 5 and their variations, using the previous 60 months' observations and allocate the estimated exposures to that year. I then roll the regression forward 12 months and repeat the process. Then, I use the resulting estimates of betas in the cross sectional second stage equation (10), and for the other risk factors respectively.

Since the independent variable in the cross sectional regression is measured with error, the second pass estimator is subject to an errors-in-variables (EIV) problem. Shanken (1992) suggests a method of correcting for the bias of the standard errors of the cross sectional regression least squares estimates in the two-pass methodology in order to produce a consistent estimator for the squared standard error of each risk premium as the time series sample size, *T* increases:

$$(1+C)(\hat{w} - \hat{\sigma}^2(\bar{\gamma}_j)/T) + \hat{\sigma}^2(\bar{\gamma}_j)/T \tag{14}$$

where

$\hat{w}$	is the squared unadjusted standard error of the risk premium;
T	is the time series sample size period;

$\hat{C}$ is the error-in-variables (EIV) adjustment term and it is calculated as follows:

$$C = \hat{\gamma}\hat{\Omega}^{-1}\hat{\gamma} \tag{15}$$

where

$\hat{\gamma}$ is the vector of the averages of the monthly risk premia estimates for each portfolio.

I use this correction to generate *t*-statistics for the time series averages for each risk premium $\hat{\gamma}$. I refer to this *t*-statistic as the SH *t*-stat in all tables.

To compare the goodness-of-fit of the factor models, I use the cross sectional R^2 measure employed by Jagannathan and Wang (1996). This measure shows how much of the cross sectional variation in average returns can be explained by the relevant asset pricing model (equations 2, 4 and 5). It is widely employed in the literature to capture the explanatory power of factor models (Li, Vassalou and Xing, 2006; Petkova, 2006). It is calculated as follows:

$$R^2 = \frac{\sigma_C^2(\overline{R}) - \sigma_C^2(\bar{\varepsilon})}{\sigma_C^2(\overline{R})} \tag{16}$$

where

$\overline{R}$ is the vector of average excess returns of the test portfolios;

$\sigma_C^2(.)$ is the cross sectional variance;

$\bar{\varepsilon}$ is the vector of the time series average estimated residuals for each portfolio.

However, there have been various concerns raised by researchers (Petkova 2006), arguing that the R^2 gives equal weight to each portfolio included in the set of test portfolios or some portfolios may be more highly correlated than others. In order to address these concerns, I apply the χ^2 test for the joint significance of the pricing errors. Using standard OLS distribution assumptions that the true errors are identically and independently distributed over time and independent of the factors, a χ^2 distribution can be constructed using pricing errors across all testing assets. If a model is not misspecified, then its pricing errors for testing assets should be close to zeros. Following Cochrane (2009), I use the χ^2 test in order to check whether the pricing errors are jointly zero using the following statistics:

$$T[1+C]^{-1}\hat{\varepsilon}\hat{\Pi}^{-1}\hat{\varepsilon} \sim \chi^2_{N-K} \tag{17}$$

where

$\hat{\Pi}$ is the variance-covariance matrix for the estimated pricing errors, with characteristic term in the *i*'th row and *j*'th column equal to $\frac{1}{T}\sum_{t=1}^{T}(\hat{\varepsilon}_{it} - E_T(\hat{\varepsilon}_i))(\hat{\varepsilon}_{jt} - E_T(\hat{\varepsilon}_j))$;

$\hat{\varepsilon}$ is the vector of the estimates of the average cross sectional pricing errors for each portfolio *i*, where the average pricing error for portfolio *i*, is calculated as follows:

$$\hat{\varepsilon}_i = (\overline{R_{it} - R_{ft}}) - (\hat{\gamma}_0 + \hat{\gamma}_{1t}\hat{\beta}_{it}) \tag{18}$$

and $$\hat{\varepsilon}_i = (\overline{R_{it} - R_{ft}}) - (\hat{\gamma}_{1t}\hat{\beta}_{it})\,. \tag{19}$$

If the intercept $\hat{\gamma}_0$ is restricted to being zero in the second stage cross sectional regressions, then $\overline{R_{it} - R_{ft}}$ is the average excess return on portfolio *i*. Equation 18 and 19 are two equivalent measures of pricing errors under different regression restrictions.

The above procedures show the test for the CAPM model. However, I also report the results for the Fama and French three-factor model, a four-factor model and three versions of new three-factor models, of which:

- model one is constructed by Mkt, CMA_S and ROE_B_S;
- model two is constructed by Mkt, CMA_S and OP_A;
- model three is constructed by Mkt, CMA_S and ROE_A_S.

Twenty-five portfolios' excess returns on size-BM, size-Investment and size-Profitability are used as left-hand-side portfolios. I report *t*-statistics after the Shanken (1992) correction, the cross-sectional R^2 measure (Jagannathan and Wang, 1996) and the χ^2 test for the distribution of joint pricing errors (Cochrane, 2009).

3.5.4 Robustness tests – industry portfolios

I also perform the asset pricing tests using the returns on 34 industry portfolios. I use the London Share Price Database industrial classification codes G17 and the FTSE Industrial Classification Benchmark (ICB) to construct 34 industry portfolios every month from July 1990 to December 2013. Value-weighted monthly returns for these portfolios are calculated. Summary statistics for the industry portfolios are reported in Table 3-14.

In constructing the 34 industry portfolios, I apply the same criteria I previously used for the construction of the 25 size-BM intersected portfolios. That is, I apply the same MV and BM definitions, dates of construction, calculations of the value-weighted portfolios, and the way of dealing with delisted firms. Amongst the 34 industry portfolios, the electricity industry has the highest average monthly return of 1.65%. Industrial transportation generates the lowest average monthly return of -1.31% during the sample period. Regarding the return volatilities, the industrial metals mining industry has the highest standard deviation of 16.22% while the food producers industry has the most stable returns with a standard deviation of 4.38%.

3.6 RESULTS

3.6.1 LHS portfolio excess returns

Firstly, I focus on the pattern of UK stock returns by looking at the average 25 intersected portfolios' excess returns. Table 3-3 shows the average excess returns with their statistical significance for the 25 size-BM; size-Profitability and size-I/A portfolios. The table allows us to have an overview of the UK stock return patterns that are relevant to BM, profitability and investment variables respectively.

The size-BM sorts show a clear value effect in the UK. Across every size group, average excess returns increase with a higher BM ratio. This result is consistent with previous findings in the UK (Gregory, Tharyan and Christidis, 2013; Michou, Mouselli and Stark, 2014) and Europe (Fama and French, 2012; 2017). The average value premiums are equal to 1.04%, 0.98%, 0.50%, 0.72% and 0.39% respectively from the smallest to the largest size groups. There is, however, no clear relation between size and excess return, which also confirms previous results of insignificant size effect in the UK (Gregory, Tharyan and Christidis, 2013; Michou, Mouselli and Stark, 2014).

The second sort, size-Profitability, employs (income before extraordinary items/TA) as its profitability formation. There is a discernible negative relation between average excess returns and profitability for every size group except for the largest. The profitability premiums mainly come from the difference between the lowest profitability quintile and the second-lowest quintile. From the smallest size to the second-largest quintile group, the difference between the two lowest quintiles of profitability portfolios are equal to 0.65%, 0.43%, 0.53% and 0.52% respectively. The UK profitability effect is in general consistent with the Europe pattern (Fama and French, 2017), with the only difference being in the largest-size quintile portfolios, where there is no profitability effect in the UK but a significant trend in the European sample.

The size-I/A sorts indicate that future return is also negatively correlated with past investment in the UK. For each size group, future excess returns are higher for the lower investment quintile. The low-minus-high investment premiums amount to 0.41%, 0.97%, 0.44%, 0.88% and 0.14% from the smallest to the largest group. Similar to the profitability effect, the investment pattern fades out in the largest group in the UK. Fama and French (2017) report similar results in their European sample, where investment provides trivial information in the largest group.

In short, there is an observable investment and profitability-related stock return pattern in the UK. The negative relation between investment and future excess returns and positive relation between profitability and future excess returns are generally in line with the results from the US and Europe markets. Whether or not those patterns are captured by existing versions of factor models will be examined.

Table 3-3

Average monthly excess returns on portfolios from July 1990 to December 2013

This table reports the average excess returns of 25 size-BM, size-profitability, size-investment portfolios. At the end of June each year I use accounting data from the end of the previous year to construct portfolios. I use quartiles of the largest 350 stocks to form size groups and combine the rest of the sample stocks into the smallest size group. Independently, I construct five groups of BM, Profitability or Investment portfolios using quintile breakpoints of the largest 350 stocks. Profitability is defined as income before extraordinary items/TA and investment is defined as investment/TA.

Excess return						**T value**					
variable	**BM**						**BM**				
	high	4	3	2	low	level	High	4	3	2	Low
size	0.63	0.53	0.32	-0.02	-0.41	small	1.97	1.67	0.98	-0.05	-1.06
	1.08	0.47	0.29	0.15	0.10	2	2.32	1.15	0.70	0.41	0.19
	0.78	0.70	0.58	0.19	0.28	3	1.88	1.67	1.64	0.55	0.72
	1.03	0.57	0.50	0.38	0.31	4	2.46	1.54	1.37	1.08	0.74
	0.73	0.57	0.53	0.43	0.34	big	2.20	1.97	1.81	1.57	1.41
	Profitability						**Profitability**				
	high	4	3	2	low	level	High	4	3	2	Low
size	0.67	0.75	0.54	0.53	-0.12	small	2.35	2.53	1.68	1.69	-0.30
	0.77	0.43	0.85	0.50	0.07	2	2.29	1.30	1.93	1.31	0.13
	0.86	0.85	0.36	0.50	-0.03	3	2.68	2.53	0.97	1.27	-0.06
	0.80	0.56	0.91	0.58	0.06	4	2.17	1.63	2.79	1.56	0.13
	0.54	0.42	0.54	0.43	0.51	big	2.16	1.52	2.04	1.51	1.50

	Investment						Investment				
	high	4	3	2	low	level	High	4	3	2	Low
size	0.03	0.38	0.60	0.60	0.44	small	0.09	1.24	2.07	1.95	1.19
	-0.14	0.15	0.58	0.67	0.83	2	-0.34	0.37	1.68	1.75	1.83
	0.49	0.42	0.64	0.91	0.93	3	1.20	1.11	1.95	2.61	2.22
	0.19	0.63	0.47	0.49	1.07	4	0.43	1.75	1.45	1.38	2.60
	0.48	0.16	0.47	0.66	0.62	big	1.51	0.50	1.96	2.66	2.12

3.6.2 Factor summary statistics

Before I move on to the information content of the time-series asset pricing factors, I focus on their statistical significance and correlations. Table 3-4 provides summary statistics for my factors. The size factor SMB has a negative mean with no statistical significance. The result is not surprising since past evidence has documented the absence of the size effect in the UK market (Gregory, Tharyan and Christidis, 2013; Michou, Mouselli and Stark, 2014).The HML factor is significantly different from zero with 0.42% premium per month. The small end of HML provides 0.19% higher monthly premiums with higher statistical significance. For the investment factor CMA, both normal and small end are significantly different from zero at the 1% level. The average premium for CMA and CMA_S are 0.55% and 0.66% respectively. Among the 12 differently constructed profitability factors, all but ROE_B exhibit average means that are statistically different from zero. The small end of ROE_A provides the highest mean among all the time-series factors (0.68% per month). The small end of OP_A provides the second-highest mean of 0.67% per month. In general, every small end of the factor has a higher mean compared with the normal version in my sample.

Table 3-5 illustrates the time series correlations between asset pricing factors. The correlations between normal factors and their corresponding small end versions are generally high. For example, 0.80 between HML and HML_S and 0.72 between CMA and CMA_S. Among the specifications of profitability factors, there are highly positive correlations between ROEs and OPs: 0.69 between ROE_B and

OP_B; 0.91 between ROE_A and OP_A. The correlations between GROs and ROEs/OPs are relatively lower: 0.50 between GRO_B and TOE_B; 0.42 between GRO_B_S and ROE_B_S, but the correlations are still higher than those with other factors. The correlations between Book value scaled and Total asset scaled profitability factors are also high: 0.76 between ROE_A and ROE_B; 0.87 for OP; and 0.82 for GRO. The combination of different factor variable formation and construction methods has the potential to dramatically influence the information content of the profitability factor. For instance, OP_B and GRO_A_S has a 0.29 correlation; ROE_B and GRO_A_S has a correlation of 0.26.

Table 3-4

Summary statistics for asset pricing factors, July 1990 to December 2013

This table reports the summary statistics of asset pricing factors with alternative definitions. (Rm-Rf) is the market risk premium (value weighted market return minus T-bill rate), SMB is the size factor (small minus big), HML is the value factor (high minus low BM), CMA is the investment factor(conservative minus aggressive). There are three specifications used to construct profitability factors: ROE represents the profitability factor based on income before extraordinary items; OP represents the profitability factor based on operating income; and GRO represents the profitability factor based on gross profit. Regarding the difference in scalers, _B and _A are used to denote book value and total asset value respectively as denominators to construct the profitability factors. Small ends of the factors are constructed and labelled with _S: for instance, GRO_A_S stands for the profitability factor constructed using the gross profit/total asset with small end method.

Variable	mean	s.d.	skewness	kurtosis	max	median	min
RMRF	0.4	4.17	-0.56	3.61	10.48	0.85	-13.61
SMB	-0.08	3.59	0.17	5.85	17.43	-0.20	-14.54
HML	0.42*	2.85	-0.23	8.48	11.62	0.31	-13.53
HML_S	0.61**	3.60	-0.09	9.66	17.25	0.48	-19.61
CMA	0.55***	2.51	0.83	5.94	12.35	0.13	-8.76
CMA_S	0.66***	2.59	0.91	7.58	15.91	0.39	-8.59
ROE_B	0.11	2.27	0.12	4.46	10.51	0.21	-7.32
ROE_B_S	0.28	2.45	-0.45	4.70	7.36	0.40	-10.17
ROE_A	0.42**	2.77	0.24	4.76	10.99	0.36	-8.41
ROE_A_S	0.68***	2.93	-0.70	6.93	10.12	0.73	-14.66
OP_B	0.3	2.67	0.76	6.90	12.58	0.13	-8.29
OP_B_S	0.43*	2.86	0.06	5.43	10.85	0.43	-12.33
OP_A	0.46**	2.75	0.45	5.95	12.06	0.25	-9.05
OP_A_S	0.67**	3.07	-0.51	7.33	12.83	0.62	-15.89
GRO_B	0.29*	2.14	0.70	4.98	9.15	0.12	-5.95
GRO_B_S	0.41**	2.41	0.10	3.41	8.01	0.30	-7.04
GRO_A	0.37**	2.33	0.32	3.61	7.77	0.16	-6.80
GRO_A_S	0.47**	2.88	0.00	4.64	12.74	0.46	-8.96

Table 3-5

Correlations

This table reports the correlations between alternative versions of asset pricing factors. (Rm-Rf) is the market risk premium (value weighted market return minus T-bill rate), SMB is the size factor (small minus big); HML is the value factor (high minus low BM), CMA is the investment factor (conservative minus aggressive). There are three specifications used to construct profitability factors: ROE represents the profitability factor based on income before extraordinary items, OP represents the profitability factor based on operating income, and GRO represents the profitability factor based on gross profit. Regarding the difference in scalers, _B and _A are used to denote book value and total asset value respectively as denominators to construct the profitability factors. Small ends of the factors are constructed and labelled with _S: for instance, GRO_A_S stands for the profitability factor constructed using the gross profit/total asset with small end method.

	RM-RF	SMB	HML	HML_S	CMA	CMA_S	ROE_B	ROE_B_S	ROE_A	ROE_A_S	OP_B	OP_B_S	OP_A	OP_A_S	GRO_B	GRO_B_S	GRO_A
SMB	0.12																
HML	0.09	-0.14															
HML_S	-0.06	-0.11	0.80														
CMA	-0.15	-0.09	0.38	0.39													
CMA_S	-0.02	0.09	0.43	0.48	0.72												
ROE_B	-0.30	-0.35	-0.30	-0.04	-0.23	-0.22											
ROE_B_S	-0.33	-0.44	-0.09	-0.06	-0.07	-0.22	0.66										
ROE_A	-0.40	-0.39	-0.22	0.09	0.09	-0.06	0.76	0.56									
ROE_A_S	-0.43	-0.53	0.00	0.10	0.13	-0.07	0.57	0.78	0.73								
OP_B	-0.32	-0.30	-0.10	0.25	0.16	0.11	0.69	0.45	0.81	0.58							
OP_B_S	-0.34	-0.45	0.10	0.18	0.17	0.11	0.54	0.69	0.63	0.76	0.74						
OP_A	-0.37	-0.37	-0.12	0.19	0.16	0.04	0.68	0.51	0.91	0.69	0.87	0.67					
OP_A_S	-0.39	-0.53	0.08	0.16	0.20	0.02	0.51	0.71	0.68	0.93	0.59	0.81	0.71				
GRO_B	-0.33	-0.15	-0.22	0.09	0.34	0.22	0.50	0.33	0.68	0.49	0.77	0.58	0.70	0.51			
GRO_B_S	-0.26	-0.12	-0.02	0.05	0.22	0.26	0.30	0.42	0.37	0.45	0.40	0.62	0.39	0.50	0.69		
GRO_A	-0.32	-0.13	-0.37	-0.10	0.22	0.11	0.43	0.32	0.63	0.50	0.57	0.48	0.66	0.52	0.82	0.63	
GRO_A_S	-0.27	-0.16	-0.22	-0.18	0.14	0.08	0.26	0.40	0.36	0.56	0.29	0.52	0.36	0.62	0.57	0.78	0.74

3.6.3 Factor-spanning tests

I now turn attention to the relative informativeness of asset pricing factors using factor-spanning tests. Table 3-6 illustrates the test results.

Panel A shows that the market factor (RM-RF) is informative in the UK. The explanatory power of the market factor is not spanned by the other factors, as the regression intercepts are statistically different from zero for all asset pricing factor combinations tested. This result is similar to the evidence from the Europe sample in Fama and French (2017). Panel B suggests that the intercepts for regressions of SMB on other factors are statistically no different from zero. The results are consistent with my previous evidence that the size effect does not exist in the UK market. SMB is therefore a redundant factor for UK asset pricing models.

Panels C and D illustrate factor-spanning test results for HML and HML_S. Both versions of value factor are spanned by the remaining factors in the factor models, leaving the intercepts indifferent from zero. The results suggest that value factor is redundant in the UK market. The redundancy of value factor is also found in the US (Fama and French, 2015a), but not in Asia Pacific, Japan, North America and Europe (Fama and French, 2017). This further confirms the argument of Fama and French (2015a; 2017) that the factor information may be sample-specific. Moreover, the factor informativeness is likely to be country-specific, as I observe noticeable differences between the US and North America (Fama and French, 2017) as well as between the UK and Europe.

Panels E and F focus on the information content of the investment factors CMA and CMA_S. In contrast to the results in Europe (Fama and French, 2017) where CMA is fully captured by the other factors, my spanning tests suggest that the investment factor is an important component of the UK factor model. All the spanning regression intercepts are highly significantly different from zero for both versions of CMA: after controlling for other factors, the intercepts range from 0.29% to 0.49% for CMA and 0.32% to 0.52% for CMA_S. My UK-specific results for CMA also suggest that the information content of asset pricing factors are likely to be heterogeneous among the European countries.

Starting from Panel G, I concentrate on the relative information content of profitability factors RMW. In Panels G and H, I test the impact of the profitability variable definition on information content. Panel G shows that when scaled by book value, ROE provides information uncaptured by OP and GRO, since regressions on ROE_Bs generate significant intercepts. When scaled by total assets, results from Panel H suggest that variable ROE and OP outperform GRO: OP_A_S regressed on GRO_A_S and other factors generates an intercept of 0.36% with statistical significance; ROE_A has significant 0.27%, 0.22% and 0.52% intercepts after controlling for other factors plus GRO_A, OP_A_S, GRO_A_S respectively; in contrast, the intercepts for GRO_A and GRO_A_S regressions are indifferent from zero. This evidence confirms Ball *et al*. (2015)'s finding that the scaler of RWM matters to its information content. To further illustrate the relative information difference, I employ RMWs based on profitability variables scaled by total assets to regress on those based on the book-value scaler together with other factors for spanning tests and vice versa, with results presented in Panel I and J. The significant intercepts across the regressions in panel I and insignificant intercepts under panel J regressions confirm Ball *et al*. (2015)'s argument that the total asset scaler provides superior information for profitability factor holds in the UK as well. In short, the dominant choices are ROE and OP for UK profitability factor variable numerator, while using total asset as the scaler outperforms book value.

However, the above results have not taken into account small-end factor construction methods. Panel K of Table 3-6 presents the additional information from the small-end factor construction method. When using CMA_S as a regressor in the spanning tests, some of the intercepts are significantly different from zero. Together with the results from Panel E and F, it seems that the small end of investment factor CMA_S should be included in the factor model to provide better explanatory power. For profitability factors based on OP and ROE, information content of small-end factors are also not fully captured by their normal versions plus other factors. Though ROE and OP dominate GRO as the denominator of variable definition, the choice of profitability factor cannot be made with certainty. There are more possibilities based on the interaction of variable scaler choices and small-end construction methods. I leave this task to the GRS tests.

Table 3-6

Spanning tests on asset pricing factors:													
(Rm-Rf) is the market risk premium (value-weighted market return minus T-bill rate), SMB is the size factor (small minus big); HML is the value factor (high minus low BM), CMA is the investment factor (conservative minus aggressive). There are three specifications used to construct profitability factors: ROE represents the profitability factor based on income before extraordinary items; OP represents the profitability factor based on operating income and GRO represents the profitability factor based on gross profit. Regarding the difference in scalers, _B and _A are used to denote book value and total asset value respectively as denominators to construct the profitability factors. Small ends of the factors are constructed and labelled with _S: for instance, GRO_A_S stands for the profitability factor constructed using the gross profit/total asset with small end method.													
Panel A: Market factor RM-RF													
VARIABLES	RM-RF	RM-RF	RM-RF	RM-RF	RM-RF	RM-RF	RM-RF	RM-RF	RM-RF	RM-RF	RM-RF	RM-RF	RM-RF
SMB	0.13*	0.01	-0.06	-0.05	-0.18**	0.03	-0.07	-0.02	-0.14*	0.06	0.08	0.06	0.05
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)
HML_S	-0.05	-0.05	-0.06	-0.01	-0.01	0.02	-0.02	0.01	-0.01	-0.07	-0.09	-0.14*	-0.17**
	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)
CMA_S	-0.01	-0.11	-0.11	-0.05	-0.06	0.01	0.05	-0.01	0.01	0.13	0.14	0.12	0.12
	(0.11)	(0.11)	(0.11)	(0.10)	(0.10)	(0.11)	(0.11)	(0.10)	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)
RMW		ROE _B	ROE _B_S	ROE _A	ROE _A_S	OP _B	OP _B_S	OP _A	OP _A_S	GRO _B	GRO _B_S	GRO _A	GRO _A_S
		-0.58***	-0.64***	-0.62***	-0.74***	-0.50***	-0.54***	-0.57***	-0.61***	-0.65***	-0.47***	-0.59***	-0.43***
		(0.11)	(0.11)	(0.09)	(0.09)	(0.10)	(0.09)	(0.09)	(0.09)	(0.11)	(0.10)	(0.11)	(0.09)
Constant	0.45*	0.57**	0.69***	0.70***	0.94***	0.54**	0.61**	0.66***	0.80***	0.56**	0.57**	0.64***	0.64**
	(0.26)	(0.25)	(0.25)	(0.24)	(0.24)	(0.25)	(0.24)	(0.24)	(0.24)	(0.24)	(0.25)	(0.25)	(0.25)
R-squared	0.02	0.10	0.12	0.16	0.21	0.10	0.12	0.14	0.16	0.12	0.08	0.12	0.10

Panel B: Size factor SMB													
VARIABLES	SMB	SMB	SMB	SMB	SMB	SMB	SMB	SMB	SMB	SMB	SMB	SMB	SMB
RM-RF	0.09*	0.01	-0.04	-0.04	-0.12**	0.02	-0.04	-0.02	-0.09*	0.05	0.06	0.05	0.04
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
HML_S	-0.19***	-0.17***	-0.17***	-0.14**	-0.10*	-0.12*	-0.12*	-0.11*	-0.09	-0.19***	-0.20***	-0.22***	-0.25***
	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)
CMA_S	0.25***	0.13	0.10	0.18**	0.13	0.25***	0.27***	0.22**	0.20**	0.30***	0.32***	0.30***	0.32***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)	(0.09)	(0.08)	(0.09)	(0.08)	(0.09)	(0.10)	(0.09)	(0.09)
RMW		ROE_B	ROE_B_S	ROE_A	ROE_A_S	OP_B	OP_B_S	OP_A	OP_A_S	GRO_B	GRO_B_S	GRO_A	GRO_A_S
		-0.53***	-0.67***	-0.50***	-0.71***	-0.37***	-0.59***	-0.47***	-0.65***	-0.27**	-0.22**	-0.25**	-0.27***
		(0.10)	(0.09)	(0.08)	(0.07)	(0.08)	(0.07)	(0.08)	(0.06)	(0.11)	(0.09)	(0.10)	(0.08)
Constant	-0.17	-0.01	0.16	0.10	0.42**	-0.07	0.08	0.06	0.31	-0.10	-0.10	-0.07	-0.03
	(0.22)	(0.21)	(0.20)	(0.21)	(0.19)	(0.21)	(0.20)	(0.21)	(0.19)	(0.22)	(0.22)	(0.22)	(0.22)
R-squared	0.05	0.14	0.22	0.17	0.31	0.11	0.24	0.16	0.30	0.07	0.07	0.07	0.09

Panel C: Value factor HML													
VARIABLES	HML	HML	HML	HML	HML	HML	HML	HML	HML	HML	HML	HML	HML
RM-RF	0.08**	0.02	0.07*	0.01	0.07*	0.04	0.08**	0.03	0.09**	-0.00	0.05	-0.02	0.03
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
SMB	-0.15***	-0.22***	-0.17***	-0.23***	-0.16***	-0.20***	-0.15***	-0.21***	-0.14***	-0.19***	-0.16***	-0.19***	-0.18***
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
CMA_S	0.50***	0.43***	0.49***	0.49***	0.50***	0.52***	0.50***	0.51***	0.49***	0.59***	0.54***	0.55***	0.52***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.06)
RMW		ROE_B	ROE_B_S	ROE_A	ROE_A_S	OP_B	OP_B_S	OP_A	OP_A_S	GRO_B	GRO_B_S	GRO_A	GRO_A_S
		-0.38***	-0.06	-0.31***	-0.03	-0.22***	0.01	-0.23***	0.03	-0.50***	-0.17***	-0.57***	-0.28***
		(0.07)	(0.07)	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)	(0.05)
Constant	0.05	0.16	0.08	0.21	0.08	0.11	0.05	0.16	0.03	0.17	0.10	0.26*	0.18
	(0.16)	(0.15)	(0.16)	(0.15)	(0.16)	(0.15)	(0.16)	(0.16)	(0.16)	(0.14)	(0.16)	(0.14)	(0.15)
R-squared	0.23	0.30	0.23	0.29	0.23	0.26	0.23	0.27	0.23	0.35	0.25	0.42	0.30

Panel D: Small end of value factor HML_S													
VARIABLES	HML_S	HML_S	HML_S	HML_S	HML_S	HML_S	HML_S	HML_S	HML_S	HML_S	HML_S	HML_S	HML_S
RM-RF	-0.03	-0.03	-0.04	-0.01	-0.01	0.01	-0.01	0.01	-0.00	-0.05	-0.06	-0.08*	-0.09**
	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)
SMB	-0.15***	-0.14***	-0.16***	-0.12**	-0.11*	-0.10*	-0.11*	-0.10*	-0.10	-0.15***	-0.16***	-0.17***	-0.19***
	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
CMA_S	0.69***	0.69***	0.68***	0.69***	0.69***	0.66***	0.67***	0.68***	0.68***	0.71***	0.73***	0.72***	0.72***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
RMW		ROE _B	ROE _B_S	ROE _A	ROE _A_S	OP _B	OP _B_S	OP _A	OP _A_S	GRO _B	GRO _B_S	GRO _A	GRO _A_S
		0.01	-0.06	0.09	0.09	0.23***	0.10	0.18**	0.11	-0.10	-0.18**	-0.32***	-0.35***
		(0.09)	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.10)	(0.08)	(0.08)	(0.06)
Constant	0.16	0.15	0.18	0.11	0.08	0.09	0.12	0.07	0.08	0.18	0.21	0.27	0.32*
	(0.19)	(0.19)	(0.20)	(0.20)	(0.20)	(0.19)	(0.20)	(0.19)	(0.20)	(0.19)	(0.19)	(0.19)	(0.19)
R-squared	0.26	0.26	0.26	0.26	0.26	0.28	0.26	0.27	0.26	0.26	0.27	0.29	0.33

Panel E: Investment factor CMA													
VARIABLES	CMA	CMA	CMA	CMA	CMA	CMA	CMA	CMA	CMA	CMA	CMA	CMA	CMA
RM-RF	-0.07**	-0.13***	-0.10***	-0.08**	-0.06*	-0.07*	-0.06*	-0.06*	-0.05	-0.02	-0.05	-0.03	-0.04
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
SMB	-0.03	-0.10***	-0.07	-0.03	-0.01	-0.02	-0.01	-0.02	0.02	-0.00	-0.01	-0.01	-0.00
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
HML_S	0.26***	0.24***	0.25***	0.26***	0.26***	0.26***	0.26***	0.26***	0.26***	0.25***	0.26***	0.29***	0.29***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
RMW		ROE _B	ROE _B_S	ROE _A	ROE _A_S	OP _B	OP _B_S	OP _A	OP _A_S	GRO _B	GRO _B_S	GRO _A	GRO _A_S
		-0.37***	-0.14**	-0.01	0.03	0.03	0.06	0.04	0.10*	0.35***	0.18***	0.27***	0.17***
		(0.06)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.05)
Constant	0.42***	0.49***	0.48***	0.43***	0.40***	0.41***	0.40***	0.40***	0.35**	0.31**	0.34**	0.29**	0.31**
	(0.14)	(0.13)	(0.14)	(0.14)	(0.15)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
R-squared	0.17	0.26	0.18	0.17	0.17	0.17	0.17	0.17	0.18	0.24	0.20	0.22	0.20

Panel F: Small end of investment factor CMA_S													
VARIABLES	CMA _S	CMA _S	CMA _S	CMA _S	CMA _S	CMA _S	CMA _S	CMA _S	CMA _S	CMA _S	CMA _S	CMA _S	CMA _S
RM-RF	-0.00	-0.03	-0.04	-0.02	-0.02	0.00	0.02	-0.00	0.00	0.04	0.04	0.04	0.03
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
SMB	0.10***	0.06	0.05	0.09**	0.07	0.11***	0.13***	0.10**	0.11**	0.12***	0.12***	0.12***	0.13***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
HML_S	0.36***	0.34***	0.34***	0.36***	0.36***	0.35***	0.35***	0.36***	0.36***	0.35***	0.35***	0.38***	0.39***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
RMW		ROE _B	ROE _B_S	ROE _A	ROE _A_S	OP _B	OP _B_S	OP _A	OP _A_S	GRO _B	GRO _B_S	GRO _A	GRO _A_S
		-0.22***	-0.19***	-0.07	-0.07	0.03	0.10*	-0.00	0.02	0.26***	0.29***	0.22***	0.20***
		(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.05)
Constant	0.45***	0.49***	0.52***	0.48***	0.50***	0.44***	0.40***	0.45***	0.43***	0.36***	0.32**	0.34**	0.32**
	(0.14)	(0.13)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.13)	(0.13)	(0.14)	(0.14)
R-squared	0.25	0.28	0.28	0.26	0.26	0.25	0.26	0.25	0.25	0.29	0.32	0.29	0.30

Panel G: Profitability factor using book value as denominator

VARIABLES	OP_B	OP_B	OP_B_S	OP_B_S	ROE_B	ROE_B	ROE_B_S	ROE_B_S	GRO_B	GRO_B	GRO_B_S	GRO_B_S
RM-RF	-0.03	-0.05*	-0.07**	-0.10***	-0.06***	-0.08***	-0.07***	-0.11***	-0.02	-0.03	-0.03	-0.06*
	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
SMB	0.00	-0.12***	-0.13***	-0.28***	-0.12***	-0.18***	-0.09***	-0.24***	0.03	0.04	0.10***	0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)
HML	0.01	0.14***			-0.11***	-0.02			-0.21***	-0.19***		
	(0.04)	(0.04)			(0.03)	(0.04)			(0.03)	(0.03)		
HML_S			0.08**	0.12***			-0.06*	0.01			-0.13***	-0.08**
			(0.04)	(0.04)			(0.03)	(0.04)			(0.03)	(0.04)
CMA	0.35***	-0.21***			-0.29***	-0.42***			0.28***	0.48***		
	(0.05)	(0.05)			(0.04)	(0.05)			(0.03)	(0.04)		
CMA_S			0.24***	-0.09*			-0.23***	-0.29***			0.25***	0.39***
			(0.05)	(0.05)			(0.04)	(0.05)			(0.05)	(0.05)
RMW	ROE_B	GRO_B	ROE_B_S	GRO_B_S	OP_B	GRO_B	OP_B_S	GRO_B_S	OP_B	ROE_B	OP_B_S	ROE_B_S
	0.89***	1.02***	0.74***	0.66***	0.54***	0.60***	-0.23***	0.41***	0.55***	0.53***	0.58***	0.49***
	(0.06)	(0.05)	(0.05)	(0.05)	(0.03)	(0.05)	(0.04)	(0.05)	(0.03)	(0.05)	(0.04)	(0.06)
Constant	0.01	0.07	0.04	0.17	0.17**	0.20**	0.25**	0.32***	0.07	0.06	0.10	0.09
	(0.11)	(0.10)	(0.12)	(0.12)	(0.08)	(0.10)	(0.10)	(0.11)	(0.07)	(0.09)	(0.11)	(0.13)
R-squared	0.59	0.65	0.59	0.57	0.65	0.55	0.59	0.45	0.71	0.55	0.48	0.33

Panel H: Profitability factor using total asset as denominator												
VARIABLES	OP_A	OP_A	OP_A_S	OP_A_S	ROE_A	ROE_A	ROE_A_S	ROE_A_S	GRO_A	GRO_A	GRO_A_S	GRO_A_S
RM-RF	-0.00	-0.10***	0.01	-0.13***	-0.05***	-0.13***	-0.07***	-0.17***	-0.02	-0.02	-0.01	-0.01
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
SMB	-0.00	-0.19***	-0.04*	-0.32***	-0.07***	-0.23***	-0.05**	-0.31***	0.03	0.04	0.14***	0.11**
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
HML	0.05*	0.12**			-0.11***	0.00			-0.33***	-0.30***		
	(0.03)	(0.05)			(0.03)	(0.05)			(0.04)	(0.04)		
HML_S			0.02	0.23***			-0.01	0.18***			-0.32***	-0.31***
			(0.02)	(0.04)			(0.02)	(0.04)			(0.04)	(0.04)
CMA	0.07**	-0.08			-0.03	-0.10*			0.26***	0.29***		
	(0.03)	(0.05)			(0.03)	(0.05)			(0.04)	(0.04)		
CMA_S			0.09***	-0.15***			-0.09***	-0.21***			0.27***	0.34***
			(0.03)	(0.05)			(0.03)	(0.05)			(0.05)	(0.06)
RWM	ROE_A	GRO_A	ROE_A_S	GRO_A_S	OP_A	GRO_A	OP_A_S	GRO_A_S	OP_A	ROE_A	OP_A_S	ROE_A_S
	0.91***	0.76***	0.96***	0.61***	0.85***	0.66***	-0.09***	0.49***	0.48***	0.45***	0.72***	0.67***
	(0.03)	(0.06)	(0.03)	(0.04)	(0.03)	(0.06)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.06)
Constant	0.01	0.19*	-0.07	0.36***	0.11	0.27**	0.22***	0.52***	0.15	0.15	0.03	-0.01
	(0.07)	(0.12)	(0.07)	(0.11)	(0.07)	(0.12)	(0.07)	(0.12)	(0.09)	(0.10)	(0.13)	(0.14)
R-squared	0.83	0.55	0.87	0.66	0.85	0.54	0.88	0.62	0.59	0.55	0.54	0.46

Panel I: Profitability factor using total asset as denominator while the profitability factor regressors use book value as denominator												
VARIABLES	OP_A	OP_A	OP_A_S	OP_A_S	ROE_A	ROE_A	ROE_A_S	ROE_A_S	GRO_A	GRO_A	GRO_A_S	GRO_A_S
RM-RF	-0.07**	-0.09***	-0.12***	-0.16***	-0.09***	-0.12***	-0.14***	-0.20***	-0.05**	-0.06**	-0.08**	-0.11***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)
SMB	-0.07**	-0.19***	-0.22***	-0.37***	-0.14***	-0.22***	-0.18***	-0.35***	-0.01	-0.00	0.03	-0.03
	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.05)
HML	-0.04	0.06			-0.15***	-0.03			-0.36***	-0.35***		
	(0.04)	(0.04)			(0.03)	(0.04)			(0.04)	(0.04)		
HML_S			0.08**	0.12***			0.01	0.09**			-0.31***	-0.26***
			(0.04)	(0.04)			(0.03)	(0.04)			(0.04)	(0.05)
CMA	0.34***	-0.15***			-0.01	-0.18***			0.28***	0.42***		
	(0.05)	(0.05)			(0.04)	(0.05)			(0.04)	(0.05)		
CMA_S			0.14***	-0.14**			-0.14***	-0.21***			0.22***	0.36***
			(0.05)	(0.06)			(0.05)	(0.06)			(0.06)	(0.07)
RWM	ROE_B	GRO_B	ROE_B_S	GRO_B_S	OP_B	GRO_B	OP_B_S	GRO_B_S	OP_B	ROE_B	OP_B_S	ROE_B_S
	0.82***	0.87***	0.72***	0.53***	0.72***	0.81***	-0.14***	0.45***	0.39***	0.38***	0.56***	0.45***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.04)	(0.06)	(0.05)	(0.05)	(0.04)	(0.06)	(0.06)	(0.07)
Constant	0.21*	0.28**	0.35***	0.51***	0.30***	0.33***	0.54***	0.63***	0.27***	0.26**	0.30**	0.31**
	(0.11)	(0.11)	(0.12)	(0.13)	(0.09)	(0.11)	(0.11)	(0.12)	(0.10)	(0.11)	(0.14)	(0.16)
R-squared	0.59	0.59	0.62	0.54	0.72	0.60	0.67	0.54	0.52	0.45	0.40	0.29

Panel J: Profitability factor using book value as denominator while the profitability factor regressors use total asset as denominator												
VARIABLES	OP_B	OP_B	OP_B_S	OP_B_S	ROE_B	ROE_B	ROE_B_S	ROE_B_S	GRO_B	GRO_B	GRO_B_S	GRO_B_S
RM-RF	0.01	-0.09***	-0.01	-0.11***	-0.05**	-0.10***	-0.05*	-0.12***	-0.02	-0.01	-0.04	-0.03
	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
SMB	0.03	-0.15***	-0.06*	-0.26***	-0.10***	-0.20***	-0.06*	-0.23***	0.05*	0.06**	0.10**	0.09**
	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.04)	(0.04)
HML	0.05	0.10*			-0.09***	-0.04			-0.20***	-0.16***		
	(0.04)	(0.06)			(0.03)	(0.05)			(0.03)	(0.03)		
HML_S			0.02	0.18***			-0.06*	0.05			-0.12***	-0.12***
			(0.03)	(0.04)			(0.03)	(0.04)			(0.04)	(0.04)
CMA	0.08*	-0.04			-0.29***	-0.32***			0.29***	0.32***		
	(0.04)	(0.06)			(0.04)	(0.05)			(0.04)	(0.04)		
CMA_S			0.16***	-0.02			-0.18***	-0.24***			0.30***	0.34***
			(0.05)	(0.06)			(0.04)	(0.05)			(0.05)	(0.05)
profit factor	ROE_A	GRO_A	ROE_A_S	GRO_A_S	OP_A	GRO_A	OP_A_S	GRO_A_S	OP_A	ROE_A	OP_A_S	ROE_A_S
	0.81***	0.63***	0.70***	0.46***	0.52***	0.38***	-0.18***	0.27***	0.49***	0.49***	0.45***	0.45***
	(0.04)	(0.07)	(0.05)	(0.05)	(0.04)	(0.06)	(0.04)	(0.04)	(0.03)	(0.04)	(0.05)	(0.05)
Constant	-0.11	0.07	-0.17	0.14	0.09	0.20*	0.10	0.31**	0.00	-0.01	0.01	-0.03
	(0.10)	(0.13)	(0.12)	(0.13)	(0.09)	(0.11)	(0.10)	(0.12)	(0.08)	(0.09)	(0.12)	(0.13)
R-squared	0.67	0.40	0.61	0.49	0.62	0.43	0.57	0.40	0.62	0.60	0.36	0.33

Panel K: Influence of the small end of factors												
VARIABLES	CMA_S	CMA_S	CMA_S	CMA_S	CMA_S	CMA_S	CMA_S	CMA_S	OP_B_S	ROE_B_S	OP_A_S	ROE_A_S
RM-RF	0.05**	0.03	0.03	0.02	0.05*	0.06**	0.04	0.03	-0.08***	-0.09***	-0.11***	-0.13***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
SMB	0.13***	0.09***	0.10***	0.08**	0.12***	0.14***	0.11***	0.10***	-0.21***	-0.17***	-0.27***	-0.24***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
HML_S	0.18***	0.18***	0.18***	0.18***	0.18***	0.18***	0.18***	0.18***	-0.04	-0.03	0.00	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
CMA	0.68***	0.66***	0.67***	0.67***	0.67***	0.66***	0.67***	0.67***				
	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)				
CMA_S									0.09*	-0.07	0.03	-0.03
									(0.05)	(0.05)	(0.05)	(0.05)
profit factor	ROE_B	ROE_B_S	ROE_A	ROE_A_S	OP_B	OP_B_S	OP_A	OP_A_S	OP_B	ROE_B	OP_A	ROE_A
	0.03	-0.10**	-0.06	-0.09**	0.01	0.06	-0.03	-0.05	0.67***	0.54***	0.60***	0.58***
	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)
Constant	0.16	0.21**	0.19*	0.23**	0.16	0.14	0.18*	0.20*	0.20*	0.30***	0.40***	0.48***
	(0.10)	(0.10)	(0.10)	(0.11)	(0.10)	(0.10)	(0.10)	(0.10)	(0.11)	(0.11)	(0.12)	(0.11)
R-squared	0.60	0.61	0.61	0.61	0.60	0.61	0.60	0.61	0.62	0.51	0.61	0.64

3.6.5 GRS tests

Based on my spanning test results, I further consider 21 different factor models in the UK, in order to compare the information content from different versions of the profitability factor. I do not include SMB in the new models as robust results have been provided of its redundancy in the UK market. Tables 3-7, 3-8 and 3-9 use 25 size-BM, 25 size-profitability and 25 size-I/A portfolio as LHS portfolio sets respectively. GRS test statistics are used to compare relative performance among the factor models.

The GRS tests results are in general consistent with my findings from the factor-spanning tests. Firstly, HML is found to be redundant in the UK factor model since it does not improve model performance with the existence of new factor RMWs and CMAs. Secondly, there is clear evidence from GRS statistics that using the small end of the CMA factor improves model performance. For every portfolio set, models with CMA_S outperform their peer models with CMA factors. Moreover, with respect to the information content of new asset pricing factors, all models with new factors CMA_S and RMW consistently outperform the CAPM model and FF three-factor model across all portfolio sets. Therefore I conclude that the information content of the new asset pricing factors improves factor model performance in the UK.

Table 3-7

GRS test results for 25 size-BM portfolios						
This table reports GRS test results for various asset pricing factor models using 25 size-BM portfolios. (Rm-Rf) is the market risk premium (value-weighted market return minus T-bill rate), SMB is the size factor (small minus big); HML is the value factor (high minus low BM), CMA is the investment factor (conservative minus aggressive). There are three specifications used to construct profitability factors: ROE represents the profitability factor based on income before extraordinary items; OP represents the profitability factor based on operating income; and GRO represents the profitability factor based on gross profit. Regarding the difference in scalers, _B and _A are used to denote book value and total asset value respectively as denominators to construct the profitability factors. Small ends of the factors are constructed and labelled with _S: for instance, GRO_A_S stands for the profitability factor constructed using the gross profit/total asset with small end method.						
Model factors	**Mean alpha**	**GRS statistic**	**P-value**	**Mean adj R2**	**Mean SE**	**Mean abs alpha**
RM-RF	0.02	1.87	0.01	0.53	0.25	0.23
RM-RF SMB HML	0.05	1.79	0.01	0.74	0.19	0.15
RM-RF SMB HML umd	0.13	1.86	0.01	0.75	0.19	0.18
RM-RF SMB HML CMA	0.10	1.61	0.04	0.74	0.19	0.17
RM-RF SMB HML_S CMA	0.09	1.55	0.05	0.75	0.19	0.17
RM-RF SMB HML CMA_S	0.05	1.42	0.09	0.74	0.19	0.14
RM-RF SMB HML_S CMA_S	0.05	1.39	0.11	0.75	0.19	0.14
RM-RF HML CMA_S ROE_B	0.10	1.44	0.08	0.60	0.24	0.15
RM-RF HML CMA_S ROE_B_S	0.16	1.34	0.13	0.60	0.25	0.19
RM-RF HML CMA_S OP_A	0.17	1.61	0.04	0.61	0.24	0.21
RM-RF HML CMA_S OP_A_S	0.31	1.52	0.06	0.63	0.24	0.31
RM-RF HML CMA_S ROE_A	0.22	1.65	0.03	0.62	0.24	0.25
RM-RF HML CMA_S ROE_A_S	0.40	1.58	0.04	0.63	0.24	0.40
RM-RF HML CMA_S GRO_A	0.12	1.43	0.09	0.59	0.25	0.17
RM-RF HML CMA_S GRO_A_S	0.06	1.33	0.14	0.58	0.25	0.15
RM-RF CMA_S ROE_B	0.07	1.43	0.09	0.57	0.25	0.15
RM-RF CMA_S ROE_B_S	0.16	1.26	0.19	0.58	0.25	0.19
RM-RF CMA_S OP_A	0.15	1.65	0.03	0.58	0.25	0.19
RM-RF CMA_S OP_A_S	0.31	1.49	0.07	0.61	0.25	0.31
RM-RF CMA_S ROE_A	0.19	1.71	0.02	0.59	0.25	0.21
RM-RF CMA_S ROE_A_S	0.40	1.58	0.04	0.61	0.25	0.40
RM-RF CMA_S GRO_A	0.05	1.60	0.04	0.56	0.26	0.16
RM-RF CMA_S GRO_A_S	0.03	1.37	0.12	0.55	0.26	0.16

Table 3-8

GRS test results for 25 size-Investment portfolios						
This table reports GRS test results for various asset pricing factor models using 25 size-Investment portfolios. (Rm-Rf) is the market risk premium (value weighted market return minus T-bill rate), SMB is the size factor (small minus big); HML is the value factor (high minus low BM), CMA is the investment factor (conservative minus aggressive). There are three specifications used to construct profitability factors: ROE represents the profitability factor based on income before extraordinary items; OP represents the profitability factor based on operating income; and GRO represents the profitability factor based on gross profit. Regarding the difference in scalers, _B and _A are used to denote book value and total asset value respectively as denominators to construct the profitability factors. Small ends of the factors are constructed and labelled with _S: for instance, GRO_A_S stands for the profitability factor constructed using the gross profit/total asset with small end method.						
Model factors	**Mean alpha**	**GRS statistic**	**P-value**	**Mean adj R2**	**Mean SE**	**Mean abs alpha**
RM-RF	0.10	1.62	0.03	0.54	0.24	0.25
RM-RF SMB HML	0.11	1.55	0.05	0.74	0.18	0.21
RM-RF SMB HML umd	0.17	1.70	0.02	0.75	0.18	0.25
RM-RF SMB HML CMA	0.15	1.50	0.06	0.76	0.18	0.19
RM-RF SMB HML_S CMA	0.13	1.37	0.12	0.76	0.18	0.17
RM-RF SMB HML CMA_S	0.10	1.18	0.26	0.76	0.18	0.15
RM-RF SMB HML_S CMA_S	0.09	1.12	0.31	0.76	0.18	0.14
RM-RF HML CMA_S ROE_B	0.13	1.07	0.38	0.60	0.23	0.16
RM-RF HML CMA_S ROE_B_S	0.20	1.09	0.35	0.60	0.24	0.22
RM-RF HML CMA_S OP_A	0.19	0.99	0.49	0.60	0.24	0.21
RM-RF HML CMA_S OP_A_S	0.33	1.31	0.15	0.63	0.23	0.34
RM-RF HML CMA_S ROE_A	0.24	1.06	0.40	0.61	0.23	0.26
RM-RF HML CMA_S ROE_A_S	0.42	1.57	0.05	0.63	0.23	0.43
RM-RF HML CMA_S GRO_A	0.15	1.33	0.14	0.59	0.24	0.18
RM-RF HML CMA_S GRO_A_S	0.10	1.13	0.31	0.58	0.24	0.14
RM-RF CMA_S ROE_B	0.11	1.10	0.35	0.59	0.24	0.16
RM-RF CMA_S ROE_B_S	0.20	1.10	0.35	0.60	0.24	0.22
RM-RF CMA_S OP_A	0.17	0.99	0.48	0.60	0.24	0.19
RM-RF CMA_S OP_A_S	0.33	1.31	0.15	0.62	0.23	0.34
RM-RF CMA_S ROE_A	0.22	1.05	0.40	0.60	0.24	0.23
RM-RF CMA_S ROE_A_S	0.42	1.56	0.05	0.63	0.23	0.43
RM-RF CMA_S GRO_A	0.09	1.29	0.17	0.58	0.24	0.15
RM-RF CMA_S GRO_A_S	0.08	1.15	0.29	0.57	0.24	0.14

Table 3-9

GRS test results for 25 size-Profitability portfolios						
This table reports GRS test results for various asset pricing factor models using 25 size-Profitability portfolios. (Rm-Rf) is the market risk premium (value weighted market return minus T-bill rate), SMB is the size factor (small minus big); HML is the value factor (high minus low BM), CMA is the investment factor (conservative minus aggressive). There are three specifications used to construct profitability factors: ROE represents the profitability factor based on income before extraordinary items; OP represents the profitability factor based on operating income; and GRO represents the profitability factor based on gross profit. Regarding the difference in scalers, _B and _A are used to denote book value and total asset value respectively as denominators to construct the profitability factors. Small ends of the factors are constructed and labelled with _S: for instance, GRO_A_S stands for the profitability factor constructed using the gross profit/total asset with small end method.						
Model factors	**Mean alpha**	**GRS statistic**	**P-value**	**Mean adj R2**	**Mean SE**	**Mean abs alpha**
RM-RF	0.09	3.25	0.00	0.55	0.24	0.27
RM-RF SMB HML	0.12	3.33	0.00	0.74	0.18	0.27
RM-RF SMB HML umd	0.19	3.22	0.00	0.75	0.18	0.27
RM-RF SMB HML CMA	0.16	3.80	0.00	0.75	0.18	0.28
RM-RF SMB HML_S CMA	0.15	3.81	0.00	0.75	0.18	0.27
RM-RF SMB HML CMA_S	0.12	3.60	0.00	0.75	0.19	0.28
RM-RF SMB HML_S CMA_S	0.11	3.63	0.00	0.74	0.19	0.28
RM-RF HML CMA_S ROE_B	0.16	3.30	0.00	0.60	0.24	0.25
RM-RF HML CMA_S ROE_B_S	0.21	3.04	0.00	0.60	0.24	0.25
RM-RF HML CMA_S OP_A	0.22	3.12	0.00	0.61	0.24	0.26
RM-RF HML CMA_S OP_A_S	0.34	2.76	0.00	0.62	0.23	0.36
RM-RF HML CMA_S ROE_A	0.27	3.02	0.00	0.62	0.23	0.30
RM-RF HML CMA_S ROE_A_S	0.43	2.42	0.00	0.63	0.24	0.44
RM-RF HML CMA_S GRO_A	0.17	3.11	0.00	0.58	0.24	0.25
RM-RF HML CMA_S GRO_A_S	0.12	3.16	0.00	0.57	0.25	0.25
RM-RF CMA_S ROE_B	0.13	3.31	0.00	0.59	0.24	0.25
RM-RF CMA_S ROE_B_S	0.21	3.01	0.00	0.59	0.24	0.25
RM-RF CMA_S OP_A	0.20	3.12	0.00	0.60	0.24	0.25
RM-RF CMA_S OP_A_S	0.34	2.72	0.00	0.62	0.23	0.36
RM-RF CMA_S ROE_A	0.25	3.04	0.00	0.61	0.24	0.28
RM-RF CMA_S ROE_A_S	0.43	2.38	0.00	0.62	0.24	0.44
RM-RF CMA_S GRO_A	0.11	3.23	0.00	0.57	0.24	0.25
RM-RF CMA_S GRO_A_S	0.09	3.22	0.00	0.57	0.25	0.25

Among the improved factor models, I attempt to identify the best at describing portfolio returns. However, it seems that there is no dominant profitability factor in the UK market. For the 25 size-BM portfolios, the dominant factor model is composed of RM-RF, CMA_S and ROE_B_S; for the size-Investment portfolios, the best performing model uses OP_A as the profitability factor; the optimal profitability factor choice that explains the 25 size-Profitability portfolios return variation is ROE_A_S. Such mixed results have also been discovered by Fama and French (2015b) in their US sample, which suggest that my versions of new factor models remain incomplete.

In general, the ROE_B_S might so far be my best choice for UK asset pricing models. Together with RM-RF and CMA_S, the new factor model fully captures the variation of size-BM and size-investment portfolios. For cross-sections among size-Profitability portfolios, the new model also provides a solid improvement in descriptive power compared with the CAPM and FF three-factor models. My results therefore suggest that future UK researchers should use an updated version of three-factor model to capture a systematic cross-section of stock returns:

$$R_{it} - R_{ft} = \alpha_0 + \beta_{iM}(R_{Mt} - R_{ft})_t + \beta_{iCMA} CMA\_S_t + \beta_{iROE} ROE\_B\_S_t + \varepsilon_{it} \quad (20)$$

3.6.6 Cross-sectional regression results

Tables 3-10 to 3-12 report the results from the rolling regressions. In general, using rolling beta does not better capture the variation across the portfolio excess returns. For the first stage regressions, the size-BM-related return pattern is captured when new factors are included (Table 3-10). The P-values of the χ^2 tests suggest that the constant terms are jointly equal to zero for the four-factor model and the new three-factor models. The size-investment return pattern is captured by all models except for the CAPM (Table 3-11). The profitability-related return pattern is not fully captured by any model, including the new three-factor models, as the χ^2 tests reject the null hypothesis H0 and the constant terms are significantly different from zero (Table 3-12).

The second stage regression results imply the pricing significance of the new factors. I find that investment and profitability factors might be useful in determining cost of capital as it is fairly constantly priced, but it depends on the left-hand-side portfolios. The investment factor is priced in the size-BM returns pattern and the size-IInvestment returns pattern. Among all the model specifications, the investment factors are significantly priced at 1% or 5% level (Tables 3-10, 3-11). Profitability is priced constantly only across size-Profitability 25 portfolios. The three profitability measures that I tested are priced significantly at the 10% level for the second-stage cross-sectional regressions.

Table 3-10

Fama-Macbeth regressions for 25 size-BM portfolios

This table reports the results of two-stage Fama-Macbeth regressions of the value-weighted returns of 25 size-BM intercepted portfolios. The regressions are conducted for five different factor models. MKT is the market risk premium, SMB is the size factor "small minus big" and HML is the value factor "high minus low" for book-to-market. CONS is the average intercepts. HML_S is the small-end version of the value factor. CMA_S is the small-end version of the investment factor. ROE_B_S is the small-end version of the profitability factor constructed using income before extraordinary items scaled by book value of equity; OP_A is the profitability factor constructed using operating income scaled by total asset; ROE_A_S is the profitability factor constructed using income before extraordinary items scaled by total asset. R_sq shows the R_square measure proposed by Jagannathan and Wang (1996). The "factor prem" column shows the average premium for each factor from the regressions. The "T" column shows the *t*-statistics for factor premium using the Shanken (1992) correction. The "Single" column shows the Fama-Macbeth regression results where the first stage runs from a single regression over the sample period, whereas the "Rolling" column shows the results where the first stage runs from the 60-months rolling regressions to allow for dynamics in beta estimation. The χ^2 and P_val show the test statistics for pricing errors are jointly equal to zero and the corresponding p-value. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels respectively.

	CAPM					FF 3-factor model			
	Single		Rolling			Single		Rolling	
	factor prem	T	factor prem	T		factor prem	T	factor prem	T
CONS	-0.26	-0.76	0.62*	1.88	CONS	-0.10	-0.29	0.13	0.48
MKT	0.66	1.45	-0.19	-0.41	MKT	0.60	1.39	0.39	0.97
					SMB	-0.19	-0.86	-0.16	-0.61
					HML	0.62***	2.94	0.56**	2.19
R_sq	0.10		0.39			0.70		0.59	
χ^2	46.63		54.00			33.68		49.50	
P_val	0.00		0.00			0.05		0.00	
	Four-factor model					New 3-factor model 1			
	Single		Rolling			Single		Rolling	
	factor prem	T	factor prem	T		factor prem	T	factor prem	T
CONS	0.04	0.14	0.12	0.46	CONS	0.13	0.40	0.21	0.76
MKT	0.48	1.14	0.50	1.24	MKT	0.39	0.91	0.32	0.79
SMB	-0.19	-0.87	-0.16	-0.64	CMA_S	0.78***	2.60	0.43	1.49
HML_S	0.56**	2.28	0.52*	1.76	ROE_B_S	0.20	0.66	-0.07	-0.25
CMA_S	1.01**	2.55	0.33	1.11					
R_sq	0.76		0.58			0.75		0.62	
χ^2	26.94		57.13			27.11		43.31	
P_val	0.17		0.00			0.21		0.00	
	New 3 factor model 2					New 3 factor model 3			
	Single		Rolling			Single		Rolling	
	factor prem	T	factor prem	T		factor prem	T	factor prem	T
CONS	0.00	-0.01	0.25	0.84	CONS	-0.01	-0.04	0.27	0.96
MKT	0.45	1.05	0.21	0.51	MKT	0.54	1.26	0.30	0.76
CMA_S	0.69**	2.27	0.56**	2.00	CMA_S	0.73**	2.43	0.52*	1.81
OP_A	0.22	0.77	0.02	0.07	ROE_A_S	0.16	0.57	0.10	0.32
R_sq	0.63		0.61			0.73		0.62	
χ^2	29.29		47.80			27.17		46.54	
P_val	0.14		0.00			0.21		0.00	

Table 3-11

Fama-Macbeth regressions for 25 size-Investment portfolios									
This table reports the results of two-stage Fama-Macbeth regressions of the value-weighted returns of 25 size-Investment intercepted portfolios. The regressions are conducted for five different factor models. MKT is the market risk premium, SMB is the size factor "small minus big" and HML is the value factor "high minus low" for book-to-market. CONS is the average intercepts. HML_S is the small-end version of the value factor. CMA_S is the small-end version of the investment factor. ROE_B_S is the small-end version of the profitability factor constructed using income before extraordinary items scaled by book value of equity; OP_A is the profitability factor constructed using operating income scaled by total asset; ROE_A_S is the profitability factor constructed using income before extraordinary items scaled by total asset. R_sq shows the R_square measure proposed by Jagannathan and Wang (1996). The "factor prem" column shows the average premium for each factor from the regressions. The "T" column shows the *t*-statistics for the factor premium using the Shanken (1992) correction. The "Single" column shows the Fama-Macbeth regression results where the first stage runs from a single regression over the sample period, whereas the "Rolling" column shows the results where the first stage runs from the 60-months rolling regressions to allow for dynamics in beta estimation. The χ^2 and P_val show the test statistics for pricing errors are jointly equal to zero and the corresponding p-value. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels respectively.									
	CAPM					**FF 3-factor model**			
	factor prem	**T**	**factor prem**	**T**		**factor prem**	**T**	**factor prem**	**T**
CONS	0.42	1.37	0.41	1.18	**CONS**	0.13	0.41	0.16	0.55
MKT	0.09	0.21	0.07	0.14	**MKT**	0.31	0.75	0.32	0.77
					SMB	-0.13	-0.58	0.02	0.08
					HML	1.08***	3.35	0.26	0.87
R_sq	0.00		0.28			0.60		0.51	
χ^2	38.52		36.42			29.84		36.84	
P_val	0.03		0.05			0.12		0.02	
	Four-factor model					**New 3-factor model 1**			
	Single		**Rolling**			**Single**		**Rolling**	
	factor prem	**T**	**factor prem**	**T**		**factor prem**	**T**	**factor prem**	**T**
CONS	0.25	0.79	0.26	0.98	**CONS**	0.28	0.92	0.47	1.59
MKT	0.22	0.54	0.25	0.60	**MKT**	0.20	0.49	-0.04	-0.11
SMB	-0.07	-0.30	0.04	0.17	**CMA_S**	0.66***	3.53	0.53**	2.40
HML_S	0.68*	1.65	0.01	0.04	**ROE_B_S**	0.03	0.13	-0.12	-0.44
CMA_S	0.62***	3.28	0.55***	2.58					
R_sq	0.70		0.62			0.69		0.60	
χ^2	25.85		34.29			25.80		34.39	
P_val	0.21		0.03			0.26		0.04	
	New 3 factor model 2					**New 3 factor model 3**			
	Single		**Rolling**			**Single**		**Rolling**	
	factor prem	**T**	**factor prem**	**T**		**factor prem**	**T**	**factor prem**	**T**
CONS	0.21	0.65	0.56*	1.82	**CONS**	0.23	0.72	0.50*	1.65
MKT	0.29	0.67	-0.18	-0.41	**MKT**	0.26	0.63	-0.06	-0.14
CMA_S	0.63***	3.37	0.58***	2.60	**CMA_S**	0.63***	3.38	0.54**	2.41
OP_A	0.25	0.76	-0.02	-0.06	**ROE_A_S**	0.07	0.28	0.01	0.03
R_sq	0.71		0.58			0.70		0.58	
χ^2	25.67		34.47			25.91		35.14	
P_val	0.27		0.04			0.26		0.04	

Table 3-12

Fama-Macbeth regressions for 25 size-Profitability portfolios

This table reports the results of two-stage Fama-Macbeth regressions of the value-weighted returns of 25 Size-profitability intercepted portfolios. The regressions are conducted for five different factor models. MKT is the market risk premium, SMB is the size factor “small minus big” and HML is the value factor “high minus low” for book-to-market. CONS is the average intercepts. HML_S is the small-end version of the value factor. CMA_S is the small-end version of the investment factor. ROE_B_S is the small-end version of the profitability factor constructed using income before extraordinary items scaled by book value of equity; OP_A is the profitability factor constructed using operating income scaled by total asset; ROE_A_S is the profitability factor constructed using income before extraordinary items scaled by total asset. R_sq shows the R_square measure proposed by Jagannathan and Wang (1996). The “factor prem” column shows the average premium for each factor from the regressions. The “T” column shows the *t*-statistics for factor premium using Shanken (1992)’s correction. The “Single” column shows the Fama-Macbeth regression results where the first stage runs from a single regression over the sample period, whereas the “Rolling” column shows the results where the first stage runs from the 60-months rolling regressions to allow for dynamics in beta estimation. The χ^2 and P_val shows the test statistics for pricing errors are jointly equal to zero and the corresponding p-value. *, ** and *** denote statistical significance at 10%, 5% and 1% levels respectively.

	CAPM					**FF 3-factor model**			
	Single		**Rolling**			**Single**		**Rolling**	
	factor prem	**T**	**factor prem**	**T**		**factor prem**	**T**	**factor prem**	**T**
CONS	1.27***	4.29	1.00***	3.09	**CONS**	1.23***	4.22	1.18***	4.28
MKT	-0.72	-1.68	-0.50	-1.05	**MKT**	-0.65	-1.63	-0.74	-1.68
					SMB	-0.16	-0.72	0.01	0.05
					HML	0.17	0.53	0.30	1.10
R_sq	0.24		0.23			0.27		0.22	
χ^2	57.63		70.66			56.82		73.55	
P_val	0.00		0.00			0.00		0.00	
	Four-factor model					**New 3-factor model 1**			
	Single		**Rolling**			**Single**		**Rolling**	
	factor prem	**T**	**factor prem**	**T**		**factor prem**	**T**	**factor prem**	**T**
CONS	1.12***	3.75	1.17***	4.41	**CONS**	0.92***	2.88	1.25***	4.54
MKT	-0.56	-1.39	-0.69	-1.60	**MKT**	-0.27	-0.64	-0.68*	-1.66
SMB	-0.15	-0.68	0.01	0.03	**CMA_S**	0.19	0.54	0.26	0.80
HML_S	0.53	1.20	0.47	1.27	**ROE_B_S**	0.38*	1.67	0.29	1.19
CMA_S	-0.05	-0.15	0.26	0.80					
R_sq	0.31		0.29			0.50		0.41	
χ^2	56.55		84.72			42.54		68.68	
P_val	0.00		0.00			0.01		0.00	
	New 3-factor model 2					**New 3-factor model 3**			
	Single		**Rolling**			**Single**		**Rolling**	
	factor prem	**T**	**factor prem**	**T**		**factor prem**	**T**	**factor prem**	**T**
CONS	0.95***	2.87	1.33***	4.78	**CONS**	0.89***	2.65	1.29***	4.59
MKT	-0.33	-0.77	-0.74*	-1.77	**MKT**	-0.23	-0.53	-0.68*	-1.65
CMA_S	0.22	0.63	0.11	0.34	**CMA_S**	0.25	0.73	0.22	0.67
OP_A	0.40*	1.88	0.35	1.43	**ROE_A_S**	0.40*	1.88	0.44*	1.64
R_sq	0.38		0.38			0.46		0.44	
χ^2	55.90		67.54			45.33		60.72	
P_val	0.00		0.00			0.00		0.00	

3.6.7 Robustness tests – industry portfolios

For the 34 industry portfolios, the GRS test results corroborate the previous left-hand-side portfolio GRS tests and the spanning regressions. The value factor HML and size factor SMB are redundant in the UK market and do not provide incremental information to the description of industry portfolios returns. The best performing factor model is a three-factor model including market factor, small end of investment factor CMA_S, and ROE_A_S, which is a small end profit factor constructed by income before extraordinary items scaled by total asset. The adjusted mean R-square is relatively low compared to the US factor models, which is consistent with Gregory and Michou (2009). None of the candidate models is able to capture the variations across industry portfolio returns.

Table 3-15 presents the factor loadings across all 34 industry portfolios for the best-performing three-factor model. The new three-factor models fail to capture nine industry portfolio returns, which have significant alphas. Consistent with the literature, all industries are positively significantly loaded on market factor. For CMA_S, 19 industries have significant positive loadings and two industries have significant negative loadings. For ROE_A_S, four industries have significant positive loadings and 11 industries have significant negative loadings. The average R-square is 37%. The most troublesome industries are banks, with 20% R-square; food producers, with 25% R-square; health care equipment services, with 9% R-square; non-life insurance and oil gas, with 14% R-square; and personal goods, with 13% R-square.

Table 3-13

GRS test results for 34-industry portfolios						
This table reports GRS test results for various asset pricing factor models using 34 industry portfolios. (Rm-Rf) is the market risk premium (value-weighted market return minus T-bill rate), SMB is the size factor "small minus big"; HML is the value factor "high minus low BM", CMA is the investment factor "conservative minus aggressive". There are three specifications used to construct profitability factors: ROE represents the profitability factor based on income before extraordinary items; OP represents the profitability factor based on operating income; and GRO represents the profitability factor based on gross profit. Regarding the difference in scalers, _B and _A are used to denote book value and total asset value respectively as denominators to construct the profitability factors. Small ends of the factors are constructed and labelled with _S: for instance, GRO_A_S stands for the profitability factor constructed using the gross profit/total asset with small end method.						
Model factors	**Mean alpha**	**GRS statistic**	**P-value**	**Mean adj R2**	**Mean SE**	**Mean abs alpha**
RM-RF	-0.14	5.71	0.00	0.35	0.36	0.45
RM-RF SMB HML	-0.15	6.10	0.00	0.41	0.34	0.47
RM-RF SMB HML umd	-0.12	6.03	0.00	0.41	0.35	0.47
RM-RF SMB HML CMA	-0.19	5.55	0.00	0.36	0.37	0.44
RM-RF SMB HML_S CMA	-0.17	5.64	0.00	0.40	0.35	0.44
RM-RF SMB HML CMA_S	-0.22	5.82	0.00	0.41	0.35	0.47
RM-RF SMB HML_S CMA_S	-0.23	5.90	0.00	0.42	0.35	0.48
RM-RF HML CMA_S ROE_B	-0.19	5.59	0.00	0.39	0.36	0.48
RM-RF HML CMA_S ROE_B_S	-0.18	5.30	0.00	0.38	0.37	0.46
RM-RF HML CMA_S OP_A	-0.21	5.64	0.00	0.39	0.36	0.52
RM-RF HML CMA_S OP_A_S	-0.17	5.32	0.00	0.38	0.37	0.47
RM-RF HML CMA_S ROE_A	-0.17	5.68	0.00	0.39	0.37	0.51
RM-RF HML CMA_S ROE_A_S	-0.14	5.30	0.00	0.39	0.38	0.49
RM-RF HML CMA_S GRO_A	-0.24	5.50	0.00	0.38	0.37	0.51
RM-RF HML CMA_S GRO_A_S	-0.25	5.34	0.00	0.38	0.37	0.48
RM-RF CMA_S ROE_B	-0.20	5.29	0.00	0.37	0.37	0.46
RM-RF CMA_S ROE_B_S	-0.18	5.06	0.00	0.37	0.37	0.46
RM-RF CMA_S OP_A	-0.21	5.24	0.00	0.38	0.37	0.50
RM-RF CMA_S OP_A_S	-0.17	5.09	0.00	0.37	0.37	0.47
RM-RF CMA_S ROE_A	-0.18	5.27	0.00	0.37	0.37	0.48
RM-RF CMA_S ROE_A_S	-0.14	5.03	0.00	0.37	0.38	0.49
RM-RF CMA_S GRO_A	-0.24	5.25	0.00	0.37	0.37	0.48
RM-RF CMA_S GRO_A_S	-0.25	5.17	0.00	0.36	0.37	0.47

Table 3-14

Summary statistics for 34 portfolio returns			
Industry	**mean %**	**median %**	**sd %**
Aerospace/Defence	1.29	1.68	6.23
Automobiles/Parts	0.87	0.79	9.36
Banks	1.06	1.03	7.22
Beverages	0.93	1.27	5.30
Chemicals	0.41	0.61	7.37
Construction Materials	0.85	1.44	6.86
Electricity	1.65	1.44	8.63
Electronic/Electrical Equipment	-0.07	1.27	8.55
Fixed Line Telecommunications	0.24	1.22	9.31
Food/Drug Retailers	0.84	0.92	5.39
Food Producers	0.67	0.73	4.38
Forestry/Paper	0.24	0.96	12.16
Gas/Water/Multi-utilities	0.83	1.30	5.16
General Industrials	0.81	1.29	6.89
General Retailers	1.00	0.72	5.82
General financial	-0.26	0.33	5.70
Health Care Equipment Services	0.85	0.33	7.40
Household Goods/Home Construction	0.85	0.89	5.25
Industrial Engineering	1.20	1.89	7.04
Industrial Metals/Mining	0.56	0.90	16.22
Industrial Transportation	-1.31	-0.13	8.62
Leisure Goods	-0.21	-0.58	10.21
Life Insurance	0.86	1.35	7.42
Media	0.74	0.90	6.54
Mining	0.38	0.47	9.79
Non-Life Insurance	-0.18	0.33	7.51
Oil Gas	0.93	0.95	5.66
Personal Goods	0.86	0.48	7.67
Pharmaceuticals/Biotechnology	0.75	0.78	5.71
Real Estate	0.12	0.53	5.46
Software/Computer Services	1.30	1.59	8.47
Support Services	0.89	1.06	5.37
Tobacco	1.34	1.87	6.16
Travel/Leisure	-0.41	0.09	6.09

Table 3-15

Time-series regression factor loadings for 34 portfolio returns									
This table reports time-series regression factor loadings on (Rm-Rf), CMA_S and ROE_A_S using 34 industrial portfolios. (Rm-Rf) is the market risk premium (value-weighted market return minus T-bill rate); CMA_S is the small end of investment factor (conservative minus aggressive), and ROE_A_S represents small end of profitability factor based on income before extraordinary items deflated by total assets. All significant loadings at 10% significance level are in boldface.									
	alpha	**T value**	**RM-RF**	**T value**	**CMA_S**	**T value**	**ROE_A_S**	**T value**	**adj R^2**
Aerospace/Defence	0.19	0.69	0.88	**12.79**	0.04	0.43	0.01	0.06	0.41
Automobiles/Parts	-0.35	-0.91	0.99	**10.37**	0.15	1.06	-0.20	-1.49	0.35
Banks	-1.01	-1.42	1.33	**7.60**	0.50	**1.97**	0.09	0.35	0.20
Beverages	0.33	0.38	1.53	**7.09**	0.38	1.21	-1.53	**-4.99**	0.32
Chemicals	-0.09	-0.17	1.11	**8.30**	0.02	0.12	-0.42	**-2.23**	0.28
Construction Materials	-0.21	-0.67	1.12	**14.65**	0.47	**4.18**	-0.12	-1.09	0.51
Electricity	0.13	0.46	1.12	**16.72**	0.42	**4.26**	0.15	1.58	0.54
Electronic/Electrical Equipment	-0.12	-0.34	0.92	**10.61**	0.48	**3.82**	-0.21	**-1.73**	0.38
Fixed Line Telecommunications	1.74	**4.26**	0.98	**9.74**	-0.20	-1.40	-1.04	**-7.25**	0.48
Food/Drug Retailers	0.47	1.59	1.17	**16.08**	0.21	**2.01**	-0.38	**-3.71**	0.59
Food Producers	-1.94	**-3.99**	0.89	**7.46**	0.18	1.02	-0.39	**-2.31**	0.25
Forestry/Paper	0.45	**2.16**	0.89	**17.62**	-0.02	-0.32	-0.41	**-5.67**	0.65
Gas/Water/Multi-utilities	-0.34	-0.76	1.44	**13.23**	0.65	**4.12**	-0.26	-1.67	0.48
General Industrials	-0.19	-0.67	0.79	**11.39**	0.22	**2.14**	0.40	**4.00**	0.32
General Retailers	-0.39	**-1.80**	0.75	**14.12**	0.24	**3.17**	0.35	**4.61**	0.42
General Financial	0.12	0.39	0.61	**8.38**	0.29	**2.77**	-0.08	-0.77	0.26
Health Care Equipment Services	-0.80	-1.25	0.58	**3.71**	0.39	**1.71**	-0.37	-1.63	0.09
Household Goods/Home Construction	-0.03	-0.07	0.83	**7.69**	0.40	**2.54**	-0.01	-0.06	0.21
Industrial Engineering	0.32	0.87	0.64	**6.97**	0.21	1.60	0.40	**3.07**	0.14
Industrial Metals/Mining	0.18	0.41	0.75	**7.17**	0.07	0.49	-0.09	-0.60	0.19
Industrial Transportation	-0.17	-0.51	0.60	**7.16**	0.22	**1.81**	0.26	**2.15**	0.16
Leisure Goods	-0.19	-0.63	0.67	**9.01**	0.27	**2.50**	0.25	**2.32**	0.23
Life Insurance	-0.01	-0.05	0.94	**13.93**	0.35	**3.56**	0.06	0.62	0.46
Media	0.32	1.16	1.03	**15.01**	-0.08	-0.84	-0.43	**-4.41**	0.57
Mining	-1.27	**-4.65**	1.04	**15.44**	0.18	**1.81**	-0.04	-0.41	0.52
Non-life insurance	-0.12	-0.22	0.81	**5.89**	-0.34	-1.67	-0.12	-0.63	0.14
Oil/Gas	-0.34	-0.70	0.78	**6.53**	-0.16	-0.91	0.17	1.02	0.14
Personal Goods	0.07	0.23	0.49	**6.55**	0.13	1.18	0.16	1.47	0.13
Pharmaceuticals/Biotechnology	-0.16	-0.60	1.42	**21.43**	0.41	**4.25**	0.05	0.55	0.67
Real eEstate	-1.12	**-2.78**	1.02	**10.32**	0.28	**1.93**	-0.04	-0.26	0.32
Software/Computer Services	-0.37	-1.14	1.34	**16.74**	0.33	**2.82**	0.11	0.98	0.54
Support Services	-0.71	**-2.83**	0.86	**14.03**	0.39	**4.42**	-0.19	**-2.23**	0.51
Tobacco	-0.65	**-3.46**	1.01	**21.92**	-0.12	**-1.75**	-0.45	**-6.88**	0.74
Travel/Leisure	1.64	**4.04**	0.92	**9.21**	-0.66	**-4.55**	-0.91	**-6.37**	0.45

3.7 CONCLUSION

To summarize, this chapter provides out-of-sample evidence for the effectiveness of the profitability factor and the investment factor from the new Fama-French five-factor model. I firstly provide evidence that investment and profitability influence UK stock market patterns. I also employ both factor-spanning tests and the GRS tests to shed light on the empirical performance of potential new factor models in the UK market.

The results using the UK data imply the following:

- Firstly, the performance of the new factor model, from a local perspective, is not entirely consistent with the US or the European results. The discrepancy suggests that the choice of optimal factor models is sensitive to market sample, which also confirms Griffin (2002)'s conclusion that factor models should be constructed at country level.
- Secondly, the results suggest that the performance of the UK factor models is improved using the two new factors, investment factor and profitability factor. On the other hand, the size factor and value factor are proved to be redundant. From a parsimonious perspective, it is not necessary to include SMB or HML in the UK factor model.
- Thirdly, the information content of the new investment factors is improved by construction using the small end.
- Furthermore, I confirm the findings from the US market that choice of profitability factor is relevant to factor performance. Amongst the factor candidates, operating profit or income before extraordinary items outperform gross profit for the profitability factor. However, the optimal choice becomes a tougher question when I take into account different scalers and small-end construction methods. The ambiguous results may suggest that my factor models remain incomplete.

Despite the inconclusive results regarding the best profitability factor the new three-factor models significantly outperform the FF three-factor model in the UK. Therefore, I suggest that future UK research should employ a new three-factor model by replacing the size and value factors with a profitability factor and an investment factor to control for time-series variations among stock returns.

CHAPTER 4

Macroeconomic Fluctuations and New Asset Pricing Factors in the UK

4.1 INTRODUCTION

Asset pricing models have been the cornerstone in finance. The CAPM and its various extensions have been widely examined by various researchers with Consumption CAPM (CCAPM) and Intertemporal CAPM (ICAPM) being the centre of attention. Under the Consumption CAPM framework (Rubinstein, 1976; Lucas, 1978; Breeden and Litzenberger, 1978), consumption is related to the state of the economy and the state of the economy can be measured by various macroeconomic indicators such as inflation rate, term structure of interest rates, GDP growth, investment growth, industrial production, etc. On the other hand, consumption and marginal utility of investors respond to “news information” of state variables whose changes usually signal changes in future income. Therefore, variables that forecast changes in the investment opportunity set or that forecast macroeconomic variables are potential candidates as pricing factors.

The performance of the Fama and French three-factor model has also attracted a great deal of debate amongst finance academics regarding the economic intuition behind its risk factors. Fama and French (1993,1995) argue that the size factor SMB and the book-to-market factor HML act in as proxies for risk and therefore as proxies for time variation in the investment opportunity set. This explanation is also consistent with Merton (1973)’s Intertemporal Capital Asset Pricing Model (ICAPM). The Intertemporal CAPM (ICAPM) developed by Merton (1973) suggests that an asset’s expected return stems from its covariance with the market portfolio return and its covariance with future available returns. The change in the investment opportunity set is represented by a group of state variables capturing the conditional distribution of future available returns. However, the ICAPM does not explicitly specify potential candidates for the state variables. Fama (1991) and Cochrane (2009) argue that the ICAPM should not be used as a “fishing licence” for proposing multiple-factor asset pricing models. Campbell (1996) argues that in implementing the ICAPM we should not be selecting important macroeconomic variables neither running a factor analysis on the returns variance covariance matrix. Instead he claims that we should choose factors on the basis of their ability to forecast changes in future investment opportunities. More recent evidence by Maio and Santa-Clara (2012) suggest a few restrictions on the multifactor models if ICAPM has been used as a theoretical justification.

There are numerous studies that link macroeconomic variables to future investment opportunities. A number of macroeconomic factors such as term spreads, default spreads, dividend yields, treasury rates and inflation are found to have predictive power over the future state of the economy in the US market. An ever-growing body of research supports the risk-based explanation behind the Fama and French risk factors by linking them to macroeconomic variables and business cycle fluctuations. The economic intuition of this relationship has been tested against various hypotheses implied by the ICAPM or the Consumption CAPM, i.e. whether the Fama-French risk factors can predict the future state of the economy, or if there is a correlation between the Fama-French risk factors and innovations to the state variables that can predict the future state of the economy, or whether the Fama-French risk factors' pricing significance is captured by innovations to the state variables known to predict the future state of the economy.

Campbell and Vuolteenaho (2003) for example argue that growth stocks are considered to be high-duration assets that behave like long-term bonds and therefore are more sensitive to shocks in the long end of the term structure. On the other hand, value stocks are more similar to short-term bonds and therefore are more sensitive to shocks in the short end of the yield curve.

Fama and French (1989) and Campbell (1996) show that term spread forecasts human capital return, which is measured as real labour income growth rate. Moreover, Hahn and Lee (2006) use changes in default spread and changes in term spread to proxy innovations to state variables in the ICAPM context and show that small stocks tend to have higher loadings on default spread innovations, whereas high book-to-market stocks tend to have higher loadings on term spread innovations. The default spread has long been used as a proxy for the state of business conditions and, in particular, as a measure of the credit market. Keim and Stambaugh (1986) document that spread between the yields of long-term BAA corporate bonds and one-month US treasury bills is positively related to ex-post bond and stock market returns. Fama and French (1989) define default spread as the difference between aggregated bond yield and AAA yield and report positive leading effects over bond and stock market aggregated returns. Consistent evidence has also been reported by Fama and Schwert (1977) and Campbell (1987). Chen (1989) demonstrates that default spread is negatively correlated with future GNP growth. Chan and Chen (1991) predict that small firms will be more sensitive to news about the state of the business cycle. Gregory, Harris and Michou (2003) extend the US literature to examine the rational explanation for the Fama-French factors in the UK market from 1980 to 1998. Their results are consistent with Vassalou (2002) and Liew and Vassalou (2000), suggesting that both HML and SMB are positively related to future GDP growth in the UK market. Dechow *et al*. (2004) argue that low book-to-market stocks are more sensitive to expected returns shocks which implies that firms with low book-to-market ratios are expected to have higher exposure to shocks in economic growth than high book-to-market firms and vice versa. This explanation is also consistent with Bagella *et al*. (2000) who claims that in the UK, value stocks covariate less with GDP growth than those of glamour stocks.

This third empirical chapter explores the information content of the two new factors by linking them to the state variables which predict future investment opportunities. Based on the findings of the previous two empirical chapters and the successful performance of the new risk factors, I attempt to examine whether both the investment factor and profitability factor can predict GDP growth, investment growth and consumption growth. I will also test whether both the investment factor and profitability factor can predict innovations to state variables related to future investment opportunities. Finally, I will compare the informativeness of innovations to state variables with investment growth and profitability factor pricing significance using a one-step Generalized Methods of Moments (GMM) methodology, a two-pass Fama-Macbeth cross-sectional regressions analysis and factor-spanning tests.

The results are to some extent consistent with the risk-based economic interpretations of the new factors. Firstly, the results confirm that the investment factor predicts future economic growth proxied by GDP growth, investment growth and consumption growth. In addition, both the investment factor and the profitability factor have a significant relation to shocks to macroeconomic state variables. The investment factor is related to dividend yield shocks, whereas the profitability factor is related to inflation. Furthermore, the two new factors provide incremental information to the macroeconomic factors in the UK market. The pricing significance of macroeconomic variable shocks disappears when loadings on the two new factors are presented in the model.

The paper mainly contributes to the literature by providing an economic interpretation to the information content of the new factors. As pointed out by Cochrane (2009), macroeconomic factor models are constructed not to outperform the Fama-French factors in asset pricing performance, but to understand why they work better and to provide better justification. Previous studies use US data and show that the investment factor "conservative minus aggressive" (CMA) is related to future economic activities (Cooper and Priestley, 2011). My research extends the evidence to the performance of both the investment factor and the profitability factor using a UK data sample.

The structure of the paper is as follows: Section 2 provides a review of the academic literature focusing on the relationship between state variables and the future state of the economy, the measures of innovations and the relationship between macroeconomic factors and stock return a comparison analysis between US and UK; Section 3 discusses the data and sample; Section 4 discusses the research design used; Section 5 presents the empirical results; and Section 6 concludes the study.

4.2 LITERATURE REVIEW

Macroeconomic factors play a vital role in asset pricing literature because of their close links to the asset pricing theorem. According to Cochrane (2009), the key to the asset pricing factor model is that investors have special concerns about the performance of their portfolio in some special states of the world. Investors are willing to accept lower average returns for good performance in those particular states of the world. Asset pricing factors should be indicators of the occurrence of those “bad states”. The most intuitive choices for “bad states” are macroeconomic factors. The importance of macroeconomic state variables is pervasive across different equilibrium asset pricing models.

The earliest attempt to identify macroeconomic asset pricing factors was made by Chen, Roll and Ross (1986). The authors construct multifactor models using a set of state variables and treating their monthly rates of change as innovations. This paper follows a Fama-Macbeth (1973) regression methodology and reports that industry production growth, expected inflation, unexpected inflation, default spread and term spread are significantly priced factors in the US stock market using a sample period 1958–1984. Additional testing does not find supportive evidence for the Consumption CAPM, as growth in real per-capita consumption is not a priced factor after controlling for other macroeconomic variable innovations.

In a related study, Breeden, Gibbons and Litzenberger (1989) investigate potential measurement errors in the Consumption CAPM empirical tests. To mitigate the measurement error, the authors use a maximum correlation portfolio to serve as proxy for current consumption and examine the explanatory power of Consumption CAPM. Their empirical evidence suggests that the consumption factor is significantly and positively priced, although the model does not pass mean-variance efficiency tests.

Fama (1990) argues that stock return variations stem from time-varying expected returns, shocks to expected returns and shocks to expected future cash flows. Dividend yield, default spread and the term spread are used to capture rational expectations in stock returns. Shocks to expected returns are measured as residual from a first-order autoregressions model to default spread and term spread. The expected future cash flows are quantified using leading industrial production. The paper provides empirical evidence for the author’s argument, showing that 59% of the annual variance in NYSE aggregated stock returns are explained by the sources stated from 1953 to 1987. Schwert (1990) replicates Fama (1990) by extending the sample period to between 1889 and 1988 and confirms the robustness of the results.

McQueen and Roley (1993) address the link between stock prices and macroeconomic news from a different perspective. The paper uses an event-study method to examine how stock prices react to macroeconomic news about different states of the economy (proxied by the monthly adjusted industrial production index). Using the Standard & Poors 500 index as an aggregated stock price measure, empirical evidence suggests that stock prices react negatively to good news in a good economic state, while in a bad economic state the association becomes positive. Further evidence reveals that the varying response can be attributed to change in expected cash flows rather than discount rates.

As suggested by the theorem, macroeconomic candidate factors should predict future state of economy. Therefore, I *firstly* review studies that link macroeconomic variables to future investment opportunities. A number of factors such as term spreads, default spreads, dividend yield, inflation and treasury rates are found to have predictive power over the future state of the economy in the US market. *Secondly*, since asset pricing theory also suggests that "news" in a state variable should be priced, I briefly review various approaches that have been proposed to measure innovations in macroeconomic variables. In this sub-section, I review macroeconomic asset pricing factor studies in the US market, especially with regard to their relevance to the information content of Fama-French factors. In the *final* sub-section, I review the existing research that focuses on the UK market.

4.2.1 State variables and future state of the economy

As noted by Campbell (1996), the choice of state variable proxies of time-varying investment opportunities should rest on the predictive power over stock market returns and explanatory power to the asset return cross-sections. Amongst all the candidates for state variables, the ones most frequently used include term spread, default spread, dividend yield of the stock market, inflation and risk-free rates. I review the US literature that bridges the connections between the popular state variables and the future state of the economy.

4.2.1.1 Term spread and future state of the economy

Term spread has been widely used as a candidate for a state variable in the ICAPM context. It is used to proxy market expectations about future interest rates because it contains information on investors' hedging concerns for future interest rate variations. The relation between term spread and investment opportunity set has been documented through various channels.

For the stock market and bond market, Keim and Stambaugh (1986) use a sample from 1928 to 1978 and show that the spread between the yields of long-term BAA corporate bonds and the one-month US treasury bill rate is directly related to return premiums of several portfolios formed in both the bond market and the stock market. Fama and French (1989) refine the spread measure into two components: the term spread and the default spread. They measure term spread as the difference between AAA bond yield and the one-month treasury bill rate. They use a sample from 1927 to 1987 and document positive relations between ex-ante term spread and ex-post NYSE stock market returns and corporate bond returns.

In addition, similar empirical evidence is also found in other aspects of an investment opportunity set. Fama and French (1989) and Campbell (1996) show that the term spread forecasts human capital return, which is measured as real labour income growth rate. Chen (1991) establishes that the term spread is negatively correlated with future GNP growth. Hong and Yogo (2012) link the term spread to the commodity market. In this study, the return premium on a portfolio of fully collateralized commodity futures is found to be negatively predicted by the term spread.

4.2.1.2 Default spread and future state of the economy

Default spread is also widely employed to proxy state variables, as it captures business conditions and default risks. As mentioned above, Keim and Stambaugh (1986) document that the spread between the yields of long-term BAA corporate bonds and one-month US treasury bills is positively related to ex-post bond and stock market returns. Fama and French (1989) define default spread as the difference of aggregated bond yield and Aaa yield and report positive leading effects over bond and stock market aggregated returns. Consistent evidence has also been reported by Fama and Schwert (1977) and Campbell (1987). Chen (1989) demonstrates that default spread is negatively correlated with future GNP growth.

4.2.1.3 Dividend yields and future state of the economy

Extensive research has shown that dividend yields predict stock market returns (Fama and French, 1988; 1989; Lewellen, 2004; Campbell and Yogo, 2006). Fama and French (1988) observe that dividend yields of the NYSE are positively linked to future stock market returns. They provide solid evidence that dividend yield explains more than 25% of the variances in the long-term stock market returns, which is robust across sub-periods in their 1927–1986 sample. Fama and French (1989) further demonstrate that dividend yield positively forecasts both bond and stock markets with positive regression slopes. Campbell (1996) reports a negative connection between dividend yields and future human capital returns.

A series of follow-up papers casts doubt on earlier evidence with regard to econometric problems. For instance, Goetzmann and Jorion (1993) and Stambaugh (1999) point out that the predictive power of dividend yields disappears after small-sample correction. A correction method proposed by Wolf (2000) also leads to insignificant predictive power of dividend yields. Lewellen (2004) argues that the correction has understated the statistical significance of dividend yield and proposes alternative correction methods, which provide evidence for the predictive power of dividend yields. Campbell and Yogo (2006) reconcile the inconsistent results and suggest a new method. They conclude that dividend yields predict future stock returns at annual frequency in the period 1926–2002. For the post-1952 sample period, dividend yields predict stock market returns at monthly, quarterly and annual frequency.

4.2.1.4 Inflation and future state of the economy

The leading effect of inflation on aggregated stock market returns has also been well documented. Miller, Jeffrey and Mandelker (1976), Bodie (1976), Nelson (1976), Fama and Schwert (1977) and Gultekin (1983) are the first papers to document a negative relation between stock market return and inflation. Fama and Schwert (1977) use the monthly treasury bill rate to proxy expected inflation and the difference between actual inflation and the ex-ante treasury bill rate to proxy unexpected inflation. They provide evidence that NYSE stock market returns are negatively related to both expected inflation and unexpected inflation in the period 1953–1971. They also find evidence that both residential real estate market returns and per-capita labour income are positively related to unexpected inflation. Miller, Jeffrey and Mandelker (1976) use similar proxies and find consistent results using a sample period 1953 to 1971. The consistent findings are confirmed by sub-period analysis. Nelson (1976) uses an autocorrelation structure to model CPI prediction and finds robust results that stock market return is negatively related to both inflation and unexpected inflation from 1953 to 1974. Gultekin (1983) employs Livingston survey data to proxy the expected inflation and provides similar results using a sample period from 1952 to 1979.

The empirical results showing a negative relation between stock market returns and inflation are puzzling, as Fisher's (1930) hypothesis suggests a positive one. A number of follow-up papers attempt to explain the anomalous results (Fama, 1981; Geske and Roll, 1983; Pearce and Roley, 1983). Fama (1981) proposes that the negative relation is induced by the proxy effect, which means the negative relation between inflation and future real activity and the positive relation between stock market return and future real activity may have led to a spurious stock return–inflation relation. However, the hypothesis is only partially supported by the empirical analysis. Geske and Roll (1983) describe the negative relation as an "empirical illusion", which is the result of a reversed adaptive inflation expectations model and reversed money growth/stock returns model. Pearce and Roley (1983) use an event study and examine the stock price reactions to weekly money supply announcement. Their empirical results suggest that stock prices only respond to unanticipated news in money supply, which support their expectation-revision theory.

4.2.1.5 Risk-free rate and future state of the economy

Treasury bill rates have a crucial impact on the discount factor in asset pricing models, early evidence showing their influence on the investment opportunity set variations. Fama and Schwert (1977) study the relationship between asset returns and inflation. Their empirical test includes the NYSE stock market index, residential real estate price index, human capital measured as per-capita labour income, and long-term government bond indices. Their sample from 1953 to 1971 shows that all asset returns co-move with the monthly treasury bill rate. Monthly treasury bill rates are reported to have a negative relation with the NYSE stock market index and positive relations with the residential real estate market and human capital returns. Ferson (1989) confirms the significant negative association between the ex-ante one-month treasury bill rate and stock market aggregated return using the period 1926–1985.

4.2.2 Measure innovations in state variable

Although both CCAPM and ICAPM suggest that innovations to state variables should be associated with risk premium, different approaches have been developed to address the connections. Brennan, Wang and Xia (2004) propose a simple model of ICAPM in which real interest rate and the maximum Sharpe ratio are used as state variables. Assuming the two variables follow Ornstein-Uhlenbeck processes, their innovations are calculated accordingly. The empirical results demonstrate that innovations to both state variables are priced significantly using size- and book-to-market-value-sorted portfolios as well as industrial portfolios.

In contrast, Hahn and Lee (2006) use changes in default spread and changes in term spread to proxy innovations in state variables in the ICAPM context. Small stocks tend to have higher loadings on default spread innovations, whereas high book-to-market stocks tend to have higher loadings on term spread innovations. The proposed model captures variations in size- and book-to-market-sorted portfolio returns. The early study by Chen, Roll and Ross (1986) adopts the same approach, although the authors also advocate using a vector autoregressive approach (VAR) to proxy state variable innovations.

Another approach involves an optimized tracking portfolio to measure state variable innovations. For instance, Breeden, Gibbons and Litzenberger (1989) propose "maximum correlation portfolios" as the proxy and confirm the pricing significance. Lamont (2001), in a follow-up study, suggests "economic tracking portfolios" may better capture changes in the investment opportunity set. He argues that a tracking portfolio approach may outperform a VAR approach since it does not require the assumption of a complete description of the time-series data-generating process. Based on a similar idea, Vassalou (2003) creates a mimicking portfolio which captures news related to future GDP growth and shows that the explanatory power of HML and SMB stems from their predictive power over future GDP growth.

The mainstream literature follows Campbell (1991) and uses a VAR approach to measure state variable innovations. Campbell (1991) decomposes the variance of stock returns in the US market using a data sample from 1927 to 1988. Empirical evidence shows that about one-third of the stock return variance is attributable to variance of news about future cash flow and another third is linked to news about future expected returns.

Lee (1992) employs a multivariate VAR method to examine the causal effect amongst asset returns, real activity and inflation in the period 1947–1987. He reports that 92.7% of the 24-month forecast error variance is captured by their own innovations, which indicates that stock returns are Granger-causally prior. In addition, he finds that stock returns explain 10.6% of the 24-month forecast error variance in industrial production, which corroborates the evidence from Fama (1990) and Schwert (1990) that stock returns are linked to future real activities.

Campbell and Ammer (1993) suggest that contemporaneous regressions can be used to explain stock return variation. The authors employ a VAR model to capture the dynamic structure of state variables using a data sample from 1952 to 1987. The empirical evidence suggests that the majority of the excess stock return variation is attributable to expected return variations. Other important sources of excess stock return variation include the change in real interest rates and innovations in dividend yield.

Petkova (2006) also uses a VAR methodology to generate innovations to state variables. She analyses a US data sample from 1963 to 2001 and shows that the information content of the Fama-French factors HML and SMB is correlated with innovations to the term spread, dividend yield, default spread and risk-free rate.

4.2.3 Macroeconomic factors and stock returns

As Fama-French type factor models have become the benchmark of risk adjustment in finance literature, their economic interpretation has become a subject of debate. While Lakonishok, Shleifer and Vishny (1994) and Daniel and Titman (1997) provide behavioural explanations for the factors, a larger literature has investigated risk-based interpretations (Lewellen, 1999; Liew and Vassalou, 2000; Vassalou, 2003, Vassalou and Xing, 2004; Zhang, 2005; Petkova, 2006). Fama and French (1993) state that HML and SMB may represent state variables that capture time variation in the investment opportunity set. As pointed out by Cochrane (2009), macroeconomic models are constructed not to outperform Fama-French factors in pricing performance, but to understand why they work. The main underlying reason is that macroeconomic models are supported with equilibrium models such as CCAPM and ICAPM, while the Fama-French factors are mostly inspired by the empirical performance of partial-equilibrium models such as q-theory, which may not justify the risk interpretation of the factors (Cooper and Priestley, 2011).

4.2.3.1 Macroeconomic factors and Fama-French factors

Much of the literature on risk-based interpretations has investigated the relationship between state variables and Fama-French factors. The economic intuition has been tested against a few hypotheses implied by ICAPM or CCAPM. The *first* and most obvious test is about whether Fama-Frech risk factors predict the future state of the economy. *Secondly*, an attempt has been made to investigate the contemporaneous correlations between Fama-French risk factors and innovations to state variables known to predict the future state of the economy. *Thirdly*, several papers examine whether the pricing significance of Fama-French risk factors is captured by innovations to state variables known to predict the future state of the economy.

Liew and Vassalou (2000) mainly focus on the first hypothesis and prove the link between Fama-French factors and future growth in the macro-economy. Their tests use quarterly international samples covering 10 developed markets and suggest that nominal GDP growth can be predicted by HML in nine markets, within which four are statistically significant after controlling for business cycle variables. GDP can also be predicted by SMB in nine markets with a positive relation, about half of which presents incremental predictive power over business cycle variables. However, the same result does not apply to the momentum factor. Griffin, Ji and

Martin (2003) confirm that the momentum factor is not related to future growth in GDP or industrial production.

Perez-Quiros and Timmermann (2000) address the second hypothesis and investigate the relation between SMB and different macroeconomic states. Using a Markov switching model, their evidence suggests that small stocks, compared with large stocks, have higher loadings on treasury bill rate, default spread, change in monetary supply and dividend yield in a bad economic state. These asymmetries lead to the difference in the higher expected returns of small stocks.

Vassalou (2003) extends Liew and Vassalou (2000) and creates a mimicking portfolio which captures news related to future GDP growth. The study develops a deeper understanding of the connection between HML, SMB and future states of the economy. HML and SMB become redundant factors in explaining stock cross-sections with the presence of mimicking portfolio in multi-factor asset pricing models.

Campbell and Vuolteenaho (2004) explain the systematic risks of SMB and HML by breaking the market portfolio beta of a stock into two components, one capturing news about the market's future cash flow and one representing news about the market's discount rates. The paper uses a VAR methodology to implement the decomposition of a market portfolio beta. As the ICAPM suggests that investors care more about permanent cash-flow-led volatilities than about impermanent discount-factor-driven changes in the aggregated market, cash-flow beta should have a higher risk price than discount-rate beta. The authors provide consistent results that small and value stocks tend to have higher cash-flow beta, which explain the relevant return cross-sections.

Consistent with Campbell and Vuolteenaho (2004), Cohen, Polk and Vuolteenaho (2009) explain the value-glamour effect using cash-flow beta. Cash-flow beta is defined as the regression coefficient of a firm's earnings on market aggregated earnings. They present evidence to suggest that value stocks tend to have higher cash-flow betas and are thus riskier to investors. Campbell, Polk and Vuolteenaho (2009) confirm the results from both studies.

Hahn and Lee (2006) develop a three-factor model using market excess return augmented by innovations in term spread and innovations in default spread. Their model accords with the studies arguing that growth stocks have higher duration than value stocks (Cornell, 1999; Dechow, Sloan and Soliman, 2004; Lettau and Wachter, 2007). By testing the second hypothesis, the authors show that high book-to-market stocks tend to have higher loadings on term-spread innovations, whereas small stocks tend to have higher loadings on default-spread innovations. The relations between SMB and default spread corroborate the findings of Perez-Quiros and Timmermann (2000)

Petkova (2006) mainly addresses the second and third hypotheses. The author employs a VAR approach to model the time-series dynamics of the state variables. The evidence presented show that the Fama-French factors HML and SMB are correlated with innovations to the five state variables mentioned above. HML is found to be closely related to innovation in term spread, while SMB contains information on default spread innovations. This paper further illustrates that the pricing significance of SMB and HML is spanned by innovations to the five state variables. Hahn and Lee (2006) report consistent results that the information content of SMB and HML can be captured by changes in default spread and changes in term spread respectively.

Aretz, Bartram and Pope (2010) consider a wide range of macroeconomic variables and attempt to test the three hypotheses. Their sample period covers 1975 to 2008 and suggests some new evidence to the information content of HML, SMB and the momentum factor. The results corroborate the earlier findings that HML and SMB are proxies for term-structure risk and default risk respectively. However, they are spanned by the innovation of macroeconomic state variables. Furthermore, the momentum factor is reported to be significantly related to default spread, term spread and foreign exchange risks.

Cooper and Priestley (2011) study the economic intuition of the investment factor CMA and establish a close relation between CMA and innovations to state variables. Their evidence suggests that CMA captures different loadings between low- and high-investment firms with respect to the Chen, Roll and Ross (1986) state variable innovations. Moreover, CMA can forecast future economic activities. Positive connections are obtained between CMA and future real industrial production growth, real GDP growth, real corporate earnings growth and real aggregate investment growth.

Wang (2013) assesses the three hypotheses regarding the profitability factor (ROE) and the investment factor proposed by Chen, Novy-Marx and Zhang (2011). He confirms evidence to suggest that the investment factor (although specified differently from CMA) contains information about future GDP growth. There is, however, little forecasting power from the profitability (ROE) factor, though both factors are closely linked to innovations in state variables. Their pricing significance is spanned by innovation in state variables employed in the asset pricing literature.

4.2.3.2 New ICAPM restrictions

More recently, literature has emerged that re-examines existing Fama-French-style factors regarding restrictions imposed by ICAPM (Maio and Santa-Clara, 2012; Boons, 2016; Cooper and Maio, 2016). Maio and Santa-Clara (2012) propose that existing multifactor models using an ICAPM justification, should be re-examined using three new criteria. *Firstly*, ICAPM state variables should be able to forecast aggregate stock market returns or volatility. *Secondly*, if an ICAPM state variable positively (negatively) predict aggregate stock market returns or volatility, it should be priced positively (negatively) in the cross-section asset pricing tests. *Thirdly*, the market price of risk factor should be economically plausible. Empirical evidence obtained suggests that out of eight multifactor models tested, only the Fama and

French three-factor model (1993) and Carhart (1997) are consistent with the restrictions.

Boons (2016) uses alternative proxies for macroeconomic activities as well as different test assets to mimic stock return cross-sections. Instead of aggregate stock market returns and volatility, he uses industrial production and the Chicago fed national activity index. His empirical evidence using stock-level returns as test assets reveals that dividend yield, default spread and term spread accord with the ICAPM restrictions. Barbalau, Robotti and Shanken (2015) propose a multivariate inequity model to test the ICAPM consistency of multiple-factor models; their findings in general corroborate Boons' (2016) findings.

Cooper and Maio (2016) study two different versions of investment and profitability factors proposed by Novy-Marx (2013), Hou, Xue and Zhang (2015; 2016) and Fama and French (2015; 2016). Their study employs 70 portfolios capturing capital market anomalous characteristics and show that the new factors' implied state variables forecast the equity premium and are priced consistently with the restrictions across the test assets. Their empirical evidence further suggests that the new factors are not spanned by other state variables such as term spread, default spread, dividend yield, one-month treasury bills and value spread.

4.2.4 Macroeconomic factors and stock returns in the UK

For the UK market, a few studies examine how macroeconomic variables forecast the future state of the economy. The empirical predictive power of innovations to state variables are similar to those of the US findings. Black and Fraser (1995) show that shocks to term spread, default spread and dividend yield help explain the conditional risk of aggregate stock returns. Cheng (1995) utilizes a canonical correlation method to examine the relation between stock returns and macroeconomic forces. The results reveal that stock returns have a positive relationship with money supply, the government securities index and unemployment rate and a negative relation to interest rate. Choi, Hauser and Kopecky (1999) use co-integration analysis and find a long-term equilibrium relationship between the UK stock market returns and future industrial production level. Lovatt and Parikh (2000) report that both dividend yield and default spread positively forecast aggregate stock market returns, while term spreads are not significantly linked to the returns. Peel and Pope (1988) and Li, Narayan and Zheng (2010) investigate the inflation–stock return relationship in the UK market. Empirical results reported corroborate the US evidence that unexpected inflation negatively predicts aggregate stock market returns in the short term.

A number of studies have attempted to address the pricing performance of state variable models in the UK market and the results are sensitive to selection of sample and methodology. Poon and Taylor (1991) extend Chen, Roll and Ross's (1986) work using a UK data sample for the period between 1965 and 1984. They present contradictory findings that none of the state variable innovations used in Chen, Roll and Ross (1986) are priced in the UK market. The authors suggest that some other macroeconomic factors may be at work, or the methodology adopted to capture the dynamics of state variable prediction has caused the inconsistent results.

Clare and Thomas (1994) use a relatively short sample period from 1983 to 1990 and test the pricing performance of macroeconomic variables. They use autoregressive models to generate macroeconomic variable innovations. The cross-section of UK market returns are represented by portfolios ranked by market betas and another set of portfolios ranked by market capitalization. A number of factors including default spread, oil price, retail price index, private bank lending, the redemption yield of UK corporate debentures and the loans index are found to have pricing significance in the UK market.

Clare, O'Brien, Thomas and Wickens (1998) construct a macroeconomic shock model to test the mean variance efficiency of the UK stock market. They use seven industrial portfolios from 1978 to 1991 as their test asset in the UK. Empirical results indicate that shocks in oil prices, the UK current account, UK short rates and UK long rates have significant influence on the covariance matrix of returns in the

UK stock market. The innovations to those state variables are thus priced in the UK market.

Antoniou, Garrett and Priestley (1998) employ a sample of 138 randomly selected UK stocks from 1980 to 1994 to test the pricing performance of macroeconomic variables. They follow Gibbons (1982) and employ a non-linear, seemingly unrelated regression time-series econometric method to test their APT settings in individual stock levels. Their results suggest that unexpected inflation, money supply and stock market excess returns are consistently priced across two sub-samples of the UK stocks.

Cuthbertson, Hayes and Nitzsche (1999) extend Campbell (1991) and decompose the variance of stock returns in the UK from 1918 to 1993 using a multivariate VAR method. Their findings suggest that the majority of the variance in expected returns stem from innovations in future discount rates, which have four times the impact of innovations in future dividends. Their results also reveal that innovations to dividends and innovations to real interest rates offset each other in the UK market.

Liew and Vassalou (2000), using an international data sample, test the predictive power of HML, SMB, the momentum factor and the market factor with regard to future GDP growth in the UK. Their results confirm that there is a significant link between HML, SMB, the market factor and future growth of GDP. The results indicate that these three factors are proxies of macroeconomic state variables in the UK market.

Nathan (2002) examines how contemporaneous and lagged exchange rate changes and interest rate changes affect stocks in the UK market. Using a sample of 106 stocks from four UK industrial sectors between 1988 and 2000, he shows that, using an OLS regression methodology, UK stocks are negatively impacted by change in both interest rates and foreign exchange rates. The results are consistent at longer-term estimation and portfolio level.

Limited research has been conducted to bridge the link between the Fama-French factors and macroeconomic activities in the UK market. Gregory, Harris and Michou (2003) extend the US literature to examine the rational explanation of the Fama-French factors in the UK market from 1980 to 1998. Their results are consistent with Liew and Vassalou (2000) and Vassalou (2002), suggesting that both HML and SMB are positively related to future GDP growth in the UK market. Furthermore, they report evidence that HML and SMB also predict future investment and consumption growth.

Evans and Speight (2006) use a set of real-time macroeconomic variables covering the period 1985 to 2002 to re-examine the pricing performance of innovation in state variables. First-order autoregressive models are used to obtain state variable innovations. Their results show that unexpected inflation and innovations in default spread are priced significantly across the 20 equal-weight portfolios ranked by firm size, while innovations based on revised data are not priced. Furthermore, the authors attempt to show the time-series dynamics of the market price for the variables. The evidence reveals that inflation shocks are priced in an expansion period while default spread is valued by the market over a recession period.

Hyde (2007) studies the response of 33 industry sector returns to market portfolio excess return, exchange rate and interest rate shocks in France, Germany, Italy and the UK. For the UK evidence, all sector returns are sensitive to market risk; 12.5% of the industries respond significantly to exchange rate with positive signs; and only two sectors load significantly on real interest rate. Moreover, he follows Campbell (1991) and uses a VAR methodology to decompose the betas as an extension. Both changes in exchange rate and changes in real interest rates contain some information in the UK as ten sectors have significant cash-flow betas, whereas for real interest rates, there are 12 sectors.

Bredin, Hyde, Nitzsche and O'Reilly (2007) study the impact of UK monetary policy on the UK stock market using a sample period between 1975 and 2004. Using an event-study methodology, the paper shows that unanticipated changes in the UK policy rate have a negative impact on aggregate stock returns in the UK. A surprise of 25 basis points in the policy rate on average attenuates FTSE returns by 0.2%. Furthermore, the authors employ a VAR approach to decompose excess returns variance and show that the majority of the excess returns variance stems from revisions to future return expectations. They also show that traditional industries tend to respond more persistently to monetary policy shocks.

The studies of the performance of macroeconomic factor models mainly centre on the US stock market. The topic attracts much attention from the empirical asset pricing researcher as there are no guidelines from the theoretical side as to what macroeconomic factors should be chosen and how investor expectations should be modelled. Existing research suggests that much of the information contained in the Fama-French factors stems from their close connection with the macroeconomic states. For empirical studies, it is reasonable to assume that the most effective formation of macroeconomic factor models varies across different economic entities and economic states. Future research is needed to address these issues.

4.3 DATA AND SAMPLE

4.3.1 Sample coverage

My sample is formed by merging the London Share Price Database (LSPD) and Datastream using UK data from January 1990 to June 2016. I extract accounting information and macroeconomic data from Datastream and monthly returns data from the LSPD. I follow exactly the same procedures to match the two databases as discussed in Chapters 2 and 3. I *exclude* stocks from the financial sector (banks, insurance companies, investment funds, unit trusts and property companies). I *exclude* companies with negative/missing book values and companies with more than one class of shares following the academic literature (Gregory, Tharyan and Christidis, 2013; Michou, Mouselli and Stark, 2014). I *include* stocks de-listed due to various events such as liquidation (LSPD death type 7), quotation cancelled for reason unknown (14), receiver appointed/liquidation (16), in administration (20), or cancelled and assumed valueless (21), following Liu, Strong and Xu (1999). The adjusted sample is then used to construct the UK Fama and French risk factors and left-hand-side portfolios for the asset pricing tests.

4.3.2 Definition of the Fama-French factor variables

For the original Fama and French three-factor model, I follow the standard methodology used in the academic literature using the equation below:

$$R_{it} - R_{ft} = a_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{iHML}HML_t + \beta_{iSMB}SMB_t + \varepsilon_{it}, \forall i \tag{1}$$

where

a_i	is the intercept term for portfolio *i*;
R_{it}	is the return of asset *i* in month *t*;
R_{ft}	is the three-month T-bill rate in month *t*;
R_{Mt}	is the return on the market in the UK in month *t*;
SMB_t	is size factor small minus big based on market capitalization;
HML_t	is value factor high minus low of book-to-market equity;
β_{iM} , β_{iHML} and β_{iSMB}	are the exposures of portfolio *i* to R_M, HML, and SMB respectively;
ε_{it}	is an error term for portfolio *i* for period *t*.

I have also introduced a new five-factor model using UK data as follows:

$$R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt} - R_{ft}) + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t + \beta_{iRMW}RMW_t + \beta_{iCMA}CMA_t + \varepsilon_{it} \tag{2}$$

where

a_i	is the intercept term for portfolio *i*;
R_{it}	is the return of asset *i* in month *t*;
R_{ft}	is the three-month T-bill rate from the UK in month *t*;
R_{mt}	is the return on the market in the UK in month *t*;
SMB_t	is size factor small minus big;
HML_t	is value factor high minus low of book-to-market equity;
RMW_t	is robust minus weak factor for profitability;
CMA_t	is conservative minus aggressive for investment factor;
β_{iM} , β_{iHML}, β_{iSMB}, β_{iRMW} , β_{iCMA}	are the exposures of portfolio *i* to R_M , *HML*, SMB , RMW and CMA respectively;
ε_{it}	is the error term for portfolio *i* for period *t*.

The investment factor CMA is constructed following Hou, Xue and Zhang (2015), which uses the change in total assets from year *t-2* to year *t-1*, divided by total asset (TA) at year *t-2*. I use Datastream total asset (WC02999) to calculate the investment measure, denoted by I/A.

Regarding the definition of the profitability factor RMW, I follow Fama and French (2015a) and Novy-Marx (2013) to use $(operating\ income/BE)_{t-1}$. The operating profit is measured using Datastream operating income (WC01250) scaled by book value calculated with Datastream market-to-book value (MTBV) and market capitalization (MV), denoted by OP/B.

4.3.3 Fama-French style factor construction

I construct Fama and French style factors for the UK stock market. The factors returns are obtained using six independently sorted portfolios using size and the corresponding factor variable. I follow Gregory, Tharyan and Christidis (2013) and use the breakpoints from the UK largest 350 stocks each year mimicking NYSE breakpoints in the US market to sort factor portfolios. At the end of June each year from 1990 to 2016, stocks are categorized into two size groups based on the median size of the largest 350 stocks at the end of year *t-1*. Independent of the size group, stocks are also sorted into three groups of other variables such as book-to-market (BM), investment (I/A) and profitability using the 30th and 70th percentiles from the largest 350 stocks as breakpoints based on data at the end of year *t-1*. The intersections of both sorting processes leads to six portfolios. The value-weighted average returns of the portfolios are then used to produce the corresponding factor-return time-series.

These independently sorted portfolios are labelled using letters: for the size group, small (S) or big (B); for the BM group, high (H), neutral (N) or low (L); for the profitability group, robust (R), neutral (N) or weak (W); for the I/A group, conservative (C), neutral (N) or aggressive (A). Intersected portfolios are obtained to build the factors. Value-weighted (VW) returns are calculated for each portfolio. For example, SL stands for the monthly value-weighted return of an intercepted portfolio with small size and low BM.

4.4 METHODOLOGY

This third empirical chapter explores the information content of the two new factors by linking them to the state variables which predict future investment opportunities. By doing this, I find confirmative evidence that the two new risk factors may proxy for state variables that capture time variation of an investment opportunity set. I find empirical evidence which confirms that the investment factor predicts future economic growth, proxied by GDP growth, investment growth and consumption growth. In addition, the investment factor is found to be related to dividend yield shocks, whereas the profitability factor is related to inflation shocks. In addition, the pricing significance of macroeconomic variable shocks disappears when loadings on the two new factors are added into the model. The evidence therefore provides an economic interpretation of the information content of the new asset pricing factors in the UK market.

I aim to test the following hypotheses:

1. Both the investment factor and profitability factor predict GDP growth, investment growth and consumption growth.
2. Both the investment factor and profitability factor predict innovation to state variables related to future investment opportunities.
3. Compare the informativeness of innovation to state variables with investment growth and profitability factor pricing significance using a one-step Generalized Methods of Moments (GMM) methodology, a two-pass stage Fama-Macbeth cross-sectional regressions analysis and factor-spanning tests.

4.4.1 Testing whether the investment factor and the profitability factor predict macroeconomic growth

In order to test the first hypothesis, I follow Liew and Vassalou (2000) to test whether the two new risk factors, namely the investment factor and the profitability factor, are linked to the future state of the economy using the following quarterly data regression:

$$Macrofactor_{t,t+4} = a + b\ FactorRet_{t-4,t} + \beta_3 TB_t + \beta_4 DY_t + \beta_5 TERM_t + \beta_6 IDPgrowth_{t-4,t} + e_{t,t+4} \quad (3)$$

where

$Macrofactor_{t,t+4}$ is the annual growth in macro-economic state variables.

I use three different measures of macroeconomic state variables for this test:

a) Gross Domestic Product (GDP) growth, based on quarterly data of seasonal adjusted GDP;
b) Consumption (CSM) growth, which is the annual growth rate based on total household consumption expenditure; and
c) Investment (INV) growth, which is measured as the annual growth rate of gross fixed capital formation.

$FactorRet_{t-4,t}$ is the vector consisting of returns of the Fama-French style model factors;

TB_t is the UK three month treasury bill rate;

DY_t is the dividend yield of FTSE all share index;

$TERM_t$ is the difference between 10 year UK government bond yield and three month treasury bill rate;

$IDPgrowth_{t-4,t}$ is the growth in UK industrial production from the past year;

$\beta_3 - \beta_6$ are the regression coefficients of the corresponding controlling variables;

$e_{t,t+4}$: is the error term.

4.4.2 Testing whether the investment factor and profitability factors predict innovation in state variables that are related to future investment opportunities

In order to test the second hypothesis, whether the investment and profitability risk factors can predict innovation to state variables that are related to future, I employ a vector autoregressive (VAR) approach proposed by Campbell (1996) to specify the time-series dynamics of the state variables. I examine whether the two new factors are correlated with innovations to state variables that track an investment opportunity set. Following Petkova (2006), I use dividend yield, term spread, default spread, monthly rate of the UK three-month treasury bill and the UK excess market return as the main state variables. Although Bulkley and Taylor (1996) suggest a rolling VAR should be used to avoid potential hindsight-bias, the vast majority of the literature use static VAR to ensure the stability of the true model (Campbell, 1991; Lee, 1992; Campbell and Ammer, 1993; Petkova, 2006). Campbell (1996) assumes that a vector $\mathbf{z_t}$ follows a first-order VAR:

$$\mathbf{z_{t+1}} = \mathbf{Az_t} + e_{\mathbf{t+1}} \tag{4}$$

where

z is the vector of variables that are known to the market by the end of period *t* and are relevant for forecasting future stock returns;

A is a matrix known as the companion matrix of VAR;

e is the vector error term.

According to Campbell (1996), the main advantage of using a first-order VAR is that it has the ability to generate multi-period forecasts of the elements in $\mathbf{z}_t$ by just multiplying $\mathbf{z}_t$ by the $j+1$ power of the matrix **A**:

$$E_t \mathbf{z}_{\mathbf{t+j+1}} = \mathbf{A}^{j+1} \mathbf{z}_{\mathbf{t}} \tag{5}$$

The first element of the vector **z** is the excess return on the market (RM-RF) while the other elements are dividend yield (DY), term spread (*TERM*), default spread (*DEF*), the risk-free rate (R_f), consumer price index (CPI) and *RMW* and *CMA*, respectively for the profitability and investment factors. If a unit root is found in any of the previous variables, then the first difference of this variable will be used in the subsequent analysis. So equation (5) can be re-written as follows:

$$\begin{Bmatrix} RM-RF_t \\ DY_t \\ TERM_t \\ DEF_t \\ RF_t \\ CPI_t \\ RMW_t \\ CMA_t \end{Bmatrix} = A \begin{Bmatrix} RM-RF_{t-1} \\ DY_{t-1} \\ TERM_{t-1} \\ DEF_{t-1} \\ RF_{t-1} \\ CPI_{t-1} \\ RMW_{t-1} \\ CMA_{t-1} \end{Bmatrix} + u_t \tag{6}$$

where

$RM-RF_t$ is the UK excess market return calculated using the FTSE All-Share Index return and monthly rate of the UK three-month treasury bill rate;

DY_t is the dividend yield of the FTSE All-Share Index;

$TERM_t$ is the difference between the ten-year UK government bond yield and the three-month treasury bill rate;

DEF_t is the default spread, which is measured as the difference between monthly return of the Financial Times Fixed Interest Security Index and the Financial Times Government Securities Price Index before April 2002. Starting from April 2002, default spread is measured as the difference between the Thomson Reuters UK Corporate Benchmark Triple-B ten-year yield and the ten-year UK government bond yield;

RF_t is the monthly return of the three-month UK treasury bill rate;

CPI_t is the UK monthly percentage change in the Consumer Price Index;

RMW_t is the monthly return of the profitability factor RMW;

CMA_t is the monthly return of the investment factor CMA;

u_t are innovations to state variables.

According to Brooks (2002), using non-stationary data could lead to a spurious regression problem. Therefore I test each variable in the VAR model with an augmented Dickey-Fuller (ADF) test for stationarity. If a unit root exists in any of the variables I test, I replace the variable with its first difference for my VAR estimation. The VAR system is estimated using AR(1) model, and the vector u_t represents innovations for each state factor (or its first difference). The variables, following Campbell (1996) and Petkova (2006), are demeaned before estimation. The VAR system is triangularized so that innovations of state variables other than excess market return are orthogonalized to innovation in excess market return. Furthermore, the innovations are scaled to have the same variance as the innovation of excess market return.

In order to test the relationship between RMW, CMA and the innovations to state variables that track investment opportunities, I use the following equation:

$$\hat{u}_t = c_0 + c_1 R_{M,t} + c_2 R_{RMW,t} + c_3 R_{CMA,t} + \varepsilon_t \quad (7)$$

where

$\hat{u}_t$ are innovations to the state variable dividend yield, term spread, default spread and risk free rate, obtained using the VAR system;

c_0 is the regression intercept;

c_1 is the regression coefficient of the UK excess market return on state variable innovations;

$R_{M,t}$ is the UK excess market return calculated using the FTSE All-Share Index return and the monthly rate of the UK three-month treasury bill rate;

c_2 is the regression coefficient of the monthly return of the profitability factor on state variable innovations;

$R_{RMW,t}$ is the monthly return of the profitability factor RMW;

c_3 is the regression coefficient of the monthly return of the profitability factor on state variable innovations;

$R_{CMA,t}$ is the monthly return of the investment factor CMA;

ε_t is the error term.

4.4.3 Comparing the relative informativeness between the two new risk factors and the innovation to state variables

To compare the relative informativeness of the new factors and innovation to macroeconomic state variables, I use both a factor-spanning test and cross-sectional regressions. The factor-spanning test provides direct evidence for the relative informativeness of the pricing factors (Fama and French, 2015). Moreover, I also employ a one-step GMM and a two-step Fama-Macbeth cross-sectional regression to examine the pricing significance of the two new factors with the existence of innovation to state variables.

4.4.3.1 Spanning tests

For the spanning tests, I use the following equation:

$$Factor_t = c_0 + C_1 FactorRet_t + C_2 \hat{u}_t + \varepsilon_t \qquad (8)$$

where

$Factor_t$ is the monthly returns of the profitability and investment factors of RMW and CMA;

c_0 is the regression intercept;

$FactorRet_t$ is the vector consisting of the monthly return of other UK Fama-French-style factors in the factor model;

C_1 is the vector of regression coefficients of the UK Fama-French-style factors on the left-hand-side factor;

C_2 is the vector of regression coefficients of the innovations in the state variables on the left-hand-side factor;

$\hat{u}_t$ is the vector which contains innovations to the state variables of dividend yield, term spread, default spread and risk free rate;

ε_t: is the error term.

4.4.3.2 Cross-sectional regressions

I follow Petkova (2006) and employ cross-sectional regressions to test the pricing significance of the state variables and the two new factors. I construct three sets of 25 independently sorted portfolios sorted by:

- size and book-to-market;
- size and profitability;
- size and investment.

I also construct one set of 34 industry portfolios to mimic the cross-section of stock returns.

I follow Gregory, Tharyan and Christidis (2013) to use breakpoints based on the largest 350 stocks in the UK market to construct the test portfolios. I construct independently sorted portfolios based on intersections of different pairs of factor measures. At the end of June each year, I use accounting information from the previous December and construct 25 size-BM; 25 size-profitability and 25 size-I/A portfolios. For size groups, the four largest size groups are constructed using the quartiles of the largest 350 stocks and the smallest size group is formed from the rest of the sample. The sort of BM, profitability and I/A are realized using quintile breakpoints of the largest 350 stocks. In addition to the 25 annually rebalanced portfolios, I also follow Lewellen, Nagel and Shanken (2010)'s suggestion to construct industry based portfolios for a robustness test. I use the London Share Price Database (LSPD) industrial classification codes G17 and FTSE Industrial Classification Benchmark (ICB) to construct the 34 industry portfolios monthly returns from 1990 to 2016.

The factor loadings indicate the significance of the risk factors in determining stock returns. For each group of the LHS portfolio excess returns, I run the following regressions:

$$R_{i,t} = \alpha_0 + \beta_1 Factor_t + \beta_2 \hat{u}_t + \varepsilon_{i,t}, \ \forall i, \qquad (9)$$

where

$R_{i,t}$ is the vector of monthly excess returns of test portfolios;

α_0 is the regression intercept;

$Factor_t$ is the vector of monthly returns of the profitability and investment factors RMW and CMA respectively;

β_1, β_2 are the vector of regression coefficients for factors and state variable innovations on the LHS portfolio excess returns;

$\hat{u}_t$ is the vector which contains innovations in the state variables of dividend yield, term spread, default spread and risk-free rate;

$\varepsilon_{i,t}$ is the error term.

$$R_{i,t} = \gamma_0 + \gamma_1\beta_1 + \gamma_2\beta_2 + \varepsilon_{i,t}, \ \forall i \qquad (10)$$

where

β_1 and β_2 are the vectors of betas obtained in the first stage of regressions for the two new factors and innovations in the state variables;

γ_1 and γ_2 are the vectors of risk premiums for the two new factors and innovations in the state variables;

γ_0 is the regression intercept.

$\varepsilon_{i,t}$ is the error term.

The significance of risk premiums shows whether the risk factors are priced in the market.

Model (9) and (10) can be estimated using an OLS regression. However, the standard error of risk premiums in model (10) needs to be adjusted using the Shanken (1992) correction to fix the error in variable issue. The above two-pass regression can also be estimated using GMM methods (Hansen, 1982), which does not require the assumption of iid (independent and identically distributed) distribution of error term. Following Cochrane (2009), I specify the GMM settings as follows:

$$A = \begin{bmatrix} I_N \otimes I_{K+1} & 0 \\ 0 & \beta \end{bmatrix}$$

$$g_T = \begin{bmatrix} E_T(R_t - a - \beta f) \\ E_T(R_t - a - \beta f) \otimes f_t \\ E_T(R_t - \lambda_0 - \beta\lambda) \end{bmatrix}$$

$$D = \begin{bmatrix} -I_N & -I_N E_{(f)} & 0 \\ -I_N E_{(f)}' & -I_N E_{(f^2)} & 0 \\ 0 & -\lambda I_N & -\beta \end{bmatrix}$$

$$\begin{bmatrix} I_N \otimes I_{K+1} & 0 \\ 0 & \beta \end{bmatrix} \begin{bmatrix} E_T(R_t - a - \beta f) \\ E_T(R_t - a - \beta f) \otimes f_t \\ E_T(R_t - \gamma_0 - \beta\gamma) \end{bmatrix} = 0 \quad (11)$$

$$\mathrm{V} = (A * D)^{-1} * A * S * A' * (A * D)'^{-1} \quad (12)$$

Models (9) and (10) can be estimated by solving Model (11), where A is the matrix that set moment conditions g_T to zero in GMM estimation. Matrix D is the Jacobian matrix of moment condition matrix $g_T$with respect to model parameters. In matrix g_T , $E_T(R_t - a - \beta f)$ and $E_T(R_t - a - \beta f) \otimes f_t$ are N*K+N moment conditions corresponding to Model (9), where N denotes the number of . $E_T(R_t - \gamma_0 - \beta\gamma)$ are N moment conditions corresponding to Model (10). β = (K+1) * N, representing all the betas in Model (7) plus one row of 1 to obtain estimation of λ_0. The specification of β leads to the same coefficient estimation for GMM and OLS two-pass regression. The covariance matrix V of GMM estimators is calculated using Model (12), where S is the autocorrelation and heteroscedasticity-consistent variance-covariance matrix of pricing errors calculated using the Newey-West (1987) estimator with lag of 12.

4.5 EMPIRICAL RESULTS

4.5.1 Testing whether the investment factor and profitability factor predict macroeconomic growth

Tables 4-1, 4-2 and 4-3 present the quarterly regression results of future economic growth on past factor returns for GDP growth, consumption and investment. The results suggest that the investment factor (CMA) in the UK is strongly correlated to future macroeconomic growth. In all three quarterly-based time-series regressions that I conducted, the investment factor positively forecast future GDP growth, investment growth and consumption growth respectively. The explanatory power of the investment factor is consistent with the ICAPM explanation and thus the investment factor in the UK may capture the dynamics of the investment opportunity set. The result is not surprising, as Gregory, Harris and Michou (2003) show some evidence that HML predicts future GDP growth, while Zhou and Michou (2017) demonstrate that the information content of the value factor HML is subsumed by the investment factor in the UK stock market. The result of my study also confirm the recent findings in Cooper and Priestley (2011) and Cooper and Maio (2016), where the authors report that CMA predicts future economic activity growth in the US market.

However, I do not find significant evidence that the profitability factor RMW is linked to economic growth in the UK market in the three scenarios that I take into account. In the US market, Wang (2013) also reports that the ROE factor suggested by Chen, Novy-Marx and Zhang (2011) does not predict future GDP growth. Cooper and Maio (2016), in their 12-month-lag time-series regressions, show an insignificant relation between the profitability factor and future macroeconomic activities.

Furthermore, my results from the predictive regressions also show that TB and DY provide information about future economic growth. While the UK treasury bill rate is positively related to future GDP growth and future investment growth, dividend yield negatively predicts future consumption growth. The relationships are consistent with what has been reported by Gregory, Harris and Michou (2003) for the UK market. My results are consistent across three macroeconomic indicators: GDP growth, investment growth and consumption growth. The investment factor CMA is strongly correlated to future macroeconomic growth. However, I do not find supportive evidence that the profitability factor RMW is linked to economic growth in the UK market.

Table 4-1

Quarterly regression results of future economic growth on past factor returns			
This table presents quarterly time-series regressions results $GDPgrowth_{t,t+4} = a + \beta_1 * (RM - RF)_{t-4,t} + \beta_2 * CMA_{t-4,t} + \beta_3 * RMW_{t-4,t} + \beta_4 TB_t + \beta_5 DY_t + \beta_6 TERM_t + \beta_7 IDPgrowth_{t-4,t} + e_{t,t+4}$. GDP growth is the UK GDP growth based on quarterly data of seasonal adjusted GDP. RM-RF is the UK excess market return calculated using the FTSE All-Share Index return and the monthly rate of the UK three-month treasury bill rate. CMA is the annual return of the investment factor. RMW is the annual return of the profitability factor. TB is the UK three-month treasury bill rate. DY is the dividend yield of the FTSE All-Share Index. TERM is the difference between the ten-year UK government bond yield and three-month treasury bill rate. IPD growth is the growth in UK industrial production from the past year. The *t*-statistics are corrected for heteroscedasticity and autocorrelation using the Newey-West estimator with three lags. The sample period is from the 3rd quarter of 1990 to the 2nd quarter of 2016.			
	(1)	**(2)**	**(3)**
VARIABLES	**GDP growth**	**GDP growth**	**GDP growth**
RM-RF	0.018	0.017	0.013
	[1.598]	[1.545]	[1.198]
CMA	0.019*	0.020*	
	[1.758]	[1.778]	
RMW	0.001		0.005
	[0.124]		[0.428]
TB	0.201***	0.202***	0.190***
	[3.964]	[4.222]	[3.398]
DY	0.031	0.030	-0.001
	[0.152]	[0.148]	[-0.005]
TERM	0.026	0.027	0.024
	[1.157]	[1.244]	[1.017]
IPD growth	-0.066	-0.066	-0.082
	[-1.244]	[-1.242]	[-1.654]
Constant	0.024***	0.024***	0.027***
	[3.012]	[3.071]	[3.442]
Adj. R-squared	18.6%	19.5%	15.7%

Table 4-2

Quarterly regression results of future economic growth on past factor returns

This table presents quarterly time-series regressions results $INVgrowth_{t,t+4} = a + \beta_1 * (RM - RF)_{t-4,t} + \beta_2 * CMA_{t-4,t} + \beta_3 * RMW_{t-4,t} + \beta_4 TB_t + \beta_5 DY_t + \beta_6 TERM_t + \beta_7 IDPgrowth_{t-4,t} + e_{t,t+4}$. INVgrowth is the UK annual growth rate of gross fixed capital formation. (RM-RF) is the UK excess market return calculated using the FTSE All-Share Index return and the monthly rate of the UK three-month treasury bill rate. CMA is the annual return of the investment factor. RMW is annual return of the profitability factor. TB is the UK three-month treasury bill rate. DY is the dividend yield of the FTSE All-Share Index. TERM is the difference between the ten-year UK government bond yield and the three-month treasury bill rate. IPD growth is the growth in UK industrial production from the past year. The *t*-statistics are corrected for heteroscedasticity and autocorrelation using the Newey-West estimator with three lags. The sample period is from the 3rd quarter of 1990 to the 2nd quarter of 2016.

VARIABLES	(1) INV growth	(2) INV growth	(3) INV growth
RM-RF	0.063	0.063	0.003
	[1.352]	[1.377]	[0.054]
CMA	0.235***	0.235***	
	[3.584]	[3.634]	
RMW	0.003		0.042
	[0.058]		[0.594]
TB	0.822**	0.824**	0.688*
	[2.311]	[2.413]	[1.824]
DY	-0.535	-0.538	-0.925
	[-0.417]	[-0.424]	[-0.555]
TERM	0.151	0.152	0.132
	[1.052]	[1.088]	[0.863]
L4. IPD growth	-0.346	-0.345	-0.540*
	[-1.191]	[-1.195]	[-1.820]
Constant	0.029	0.029	0.066
	[0.551]	[0.564]	[1.099]
Observations	96	96	96
Adj. R-squared	21.6%	22.4%	10.5%

Table 4-3

Quarterly regression results of future economic growth on past factor returns

This table presents quarterly time-series regressions results $CSMgrowth_{t,t+4} = a + \beta_1 * (RM - RF)_{t-4,t} + \beta_2 * CMA_{t-4,t} + \beta_3 * RMW_{t-4,t} + \beta_4 TB_t + \beta_5 DY_t + \beta_6 TERM_t + \beta_7 IDPgrowth_{t-4,t} + e_{t,t+4}$. CSM growth is the UK annual growth rate based on quarterly total household consumption expenditure. (RM-RF) is the UK annual excess market return calculated using the FTSE All-Share Index return and monthly rate of the UK three month treasury bill rate. CMA is annual return of the investment factor. RMW is annual return of the profitability factor. TB is the UK three month treasury bill rate. DY is the dividend yield of FTSE All-Share Index. TERM is the difference between the ten-year UK government bond yield and three-month treasury bill rate. IPD growth is the growth in UK industrial production from the past year. The *t*-statistics are corrected for heteroscedasticity and autocorrelation using the Newey-West estimator with three lags. The sample period is from the 3rd quarter of 1990 to the 2nd quarter of 2016.

VARIABLES	**(1) CSM growth**	**(2) CSM growth**	**(3) CSM growth**
RM-RF	0.013	0.012	0.005
	[0.784]	[0.752]	[0.319]
CMA	0.030**	0.031**	
	[2.248]	[2.362]	
RMW	0.004		0.009
	[0.252]		[0.523]
TB	0.069	0.072	0.052
	[0.779]	[0.824]	[0.559]
DY	-0.496*	-0.499*	-0.546*
	[-1.853]	[-1.909]	[-1.922]
TERM	-0.019	-0.017	-0.021
	[-0.538]	[-0.514]	[-0.572]
IPDgrowth	-0.027	-0.026	-0.052
	[-0.365]	[-0.360]	[-0.687]
Constant	0.045***	0.045***	0.050***
	[4.162]	[4.345]	[4.583]
Observations	96	96	96
Adj. R-squared	7.8%	8.8%	3.4%

4.5.1.1 ADF test results, summary statistics and correlations

Table 4-4 presents the results from the ADF test statistics. According to the ADF test statistics, default spread and risk-free rate do not pass the unit root test. Since I cannot reject the null hypothesis that default spread and risk-free rate do not have a unit root, I replace the variables with their first difference for my VAR estimation.

After taking the first difference, both variables pass the ADF test and thus are included in my VAR system.

Tables 4-5 and 4-6 present the summary statistics and the correlations of all variables used to test the first hypothesis. The summary statistics show that both the investment factor and the profitability factor have strong premia in the UK market, compared with the value factor HML with 0.38% monthly return premium at 10% level. The investment factor CMA has a 0.5% monthly return premium at 1% significant level, while the profitability factor RMW also has a 0.51% monthly return at the same significant level. In the correlation matrix, I can see a relatively high correlation between CMA and HML at 0.357. There are relatively low correlations between the two new factors and innovations in the state variables.

Table 4-4

ADF test statistics

This table presents the ADF test statistics of all variables included in the VAR system. Twelve lags are used in the ADF test. If the test statistic exceeds the critical value, then the null hypothesis is rejected, indicating stationarity of the tested variable. If the test statistic does not exceed the critical value, the null hypothesis of unit root existence cannot be rejected, the variable is therefore non-stationary. Critical values of the ADF test are -3.4563 at the 1% level, -2.8724 at the 5% level and -2.5725 at the 10% level.

Variable	**ADF test statistic**
Rm-rf	-4.546***
CMA	-4.470***
RMW	-4.654***
DY	-2.935**
TERM	-4.611***
DEF	-1.359
RF	-2.017
CPI	-4.009***

Table 4-5

Summary statistics of all variables used								
This table presents the summary statistics of all variables used. (RM-RF) is the UK monthly excess market return calculated using the FTSE All-Share Index return and monthly rate of the UK three-month treasury bill rate. CMA is the monthly return of the investment factor. RMW is the monthly return of the profitability factor. SMB is the monthly return of the size factor. HML is the monthly return of the value factor. $\hat{u}^{\mathrm{DY}}$, $\hat{u}^{\mathrm{TERM}}$, $\hat{u}^{\mathrm{RF}}$, $\hat{u}^{\mathrm{DEF}}$, $\hat{u}^{\mathrm{CPI}}$ are innovations in the state variables dividend yield, term spread, default spread and risk-free rate. DY is the dividend yield of the FTSE All-Share Index. TERM is the difference between the ten-year UK government bond yield and three-month treasury bill rate. RF is the monthly return of three-month UK Treasury Bill rate. DEF is the default spread, which is measured as the difference between the monthly return of the Financial Times fixed interest security index and the Financial Times government securities price index before April 2002. Starting from April 2002, default spread is the difference between the Thomson Reuters UK Corporate Benchmark Triple-B ten-years yield and the ten-year UK government bond yield. CPI is the UK monthly percentage change in the Consumer Price Index. Newey-West *t*-statistics using six lags are reported.								
Variable	**Mean**	**Median**	**Max**	**Min**	**SD**	**Skewness**	**Kurtosis**	***t*-statistics**
RM-RF	0.0040*	0.0085	0.0990	-0.1361	0.0399	-0.57	3.71	1.75
CMA	0.0050***	0.0035	0.1234	-0.0806	0.0238	0.50	5.69	3.07
RMW	0.0051***	0.0022	0.2504	-0.0972	0.0299	2.11	19.21	2.79
SMB	-0.0012	-0.0014	0.1833	-0.1517	0.0401	0.32	5.83	-0.47
HML	0.0038*	0.0034	0.0888	-0.1159	0.0280	-0.38	5.06	1.87
$\hat{u}^{\mathrm{DY}}$	0.0001	0.0014	0.1905	-0.2715	0.0402	-1.84	18.37	0.05
$\hat{u}^{\mathrm{TERM}}$	0.0000	0.0021	0.1232	-0.1201	0.0402	0.00	3.32	0.02
$\hat{u}^{\mathrm{RF}}$	0.0001	0.0035	0.1442	-0.2712	0.0402	-2.25	17.14	0.05
$\hat{u}^{\mathrm{DEF}}$	0.0000	-0.0002	0.2180	-0.1343	0.0401	0.42	6.12	0.00
$\hat{u}^{\mathrm{CPI}}$	-0.0001	-0.0003	0.2313	-0.2834	0.0403	-0.40	13.70	-0.04

Table 4-6

Correlations of all variables used

This table presents the correlations of all variables used. (RM-RF) is the UK monthly excess market return calculated using the FTSE All-Share Index return and the monthly rate of the UK three-month treasury bill rate. CMA is the monthly return of the investment factor. RMW is the monthly return of the profitability factor. SMB is the monthly return of the size factor. HML is the monthly return of the value factor. $\hat{u}^{\mathrm{DY}}$, $\hat{u}^{\mathrm{TERM}}$, $\hat{u}^{\mathrm{RF}}$, $\hat{u}^{\mathrm{DEF}}$, $\hat{u}^{\mathrm{CPI}}$ are innovations in the state variables dividend yield, term spread, default spread and risk-free rate. DY is the dividend yield of the FTSE All-Share Index. TERM is the difference between the ten-year UK government bond yield and the three-month treasury bill rate. RF is the monthly return of the three-month UK Treasury Bill rate. DEF is the default spread, which is measured as the difference between the monthly return of the Financial Times fixed interest security index and the Financial Times government securities price index before April 2002. Starting from April 2002, default spread is the difference between the Thomson Reuters UK Corporate Benchmark Triple-B ten years yield and the the ten-year UK government bond yield. CPI is the UK monthly percentage change in the Consumer Price Index.

	RM-RF	**CMA**	**RMW**	**SMB**	**HML**	$\hat{u}^{\mathrm{DY}}$	$\hat{u}^{\mathrm{TERM}}$	$\hat{u}^{\mathrm{RF}}$	$\hat{u}^{\mathrm{DEF}}$
CMA	-0.132								
RMW	-0.262	0.156							
SMB	-0.029	-0.047	-0.134						
HML	0.090	0.357	-0.178	-0.186					
$\hat{u}^{\mathrm{DY}}$	0.003	-0.190	-0.040	-0.048	-0.092				
$\hat{u}^{\mathrm{TERM}}$	-0.006	0.010	0.094	-0.207	-0.121	-0.144			
$\hat{u}^{\mathrm{RF}}$	0.009	-0.141	-0.054	0.065	0.020	0.154	-0.373		
$\hat{u}^{\mathrm{DEF}}$	0.004	0.064	-0.001	0.119	0.165	0.129	-0.521	0.123	
$\hat{u}^{\mathrm{CPI}}$	-0.001	0.014	0.109	-0.032	-0.048	0.119	-0.087	0.042	0.012

4.5.1.2 Results on the relationship between the profitability and investment factors and the innovations to state variables that track investment opportunities

Table 4-7 presents the results from time-series regressions that show the relationship between the profitability and investment factors and the innovations to state variables that track investment opportunities. The time series regression results indicate that the source of the predictive power of the value factor comes from its correlation with the term spread and default spread. The source of informativeness of the investment factor stems from its relationship to changes in dividend yield and shocks to the risk-free rate. As change in the risk-free rate and dividend/investment policy are likely to be related to the return of firms with extremely high and low investment, it is no surprise to find a connection between shocks to these state variables and the return of investment factor.

The monthly contemporaneous regression results indicate that the source of informativeness of the investment factor may stem from its relationship to shocks in dividend yield, as dividend yields are generally treated as significant indicators of discount rates and expected returns about future stock market (Campbell and Shiller, 1988; Fama and French, 1988; 1989; Lewellen, 2004). The significant negative correlation may suggest that CMA may have captured the discrepancy between high investment firms and low investment firms regarding their price sensitivity to shocks to the overall market discount rate and expected returns.

Moreover, the regression also suggests significant linkage between the profitability factor and shocks to inflation. As suggested by Feldstein (1980) and Pearce and Roley (1983), shocks to inflation induce investors to revise their expectations of future inflation which attenuates the stock price. It is therefore not surprising to find a connection between innovation to inflation and returns between high profitability stocks and low profitability stocks. Profitable firms seem to be less price-sensitive to inflation shocks compared with their low-profitable peers.

Table 4-7

Time-series regression results					
This table presents time series regression $\hat{u}_t = c_0 + c_1 R_{M,t} + c_2 R_{RMW,t} + c_3 R_{CMA,t} + \varepsilon_t$. (RM-RF) is the UK monthly excess market return calculated using the FTSE All-Share Index return and the monthly rate of the UK three-month treasury bill rate. CMA is the monthly return of the investment factor. RMW is the monthly return of the profitability factor. $\hat{u}^{\mathrm{DY}}$, $\hat{u}^{\mathrm{TERM}}$, $\hat{u}^{\mathrm{RF}}$, $\hat{u}^{\mathrm{DEF}}$, $\hat{u}^{\mathrm{CPI}}$ are innovations in the state variables dividend yield, term spread, default spread and risk-free rate. DY is the dividend yield of the FTSE All-Share Index. TERM is the difference between the ten-year UK government bond yield and the three-month treasury bill rate. RF is the monthly return of three-month UK treasury bill rate. DEF is the default spread, which is measured as the difference between the monthly return of the Financial Times fixed interest security index and the Financial Times government securities price index before April 2002. Starting from April 2002, default spread is the difference between the Thomson Reuters UK Corporate Benchmark Triple-B ten years yield and the ten-year UK government bond yield. CPI is the UK monthly percentage change in the Consumer Price Index. The sample period is from June 1990 to June 2016 The *t*-statistics are corrected for heteroscedasticity and autocorrelation using the Newey-West estimator with three lags.					
DEPENDENT VARIABLES	$\hat{\boldsymbol{u}}^{\mathbf{DY}}$	$\hat{\boldsymbol{u}}^{\mathbf{TERM}}$	$\hat{\boldsymbol{u}}^{\mathbf{RF}}$	$\hat{\boldsymbol{u}}^{\mathbf{DEF}}$	$\hat{\boldsymbol{u}}^{\mathbf{CPI}}$
RM-RF	-0.036	0.018	-0.021	0.010	0.033
	[-0.363]	[0.185]	[-0.209]	[0.143]	[0.450]
RMW	-0.030	0.131	-0.054	-0.011	0.160**
	[-0.449]	[1.460]	[-0.795]	[-0.126]	[2.089]
CMA	-0.319**	-0.005	-0.233	0.112	-0.002
	[-2.457]	[-0.054]	[-1.576]	[1.311]	[-0.019]
Constant	0.002	-0.001	0.002	-0.001	-0.001
	[0.674]	[-0.264]	[0.713]	[-0.378]	[-0.378]
Observations	304	304	304	304	304
Adj. R-squared	0.03	-0.00	0.01	-0.01	0.00

4.5.2 A comparison of the relative informativeness of the two new risk factors and the innovation to state variables

4.5.2.1 Spanning test results

Table 4-8 presents results from the spanning tests. The factor-spanning test results provide several findings. Firstly, consistent with Zhou and Michou (2017)'s results, the investment and profitability factors are significantly correlated with SMB and HML in the UK market. The profitability factor RMW is negatively linked to the market portfolio excess return, SMB and HML. The investment factor CMA has a significant overlap with information on the value factor HML, with a significant 0.337 coefficient in the regression. The significant intercept terms in both regressions show that CMA and RMW are not captured by SMB and HML. A more important finding here is that controlling for innovations to the state variables does not change the significance of the intercept terms, which means that the information content in RMW and CMA exceeds that contained in state variable shocks in the UK market. I therefore would expect the pricing performance of RMW and CMA not to be captured by the innovation in state variables in my sample.

4.5.2.2 Cross-sectional regression results

From Table 4-9 to Table 4-12, I report results for two-pass cross-sectional regressions for the pricing significance of the state variable models and new factor models. "SH t-stat" demonstrates the *t*-statistics obtained using the Shanken (1992) correction for the error-in-variable problem in the Fama-Macbeth (1973) regression. "GMM t-stat" reports the *t*-statistics obtained using a one-step GMM estimation with the Newey-West Variance-Covariance matrix. The statistics from both approaches are qualitatively similar across all of my samples tested. Across the samples, I find that the CMA factor is marginally priced at a 10% level, though with two positive prices and two negative ones. The puzzling pricing performance may be attributed to the choice of testing portfolios. The RMW factor is significantly priced only in size-profitability portfolios. However, I confirm that the information content of state variable innovations is spanned by CMA and RMW since none of the state variable innovation factors are significantly priced when CMA and RMW are included in the factor model. Moreover, CMA and RMW bring in incremental adjusted R-squared to the state variable models in all scenarios.

The cross-section in 25 size-BM portfolios (Table 4-9) is captured by the eight factor models. The null hypothesis that all pricing errors are jointly equal to zero cannot be rejected at the 5% level. And the intercept terms are statistically insignificant. For the state variable model, I find that shocks to both dividend yield and inflation are negatively priced. However, their pricing significance disappears once CMA and RMW factors are included in the model. CMA is marginally significant at a 10% level with a positive price. Including RMW and CMA also improves the explanatory power of the state variable innovation factors with additional 10% in adjusted R-squared.

Table 4-10 shows the regression results for the 25 size-Profitability portfolios. Neither of the models explain the cross sections in returns, as the χ^2 test is rejected, pricing errors are not jointly equal to zero. In the state variable model, the market portfolio risk premium is significant and negatively priced, while innovations in default spreads are positive and significantly priced. In the augmented model, both CMA and RMW are positively significantly priced.

For the 25 size-Investment portfolios, as illustrated in Table 4-11, only the CMA factor is negatively priced in the augmented model. The state variable shocks are not priced. The pricing errors are not significantly different from zero while the intercepts are significantly priced. For the 34 industry portfolios, the CMA factor is also negatively priced at the 10% level. The explanatory power of both models is notably low at 14% and 11%, indicating that my current models do not capture variations across different industries.

Table 4-8

Spanning test results

This table presents time series factor spanning test results. CMA is the monthly return of the investment factor. RMW is the monthly return of the profitability factor. $\hat{u}^{\mathrm{RM-RF}}$, $\hat{u}^{\mathrm{DY}}$, $\hat{u}^{\mathrm{TERM}}$, $\hat{u}^{\mathrm{RF}}$, $\hat{u}^{\mathrm{DEF}}$, $\hat{u}^{\mathrm{CPI}}$ are innovations in market excess return and the state variables dividend yield, term spread, default spread and risk free rate. (RM-RF) is the UK monthly excess market return calculated using the FTSE All-Share Index return and the monthly rate of the UK three-month treasury bill rate. DY is the dividend yield of the FTSE All-Share Index. TERM is the difference between the ten-year UK government bond yield and the three-month treasury bill rate. RF is the monthly return of the three-month UK treasury bill rate. DEF is the default spread, which is measured as the difference between the monthly return of the Financial Times fixed interest security index and the Financial Times government securities price index before April 2002. Starting from April 2002, default spread is the difference between the Thomson Reuters UK Corporate Benchmark Triple-B ten years yield and the ten-year UK government bond yield. CPI is the UK monthly percentage change in the Consumer Price Index. The sample period is from June 1990 to June 2016. The *t*-statistics are corrected for heteroscedasticity and autocorrelation using the Newey-West estimator with three lags.

DEPENDENT VARIABLES	**RMW**	**CMA**
Constant	0.005***	0.003**
	[3.462]	[2.119]
$\hat{u}^{\mathrm{DY}}$	-0.036	-0.077**
	[-1.066]	[-2.169]
$\hat{u}^{\mathrm{TERM}}$	0.058	0.001
	[1.214]	[0.013]
$\hat{u}^{\mathrm{RF}}$	0.009	-0.074
	[0.265]	[-1.602]
$\hat{u}^{\mathrm{DEF}}$	0.072	0.015
	[1.512]	[0.518]
$\hat{u}^{\mathrm{RM-RF}}$	-0.163**	-0.070*
	[-2.438]	[-1.722]
$\hat{u}^{\mathrm{CPI}}$	0.073*	0.020
	[1.842]	[0.670]
SMB	-0.134***	0.027
	[-2.669]	[0.665]
HML	-0.288***	0.337***
	[-3.691]	[4.773]
CMA	0.250	
	[1.441]	
RMW		0.149
		[1.625]
Observations	303	303
Adj. R-squared	0.154	0.206

Table 4-9

Cross-sectional regressions on 25 sizeBook-to-market portfolios											
This table presents Fama-Macbeth cross-sectional regressions of a linear factor model for 25 portfolios sorted independently by size and book-to-market. The risk premiums are calculated for market excessive returns (RF-RM), the UK monthly excess market return is calculated using the FTSE All-Share Index return and the monthly rate of the UK three-month treasury bill rate, denoted by γ_M, and innovations in the stated variables dividend yield, term spread, default spread and risk-free rate. DY is the dividend yield of the FTSE All-Share Index. TERM is the difference between the ten-year UK government bond yield and the three-month treasury bill rate. RF is the monthly return of three-month UK treasury bill rate. DEF is the default spread, which is measured as the difference between the monthly return of the Financial Times fixed interest security index and the Financial Times government securities price index before April 2002. Starting from April 2002, default spread is the difference between the Thomson Reuters UK Corporate Benchmark Triple-B ten years yield and the ten-year UK government bond yield. CPI is the UK monthly percentage change in the Consumer Price Index. The GMM *t*-statistic is corrected for serial correlation and heteroscedasticity using a 12-lag Newey-West variance-covariance matrix of pricing errors. The SH *t*-stat is the adjusted *t*-statistic of OLS results following the Shanken (1992) approach to the error-in-variable problem. The last column reports χ^2 statistics and the corresponding P value, to the null hypothesis that pricing errors in the first pass regression are jointly equal to zero. The estimated coefficients are presented as percentages per month. Sample period: June 1990 to June 2016.											
Variable	γ_0	γ_M	$\gamma_{\hat{u}}DIV$	$\gamma_{\hat{u}}TERM$	$\gamma_{\hat{u}}RF$	$\gamma_{\hat{u}}DEF$	$\gamma_{\hat{u}}CPI$	γCMA	γRMW	**Adj.** R^2	χ^2
estimate	0.34	0.56	-1.37	0.77	0.26	1.23	-1.63	0.51*	0.19	0.61	26.74
SH *t*-stat	0.86	0.90	-1.08	0.74	0.20	1.23	-1.25	1.45	0.49		0.06
GMM *t*-stat	0.68	0.94	-1.17	0.78	0.21	1.14	-1.32	1.75	0.50		
Variable	γ_0	γ_M	$\gamma_{\hat{u}}DIV$	$\gamma_{\hat{u}}TERM$	$\gamma_{\hat{u}}RF$	$\gamma_{\hat{u}}DEF$	$\gamma_{\hat{u}}CPI$			**Adj.** R^2	χ^2
estimate	0.51	0.37	-2.03**	1.38	-0.25	1.40	-2.78*			0.51	32.60
SH *t*-stat	1.49	0.67	-1.82	1.21	-0.18	1.34	-1.65				0.03
GMM *t*-stat	1.04	0.63	-2.08	1.32	-0.18	1.15	-1.71				

Table 4-10

Cross-sectional regressions on 25 size-Pprofitability portfolios											
This table presents Fama-Macbeth cross-sectional regressions of a linear factor model for 25 portfolios sorted independently by size and OP/B. The risk premiums are calculated for market excessive returns (RF-RM), the UK monthly excess market return is calculated using the FTSE All-Share Index return and the monthly rate of the UK three-month treasury bill rate, denoted by γ_M; and innovations in the stated variables dividend yield, term spread, default spread and risk free rate. DY is the dividend yield of the FTSE All-Share Index. TERM is the difference between the ten-year UK government bond yield and the three-month treasury bill rate. RF is the monthly return of three-month UK treasury bill rate. DEF is the default spread, which is measured as the difference between the monthly return of the Financial Times fixed interest security index and the Financial Times government securities price index before April 2002. Starting from April 2002, default spread is the difference between the Thomson Reuters UK Corporate Benchmark Triple-B ten years yield and the ten-year UK government bond yield. CPI is the UK monthly percentage change in the Consumer Price Index. The GMM *t*-statistic is corrected for serial correlation and heteroscedasticity using a 12-lag Newey-West variance-covariance matrix of pricing errors. The SH *t*-stat is the adjusted *t*-statistic of OLS results following the Shanken (1992) approach to the error-in-variable problem. The last column reports χ^2 statistics and the corresponding P value, to the null hypothesis that pricing errors in the first pass regression are jointly equal to zero. The estimated coefficients are presented as percentages per month. Sample period: June 1990 to June 2016.											
Variable	γ_0	γ_M	$\gamma_{\hat{u}}DIV$	$\gamma_{\hat{u}}TERM$	$\gamma_{\hat{u}}RF$	$\gamma_{\hat{u}}DEF$	$\gamma_{\hat{u}}CPI$	γCMA	γRMW	**Adj.** R^2	χ^2
Estimate	1.17**	-0.25	0.25	-0.48	-0.50	1.15	-1.48	0.93*	0.67***	0.62	59.37
SH *t*-stat	2.76	-0.41	0.26	-0.43	-0.48	1.36	-1.07	2.01	2.61		0.00
GMM *t*-stat	2.04	-0.38	0.26	-0.45	-0.49	1.49	-0.98	1.70	2.46		
Variable	γ_0	γ_M	$\gamma_{\hat{u}}DIV$	$\gamma_{\hat{u}}TERM$	$\gamma_{\hat{u}}RF$	$\gamma_{\hat{u}}DEF$	$\gamma_{\hat{u}}CPI$			**Adj.** R^2	χ^2
Estimate	2.18***	-1.32**	0.30	0.18	-1.28	1.62***	0.55			0.46	80.06
SH *t*-stat	5.57	-2.57	0.36	0.20	-1.34	2.04	0.42				0.00
GMM *t*-stat	4.34	-2.24	0.34	0.17	-1.20	2.31	0.41				

Table 4-11

Cross-sectional regressions on 25 size Investment portfolio											
This table presents Fama-Macbeth cross-sectional regressions of a linear factor model for 25 portfolios sorted independently by size and I/A. The risk premiums are calculated for market excessive returns (RF-RM), the UK monthly excess market return calculated using the FTSE All-Share Index return and the monthly rate of the UK three-month treasury bill rate, denoted by γ_M, and innovations in the stated variables dividend yield, term spread, default spread and risk free rate. DY is the dividend yield of FTSE All-Share Index. TERM is the difference between the ten-year UK government bond yield and the three-month treasury bill rate. RF is the monthly return of three month UK treasury bill rate. DEF is the default spread, which is measured as the difference between the monthly return of the Financial Times fixed interest security index and the Financial Times government securities price index before April 2002. Starting from April 2002, default spread is the difference between the Thomson Reuters UK Corporate Benchmark Triple-B ten years yield and the ten-year UK government bond yield. CPI is the UK monthly percentage change in the Consumer Price Index. The GMM *t*-statistic is corrected for serial correlation and heteroscedasticity using a 12-lag Newey-West variance-covariance matrix of pricing errors. The SH *t*-stat is the adjusted *t*-statistic of OLS results following the Shanken (1992) approach to the error-in-variable problem. The last column reports χ^2 statistics and the corresponding P value, to the null hypothesis that pricing errors in the first pass regression are jointly equal to zero. The estimated coefficients are presented as percentages per month. The sample period is from June 1990 to June 2016.											
Variable	γ_0	γ_M	$\gamma_{\hat{u}}DIV$	$\gamma_{\hat{u}}TERM$	$\gamma_{\hat{u}}RF$	$\gamma_{\hat{u}}DEF$	$\gamma_{\hat{u}}CPI$	γCMA	γRMW	**Adj. R^2**	χ^2
Estimate	1.29***	-0.42	0.99	0.04	-0.37	-0.72	-0.02	-0.41*	0.20	0.47	25.18
SH t-stat	3.70	-0.90	0.95	0.04	-0.47	-0.61	-0.02	-1.72	0.48		0.09
GMM t-stat	2.92	-0.81	0.83	0.04	-0.43	-0.56	-0.01	-1.57	0.38		
Variable	γ_0	γ_M	$\gamma_{\hat{u}}DIV$	$\gamma_{\hat{u}}TERM$	$\gamma_{\hat{u}}RF$	$\gamma_{\hat{u}}DEF$	$\gamma_{\hat{u}}CPI$			**Adj. R^2**	χ^2
Estimate	1.17***	-0.27	1.37	-0.02	0.34	-1.10	1.33			0.27	23.60
SH t-stat	3.48	-0.56	1.21	-0.02	0.37	-0.90	0.94				0.21
GMM t-stat	2.88	-0.53	1.02	-0.02	0.31	-0.79	0.75				

Table 4-12

Cross-sectional regressions on 34 Industry portfolios											
This table presents Fama-Macbeth cross-sectional regressions of a linear factor model for 34 industry portfolios. The risk premiums are calculated for market excessive returns (RF-RM), the UK monthly excess market return calculated using the FTSE All-Share Index return and the monthly rate of the UK three-month treasury bill rate, denoted by γ_M, and innovations in the ten-year UK government bond yield and the three-month treasury bill rate. RF is the monthly return of three-month UK treasury bill rate. DEF is the default spread, which is measured as the difference between the monthly return of the Financial Times fixed interest security index and the Financial Times government securities price index before April 2002. Starting from April 2002, default spread is the difference between the Thomson Reuters UK Corporate Benchmark Triple-B ten years yield and the ten-year UK government bond yield. CPI is the UK monthly percentage change in the Consumer Price Index. The GMM *t*-statistic is corrected for serial correlation and heteroscedasticity using a 12-lag Newey-West variance-covariance matrix of pricing errors. The SH *t*-stat is the adjusted *t*-statistic of OLS results following the Shanken (1992) approach to the error-in-variable problem. The last column reports χ^2 statistics and the corresponding P value, to the null hypothesis that pricing errors in the first pass regression are jointly equal to zero. The estimated coefficients are presented as percentages per month. The sample period is from June 1990 to June 2016.											
Variable	$\boldsymbol{\gamma_0}$	$\boldsymbol{\gamma_M}$	$\boldsymbol{\gamma_{\hat{u}}DIV}$	$\boldsymbol{\gamma_{\hat{u}}TERM}$	$\boldsymbol{\gamma_{\hat{u}}RF}$	$\boldsymbol{\gamma_{\hat{u}}DEF}$	$\boldsymbol{\gamma_{\hat{u}}CPI}$	$\boldsymbol{\gamma CMA}$	$\boldsymbol{\gamma RMW}$	**Adj.** $\boldsymbol{R^2}$	$\boldsymbol{\chi^2}$
Estimate	0.75*	0.28	1.26	1.36	-0.67	-0.56	-1.18	-0.60*	0.01	0.14	135.27
SH t-stat	1.93	0.63	1.56	1.29	-0.89	-0.49	-1.17	-1.72	0.02		0.00
GMM t-stat	1.75	0.02	1.50	1.27	-0.78	-0.45	-1.02	-1.81	0.67		
Variable	γ_0	γ_M	$\gamma_{\hat{u}}DIV$	$\gamma_{\hat{u}}TERM$	$\gamma_{\hat{u}}RF$	$\gamma_{\hat{u}}DEF$	$\gamma_{\hat{u}}CPI$			Adj. R^2	χ^2
Estimate	0.72*	-0.02	1.36*	0.88	-0.36	-0.28	-0.23			0.11	159.02
SH t-stat	1.88	-0.03	1.81	0.95	-0.55	-0.26	-0.25				0.00
GMM t-stat	1.71	-0.03	1.71	0.87	-0.44	-0.23	-0.24				

4.6 CONCLUSION

This third empirical chapter explores the information content of two new risk factors, the profitability factor and the investment factor and attempts to link them to the state variables that predict future investment opportunities. I have explored this link by attempting a numbers of tests: *In the first stage*, I attempt to examine whether both the investment factor and profitability factor can predict GDP growth, investment growth and consumption growth. *Secondly*, I test whether both the investment factor and profitability factor can predict innovations to state variables related to future investment opportunities. *Finally*, I compare the informativeness of innovations to state variables with investment growth and profitability factor pricing significance using a number of methodological procedures: a) a one-step Generalized Methods of Moments (GMM) methodology, b) a two-pass Fama-Macbeth cross-sectional regressions analysis and c) a factor-spanning analysis.

The first set of results suggests that that the investment factor (CMA) in the UK is strongly correlated to future macroeconomic growth. In all three quarterly-based time-series regressions, the investment factor can positively forecast future GDP growth, investment growth and consumption growth respectively. However, I do not find significant evidence that the profitability factor RMW is linked to economic growth in the UK market in the three scenarios that I take into account.

The second set of results from the time series regression analysis shows that the source of the predictive power of the value factor comes from its correlation with the term spread and default spread. The source of informativeness of the investment factor stems from its relationship to changes in dividend yield and shocks to the risk-free rate.

The third set of results indicate that the information content of state variable innovations is spanned by the CMA and RMW factors since none of the state variable innovation factors are significantly priced when CMA and RMW are included in the factor model.

To summarise, the results are to some extent consistent with the risk-based economic interpretations of the new factors. Firstly, the results confirm that the investment factor predicts future economic growth proxied by GDP growth, investment growth and consumption growth. In addition, both the investment factor and the profitability factor have a significant relationship with shocks to macroeconomic state variables. The investment factor is related to dividend yield shocks, whereas the profitability factor is related to inflation. Furthermore, the two new factors provide incremental information to the macroeconomic factors in the UK market. The pricing significance of macroeconomic variable shocks disappears when loadings on the two new factors are presented in the model.

CHAPTER 5

Conclusion

This main purpose of this thesis has been to provide an out-sample analysis of various asset pricing techniques using UK stock market data. The first empirical chapter examined the existence of a "net equity issuance" (NEI) effect in the UK stock market. Net Equity Issuance (NEI) refers to the change in a firm's shares outstanding due to events such as SEOs, acquisitions financed by share issues, issues to staff and share repurchases. The NEI effect is the ability of share issuance by firms to predict their subsequent stock returns. My results mainly suggest that there is an NEI effect in the UK. However, a discrepancy exists between the UK results and those found in the US. In the UK market, negative-NEI stocks tend to show negative subsequent returns while zero-NEI stocks have the highest subsequent returns. I also find that the abnormal returns from the NEI effect disappear when transaction costs are taken into account. Furthermore, the asset pricing test results suggest that the new factor models partially explain the NEI effect in the UK.

The first empirical chapter has important implications for investors in the UK stock market. It shows that share-issuance contains significant information for future stock returns in the UK stock market apart from the other variables. Although the gains of the hedge portfolio consisting of a long position in zero-NEI shares and short position in high-NEI portfolios are offset by the transaction costs, NEI may contribute to a profitable investment strategy after combining with other informative factors in the UK. Alternatively, investors may consider constructing portfolios with different rebalance frequencies, which may lead to profitable strategies.

The main limitation to the first empirical chapter is that my data set only includes the NEI variable, which measures the aggregated change in shares outstanding. In the US study, Pontiff and Woodgate (2008) confirm the robustness of the NEI effect by excluding NEI changes due to events such as SEOs and stock-financed acquisitions. The first chapter does not disaggregate the NEI variable and trace its source of predictive power, especially for the positive NEI portfolios. It remains unclear what the driving forces of the NEI effect are in the UK market. In addition, the UK NEI effect does not include positive significant returns for the negative-NEI stocks. It is therefore unlikely to construct an NEI factor with bottom-minus-top portfolio returns, which might contribute to the existing linear asset pricing factor models in the UK.

Future research may investigate the underpinning reasons for the NEI effect in the UK by disaggregating the NEI variable into different categories. Firstly, although Pontiff and Woodgate (2008) suggest that the NEI effect in the US could be driven by timing by managers for SEOs and stock-financed acquisitions when shares are overvalued, and for repurchases when shares are undervalued, the US NEI results remain robust after excluding SEOs and M&A events. The NEI variable could be disaggregated into different events such as SEOs, share-based acquisitions, issues to staff, etc. Testing the predictive power of each NEI component may provide further insight into the underpinning reason for the effect as well as exploitable investment strategies in the UK market. Secondly, future research may consider following the spirit of Stambaugh and Yuan (2016) to combine NEI information with the other informative factors to construct a mispricing factor model in the UK market to better explain the cross-section of stock returns.

The second empirical chapter evaluates the information content of the new asset pricing factors in the UK. I find that two new risk factors, the investment factor and the profitability factor, improve the factor model's performance in the UK while both the size factor "small minus big" (SMB) and the value factor "high minus low" (HML) are redundant. There is also evidence that factor construction methods matter to the information content of the profitability factor. The most informative profitability factor in the UK among the possible candidates is constructed using income before extraordinary items scaled by book equity.

The second empirical chapter has important implications for policy-makers and investors. Firstly, the investment factor (CMA) and the profitability factor (RMW), together with the market factor, provide the best performance in explaining the cross-section of expected returns in the UK amongst various candidate models. Therefore the regulatory authorities may consider employing the new three-factor model rather than the Fama-French three-factor model to estimate systematic risks to equities. For investors and finance researchers, the new three-factor model may replace the role of the Fama-French three-factor model to become the baseline model to calculate risk-adjusted return. From a corporate finance perspective, the new three-factor model provides an alternative method to capture the cost of equity. Despite the low average model explanatory power across all industries, the new three-factor model does offer valid estimation of expected returns for some industries in the UK market.

There are a few limitations to the second empirical chapter. The first limitation is the low explanatory power of the factor models. The size-profitability portfolio returns' cross-section is not captured by the new three-factor model, neither is that of the industry portfolio returns. The new three-factor model, although it outperforms the Fama-French three-factor model and the CAPM model, may still be subject to "bad model" criticism. In addition, the investment factor and the profitability factor are not constantly priced across all sets of left-hand-side portfolios. One possible reason for the inconstancy is the function form of the factor models, as I restrict my attempt to linear and unconditional versions of factor models in this chapter. Moreover, I do not take into account the characteristics models in the UK, which, according to Lee et al. (2007), outperform the covariance-based Fama-French three-factor model.

For future research, the first possibility is to test conditional versions of the new factor models. For instance, Jagannathan and Wang (1996) and Ferson and Harvey (1999) propose frameworks for constructing conditional factor models. The conditional versions of new factor models may provide better performance in explaining the cross-section of stock returns as well as capturing cost of equity in the UK market. Future research may also investigate other potential formations of the investment factors and the profitability factors. For instance, Yan and Zheng (2017) show that unexplored fundamental signals constructed from financial statements may contain superior information about future stock returns. Their data-mining approach can be employed to obtain a more informative formation of the new risk factors. Moreover, the debate on the characteristics versus covariance model in the UK could be extended. Due to the lack of explicit implications from the asset pricing theory. Both characteristics-based and factor-based asset pricing models have been proposed (Fama and French, 1993; Daniel and Titman, 1997; Daniel, Titman and Wei, 2001; Fama and French, 2015a), the former assumes the correlation structure among asset are explained by firm characteristics while the latter assumes that covariance with factors captures the correlations. Although the existing UK study shows that characteristics model outperform Fama-French three-factor model (Lee et al., 2007), it remains unclear whether the model-misspecification problem has led to the misleading results. Green et al. (2016) use the US sample and find 94 characteristics provide only marginal incremental information to the new factor models. Therefore future research may consider comparing the information content between the new factor models and the characteristics-based models in the UK to provide a better understanding to the UK empirical asset pricing.

The third empirical chapter explores the information content of the two new factors by linking them to the state variables which predict future investment opportunities. By doing this, I find confirmative evidence that the two new risk factors may proxy for state variables that capture time variations in the investment opportunity set. I find empirical evidence which confirms that the investment factor predicts future economic growth, proxied by GDP growth, investment growth and consumption growth. In addition, the investment factor is found to be related to dividend yield shocks, whereas the profitability factor is related to inflation shocks. In addition, the pricing significance of macroeconomic variable shocks disappears when loadings on the two new factors are presented in the model. The evidence therefore provides economic interpretation to the information content of the new asset pricing factors in the UK market.

The third chapter has important implications for investors and finance researchers. It is crucial for the factor-model users to understand the mechanism underlying the risk factors. The results of the third empirical chapter provide guidance to the factor-model users by illustrating the link between the two new risk factors and macroeconomic states in the UK stock market. More importantly, from a pragmatic perspective, my results compare the relative information content between the new risk factors and the economic state variables. As the information content of the macroeconomic state variables is captured by the two new risk factors, investors or fund managers who use linear models based on macroeconomic shocks may consider using the new three-factor models to serve as one of the baseline models to control for systematic risks of the investment strategies.

The third empirical chapter also has its limitations. Firstly, I restrict my research question to only two of the empirical implications of the asset pricing theory. I attempt to link the information content of risk factors to future macroeconomic activities and contemporaneous shocks to macroeconomic state variables. There are, however, further hypotheses that could be tested for the new asset pricing factors in the context of ICAPM. The second limitation is related to my use of VAR to model investors' expectations. The VAR model assumes a first-order autocorrelation model to capture the dynamics of all candidate state variables, which may suffer from some measurement errors. Moreover, the VAR system assumes that all state variables that the UK investors hedge against are included in the model. Although my evidence suggests that some of the state variable shocks have explanatory power over the cross-section of stock returns, it does not rule out the possibility that there are additional factors that UK investors take into account. Finally, my VAR specification assumes a static VAR correlation structure. As suggested by Bulkley and Taylor (1996), forecasters use only the available information to construct predicting model. Static VAR correlation structure may generate invalid results as future information is used to construct the VAR model. However the authors are aware of the trade-off between hindsight bias and the instability of the true VAR model. Using a rolling-based VAR may contribute to the detection of model stability regarding how the UK stock market investors form their forecasts.

The third chapter may be extendable in the following ways. *Firstly,* future research may attempt to examine additional restrictions implied by ICAPM for the new risk factors. For instance, Maio and Santa-Clara (2012) propose three new restrictions. The first restriction is that ICAPM state variables should be able to forecast aggregate stock market returns or volatility. Restriction 2 implies that if an ICAPM state variable positively (negatively) predicts aggregate stock market returns or volatility, it should be priced positively (negatively) in the cross-section asset pricing tests. Restriction 3 suggests that the market price of a risk factor should be economically plausible. Cooper and Maio (2016) investigate the information content of the investment factor and the profitability factor regarding the new restrictions in the US market. However, out-sample evidence in major international stock markets such as the UK market is desirable. *Secondly*, future research may extend the literature by considering alternative measures of investors' expectations of macroeconomic state variables. For instance, economic forecasts provided by the central bank may serve as alternative proxies for investor expectations to mitigate potential errors of measurement. *Thirdly*, as suggested by Hou, Karolyi and Kho (2011), there is a gap for future research to link characteristic-based factors to global and country-specific macroeconomic state variables on the global scale. Future research can therefore explore ICAPM restrictions for factor models using an international data set including the emerging markets.

To conclude, this thesis has revealed a few aspects of the UK stock market returns. Three empirical chapters provide evidence that the stock market return patterns in the UK market are not entirely consistent with the US results. These differences have important implications for regional asset pricing studies as well as future research. More research is required for important stock markets such as the UK market regarding the capital market anomalies as well as the choice of asset pricing factor models to control for systematic risks. The stock market return patterns differ across different institutional backgrounds. As there is a notable ongoing development of machine learning and algorithm trading in the investment industry, future research may need to examine both the cross-sectional differences and time-series dynamics of the market states. It would be interesting to further investigate how the technology shocks have influenced the stock market return patterns.

References

Agarwal, V. and Taffler, R., 2008. Does financial distress risk drive the momentum anomaly?. *Financial Management*, *37*(3), pp.461-484.

Agyei-Ampomah, S., 2007. The post-cost profitability of momentum trading strategies: further evidence from the UK. *European Financial Management*, *13*(4), pp.776-802.

Al-Horani, A., Pope, P.F. and Stark, A.W., 2003. Research and development activity and expected returns in the United Kingdom. *Review of Finance*, *7*(1), pp.27-46.

Altı, A. and Sulaeman, J., 2012. When do high stock returns trigger equity issues?. *Journal of Financial Economics*, *103*(1), pp.61-87.

Amihud, Y. and Mendelson, H., 1986. Asset pricing and the bid-ask spread. *Journal of Financial Economics*, *17*(2), pp.223-249.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, *5*(1), pp.31-56.

Antoniou, A., Garrett, I. and Priestley, R., 1998. Macroeconomic variables as common pervasive risk factors and the empirical content of the arbitrage pricing theory. *Journal of Empirical Finance*, *5*(3), pp.221-240.

Aretz, K., Bartram, S.M. and Pope, P.F., 2010. Macroeconomic risks and characteristic-based factor models. *Journal of Banking & Finance*, *34*(6), pp.1383-1399.

Armitage, S. and Capstaff, J., 2009. Comment on ‘Earnings management around UK open offers’. *The European Journal of Finance*, *15*(1), pp.53-60.

Armitage, S., 1998. Seasoned equity offers and rights issues: a review of the evidence. *The European Journal of Finance*, *4*(1), pp.29-59.

Armitage, S., 2007. Discounts in placing pre-renounced shares in rights issues. *Journal of Business Finance & Accounting*, *34*(7-8), pp.1345-1369.

Armitage, S., 2007. Discounts in placing pre-renounced shares in rights issues. *Journal of Business Finance & Accounting*, *34*(7-8), pp.1345-1369.

Asness, C., Frazzini, A. and Pedersen, L.H., 2013. Quality minus junk. *Available at SSRN*. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2312432

Babenko, I., Tserlukevich, Y. and Vedrashko, A., 2012. The credibility of open market share repurchase signaling. *Journal of Financial and Quantitative Analysis*, *47*(5), pp.1059-1088.

Bagella, M., Becchetti, L. and Carpentieri, A., 2000. "The first shall be last". Size and value strategy premia at the London Stock Exchange. *Journal of Banking & Finance*, *24*(6), pp.893-919.

Bagella, M., Becchetti, L. and Carpentieri, A., 2000. "The first shall be last". Size and value strategy premia at the London Stock Exchange. *Journal of Banking & Finance*, *24*(6), pp.893-919.

Baker, M. and Wurgler, J., 2002. Market timing and capital structure. *The Journal of Finance*, *57*(1), pp.1-32.

Ball, R., Gerakos, J., Linnainmaa, J.T. and Nikolaev, V., 2016. Accruals, cash flows, and operating profitability in the cross section of stock returns. *Journal of Financial Economics*, *121*(1), pp.28-45.

Ball, R., Gerakos, J., Linnainmaa, J.T. and Nikolaev, V.V., 2015. Deflating profitability. *Journal of Financial Economics*, 117(2), pp.225-248.

Banz, R.W., 1981. The relationship between return and market value of common stocks. *Journal of Financial Economics*, *9*(1), pp.3-18.

Barbalau, A.D.E.L.I.N.A., Robotti, C.E.S.A.R.E. and Shanken, J., 2015. *Testing inequality restrictions in multifactor asset-pricing models*. Working paper, Imperial

College London. Available at https://workspace.imperial.ac.uk/business-school/Public/people/crobotti/icapm.pdf

Basu, S., 1977. Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. *The Journal of Finance, 32*(3), pp.663-682.

Berk, J.B., 1995. A critique of size-related anomalies. *The Review of Financial Studies, 8*(2), pp.275-286.

Berk, J.B., 2000. Sorting out sorts. *The Journal of Finance*, *55*(1), pp.407-427.

Berk, J.B., Green, R.C. and Naik, V., 1999. Optimal investment, growth options, and security returns. *The Journal of Finance, 54*(5), pp.1553-1607.

Bessembinder, H., Cooper, M.J. and Zhang, F., 2016. Characteristic-based expected returns and corporate events. *Available at SSRN. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2658849*

Bhandari, L.C., 1988. Debt/equity ratio and expected common stock returns: Empirical evidence. *The Journal of Finance*, *43*(2), pp.507-528.

Bilinski, P., Liu, W. and Strong, N., 2012. Does liquidity risk explain low firm performance following seasoned equity offerings?. *Journal of Banking & Finance, 36*(10), pp.2770-2785.

Billett, M.T., Flannery, M.J. and Garfinkel, J.A., 2011. Frequent issuers' influence on long-run post-issuance returns. *Journal of Financial Economics, 99*(2), pp.349-364.

Black, A. and Fraser, P., 1995. UK stock returns: predictability and business conditions. *The Manchester School*, *63*(S1), pp.85-102.

Blume, M.E. and Friend, I., 1973. A new look at the capital asset pricing model. *The Journal of Finance*, *28*(1), pp.19-34.

Bodie, Z., 1976. Common stocks as a hedge against inflation. *The Journal of Finance*, *31*(2), pp.459-470.

Bondt, W.F. and Thaler, R., 1985. Does the stock market overreact?. *The Journal of Finance*, *40*(3), pp.793-805.

Boons, M., 2016. State variables, macroeconomic activity, and the cross section of individual stocks. *Journal of Financial Economics*, *119*(3), pp.489-511.

Bradford, B.M., 2008. Open-market common stock repurchases and subsequent market performance. *The Journal of Business and Economic Studies*, *14*(1), pp.45.

Bredin, D., Hyde, S., Nitzsche, D. and O'reilly, G., 2007. UK stock returns and the impact of domestic monetary policy shocks. *Journal of Business Finance & Accounting*, *34*(5-6), pp.872-888.

Breeden, D.T. and Litzenberger, R.H., 1978. Prices of state-contingent claims implicit in option prices. *Journal of Business*, 51(4), pp.621-651.

Breeden, D.T., Gibbons, M.R. and Litzenberger, R.H., 1989. Empirical tests of the consumption-oriented CAPM. *The Journal of Finance*, *44*(2), pp.231-262.

Brennan, M.J., Chordia, T. and Subrahmanyam, A., 1998. Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. *Journal of Financial Economics*, *49*(3), pp.345-373.

Brennan, M.J., Wang, A.W. and Xia, Y., 2004. Estimation and test of a simple model of intertemporal capital asset pricing. *The Journal of Finance*, *59*(4), pp.1743-1776.

Brooks, C., 2002. *Introductory Econometrics for Finance*. Cambridge university press.

Bulkley, G. and Taylor, N., 1996. A cross-section test of the present value model. *Journal of Empirical Finance*, 2(4), pp.295-306.

Butler, A.W. and Wan, H., 2010. Stock market liquidity and the long-run stock performance of debt issuers. *The Review of Financial Studies*, *23*(11), pp.3966-3995.

Cameron, A.C., Gelbach, J.B. and Miller, D.L., 2008. Bootstrap-based improvements for inference with clustered errors. *The Review of Economics and Statistics*, *90*(3), pp.414-427.

Campbell, J.Y. and Ammer, J., 1993. What moves the stock and bond markets? A variance decomposition for long-term asset returns. *The Journal of Finance*, *48*(1), pp.3-37.

Campbell, J.Y. and Shiller, R.J., 1988. The dividend-price ratio and expectations of future dividends and discount factors. *The Review of Financial Studies*, *1*(3), pp.195-228. (Campbell and Yogo, 1988)

Campbell, J.Y. and Vuolteenaho, T., 2004. Bad beta, good beta. *The American Economic Review*, *94*(5), pp.1249-1275.

Campbell, J.Y. and Yogo, M., 2006. Efficient tests of stock return predictability. *Journal of Financial Economics*, *81*(1), pp.27-60.

Campbell, J.Y., 1987. Stock returns and the term structure. *Journal of Financial Economics*, *18*(2), pp.373-399.

Campbell, J.Y., 1991. A variance decomposition for stock returns. *Economic Journal*, *101*(405), pp.157-79.

Campbell, J.Y., 1996. Understanding risk and return. *Journal of Political Economy*, *104*(2), pp.298-345.

Campbell, J.Y., Lo, A.W.C. and MacKinlay, A.C., 1997. *The Econometrics of Financial Markets*. princeton University press.

Campbell, J.Y., Polk, C. and Vuolteenaho, T., 2009. Growth or glamour? Fundamentals and systematic risk in stock returns. *The Review of Financial Studies*, *23*(1), pp.305-344.

Campello, M. and Graham, J.R., 2013. Do stock prices influence corporate decisions? Evidence from the technology bubble. *Journal of Financial Economics*, *107*(1), pp.89-110.

Capstaff, J. and Fletcher, J., 2011. Long term performance and choice of SEO method by UK firms. *Journal of Business Finance & Accounting*, *38*(9-10), pp.1262-1289.

Carhart, M.M., 1997. On persistence in mutual fund performance. *The Journal of Finance*, *52*(1), pp.57-82.

Carlson, M., Fisher, A. and Giammarino, R., 2006. Corporate investment and asset price dynamics: Implications for SEO event studies and long-run performance. *The Journal of Finance*, *61*(3), pp.1009-1034.

Chan, A. and Chui, A.P., 1996. An empirical re-examination of the cross-section of expected returns: UK Evidence. *Journal of Business Finance & Accounting*, *23*(9-10), pp.1435-1452.

Chan, K., Ikenberry, D. and Lee, I., 2004. Economic sources of gain in stock repurchases. *Journal of Financial and Quantitative Analysis*, *39*(3), pp.461-479.

Chan, K., Ikenberry, D.L. and Lee, I., 2007. Do managers time the market? Evidence from open-market share repurchases. *Journal of Banking & Finance*, *31*(9), pp.2673-2694.

Chan, K.C. and Chen, N.F., 1991. Structural and return characteristics of small and large firms. *The Journal of Finance*, *46*(4), pp.1467-1484.

Chen, L., Novy-Marx, R. and Zhang, L., 2011. An alternative three-factor model. *Available at SSRN*. Available at: *https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1418117*

Chen, N.F., 1991. Financial investment opportunities and the macroeconomy. *The Journal of Finance*, *46*(2), pp.529-554.

Chen, N.F., Roll, R. and Ross, S.A., 1986. Economic forces and the stock market. *Journal of Business*, *59*(3), pp.383-403.

Cheng, A., 1995. The UK stock market and economic factors: a new approach. *Journal of Business Finance & Accounting*, *22*(1), pp.129-142.

Choi, J.J., Hauser, S. and Kopecky, K.J., 1999. Does the stock market predict real activity? Time series evidence from the G-7 countries. *Journal of Banking & Finance*, *23*(12), pp.1771-1792.

Clare, A., O'Brien, R., Thomas, S. and Wickens, M., 1998. Macroeconomic Shocks and the CAPM: Evidence from the UK Stockmarket. *International Journal of Finance & Economics*, *3*(2), p.111.

Clare, A.D. and Thomas, S.H., 1994. Macroeconomic Factors, the APT and the UK Stockmarket. *Journal of Business Finance & Accounting*, *21*(3), pp.309-330.

Clubb, C. and Naffi, M., 2007. The usefulness of book-to-market and roe expectations for explaining UK stock returns. *Journal of Business Finance & Accounting*, *34*(1-2), pp.1-32.

Cochrane, J.H., 1991. Production-based asset pricing and the link between stock returns and economic fluctuations. *The Journal of Finance*, *46*(1), pp.209-237.

Cochrane, J.H., 2009. *Asset Pricing:(Revised Edition)*. Princeton university press.

Cohen, D.A. and Zarowin, P., 2010. Accrual-based and real earnings management activities around seasoned equity offerings. *Journal of Accounting and Economics*, *50*(1), pp.2-19.

Cohen, R.B., Gompers, P.A. and Vuolteenaho, T., 2002. Who underreacts to cash-flow news? Evidence from trading between individuals and institutions. *Journal of Financial Economics*, *66*(2), pp.409-462.

Cohen, R.B., Polk, C. and Vuolteenaho, T., 2009. The price is (almost) right. *The Journal of Finance*, *64*(6), pp.2739-2782.

Cooper, I. and Maio, P.F., 2016. Equity risk factors and the Intertemporal CAPM. *Cross-section of stock returns*. *Available at SSRN.* Available at *https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2554706*

Cooper, I. and Priestley, R., 2011. Real investment and risk dynamics. *Journal of Financial Economics*, *101*(1), pp.182-205.

Cooper, M.J., Gulen, H. and Schill, M.J., 2008. Asset growth and the cross-section of stock returns. *The Journal of Finance, 63*(4), pp.1609-1651.

Cornell, B., 1999. Risk, duration, and capital budgeting: New evidence on some old questions. *The Journal of Business*, *72*(2), pp.183-200.

Crawford, I. and Wang, Z., 2012. Is the market underreacting or overreacting to open market share repurchases? A UK perspective. *Research in International Business and Finance*, *26*(1), pp.26-46.

Cuthbertson, K., Hayes, S. and Nitzsche, D., 1999. Explaining movements in UK stock prices. *The Quarterly Review of Economics and Finance*, *39*(1), pp.1-19.

Daniel, K. and Titman, S., 1997. Evidence on the characteristics of cross sectional variation in stock returns. *The Journal of Finance*, *52*(1), pp.1-33.

Daniel, K. and Titman, S., 2006. Market reactions to tangible and intangible information. *The Journal of Finance*, *61*(4), pp.1605-1643.

Datar, V.T., Naik, N.Y. and Radcliffe, R., 1998. Liquidity and stock returns: An alternative test. *Journal of Financial Markets*, *1*(2), pp.203-219.

Davis, J.L., Fama, E.F. and French, K.R., 2000. Characteristics, covariances, and average returns: 1929 to 1997. *The Journal of Finance*, *55*(1), pp.389-406.

De Bondt, W.F. and Thaler, R.H., 1987. Further evidence on investor overreaction and stock market seasonality. *The Journal of Finance*, *42*(3), pp.557-581.

DeAngelo, H., DeAngelo, L. and Stulz, R.M., 2010. Seasoned equity offerings, market timing, and the corporate lifecycle. *Journal of Financial Economics*, *95*(3), pp.275-295.

Dechow, P.M., Sloan, R.G. and Soliman, M.T., 2004. Implied equity duration: A new measure of equity risk. *Review of Accounting Studies*, *9*(2-3), pp.197-228.

Dichev, I.D., 1998. Is the risk of bankruptcy a systematic risk?. *The Journal of Finance*, *53*(3), pp.1131-1147.

Dimson, E. and Marsh, P., 1999. Murphy's law and market anomalies. *The Journal of Portfolio Management*, *25*(2), pp.53-69.

Dimson, E. and Marsh, P., 2001. UK financial market returns, 1955–2000. *The Journal of Business*, *74*(1), pp.1-31.

Dimson, E., Nagel, S. and Quigley, G., 2003. Capturing the value premium in the United Kingdom. *Financial Analysts Journal*, *59*(6), pp.35-45.

Dissanaike, G., 2002. Does the size effect explain the UK winner-loser effect?. *Journal of Business Finance & Accounting*, *29*(1-2), pp.139-154.

Douglas, G.W., 1968. Risk in the equity markets: an empirical appraisal of market efficiency. *Yale Econ. Essays 9 (Spring 1969)*, pp.3-45.

Downes, J.F., Gorman, L. and Rao, R.P., 2013. Real Earnings Management Around Stock Repurchases. Available at SSRN. Available at https://mediacast.blob.core.windows.net/production/Faculty/StoweConf/submissions/swfa2014_submission_210.pdf

DuCharme, L.L., Malatesta, P.H. and Sefcik, S.E., 2004. Earnings management, stock issues, and shareholder lawsuits. *Journal of Financial Economics*, *71*(1), pp.27-49.

Eckbo, B.E. and Norli, Ø., 2005. Liquidity risk, leverage and long-run IPO returns. *Journal of Corporate Finance*, *11*(1), pp.1-35.

Eckbo, B.E., Masulis, R.W. and Norli, Ø., 2000. Seasoned public offerings: resolution of the 'new issues puzzle'. *Journal of Financial Economics*, *56*(2), pp.251-291.

Erwin, G.R. and Miller, J.M., 1998. The intra-industry effects of open market share repurchases: contagion or competitive?. *Journal of Financial Research*, *21*(4), pp.389-406.

Evans, K.P. and Speight, A.E., 2006. Real-time risk pricing over the business cycle: some evidence for the UK. *Journal of Business Finance & Accounting*, *33*(1-2), pp.263-283.

Fama, E.F. and French, K.R., 1988. Dividend yields and expected stock returns. *Journal of Financial Economics*, *22*(1), pp.3-25.

Fama, E.F. and French, K.R., 1989. Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics*, *25*(1), pp.23-49.

Fama, E.F. and French, K.R., 1989. Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics*, *25*(1), pp.23-49.

Fama, E.F. and French, K.R., 1992. The cross-section of expected stock returns. *The Journal of Finance*, *47*(2), pp.427-465.

Fama, E.F. and French, K.R., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), pp.3-56.

Fama, E.F. and French, K.R., 1995. Size and book-to-market factors in earnings and returns. *The Journal of Finance*, *50*(1), pp.131-155.

Fama, E.F. and French, K.R., 1996. Multifactor explanations of asset pricing anomalies. *The Journal of Finance*, *51*(1), pp.55-84.

Fama, E.F. and French, K.R., 1997. Industry costs of equity. *Journal of Financial Economics*, *43*(2), pp.153-193.

Fama, E.F. and French, K.R., 2002. The equity premium. *The Journal of Finance*, *57*(2), pp.637-659.

Fama, E.F. and French, K.R., 2004. The capital asset pricing model: Theory and evidence. *The Journal of Economic Perspectives*, *18*(3), pp.25-46.

Fama, E.F. and French, K.R., 2005. Financing decisions: who issues stock?. *Journal of Financial Economics*, *76*(3), pp.549-582.

Fama, E.F. and French, K.R., 2006. Profitability, investment and average returns. *Journal of Financial Economics*, *82*(3), pp.491-518.

Fama, E.F. and French, K.R., 2008. Dissecting anomalies. *The Journal of Finance*, *63*(4), pp.1653-1678.

Fama, E.F. and French, K.R., 2012. Size, value, and momentum in international stock returns. *Journal of Financial Economics*, *105*(3), pp.457-472.

Fama, E.F. and French, K.R., 2015a. A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), pp.1-22.

Fama, E.F. and French, K.R., 2015b. Choosing Factors. *Fama-Miller Working Paper*. *Available at SSRN*. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2834871

Fama, E.F. and French, K.R., 2015c. Dissecting anomalies with a five-factor model. *Fama-Miller Working Paper*. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2503174

Fama, E.F. and French, K.R., 2017. International tests of a five-factor asset pricing model. *Journal of Financial Economics*, *123*(3), pp.441-463.

Fama, E.F. and MacBeth, J.D., 1973. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, *81*(3), pp.607-636.

Fama, E.F. and Schwert, G.W., 1977. Asset returns and inflation. *Journal of Financial Economics*, *5*(2), pp.115-146.

Fama, E.F., 1981. Stock returns, real activity, inflation, and money. *The American Economic Review*, *71*(4), pp.545-565.

Fama, E.F., 1990. Stock returns, expected returns, and real activity. *The Journal of Finance, 45*(4), pp.1089-1108.

Fama, E.F., 1991. Efficient capital markets: II. *The Journal of Finance*, *46*(5), pp.1575-1617.

Fama, E.F., 1998. Determining the number of priced state variables in the ICAPM. *Journal of Financial and Quantitative Analysis*, *33*(2), pp.217-231.

Fama, E.F., 1998. Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics*, *49*(3), pp.283-306.

Fama, E.F., 2015. Cross-section versus time-series tests of asset pricing models. *Working paper. Available at SSRN*. Available at https://papers.ssrn.com /sol3/papers.cfm?abstract_id=2685317

Feldstein, M., 1980. Inflation, tax rules and the stock market. *Journal of Monetary Economics*, *6*(3), pp.309-331.

Ferson, W.E., 1989. Changes in expected security returns, risk, and the level of interest rates. *The Journal of Finance*, *44*(5), pp.1191-1217.

Fisher, I., 1930. The theory of interest. *New York*: Macmillan.

Fletcher, J. and Forbes, D., 2002. An exploration of the persistence of UK unit trust performance. *Journal of Empirical Finance*, *9*(5), pp.475-493.

Fletcher, J. and Kihanda, J., 2005. An examination of alternative CAPM-based models in UK stock returns. *Journal of Banking & Finance*, *29*(12), pp.2995-3014.

Fletcher, J., 2001. An examination of alternative factor models in UK stock returns. *Review of Quantitative Finance and Accounting*, *16*(2), pp.117-130.

Frankel, R. and Lee, C.M., 1998. Accounting valuation, market expectation, and cross-sectional stock returns. *Journal of Accounting and Economics*, *25*(3), pp.283-319.

Friend, I. and Blume, M., 1970. Measurement of portfolio performance under uncertainty. *The American Economic Review*, pp.561-575.

Fu, F., Huang, S. and Lin, H., 2012. The persistence of long-run abnormal stock returns: Evidence from stock repurchases and offerings. *Unpublished working paper, Singapore Management University*. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1936187

George, T.J. and Hwang, C.Y., 2004. The 52-week high and momentum investing. *The Journal of Finance, 59*(5), pp.2145-2176.

George, T.J., Hwang, C.Y. and Li, Y., 2017. The 52-Week High, q Theory and the Cross-Section of Stock Returns. *Working paper. Available at SSRN*. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2500335

Geske, R. and Roll, R., 1983. The fiscal and monetary linkage between stock returns and inflation. *The Journal of Finance*, *38*(1), pp.1-33.

Ghysels, E., 1998. On stable factor structures in the pricing of risk: do time-varying betas help or hurt?. *The Journal of Finance*, *53*(2), pp.549-573.

Gibbons, M.R., 1982. Multivariate tests of financial models: A new approach. *Journal of Financial Economics*, *10*(1), pp.3-27.

Gibbons, M.R., Ross, S.A. and Shanken, J., 1989. A test of the efficiency of a given portfolio. *Econometrica*, *57(5),* pp.1121-1152.

Goetzmann, W.N. and Jorion, P., 1993. Testing the predictive power of dividend yields. *The Journal of Finance, 48*(2), pp.663-679.

Gong, G., Louis, H. and Sun, A.X., 2008. Earnings management and firm performance following open-market repurchases. *The Journal of Finance*, *63*(2), pp.947-986.

Graham, J.R. and Harvey, C.R., 2001. The theory and practice of corporate finance: Evidence from the field. *Journal of Financial Economics*, *60*(2), pp.187-243.

Graham, J.R., Harvey, C.R. and Rajgopal, S., 2006. Value destruction and financial reporting decisions. *Financial Analysts Journal*, *62*(6), pp.27-39.

Gregory, A., Harris, R.D. and Michou, M., 2001. An analysis of contrarian investment strategies in the UK. *Journal of Business Finance & Accounting*, *28*(9-10), pp.1192-1228.

Gregory, A., Harris, R.D. and Michou, M., 2003. Contrarian investment and macroeconomic risk. *Journal of Business Finance & Accounting*, *30*(1-2), pp.213-256.

Gregory, A., Tharyan, R. and Christidis, A., 2013. Constructing and testing alternative versions of the Fama–French and Carhart models in the UK. *Journal of Business Finance & Accounting*, *40*(1-2), pp.172-214.

Griffin, J.M., 2002. Are the Fama and French factors global or country specific?. *Review of Financial Studies*, *15*(3), pp.783-803.

Griffin, J.M., Ji, X. and Martin, J.S., 2003. Momentum investing and business cycle risk: Evidence from pole to pole. *The Journal of Finance*, *58*(6), pp.2515-2547.

Grullon, G., Michaely, R. and Swaminathan, B., 2002. Are dividend changes a sign of firm maturity?. *The Journal of Business*, *75*(3), pp.387-424.

Gultekin, N.B., 1983. Stock market returns and inflation forecasts. *The Journal of Finance*, *38*(3), pp.663-673.

Hahn, J. and Lee, H., 2006. Yield spreads as alternative risk factors for size and book-to-market. *Journal of Financial and Quantitative Analysis*, *41*(2), pp.245-269.

Hansen, L.P., 1982. Large sample properties of generalized method of moments estimators. *Econometrica*, *50*(4), pp.1029-1054.

Harvey, C.R., Liu, Y. and Zhu, H., 2016. … and the cross-section of expected returns. *The Review of Financial Studies*, *29*(1), pp.5-68.

Haugen, R.A. and Baker, N.L., 1996. Commonality in the determinants of expected stock returns. *Journal of Financial Economics*, *41*(3), pp.401-439.

Haugen, R.A., 1995. *The new finance: the case against efficient markets*. Prentice Hall.

Ho, K.Y., 2005. Long-horizon abnormal performance following rights issues and placings: Additional evidence from the uk market. *Review of Financial Economics*, *14*(1), pp.25-45.

Hong, H. and Yogo, M., 2012. What does futures market interest tell us about the macroeconomy and asset prices?. *Journal of Financial Economics*, *105*(3), pp.473-490.

Hou, K., Karolyi, G.A. and Kho, B.C., 2011. What factors drive global stock returns?. *The Review of Financial Studies*, *24*(8), pp.2527-2574.

Hou, K., Xue, C. and Zhang, L., 2015. Digesting anomalies: An investment approach. *The Review of Financial Studies*, *28*(3), pp.650-705.

Hou, K., Xue, C. and Zhang, L., 2017. A comparison of new factor models. *Working paper. Available at SSRN*. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2520929

Huang, S. and Thakor, A.V., 2013. Investor heterogeneity, investor-management disagreement and share repurchases. *The Review of Financial Studies*, *26*(10), pp.2453-2491.

Huberman, G. and Kandel, S., 1987. Mean-variance spanning. *The Journal of Finance*, *42*(4), pp.873-888.

Hung, D.C.H., Shackleton, M. and Xu, X., 2004. CAPM, higher co-moment and factor models of UK stock returns. *Journal of Business Finance & Accounting*, *31*(1-2), pp.87-112.

Hyde, S., 2007. The response of industry stock returns to market, exchange rate and interest rate risks. *Managerial Finance*, *33*(9), pp.693-709.

Ibbotson, R.G., 1975. Price performance of common stock new issues. *Journal of Financial Economics*, *2*(3), pp.235-272.

Ikenberry, D., Lakonishok, J. and Vermaelen, T., 1995. Market underreaction to open market share repurchases. *Journal of Financial Economics*, *39*(2), pp.181-208.

Ikenberry, D., Lakonishok, J. and Vermaelen, T., 2000. Stock repurchases in Canada: Performance and strategic trading. *The Journal of Finance*, *55*(5), pp.2373-2397.

Ikenberry, D.L. and Vermaelen, T., 1996. The option to repurchase stock. *Financial Management*, 25(4), pp.9-24.

Iqbal, A., Espenlaub, S. and Strong, N., 2009. Earnings management around UK open offers. *The European Journal of Finance*, *15*(1), pp.29-51.

Jagannathan, R. and Wang, Z., 1996. The conditional CAPM and the cross-section of expected returns. *The Journal of Finance*, *51*(1), pp.3-53.

Jalilvand, A. and Harris, R.S., 1984. Corporate behavior in adjusting to capital structure and dividend targets: An econometric study. *The Journal of Finance, 39*(1), pp.127-145.

Jegadeesh, N. and Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance, 48*(1), pp.65-91.

Jegadeesh, N. and Titman, S., 2001. Profitability of momentum strategies: An evaluation of alternative explanations. *The Journal of Finance, 56*(2), pp.699-720.

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. *The Journal of Finance, 45*(3), pp.881-898.

Jegadeesh, N., 2000. Long-term performance of seasoned equity offerings: Benchmark errors and biases in expectations. *Financial Management*, 29(3) pp.5-30.

Jensen, M.C., Black, F. and Scholes, M.S., 1972. The capital asset pricing model: Some empirical tests. *Working paper. Available at SSRN*. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=908569

Jung, K., Kim, Y.C. and Stulz, R., 1996. Timing, investment opportunities, managerial discretion, and the security issue decision. *Journal of Financial Economics*, *42*(2), pp.159-186.

Keim, D.B. and Stambaugh, R.F., 1986. Predicting returns in the stock and bond markets. *Journal of Financial Economics, 17*(2), pp.357-390.

Kelly, P.J., 2003. Real and inflationary macroeconomic risk in the Fama and French size and book-to-market portfolios. *Available at SSRN*. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=407800

Khan, M., Kogan, L. and Serafeim, G., 2012. Mutual fund trading pressure: Firm-level stock price impact and timing of SEOs. *The Journal of Finance, 67*(4), pp.1371-1395.

Kim, W. and Weisbach, M.S., 2008. Motivations for public equity offers: An international perspective. *Journal of Financial Economics*, *87*(2), pp.281-307.

Kothari, S.P., Mizik, N. and Roychowdhury, S., 2015. Managing for the moment: The role of earnings management via real activities versus accruals in SEO valuation. *The Accounting Review*, *91*(2), pp.559-586.

La Porta, R., 1996. Expectations and the cross-section of stock returns. *The Journal of Finance*, *51*(5), pp.1715-1742.

Lakonishok, J. and Vermaelen, T., 1990. Anomalous price behavior around repurchase tender offers. *The Journal of Finance, 45*(2), pp.455-477.

Lakonishok, J., Shleifer, A. and Vishny, R.W., 1994. Contrarian investment, extrapolation, and risk. *The Journal of Finance*, *49*(5), pp.1541-1578.

Lakonishok, J., Shleifer, A. and Vishny, R.W., 1994. Contrarian investment, extrapolation, and risk. *The Journal of Finance*, *49*(5), pp.1541-1578.

Lamont, O.A., 2001. Economic tracking portfolios. *Journal of Econometrics*, *105*(1), pp.161-184.

Lee, B.S., 1992. Causal relations among stock returns, interest rates, real activity, and inflation. *The Journal of Finance*, *47*(4), pp.1591-1603.

Lee, C.I., Ejara, D.D. and Gleason, K.C., 2010. An empirical analysis of European stock repurchases. *Journal of Multinational Financial Management*, *20*(2), pp.114-125.

Leledakis, G. and Davidson, I., 2001. Are two factors enough? The UK evidence. *Financial Analysts Journal*, *57*(6), pp.96-105.

Lettau, M. and Ludvigson, S., 2001. Resurrecting the (C) CAPM: A cross-sectional test when risk premia are time-varying. *Journal of Political Economy*, *109*(6), pp.1238-1287.

Lettau, M. and Wachter, J.A., 2007. Why is long-horizon equity less risky? a duration-based explanation of the value premium. *The Journal of Finance*, *62*(1), pp.55-92.

Levis, M., 1989. Stock market anomalies: A re-assessment based on the UK evidence. *Journal of Banking & Finance*, *13*(4-5), pp.675-696.

Levis, M., 1995. Seasoned equity offerings and the short-and long-run performance of initial public offerings in the UK. *European Financial Management*, *1*(2), pp.125-146.

Lewellen, J., 1999. The time-series relations among expected return, risk, and book-to-market. *Journal of Financial Economics*, *54*(1), pp.5-43.

Lewellen, J., 2004. Predicting returns with financial ratios. *Journal of Financial Economics*, *74*(2), pp.209-235.

Lewellen, J., Nagel, S. and Shanken, J., 2010. A skeptical appraisal of asset pricing tests. *Journal of Financial Economics*, *96*(2), pp.175-194.

Li, E.X., Livdan, D. and Zhang, L., 2009. Anomalies. *The Review of Financial Studies*, *22*(11), pp.4301-4334.

Li, L., Narayan, P.K. and Zheng, X., 2010. An analysis of inflation and stock returns for the UK. *Journal of International Financial Markets, Institutions and Money*, *20*(5), pp.519-532.

Li, Q., Vassalou, M. and Xing, Y., 2006. Sector investment growth rates and the cross section of equity returns. *The Journal of Business*, *79*(3), pp.1637-1665.

Lie, E., 2005. Operating performance following open market share repurchase announcements. *Journal of Accounting and Economics*, *39*(3), pp.411-436.

Liew, J. and Vassalou, M., 2000. Can book-to-market, size and momentum be risk factors that predict economic growth?. *Journal of Financial Economics*, *57*(2), pp.221-245.

Lintner, J., 1965. The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics*, *47*(1), pp.13-37.

Liu, W., 2006. A liquidity-augmented capital asset pricing model. *Journal of Financial Economics*, *82*(3), pp.631-671.

Liu, W., Strong, N. and Xu, X., 1999. The profitability of momentum investing. *Journal of Business Finance & Accounting*, *26*(9-10), pp.1043-1091.

Loughran, T. and Ritter, J.R., 1995. The new issues puzzle. *The Journal of Finance*, *50*(1), pp.23-51.

Loughran, T. and Ritter, J.R., 1997. The operating performance of firms conducting seasoned equity offerings. *The Journal of Finance*, *52*(5), pp.1823-1850.

Lovatt, D. and Parikh, A., 2000. Stock returns and economic activity: The UK case. *The European Journal of Finance*, *6*(3), pp.280-297.

Lucas Jr, R.E., 1978. Asset prices in an exchange economy. *Econometrica*, 46(6), pp.1429-1445.

Lui, W., Strong, N. and Xu, X., 1999. The profitability of momentum investing. *Journal of Business Finance & Accounting*, *26*(9-10), pp.1043-1091.

Lyandres, E., Sun, L. and Zhang, L., 2007. The new issues puzzle: Testing the investment-based explanation. *The Review of Financial Studies*, *21*(6), pp.2825-2855.

Maio, P. and Santa-Clara, P., 2012. Multifactor models and their consistency with the ICAPM. *Journal of Financial Economics*, *106*(3), pp.586-613.

Markowitz, H., 1952. Portfolio selection. *The Journal of Finance*, *7*(1), pp.77-91.

Markowitz, H., 1959. Portfolio selection: efficient diversification of investments. Cowles foundation monograph no. 16.

Marsh, P., 1982. The choice between equity and debt: An empirical study. *The Journal of Finance*, *37*(1), pp.121-144.

McLean, R.D., 2011. Share issuance and cash savings. *Journal of Financial Economics*, *99*(3), pp.693-715.

McLean, R.D., Pontiff, J. and Watanabe, A., 2009. Share issuance and cross-sectional returns: International evidence. *Journal of Financial Economics*, *94*(1), pp.1-17.

McQueen, G. and Roley, V.V., 1993. Stock prices, news, and business conditions. *The Review of Financial Studies*, *6*(3), pp.683-707.

Merton, R.C., 1973. An intertemporal capital asset pricing model. *Econometrica, 41*(5), pp.867-887.

Michailides, C., 2000. *Timing of initial public offerings, seasoned equity offerings and takeover bids financed with equity: UK evidence* (Doctoral dissertation, City University London).

Michou, M., Mouselli, S. and Stark, A., 2014. On the differences in measuring SMB and HML in the UK–Do they matter?. *The British Accounting Review*, *46*(3), pp.281-294.

Miles, D. and Timmermann, A., 1996. Variation in expected stock returns: evidence on the pricing of equities from a cross-section of UK companies. *Economica*, *63*(251),pp.369-382.

Miller, K.D., Jeffrey, F.J. and Mandelker, G., 1976. The “Fisher effect” for risky assets: An empirical investigation. *The Journal of Finance, 31*(2), pp.447-458.

Miller, M.H. and Scholes, M., 1972. Rates of return in relation to risk: A reexamination of some recent findings. *Studies in the theory of capital markets*, *23*. New York: Praeger.

Mitchell, M.L. and Stafford, E., 2000. Managerial decisions and long-term stock price performance. *The Journal of Business*, *73*(3), pp.287-329.

Mossin, J., 1966. Equilibrium in a capital asset market. *Econometrica*, *34*(4), pp.768-783.

Muradoglu, Y.G. and Sivaprasad, S., 2012. Using Firm-Level Leverage as an Investment Strategy. *Journal of Forecasting*, 31(3), pp.260-279.

Nagel, S., 2001. Accounting information free of selection bias: A new UK database 1953-1999. *Working paper. Available at SSRN*. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=286272

Nathan, L.J., 2002. Modelling the impacts of interest rate and exchange rate changes on UK stock returns. *Journal of Derivatives & Hedge Funds*, *7*(4), p.306.

Nelson, C.R., 1976. Inflation and rates of return on common stocks. *The Journal of Finance*, *31*(2), pp.471-483.

Newey, W.K. and West, K.D., 1987. Hypothesis testing with efficient method of moments estimation. *International Economic Review*, 28(3), pp.777-787.

Ngatuni, P., Capstaff, J. and Marshall, A., 2007. Long-Term Performance Following Rights Issues and Open Offers in the UK. *Journal of Business Finance & Accounting*, *34*(1-2), pp.33-64.

Novy-Marx, R., 2013. The other side of value: The gross profitability premium. *Journal of Financial Economics*, *108*(1), pp.1-28.

Oswald, D. and Young, S., 2004. What role taxes and regulation? A second look at open market share buyback activity in the UK. *Journal of Business Finance & Accounting*, *31*(1-2), pp.257-292.

Oswald, D. and Young, S., 2008. Share reacquisitions, surplus cash, and agency problems. *Journal of Banking & Finance*, *32*(5), pp.795-806.

Pearce, D.K. and Roley, V.V., 1983. The reaction of stock prices to unanticipated changes in money: A note. *The Journal of Finance*, *38*(4), pp.1323-1333.

Peel, D.A. and Pope, P.F., 1988. Stock Returns and expected inflation in the UK: some new evidence. *Journal of Business Finance & Accounting*, *15*(4), pp.459-467.

Perez-Quiros, G. and Timmermann, A., 2000. Firm size and cyclical variations in stock returns. *The Journal of Finance*, *55*(3), pp.1229-1262.

Petersen, M.A., 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies*, *22*(1), pp.435-480.

Petkova, R., 2006. Do the Fama–French factors proxy for innovations in predictive variables?. *The Journal of Finance*, *61*(2), pp.581-612.

Petrovic, N., Manson, S. and Coakley, J., 2016. Changes in non-current assets and in property, plant and equipment and future stock returns: the UK evidence. *Journal of Business Finance & Accounting*, *43*(9-10), pp.1142-1196.

Peyer, U. and Vermaelen, T., 2008. The nature and persistence of buyback anomalies. *The Review of Financial Studies*, *22*(4), pp.1693-1745.

Polk, C. and Sapienza, P., 2008. The stock market and corporate investment: A test of catering theory. *The Review of Financial Studies*, *22*(1), pp.187-217.

Pontiff, J. and Woodgate, A., 2008. Share issuance and cross-sectional returns. *The Journal of Finance*, *63*(2), pp.921-945.

Poon, S. and Taylor, S.J., 1991. Macroeconomic factors and the UK stock market. *Journal of Business Finance & Accounting*, *18*(5), pp.619-636.

Rajan, R.G. and Zingales, L., 1995. What do we know about capital structure? Some evidence from international data. *The Journal of Finance*, *50*(5), pp.1421-1460.

Rangan, S., 1998. Earnings management and the performance of seasoned equity offerings. *Journal of Financial Economics*, *50*(1), pp.101-122.

Rau, P.R. and Vermaelen, T., 2002. Regulation, taxes, and share repurchases in the United Kingdom. *The Journal of Business*, *75*(2), pp.245-282.

Rees, W., 1996. The impact of open market equity repurchases on UK equity prices. *The European Journal of Finance*, *2*(4), pp.353-370.

Ritter, J.R., 2003. Investment banking and securities issuance. *Handbook of the Economics of Finance*, *1(A)*, pp.255-306.

Roll, R., 1977. A critique of the asset pricing theory's tests Part I: On past and potential testability of the theory. *Journal of Financial Economics*, *4*(2), pp.129-176.

Rosenberg, B., Reid, K. and Lanstein, R., 1985. Persuasive evidence of market inefficiency. *The Journal of Portfolio Management*, *11*(3), pp.9-16.

Ross, S.A., 1976. The arbitrage theory of capital asset pricing. *Journal of Economic Theory*, *13*(3), pp.341-360.

Rubinstein, M., 1976. The valuation of uncertain income streams and the pricing of options. *The Bell Journal of Economics*, 7(2), pp.407-425.

Schwert, G.W., 1990. Stock returns and real activity: A century of evidence. *The Journal of Finance*, *45*(4), pp.1237-1257.

Shanken, J., 1992. On the estimation of beta-pricing models. *TheRreview of Financial Studies*, *5*(1), pp.1-33.

Sharpe, W.F., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, *19*(3), pp.425-442.

Shivakumar, L., 2000. Do firms mislead investors by overstating earnings before seasoned equity offerings?. *Journal of Accounting and Economics*, *29*(3), pp.339-371.

Shumway, T., 1997. The delisting bias in CRSP data. *The Journal of Finance*, *52*(1), pp.327-340.

Sloan, A., 1996. Create an account or Log In. *Accounting Review*, *71*(3), pp.289-315.

Soares, N. and Stark, A.W., 2009. The accruals anomaly–can implementable portfolio strategies be developed that are profitable net of transactions costs in the UK?. *Accounting and Business Research*, *39*(4), pp.321-345.

Soares, N. and Stark, A.W., 2011. Is there an accruals or a cash flow anomaly in UK stock returns?. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1734507

Spiess, D.K. and Affleck-Graves, J., 1995. Underperformance in long-run stock returns following seasoned equity offerings. *Journal of Financial Economics*, *38*(3), pp.243-267.

Stambaugh, R.F. and Yuan, Y., 2016. Mispricing factors. *The Review of Financial Studies*, *30*(4), pp.1270-1315.

Stambaugh, R.F., 1982. On the exclusion of assets from tests of the two-parameter model: A sensitivity analysis. *Journal of Financial Economics*, *10*(3), pp.237-268.

Stambaugh, R.F., 1999. Predictive regressions. *Journal of Financial Economics*, *54*(3), pp.375-421.

Strong, N. and Xu, X.G., 1997. Explaining the cross-section of UK expected stock returns. *The British Accounting Review*, *29*(1), pp.1-23.

Suzuki, K., 2000. Seasoned equity offerings in the UK, usage of funds, method of issue and share price reaction of issuers. Working Paper, London Business School.

Teoh, S.H., Welch, I. and Wong, T.J., 1998. Earnings management and the underperformance of seasoned equity offerings. *Journal of Financial Economics*, *50*(1), pp.63-99.

Thompson, S.B., 2011. Simple formulas for standard errors that cluster by both firm and time. *Journal of financial Economics*, *99*(1), pp.1-10.

Titman, S., Wei, K.J. and Xie, F., 2004. Capital investments and stock returns. *Journal of financial and Quantitative Analysis*, *39*(4), pp.677-700.

Vassalou, M. and Xing, Y., 2004. Default risk in equity returns. *The Journal of Finance*, *59*(2), pp.831-868.

Vassalou, M., 2003. News related to future GDP growth as a risk factor in equity returns. *Journal of Financial Economics*, *68*(1), pp.47-73.

Vermaelen, T., 1981. Common stock repurchases and market signalling: An empirical study. *Journal of Financial Economics*, *9*(2), pp.139-183.

Wang, C.S., Strong, N., Tung, S. and Lin, S., 2009. Share repurchases, the clustering problem, and the free cash flow hypothesis. *Financial Management*, *38*(3), pp.487-505.

Wang, Z., 2013. Do the investment and return-on-equity factors proxy for economic risks?. *Financial Management*, *42*(1), pp.183-209.

White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica: Journal of the Econometric Society*, pp.817-838.

Wooldridge, J.M., 2006. *Introductory econometrics: A modern approach*. Nelson Education.

Yan, X. and Zheng, L., 2017. Fundamental analysis and the cross-section of stock returns: a data-mining approach. *The Review of Financial Studies*, *30*(4), pp.1382-1423.

Yook, K.C., 2010. Long-run stock performance following stock repurchases. *The Quarterly Review of Economics and Finance*, *50*(3), pp.323-331.

Zhang, L., 2005. The value premium. *The Journal of Finance*, *60*(1), pp.67-103.

Zhou, H. and Michou, M., 2017. On the information content of new asset pricing factors in the UK. Working paper.