DISTRESS RISK, FINANCIAL CRISIS AND INVESTMENT STRATEGIES – EVIDENCE FROM THE UNITED KINGDOM

DOVE, HOWARD

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HOWARD DOVE

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Author: Howard Dove

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Abstract

The thesis focuses on the impacts of market distress conditions and firms' default probability on two key investment strategies in the UK. These are investment decisions in value firms versus growth firms (chapter 3), and well-performing firms versus poorly-performing firms (chapter 4). Although distress risk (measured by the market conditions and default probability) is a relevant factor in explaining the general movement of stock returns, this is the first study addressing a direct link between these distress elements and the above two investment choices. The thesis employs a range of distress indicators, including the following: firm-specific proxies such as Fama-French's (1993) three factors (i.e. the market beta, firm size and book-to-market factors), idiosyncratic volatility, default risk, and market-related factors (e.g. business cycles, market downturn and upturn conditions). More recent data and well-developed proxies are used to make sure the results are valid and robust. First of all, the thesis finds positive abnormal returns from investing in value and momentum companies. Among these investment strategies, momentum stocks generate significant profitability in the short run. However, the value firms' investments generate positive but insignificant profit. In terms of explanatory ability, distress risk is found to play an important role in explaining value and momentum anomalies. For example, there is evidence that highly volatile stocks tend to suffer greater default risk, and that stocks with a higher default risk generate lower returns. The results in this study also suggest that momentum-oriented investors would benefit from significantly high returns during market upturns, however these strategies would lead to great losses during recessions.

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BM: Book-to-market equity

CAPM: Capital Asset Pricing Model

CCAPM: Consumption-based Capital Asset Pricing Model

CASHMTA: Cash and Short-term investments over the Market value of Total Assets

CHS: Campbell, Hilscher and Szilagy's (2008) default probability variable

C/P: Cash flow to Price

DEF: Default risk

DES: Default spread

DIV: Dividend yield

EBIT: Earnings Before Interest and Taxes

EFF: Expected Default Frequency index

E-GARCH: Exponential General AutoRegressive Conditional Heteroskedastic model

E/P: Earnings to Price

EU: European Union

FF: Fama and French

FTSE: Financial Times Stock Exchange index

FTSE ICB: Financial Times Stock Exchange Industry Classification Benchmark

GBP: Great British Pound

GDP: Gross Domestic Product

GNP: Gross National Product

High Vo: High Volatility

HML: High-minus-Low

ICAPM: Intertemporal Capital Asset Pricing Model

IV: Instrumental Variables

LIBOR: London Interbank Offered Rate

Low Vo: Low Volatility

Med Vo: Medium Volatility

MTBV: Market to Book Value

NIMTA: Net Income over Market value of Total Asset

OLS: Ordinary Least Squares

OCF: Operating Cash Flow ratio

ROA: Return on Assets

ROI: Return on Investment

SD: Standard Deviation

SDF: Stochastic Discount Factor

SMB: Small-minus-Big

T-Bill: Short-term Treasury Bill

TERM: Term spread

TLMTA: Total Liabilities over Market value of Total Asset

UKAEA: UK Atomic Energy Authority

VAR: Vector AutoRegression

VIF: Variance Inflation Factor

WML: Winner-minus-Loser

Glossary

Since there are many technical terms and concepts have different meanings in the literature depend upon the context they are in, this section will define what they mean in this thesis as well as their interchangeable terms.

1. *Default probability:* sometimes used as an alternative for *probability of bankruptcy* and *probability of default*. The term refers to the likelihood of a firm failing to meet its financial obligations and having to shut down the business as a result. There have been a number of studies constructing a method to quantify this default probability. Some of them are Z-score proposed by Altman (1968), O-score by Ohlson (1980), Merton's (1974) Distance-to-Default and Campbell, Hilscher and Szilagy's (2008) method. See Appendix 3 for details of the formula and method of constructing each score.

2. *Distressed firms (stocks)* or firms in *financial distress conditions:* are defined as firms that are at risk of not meeting their financial obligations either in the short- or long-run. In this thesis, they refer to firms with a high probability of bankruptcy.

3. *Distress risk:* refers to the risk elements associated with firm-level distress, such as default risk, volatility risk, size, and default spread etc.

4. *Firm size*: Market capitalisation or market value of a firm's outstanding shares.

5. *Fundamental variables*: refer to a key firm's accounting variables that can provide a primary assessment of the firm value, cash flows and growth prospects. Some examples are market capitalisation, book-to-market equity ratio, earnings to price, cash flow to price, leverage and dividend yield.

6. *Volatility or Idiosyncratic Volatility:* is the time-series standard deviation of individual share prices.

7. *Business cycle variables:* are four variables that reflect changes in investment choices in the market, including Default spread, Dividend yield, Term spread and Short-term Treasury Bill.

8. *An augmented model:* is a modified version of a model that is built in an effort to improve the original model. In this thesis, an augmented model refers to an

extension of the original model including a Default factor. For example, an augmented Fama and French model is a model whose explanatory variables are the Fama and French three factors and a Default factor. The Default variable can be one of the following three proxies for Default risk: Default risk based on O-score (DEF), Default risk based on Z-score (DEF') or Default risk based on CHS score (CHS).

9. *Robust:* A result (or a value) is robust is when it is not sensitive to the choice of testing method, proxies used (or measurement). If other methods and measures are used instead, the conclusions remain unchanged. The process used to verify whether a result is robust is called *a robustness check*.

Declaration

The work presented in this thesis is entirely my own and has not previously been submitted for a degree in this or any other institution.

Statement of Copyright

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Chapter 1: Introduction

A primary motivation for carrying out this research is to collectively study the relation between distress risks and two key investment strategies in the UK. They are value strategies and momentum. The topic of market anomalies including value premium and momentum have been discussed mostly in relation to the U.S market or to a group of countries. Studies focusing exclusively on the UK market are limited and date back to the 1990s and early 2000s. Given the important role of the UK in the global economy and the possible impact of the global recessions that have occurred recently, it is worth revisiting the question of whether value and momentum abnormal returns exist in the UK market. Secondly, the thesis aims to bridge a gap in the literature between firm default risks, business cycles and investment strategies. Under a risk-based explanation, there are studies supporting the idea that these factors could contribute to capturing the movement? in return of assets. On the one hand, among others, Fama and French's (1993) study shows that market- and firm-related risk factors play a leading role in explaining the movement of equity returns. On the other hand, Agarwal and Taffler (2008) document that Fama and French's three factors have not been able to capture firm distress risk when pricing assets. Therefore, distress risk, such as firm default risk, business cycles and market downturns, may be able to explain asset returns. This study first looks at the potential links between those factors and asset returns, and the results confirm that they are indeed important in capturing the movement of asset returns in the UK.

More importantly, this thesis pays particular attention to the performance of those investment strategies over different market conditions, i.e. recessions versus expansions. This could significantly benefit the investment decision-making process, given the current situation in which the UK market is experiencing market downturns as a result of the recent financial crisis.

Lastly, the thesis employs a wide range of recently-researched indicators for firm default risk, including the Campbell, Hilscher and Szilagyi (2008) probability (CHS), along with the conventional measures: Ohlson's O-score (1980) and Altman's Z-score (1968) to proxy for firm default risk. It, furthermore, employs idiosyncratic volatility to proxy for stock volatility risk, and business cycle variables to capture the impacts of market downturns. This approach contributes to a more comprehensive and robust analysis of the relationship between firm default risk, business cycles and performance of the above investment strategies.

In summary for the proxies, we consider three main group of proxies for distress conditions: (i) firm's probability of bankruptcy, (ii) idiosyncratic stock volatility and (iii) the traditional indicators including market beta, firm size and book-to-market equity ratio. The main focus of this thesis is on distress risks, it finds that market conditions such as financial crises and business cycles are indeed relevant factors. Therefore, these factors are also included for the purpose of further capturing the impact of changes in investment opportunities during market downturns.

The thesis' objective is to study the impacts of the proxied distress conditions and firms' default probability on investment strategies. It focuses on value and growth strategies, and momentum strategies. Their role in investment appraisals has attracted much more attention, especially since the 2008 financial crisis when the impact of distress risk manifested and when investment decisions became more challenging. Yet, there have not been constructive efforts to understand the potential links between distress conditions, default risk and the performance of the above prominent investment strategies.

Given the result of the European Union (EU) referendum, many economists and policymakers are warning of a period of uncertainty for the UK economy. For example, a report by HM Government (2016) predicted that a vote to leave the EU would lead to a decade of uncertainty which would have a negative impact on UK businesses, trade and investment. Open Europe, a leading independent think tank, estimated the impact of leaving the EU would be between -2.2% and 1.6% in Gross Domestic Product (GDP) for the UK in 2030 (Booth, Howarth, Persson, Ruparel and Swidlicki 2015). Signs of low investment into the UK have been reported from both EU and non-EU investors following the vote. The Financial Times reported a third of top employers surveyed by the Institute of Directors are considering reducing their investment plans as a result of the vote (Tetlow and O'Connor 27th June 2016). Virgin Group, a multinational conglomerate, also announced its cancellation of a deal to buy a UK company employing 3,000 staff (Gordon, 28th June 2016). Moreover, the Financial Times Stock Exchange 350 (FTSE350) index fell by 7% just 2 days after the EU Referendum outcome was released. It has been gradually picking up but was still considered to be more volatile than the DAX30 index in Germany after the vote (Weale, 2016). It is unclear what arrangement the UK government would achieve after triggering Article 50 (a withdrawal clause of the Lisbon Treaty) and what the alternative agreements between the UK and the rest of the world would be. The UK has notified the EU of its intention to exit the trading blocs and has started a minimum 2 years of negotiation between the UK and the EU. As this article has not been exercised before, the level of market uncertainty and investor confidence in the UK assets are hard to predict accurately. Some have even said that the consequence could be comparable to the 2008 financial crisis (Tetlow, 2016). It is, therefore, a particularly crucial time to study the impacts of market downturns and firm distress risk on the returns of investment strategies, and this hopefully will help in explaining the link between those risks and investment decision when the future of the UK is made a bit clearer.

The rest of this thesis is structured as follows. Chapter 2 introduces the research methodology used in the thesis. Chapter 3 studies how firm distress risks, including default risk and stock volatility, contribute to explaining value anomaly in the UK. Chapter 4 also looks at the role of distress conditions in capturing momentum anomaly. Chapter 5 summarises the main contributions and findings of each chapter, and concludes the thesis with potential areas for future research.

Chapter 2: Research Methodology

2.1 INTRODUCTION

This chapter defines variables, methodology and statistical processes used in the thesis. It first describes characteristics of the sample, the construction of each variable and the initial analysis of the variables in question. The chapter then provides a source code on which Chapter 4 relies to generate CHS – a highly complex proxy for default risks proposed by Campbell, Hilscher and Szilagyi (2008). Although formation of the CHS variable was presented in the Campbell et al. (2008) paper, this program would provide researchers and practitioners with a statistical tool to apply this algorithm in practice. The use of this method when predicting the risk of corporate failure could also significantly reduce calculation errors.

2.2 SAMPLE

All equity data were obtained from the DataStream Thomson Reuters database, except the market factor for the UK market which was made available on Kenneth R. French's database. Where company accounting data such as Earnings Before Interest and Taxes was not available on these databases, they were collected from Bloomberg and cross checked in company financial statements. The UK Gilt rates were obtained from the UK Debt Management Office database.

The sample used in this thesis consists of 290 firms in the FTSE350 and covers a period from 31st January 1990 to 31st December 2012. As of 31st December 2012, when the data were collected, the FTSE350 index incorporated the largest 354 UK firms by capitalisation listed in the London Stock Exchange. Among these companies, 64 were new firms with less than a year of data. The rationale behind excluding newly added firms is based on the following reasons. Firstly, investment strategies considered in this thesis are based on past performance of stocks, therefore it is necessary that they have some historic data. Secondly, a minimum one-year period would allow investors to filter noise and unverified information in regard to the new companies before making any investment decisions. This then creates a sample of 290 firms across 276 months, forming a dataset of 79,246 firm-month observations[1]. The companies' name and their

[1] Note that not all 290 firms have a lifespan of 276 months. Therefore, the number of observations in the dataset is less that the value of 290 times 276.

trading details, such as company ticker, sector and IPO date are presented in Appendix 1.

During the sample period, if any newly listed firm became eligible, they were added to the portfolios of that year. Similarly, any de-listed firms were not included in the portfolios from the year they were de-listed. This is to reflect the real trading options that were available at the time of investment.

It is worth noting that the sample used in Chapter 3 excludes financial firms and firms with no BM data. This results in a sample of 269 companies. This approach is in line with the existing literature on value anomaly. The reason for this exclusion is that financial firms have a very different capital structure compared with non-financial firms. For example, the high leverage observed in financial institutions does not necessarily mean they are in financial distress, which is usually the case for non-financial firms (Fama and French 1992). This constraint does not apply to momentum research, thus the analysis in Chapter 4 is based on a full sample of 290 companies.

In summary, all portfolio-based factors in the thesis are constructed from the full sample of 290 firms. The exception is in constructing dependent variables. The sample used to compute portfolios in Chapter 4 is again based on the full sample of 290 companies; however, Chapter 3's dependent variables are constructed from a sample of 269 non-financial firms because of the reasons given above.

2.3. METHODOLOGICAL FRAMEWORK

The thesis follows one particular school of thought that attributes market anomalies to risk elements that have not been correctly priced by the market. It then develops a range of risk-based models, trying to capture the risk patterns in stock returns. Although the thesis does not engage in the debate on best-fit models, it has an ambition to explore possible approaches to measuring key risk elements in average stock returns. There are two main methods used in this study to aim to achieve these objectives. They are discussed in turn as follows.

- **Regression method (Chapters 3 and 4)**

  Regression method is a dominant statistical approach in economics, finance and investing for modelling the relationship between one dependent variable and a series of explanatory variables. As the regression system has been discussed extensively in textbooks as well as in the literature, it is not the intention of this section to cover the characteristics and estimating procedures, or to model diagnostics in regression analysis. It is rather to highlight how regression method is implemented in examining the research questions set out in this thesis.

In the asset pricing literature, building and using risk factors as explanatory variables in regression modelling has been widely used by both academics and practitioners. In order to model the relationship between distress risk among other risk elements and value anomaly (Chapter 3), and their relationship with momentum anomaly (Chapter 4), the thesis uses a traditional CAPM-based linear regression method.

This approach assumes excess return of asset *i* at time *t* is explained by the following model:

$$\left(R_{i,t} - R_{f,t}\right) = \gamma_o + \gamma_m \left(R_{m,t} - R_{f,t}\right) + \sum_{k=1}^{u} \gamma_{k,t} X_{k,t} + \varepsilon_{i,t} \tag{2.1}$$

Where, $R_{i,t}$ is the return on asset *i* at the end of period *t*; $R_{f,t}$ is the risk-free asset at time *t*; $R_{m,t}$ is the market portfolio at the end of period *t*; $X_{k,t}$ is the risk factor at the end of period *t; u* is the number of risk factors included in the regression apart from the market factor; and $\varepsilon_{i,t}$ is an error term. As all of the above variables are return-based variables, they are real numbers and can take both negative and positive values. This applies to all variables used in the rest of the thesis, unless otherwise stated.

Regression coefficients are the estimated parameters on the corresponding explanatory variable vectors. The model (2.1) then can be re-written as follows.

$$\left(\begin{bmatrix} R_{t0}^{i} \\ R_{t1\dots}^{i} \\ R_{tn}^{i} \end{bmatrix} - \begin{bmatrix} R_{t0}^{f} \\ R_{t1\dots}^{f} \\ R_{tn}^{f} \end{bmatrix}\right) = \gamma_o + \gamma_m \left(\begin{bmatrix} R_{t0}^{m} \\ R_{t1\dots}^{m} \\ R_{tn}^{m} \end{bmatrix} - \begin{bmatrix} R_{t0}^{f} \\ R_{t1\dots}^{f} \\ R_{tn}^{f} \end{bmatrix}\right) + \sum_{k=1}^{u} \gamma_{k,t} \begin{bmatrix} X_{t0}^{k} \\ X_{t1}^{k} \dots \\ X_{tn}^{k} \end{bmatrix} + \varepsilon_{i,t} \tag{2.2}$$

Where, R_{tn}^{i} is the return on asset *i* at the end of period t_n where n takes values from 1 to n; *n* is the number of time intervals in the sample period; R_{tn}^{f} is the risk-free asset at time t_n; R_{tn}^{m} is the market portfolio at the end of period t_n; $X_{tn}^{k}$is the risk factor k^{th} at the end of period t_n*; u* is the number of risk factors included in the regression apart from the market factor; and $\varepsilon_{i,t}$ is an error term.

In asset pricing, explanatory variables are usually constructed using the mimicking portfolio approach. According to this approach, the risk variables are the return differentials between two portfolios of different risk levels.

In this model, the risk variables $X_{k,t}$ need to meet certain criteria in order for the regression method to deliver the desirable outcomes.

Firstly, $X_{k,t}$ should be selected and constructed in a way that it can capture the risk element it is meant to proxy for. In the thesis, the set of explanatory variables are selected from mainstream literature on asset pricing models. For BM and firm size effect, it uses High-minus-Low (HML) and Small-minus-Big (SMB) variables suggested by Fama and French (1993), based on ranking firm BM ratios and market capitalisation, respectively. To proxy for momentum (or past return) effect, Carhart (1997) proposes the use of the Winner-minus-Loser (WML) factor which is based on stock past returns. The set of proxies used in this thesis for business cycle variables have been widely implemented in asset pricing studies, for example Petkova (2005), Zhang (2005) and Henkel, Martin and Nardari (2011). In terms of proxies for default risk, following Griffin and Lemmon (2002), the thesis constructs a default factor from a number of probability-of-bankruptcy indicators, such as O-score and Z-score. To enhance the analysis, it also proposes using CHS, a new measure of probability of corporate failure first built by Campbell et al. (2008). In this thesis, the above risk variables have demonstrated the ability to proxy for the risk patterns that we aim to capture in average stock returns. As the literature grows, there may be alternative proxies developed. However, in this study we do not pursue this possibility which would be an area for future research.

Secondly, country-specific characteristics are also taken into account when building the variables for the UK market. For example, when constructing CHS default proxy for FTSE350 companies, the Logit regression does not include the price-per-share variable as a predictor variable. For US firms, they are required to have a minimum $1 price per share, and are delisted if they do not, regardless of their performance. However, the London Stock Exchange does not have that listing requirement. Therefore, unlike in the US, companies in the UK are not de-listed on the basis of low price-per-share.

Thirdly, explanatory variables $X_{k,t}$ are treated in a consistent way. In this thesis, risk factors are formed with a 6-month lag with an exception of the WML variable. This is to allow investors to make informed decisions, given that information, such as accounting announcement and financial ratios, is usually made available to the public a few months after the financial year ends. This lag is shorter (1 month) for the WML variable as it is based on past stock prices and this information is published almost instantly. In addition, where risk variables are constructed based on forming portfolios, the same breakpoint of 30:40:30 is applied throughout. This means that if the sample is split into 3 groups of High, Medium and Low, the composite stocks will be among the top 30%, the middle 40% and the bottom 30% of the sample, respectively. This is seen in forming variables proxied for BM and size effects (i.e. HML, SMB)[2], momentum (WML), three default risk factors (denoted as DEF, DEF', and CHS in subsequent sections) and default spread variable.

Finally, possible econometric problems should be assessed when constructing risk variables to make sure the estimations are efficient and unbiased. There are a number of econometric issues that particularly concern the way explanatory variables are built, such as autocorrelation and multicollinearity. For example, to avoid multicollinearity biases there must be no correlation between risk factors.

The thesis takes as a starting point the three-factor model proposed by Fama and French (1993) and the four-factor model proposed by Carhart (1997). From each model, it develops an augmented model with a number of default risk variables. This is to examine the role of distress risk in explaining value and momentum anomalies in different settings – the main hypotheses set out in Chapters 3 and 4 of the thesis.

- **Portfolio-based approach (Chapter 3)**

Sometimes, it is not possible to construct a risk factor or it does not make economic sense to build one. In these cases, a more appropriate method to capture the risk element in question would be by looking at the difference in performance of two (or more) portfolios which react differently to that particular risk element. In

[2] HML, SMB variables are obtained from Kenneth R. French's data library which also used the same 30:40:30 breakpoint.

addition, if comparing the performance between those portfolios is also one of the research objectives, as for example in Fama and French (1992, 1993), the portfolio-based approach has been proven to be useful. This is the case in Chapter 3 which addresses performance of stock with different idiosyncratic volatility levels.

In line with previous studies in value strategies literature[3], Chapter 3 combines both risk-based regression and portfolio grouping approaches. Besides constructing risk factors which are used as explanatory variables, the portfolio grouping method applied to dependent variables helps to understand the risk patterns in the portfolio-based dependent variables.

According to this method, the sample is split into a number of portfolios based on a set of criteria. Stocks in each portfolio should share similar characteristics. The excess returns on these portfolios are then used as the dependent variable in regression (2.2). In theory, if the difference in performance of these portfolios is explained by the model, the estimated parameters will indicate the extent to which the movement in stock returns in each portfolio is captured by the risk factors included in the model. In other words, this approach shows the relative relationship (but not causal relationship) between the risk patterns associated with the characteristics that stocks in one portfolio have in common, and the risk factors in the estimation model.

Depending on the number of criteria applied to forming the portfolios, stock in each portfolio will be examined in different dimensions. For example, in Chapter 3 the sample is classified into 2 size portfolios, *Small* and *Big*, and separately into 3 Book-to-Market portfolios, *High BM, Medium BM* and *Low BM*. As a result, there are 6 portfolios which are intersections between these 2 size and 3 book-to-market portfolios. They are *Small/High BM, Big/High BM, Small/Medium BM, Big/Medium BM, Small/Low BM* and *Big/Low BM.* A regression approach is then applied to these portfolios. In this example, the regression model (2.2) can be re-written.

[3] See Fama and French (1992, 1993, 1995), and Zhang (2005) for examples in the US, Griffin and Lemmon (2002) for the UK and Fama and French (2012) for international examples.

$$\left(\begin{bmatrix} R_t^{S/H} & R_t^{B/H} \\ R_t^{S/M} & R_t^{B/M} \\ R_t^{S/L} & R_t^{B/L} \end{bmatrix} - \begin{bmatrix} R_t^f & R_t^f \\ R_t^f & R_t^f \\ R_t^f & R_t^f \end{bmatrix}\right) = \begin{bmatrix} \gamma_0^{S/H} & \gamma_0^{B/H} \\ \gamma_0^{S/M} & \gamma_0^{B/M} \\ \gamma_0^{S/L} & \gamma_0^{B/L} \end{bmatrix} + \begin{bmatrix} \gamma_m^{S/H} & \gamma_m^{B/H} \\ \gamma_m^{S/M} & \gamma_m^{B/M} \\ \gamma_m^{S/L} & \gamma_m^{B/L} \end{bmatrix} \left(\begin{bmatrix} R_t^m & R_t^m \\ R_t^m & R_t^m \end{bmatrix} - \begin{bmatrix} R_t^f & R_t^f \\ R_t^f & R_t^f \end{bmatrix}\right) +$$

$$\sum_{k=1}^{u} \begin{bmatrix} \gamma_{k,t}^{S/H} & \gamma_{k,t}^{B/H} \\ \gamma_{k,t}^{S/M} & \gamma_{k,t}^{B/M} \\ \gamma_{k,t}^{S/L} & \gamma_{k,t}^{B/L} \end{bmatrix} x \begin{bmatrix} X_t^k & X_t^k \\ X_t^k & X_t^k \end{bmatrix} + \varepsilon_{i,t} \qquad (2.3)$$

Where, $R_t^{S/H}$, for example, is the return on the small/high BM portfolio at the end of period *t*; $R_t^{S/M}$ is the return on the small/medium BM portfolio at time *t*; $R_t^{S/L}$ is the return on the small/low BM portfolio at time *t*; $R_t^{B/H}$ is the return on the big/high BM portfolio at time *t*; $R_t^{B/M}$ is the return on the big/medium BM portfolio at time *t*; $R_t^{B/L}$ is the return on the big/low BM portfolio; and $\varepsilon_{i,t}$ is an error term.

In Chapter 4, which concerns momentum anomaly, the portfolio-based approach is, however, not suitable for a number of reasons. Firstly, it is well recognised in the literature that the Winner-minus-Loser variable can capture the momentum effects in common stock returns. It was suggested that this variable should be used by Carhart (1997) in the four-factor model. Secondly, the aim of Chapter 4 is to explain momentum anomaly. While it is unprecedented in the literature about momentum to use a portfolio-based approach, the thesis finds no evidence suggesting that this method would improve understanding of the underlying reasons behind momentum anomaly. Lastly, the trading rules in momentum strategies distinguish companies performing well in the past from those performing poorly. In the FTSE350, it is observed that in either group of companies there is no clear pattern with respect to other company characteristics, such as size, and book-to-market values. That means if one determines to use the portfolio-based approach, the resultant portfolios would not have a consistent set of characteristics, and, therefore, there is a risk of sample biases.

Either of the above approaches would need a base asset pricing model which consists of a dependent variable and a set of independent (or explanatory) variables. The next section will describe the definition, data source and procedure involved in constructing each variable used in this thesis. More details on the variable construction are also summarised in Appendix 3 at the end of this thesis.

2.4. DEPENDENT VARIABLES

2.4.1. Defining variables

Dependent variables, denoted by (**R_i – R_f)**, are the excess returns on equity investment relative to risk free investment. The first component, **R_i**, is the monthly value-weighted rate of returns on equity investment. The monthly compound rate of return of stock *u*, $r_{u,t}$, in month *t* is computed from the price index using the following formula.

$$r_{u,t} = Ln\left(Price\ index_{u,t}\right) - Ln\ (\left(Price\ index_{u,t-1}\right) \qquad (2.4)$$

Where, $r_{u,t}$, is the monthly compound rate of return of stock *u* in month *t*;

Price index $_{u,t}$, is the price index of stock *u* in month *t*; and

Price index $_{u,t-1}$, is the price index of stock *u* in month *t-1*.

$R_{i,t}$ is the value-weighted rate of returns of portfolio *i*, consisting of *n* stocks in month *t*. It is the average rate of returns of all constituent stocks, where the weights are proportional to outstanding market value (i.e. market capitalisation).

$$R_{i,t} = \sum_{u=1}^{n} w_u\, r_{u,t} \qquad (2.5)$$

Where, $R_{i,t}$ is the value-weighted rate of returns of portfolio *i* in month *t*, consisting of *n* stocks; the weights w_u is equal to market value of stock r_u at time *t* divided by the total market value of all constituent stocks.

The second component, **R_f**, is the risk-free rate of return. In line with previous studies in the UK stock market, the UK LIBOR 1-month is chosen to proxy for the risk-free asset. In theory, it is the return on asset that bears no risk. In practice, it is usually the safest asset available, having a short-term maturity and being guaranteed by the government. Although there are LIBOR with a shorter maturity, such as overnight or one-week rates, the thesis limits its analysis to monthly trading frequency. Firstly, this is because, in line with the literature, this thesis does not focus on arbitrage or high frequency trading, but rather on long-term investment strategies. Secondly, high frequency trading can be costly due to transaction costs, which are assumed to be marginal in most studies on investment strategies. Also, in the long run high transaction costs due to high frequency trading can outweigh profits.

LIBOR 1-month middle rates are obtained monthly between January 1990 and December 2012 (DataStream mnemonic code: BOELI1M). The LIBOR 1-month rates over this period were greater than zero, ranging between 0.455% and 18.29% per year (approximately 0.04% and 1.41% per month). It is worth noticing that the LIBOR rates reported on the majority of mainstream databases, including DataStream, are on a yearly basis. They can be converted to compound monthly rates using the following formula:

$$r_{monthly} = (1 + r_{yearly})^{\frac{1}{12}} - 1 \tag{2.6}$$

Where, $r_{monthly}$ is the compound monthly rate of returns (in percentage), and

r_{yearly} is the annual rate of returns (in percentage).

The final step of constructing the dependant variable is calculating portfolio excess returns. The excess rates of return on equity are then computed monthly as the difference between value-weighted rates of return on equity investment and LIBOR 1-month rates. The excess returns can take both positive and negative values because investing in stock markets is riskier but not necessarily more profitable than the risk-free asset.

The above explains the general method by which returns for each portfolio are constructed. For each chapter, the investment strategy that is addressed in the chapter will determine the size and characteristics of constituent stocks that made up the dependent valuables. More specifically, Chapter 3 aims to explain the relationship between value premium and default risks from three different angles: size/BM effects, idiosyncratic stock volatility, and default probability.

(i) In Chapter 3, we form 6 portfolios consisting of stocks with different sizes and BM characteristics. They are Small/Low, Small/Medium, Small/High, Big/Low, Big/Medium and Big/High portfolios.

(ii) Separately, we also form 9 portfolios based on firm-level idiosyncratic volatility and BM ratio. They are constructed as intersections between 3 volatility portfolios and 3 BM portfolios. They include: High Vo/High BM, High Vo/Medium BM, High Vo/Low BM, Medium Vo/High BM, Medium Vo/Medium BM, Medium Vo/Low BM, Low Vo/ High BM, Low Vo/Medium BM, and Low Vo/Low BM.

(iii) For robustness purposes, 9 different intersection portfolios are constructed from 3 default probability portfolios (measured by O-score) and 3 book-to-market portfolios. They are intersections between 3 DEF portfolios and 3 BM portfolios. They include: High DEF/High BM, High DEF/Medium BM, High DEF/Low BM, Medium DEF/High BM, Medium DEF/Medium BM, Medium DEF/Low BM, Low DEF/High BM, Low DEF/Medium BM, and Low DEF/Low BM.

The dependent variables are the excess returns on each of the above portfolios relative to the risk-free rate. Tables 2.1 to 2.3 summarise descriptive statistics of these variables, and figures 2.1 to 2.3 plot the variables.

This chapter uses scatter diagrams to display dependent variables (in Section 2.4.2) whilst using line charts to provide a visualisation of independent variables (later in Section 2.5.3). While this different treatment is for visualisation purposes only and should not affect the analysis, the reasons for doing this lie in the way each type of diagram displays values for the variable in question:

(i) The primary objectives of the thesis are assessing whether there are abnormal returns in value and momentum investing, and studying the underlying factors that explain the anomalies. Therefore, for dependent variables scatter diagrams could draw attention to the *magnitude* of abnormal returns or the extent to which value and momentum strategies generate abnormal returns; and

(ii) For independent variables, it is the *risk patterns* in these variables and their *value changes over time* that could potentially explain the abnormal returns (proxied by the dependent variables). Thus, line graphs could fit the role better than scatter graphs.

It is worth mentioning that in line with the study of Dimson et al. (2003) for the UK, in terms of dependent variables, the above portfolios are constructed using the 40:20:40 breakpoint. As non-US markets have significantly fewer listed companies, the above breakpoint is to cover more of the value and growth characteristics. However, this line of explanation does not apply to independent variables which are constructed using a 30:40:30 breakpoint. This is because independent variables are meant to proxy for risk components, and therefore should capture the most representative stocks in the top and bottom 30%.

In Chapter 4, concerning momentum anomaly, dependent variables are the return differentials between winner and loser portfolios and the risk-free rates. First of all, the sample of 290 stocks is grouped into 10 portfolios based on ranking their past returns. The 10 portfolios are denoted by P1 to P10, in which P1 is the losers and P10 is the winners. Dependent variables in Chapter 4 are the excess returns on the Winners (P10) relative to risk free investment, and the excess returns on the losers (P1) in relation to the risk-free asset. For the UK market, LIBOR 1-month is used as a proxy for the risk - free rate. Table 2.4 summarises descriptive statistics and Figure 2.4 plots the variables.

The next section will describe these tables and figures in turn.

2.4.2. Descriptive statistics of dependent variables

Tables 2.1 to 2.3 summarise the characteristics of dependent variables used in Chapter 3 and the corresponding Figures 2.1 to 2.3 plot their monthly values. This chapter uses scatter diagrams to visualise dependent variables instead of using line charts because scatter diagrams could better present the extent to which value and momentum strategies generate abnormal returns.

The first group of dependent variables are excess returns on 6 size/BM portfolios, which are the intersections between 2 size and 3 BM stock groups. The second set of Chapter 3 dependent variables are excess returns on 9 Volatility/BM portfolios, being the intersections between 3 Volatility and 3 BM portfolios. Finally, the third group of dependent variables are excess returns on 9 Default/BM portfolios, formed from 3 Default and 3 BM portfolios. These portfolios are constructed from a sample of 269 non-financial companies in the FTSE350 as described in section 2.2. The portfolio returns are value-weighted, calculated monthly and rebalanced annually.

Table 2.1 shows that the excess returns on 6 size/BM portfolios differ mostly due to whether they consist of Small or Big companies. The excess returns are positive for small stocks, slightly higher if companies are also high BM firms. On average, the monthly excess return on the Small/Low BM portfolio is 0.22%, ranging between -18.78% and 15.57%. The Small/High BM excess returns deviate the most from the mean. They range from -28.88% to 23.79% and the standard deviation is 0.0633. The Small/High BM equities are also among the most volatile stocks.

On the contrary, big stocks tend to generate negative excess returns. The three portfolios, Big/High BM, Big/Medium BM and Big/Low BM, have excess returns of -0.32%, -0.26% and -0.08%, respectively. Big equities are among the less volatile stocks. The stock returns also vary according to market conditions. As can be seen from Figure 2.1, the periods which witness large fluctuations within one group of stocks are market slowdowns. For example, the Dotcom bust that saw the UK FTSE100 drop by more than 50% in 2003, and the recent financial crisis that led to the sharpest drop since the current index was created in 1984.

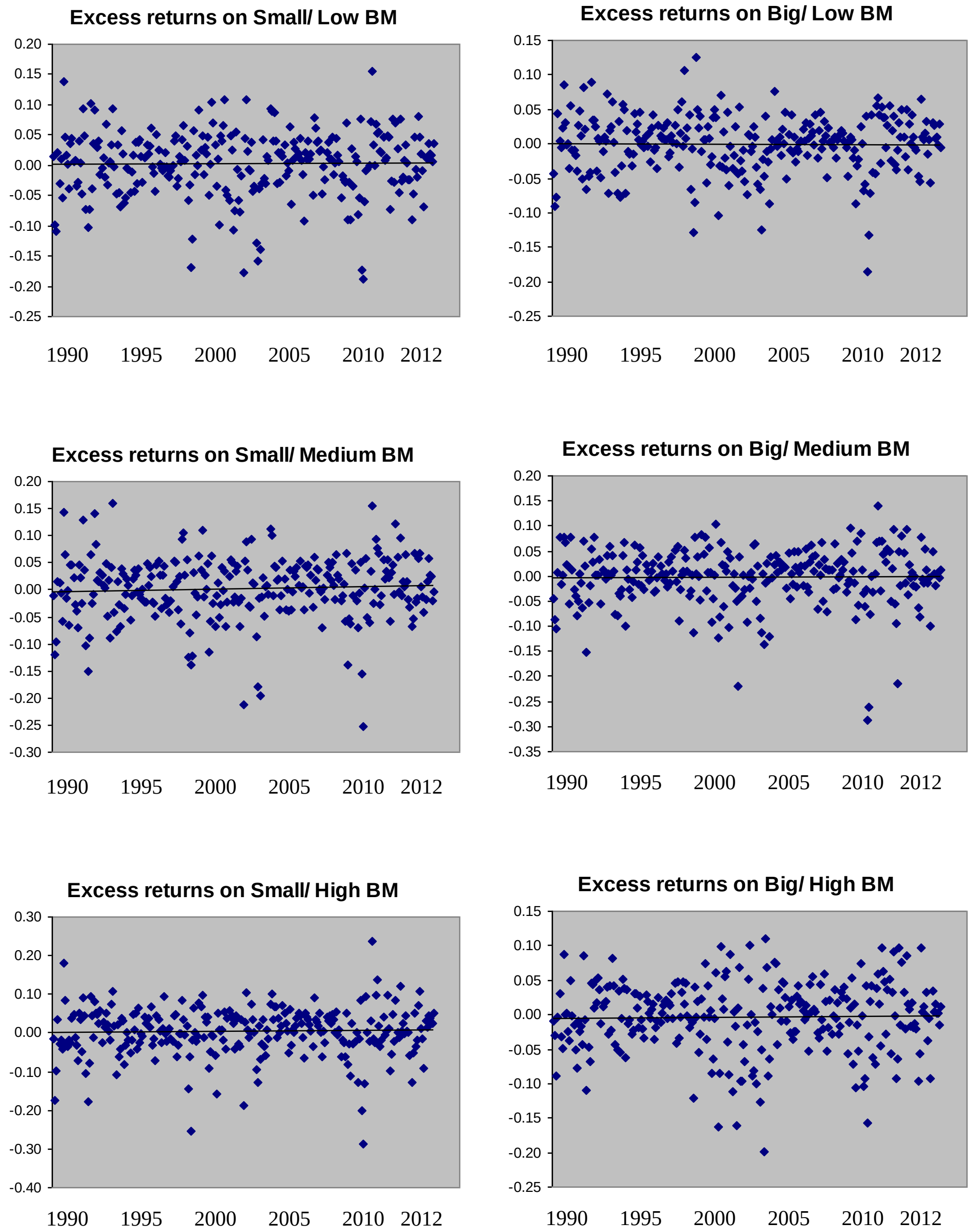
Table 2.1: Characteristics of Chapter 3 dependent variables – Monthly Excess returns on 6 Size/BM portfolios

The table summarises descriptive statistics for Chapter 3 dependent variables (R_i – R_f), in which R_i are size/BM portfolios and R_f is the LIBOR 3-month rates. To construct R_i, non-financial stocks are split into Big and Small portfolios based on their market capitalisation by the statistical median. At the same time, these stocks are also grouped into High BM, Medium BM and Low BM using a 40:20:40 breakpoint. Six size/BM portfolios are the intersections between two size and three BM portfolios. For example, the Small/Low portfolio consists of stocks that are in the Small group and also classified as Low BM stocks. All monthly excess returns are represented in decimal form. Section 3.3.2 of Chapter 3 explains the construction of these portfolios in more detail.

Excess returns	No. of companies	Mean	SD	Median	Max	Min
Small/Low	52	0.0022	0.0533	0.0085	0.1557	-0.1878
Small/Medium	22	0.0022	0.0583	0.0064	0.1587	-0.2521
Small/High	60	0.0033	0.0633	0.0063	0.2379	-0.2888
Big/Low	57	-0.0008	0.0411	0.0042	0.1248	-0.1851
Big/Medium	31	-0.0026	0.0564	0.0040	0.1390	-0.2876
Big/High	46	-0.0032	0.0508	-0.0004	0.1096	-0.1991

Figure 2.1: Plotting Chapter 3 dependent variables – Monthly excess returns on 6 size/BM portfolios

The figures plot monthly excess returns on 6 size/BM portfolios, (R_i –R_f), over a period from July 1990 to December 2012 (276 data points). Scatter diagrams are used to visualise dependent variables instead of line charts because they could present the extent to which value strategies generate abnormal returns. The risk-free asset (R_f) is the LIBOR 1-month rate. A trendline is added to show the performance of each portfolio over time. All monthly excess returns are represented in decimal form. The Y axis shows the value of monthly excess returns on each portfolio (in decimal), and the X axis represents years.



When assessing performance of Volatility/BM portfolios in Chapter 3, we carry out regression analysis on excess returns on 9 portfolios which are the intersections between 3 volatility and 3 BM portfolios. The descriptive statistics of these dependent variables are presented in Table 2.2 and Figure 2.2.

In Table 2.2, it is unsurprising that highly volatile stocks are those with the highest standard deviations but their performance in the UK is also better than medium and low volatility stocks. Among the three volatility portfolios, the average returns on High Vo/Medium BM are the highest, approximately 0.34% higher than the risk-free asset. High Vo/High BM and High Vo/Low BM portfolios both generate positive excess returns of about 0.18% and 0.07% per month, respectively. The largest changes in monthly excess returns are within the High Vo/Medium BM stocks, which can reach a maximum of 50.95% and a minimum of -24.11%. From Figure 2.2, the plot diagram for High Vo/Medium BM excess returns shows that the high excess returns were seen in September 2010, which coincided with the period when the UK economy started to pick up after the 2008 financial crisis.

Low volatility portfolios perform worst in terms of excess returns with the monthly excess returns are between -1.21% and -0.85%. Although having slightly lower standard deviations comparing to Medium Volatility companies, Low Volatility portfolios generate much lower excess returns. The return differentials are between 0.2% and 0.6% per month. In addition, it can be seen from Figure 2.2 that Low Vo/High BM portfolios are more volatile than Low Vo/Medium BM and Low Vo/Low BM. Average excess returns on the Low Volatility portfolios recorded a clear upward trend over time, with the excess returns on the Low Vo/Low BM increasing more quickly than those on other Low Volatility portfolios.

One might notice that there are a smaller number of companies in medium volatility portfolios. It is because they account for about 20% of the total sample. The Medium Vo/Medium BM portfolio has even fewer firms as they consist of only 10% of the total sample. This, however, will not necessarily compromise the quality of the Chapter 3 econometrics estimation since the analysis pays more attention to the performance of high and low Volatility stocks. The rest of this section, therefore, will not discuss the medium portfolios in great detail.

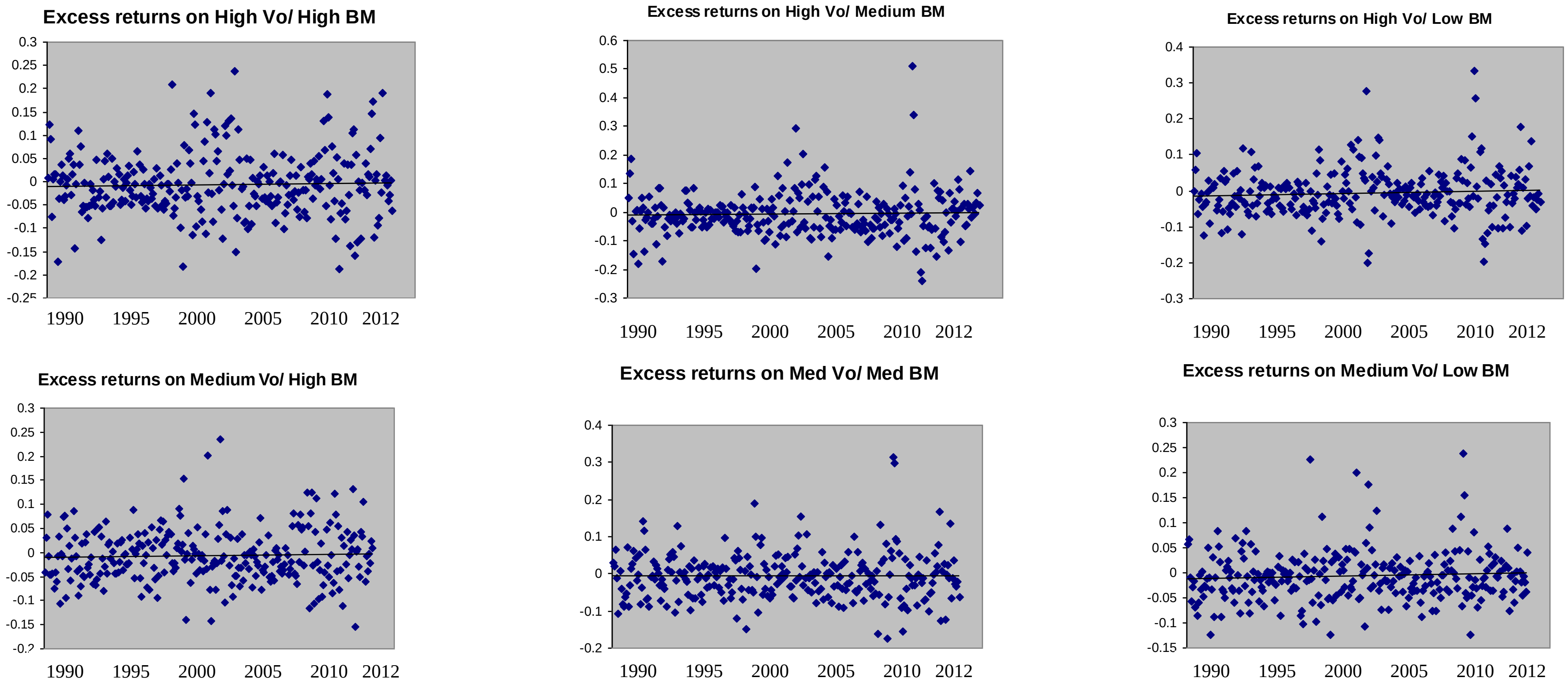
Table 2.2: Characteristics of Chapter 3 dependent variables – Monthly Excess returns on 9 Volatility/ BM portfolios

The table summarises descriptive statistics for Chapter 3 dependent variables ($R_i - R_f$), in which R_i are Volatility/BM portfolios and R_f is the LIBOR 1-month rates. To construct R_i, non-financial stocks are split into High Vo, Medium Vo and Low Vo based on firm-level standard deviation. The breakpoint used for dependent variables is 40:20:40. At the same time, these stocks are also grouped into High BM, Medium BM and Low BM using the 40:20:40 breakpoint. Nine dependent variables are the intersections between three idiosyncratic volatility and three BM portfolios. For example, the High Vo/Low BM portfolio consists of stocks that are in the High idiosyncratic volatility group and also classified as Low BM stocks. All monthly excess returns are represented in decimal form. Section 3.3.2 of chapter 3 explains the construction of these portfolios in more detail.

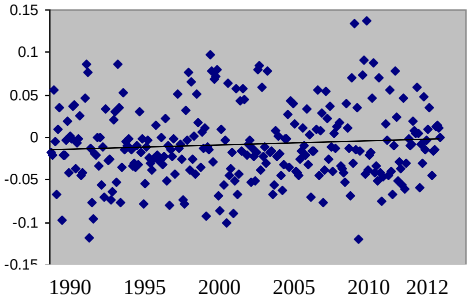
Excess returns	**No. of companies**	**Mean**	**SD**	**Median**	**Max**	**Min**
High Vo/High BM	42	0.0018	0.0780	-0.0084	0.2362	-0.1886
High Vo/Medium BM	24	0.0034	0.0985	-0.0131	0.5095	-0.2411
High Vo/Low BM	43	0.0007	0.0872	-0.0129	0.3348	-0.2010
Medium Vo/High BM	21	-0.0069	0.0551	-0.0122	0.2361	-0.1538
Medium Vo/Medium BM	10	-0.0066	0.0638	-0.0086	0.3142	-0.1744
Medium Vo/Low BM	23	-0.0066	0.0506	-0.0087	0.2386	-0.1247
Low Vo/High BM	44	-0.0085	0.0444	-0.0143	0.1369	-0.1204
Low Vo/Medium BM	20	-0.0121	0.0322	-0.0175	0.1705	-0.1453
Low Vo/Low BM	43	-0.0091	0.0411	-0.0121	0.1254	-0.1657

Figure 2.2: Plotting Chapter 3 dependent variables – Monthly excess returns on 9 Volatility/BM portfolios

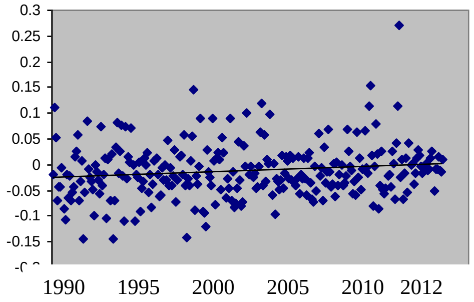
The figures plot monthly excess returns on 9 Volatility/BM portfolios, (R_i –R_f), over a period from July 1990 to December 2012 (276 datapoints). Scatter diagrams are used to visualise dependent variables instead of line charts because they could present the extent to which value strategies generate abnormal returns. The risk-free asset (R_f) is the LIBOR 1-month rate. A trendline is added to show the performance of each portfolio over time. The Y axis shows the value of monthly excess returns on each portfolio (in decimal), and the X axis represents years.



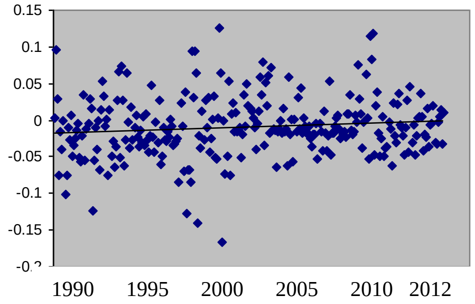
Excess returns on Low Vo/ High BM



Excess returns on Low Vo/ Med BM



Excess returns on Low Vo/ Low BM



In regard to excess returns on the Default/BM portfolios, Table 2.3 shows that High DEF stocks generate lower average returns in relation to the risk-free asset. Within the High DEF group, the excess returns are lower on High and Low , compared with the Medium portfolios. On average, they yield monthly excess returns of -0.83%, -0.72% and -0.56%, respectively. High DEF stocks are also among those with the highest standard deviation. Their monthly excess returns range from as low as -35.53% to as high as 48.95%.

In contrast, Low DEF stocks generate positive excess returns and they do not deviate from the mean as much as their High DEF counterpart. In particular, Low DEF/High BM returns are nearly 10% higher than the risk-free asset, while this is only around 0.2% in the cases of Low DEF/Medium BM and Low DEF/Low BM portfolios. Standard deviations of Low DEF portfolios are about 0.04, compared with 0.08 for the High DEF portfolios. This implies that the Low DEF stocks tend to be less volatile than High DEF. The largest changes are seen in the Low DEF/Medium BM portfolio, with a maximum value of 16.03% and a minimum value of -11.23% per month.

It can be seen from Figure 2.3 that there is an upward trend in monthly excess returns on low DEF portfolios. Within the Low DEF group, the Low DEF/High BM portfolio experiences a downward trend at a much faster pace than the Low DEF/Low BM portfolio. The figure also shows that in the low DEF group, High BM stocks tend to be more sensitive to changes in market condition than Low BM stocks. The figure also confirms that the High DEF stocks tend to deviate more from the mean than the Medium DEF and Low DEF stocks do.

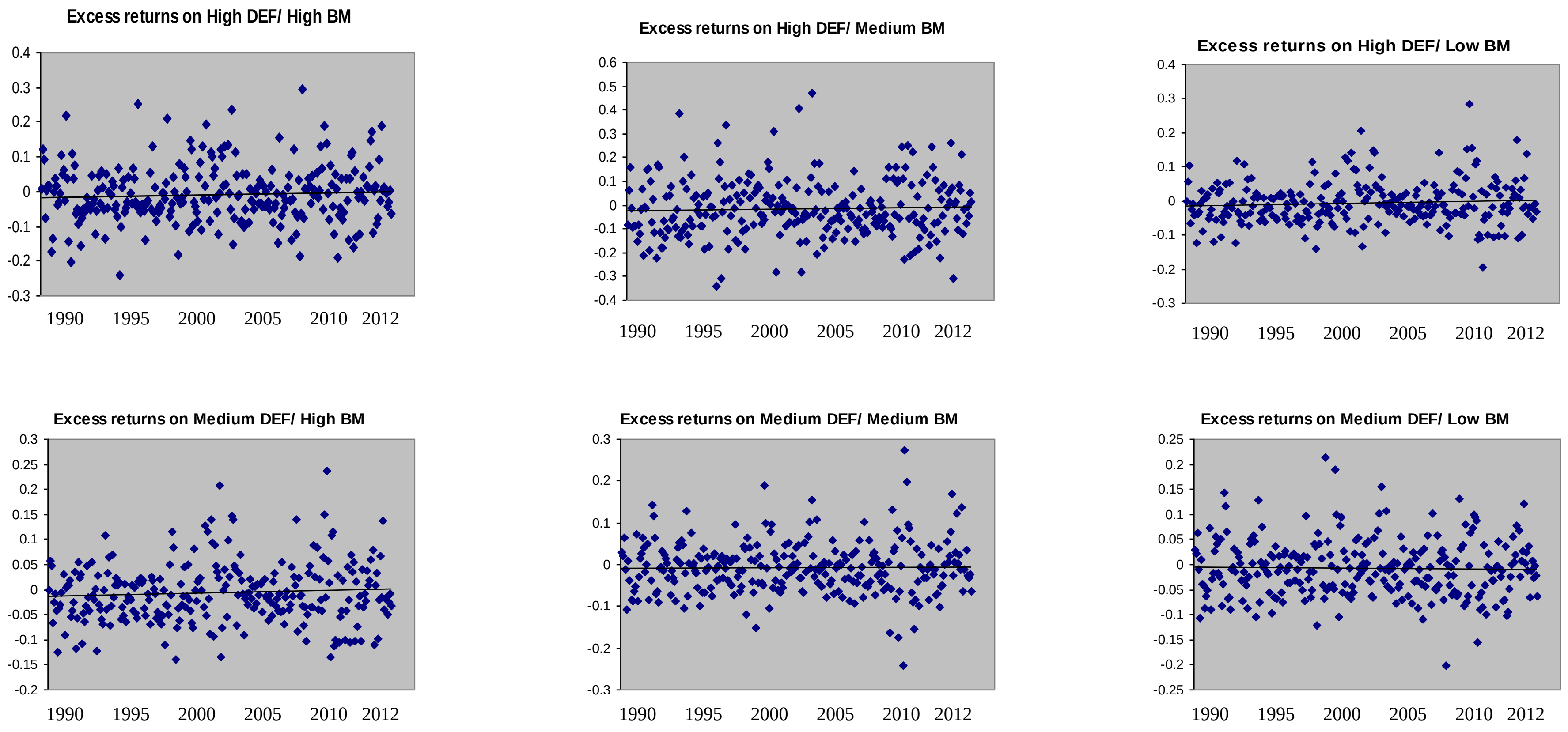
Table 2.3: Characteristics of Chapter 3 dependent variables – Monthly excess returns on 9 Default/BM portfolios

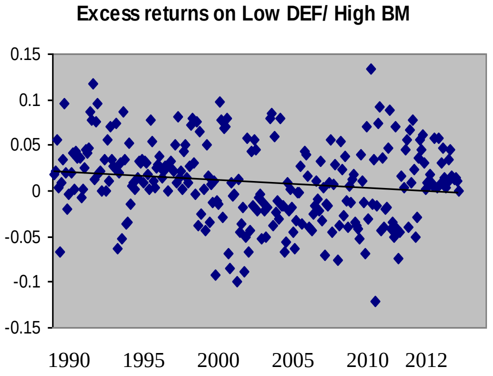
The table summarises descriptive statistics for Chapter 3 dependent variables ($R_i - R_f$), in which R_i are Default/BM portfolios and R_f is the LIBOR 1-month rates. To construct R_i, non-financial stocks are split into High DEF, Medium DEF and Low DEF based on their O-score. The breakpoint used for dependent variables is 40:20:40. At the same time, these stocks are also grouped into High BM, Medium BM and Low BM using the 40:20:40 breakpoint. Nine dependent variables are the intersections between the three DEF and three BM portfolios. For example, the High DEF/Low BM portfolio consists of stocks that are classified as having a high probability of default and are also in the Low BM group. All monthly excess returns are represented in decimal form. Section 3.4.4 of Chapter 3 explains the construction of these portfolios in more detail.

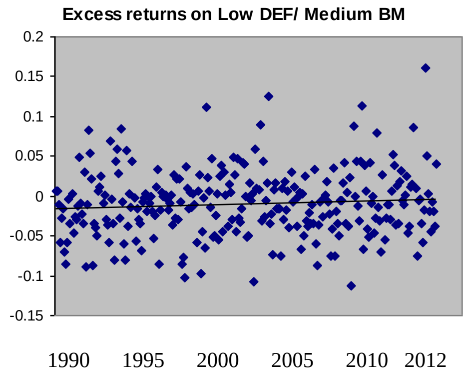
Excess returns	**No. of companies**	**Mean**	**SD**	**Median**	**Max**	**Min**
High DEF/High BM	43	-0.0083	0.0725	-0.0152	0.2939	-0.1812
High DEF/Medium BM	22	-0.0056	0.0842	-0.0092	0.4895	-0.3553
High DEF/Low BM	44	-0.0072	0.0736	-0.0086	0.2857	-0.1945
Medium DEF/High BM	21	-0.0034	0.0632	-0.0027	0.2362	-0.1342
Medium DEF/Medium BM	10	-0.0033	0.0554	-0.0014	0.2729	-0.2415
Medium DEF/Low BM	23	-0.0027	0.0501	-0.0019	0.2103	-0.2010
Low DEF/High BM	43	0.0099	0.0429	0.0045	0.1462	-0.1107
Low DEF/Medium BM	21	0.0021	0.0327	0.0022	0.1603	-0.1123
Low DEF/Low BM	42	0.0019	0.0322	0.0034	0.1348	-0.0902

Figure 2.3: Plotting Chapter 3 dependent variables – Monthly excess returns on 9 Default/BM portfolios

The figures plot monthly excess returns on 9 DEF/BM portfolios, ($R_i - R_f$), over a period from July 1990 to December 2012 (276 data points). Scatter diagrams are used to visualise dependent variables instead of line charts because they could present the extent to which value strategies generate abnormal returns. The Risk-free asset (R_f) is the LIBOR 1-month rate. A trendline is added to show the performance of each portfolio over time. The Y axis shows the value of excess returns on each portfolio (in decimal), and the X axis represents years.




Excess returns on Low DEF/ High BM
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
1990
1995
2000
2005
2010
2012


Excess returns on Low DEF/ Medium BM
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
1990
1995
2000
2005
2010
2012

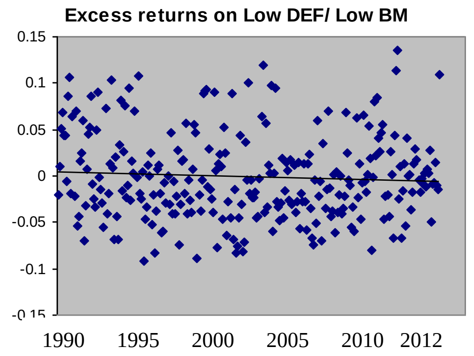

Excess returns on Low DEF/ Low BM
0.15
0.1
0.05
0
-0.05
-0.1
1990
1995
2000
2005
2010
2012

Table 2.4 summaries the characteristics of variables used in Chapter 4. They are the excess returns on 10 momentum portfolios, which are equally split based on their past 6-month returns with a 6-month lag. The excess returns on the Winner and on the Loser portfolios are the dependent variables in the regression analysis in Chapter 4. Each portfolio consists of between 28-30 companies (split equally from a full sample of 290 companies in the FTSE350), and the portfolios are rebalanced annually.

On average, the monthly excess returns on the Loser stocks are much lower than those on the Winners (0.07% and 1.08%, respectively). This indicates that there is a momentum premium among the FTSE350 companies in the long run. The Loser portfolio, however, deviates from the mean at a lower rate than the Winners do. Their standard deviation is 0.0738, with the lowest observed value of -12.17% and the highest value of 27.21%. On the other hand, their Winners counterpart has a standard deviation of 0.0977. The observations range from -25.28% to 44.15%.

Other portfolios that are between the Winners and the Losers in the performance ranking vary in terms of variable properties. The excess return averages unsurprisingly range from the Losers' mean to the Winners' mean. Standard deviations are between 0.0512 (P8 portfolio) and 0.0854 (P3 portfolio). As Chapter 4 focuses on the Winners and the Losers only, portfolios P2 to P9 are less relevant and will not be discussed further.

As can be seen from Figure 2.4, the excess returns on the Losers tend to be negative and more volatile during market downturn periods, such as during the 2008 financial crisis (2008-2010). Their values are more widely scattered than the values of the Winner excess returns. In contrast, the Winner returns tend to be positive and less volatile during the market downturns and achieve higher excess returns during market upturns, for example the post-2010 period. The initial analysis shows that the differing states of the economy and market conditions have a significant impact on the performance of momentum strategies in the UK, and therefore it is important to take these factors into account in explaining momentum anomaly in the study. The performance of these portfolios during different market conditions will be analysed in greater detail in Chapter 4.

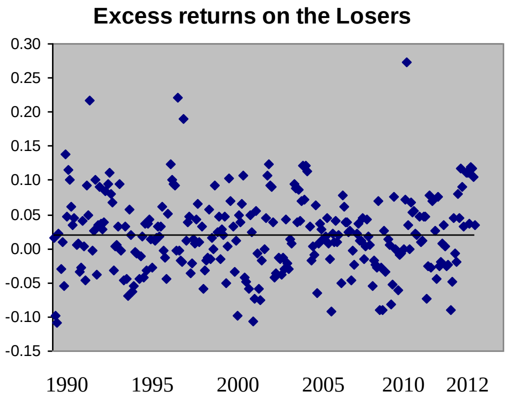
Table 2.4: Monthly excess returns on 10 momentum portfolios (Chapter 4)

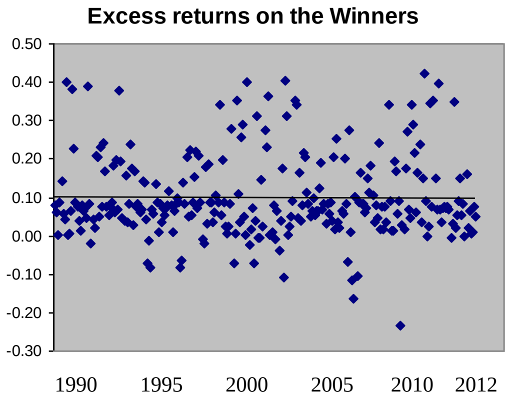
The table summarises descriptive statistics for Chapter 4 dependent variables (R_i – R_f), in which R_i are momentum portfolios and R_f is the LIBOR 1-month rates. To form R_i, a sample of 290 companies (including eligible financial and non-financial firms) is split equally into 10 portfolios based on ranking past 6-month lagged return and hold for 6 months. The lowest past return is denoted by P1 and the highest past return is denoted by P10. That means P1 (P10) consists of 10% of the stocks with the lowest (highest) returns over the previous 6 months. Although 10 momentum portfolios are formed, the dependent variables in Chapter 4 are the excess returns on P1 (the Losers) and P10 (the Winners). All monthly excess returns are represented in decimal form. Section 4.3.2 B of Chapter 4 explains the steps in which these 10 portfolios are constructed in more detail.

Excess returns	No. of companies	Mean	SD	Median	Max	Min
P1	30	0.0007	0.0738	-0.0121	0.2721	-0.1217
P2	28	0.0010	0.0802	-0.0001	0.2979	-0.1509
P3	29	0.0015	0.0854	0.0023	0.3342	-0.2037
P4	29	0.0018	0.0719	-0.0327	0.3419	-0.2315
P5	29	0.0024	0.0650	-0.0165	0.3726	-0.2511
P6	29	0.0027	0.0667	-0.0226	0.3729	-0.2742
P7	29	0.0042	0.0541	-0.0372	0.4125	-0.2119
P8	29	0.0049	0.0512	0.0108	0.4307	-0.2367
P9	29	0.0075	0.0742	-0.0236	0.4397	-0.2809
P10	29	0.0108	0.0977	0.0117	0.4415	-0.2528

Figure 2.4: Plotting Chapter 4 dependent variables – monthly excess returns on Winners and Losers portfolios

Chapter 4 dependent variables are excess returns on 2 momentum portfolios, the Winners and the Losers. Scatter diagrams are used to visualise these dependent variables instead of line charts because they could present the extent to which momentum strategies generate abnormal returns. The figures plot monthly excess returns on the 2 momentum portfolios, (R_i –R_f), over a period from July 1990 to December 2012 (276 data points). 2 momentum portfolios include the Winners (P10), consisting of firms in the top 10%, and the Losers (P1), consisting of firms in the lowest 10% of the sample. The risk-free asset (R_f) is the LIBOR 1-month rate. A trendline is added to show the performance of each portfolio over time. The Y axis shows the value of excess returns on each portfolio (in decimal), and the X axis represents years.





2.5. INDEPENDENT VARIABLES

The section contains a description of each independent variable used in the thesis and the method with which they are constructed. The section also includes a variable correlation matrix and diagrams.

2.5.1. Variable construction

2.5.1.A. Chapter 3 variables

(i) Market factor

The market factor (**R_m - R_f**) is obtained from Prof Kenneth R. French's website[4]. The market return data for the UK market are available under the section "*Country Portfolios formed on B/M, E/P, CE/P and D/P*", in which data on all four valuation ratios (i.e. BM, E/P, C/P and D/P) are not required. According to Prof French's description, the UK market portfolio includes all UK firms with BM data. Although the database also provides market returns on portfolios including only firms with all four ratios, using these data points will undermine the robustness of analyses of the UK market as a large number of UK firms do not provide D/P data or pay zero dividend.

(ii) High-minus-Low

The High-minus-Low (**HML**) variable is constructed to mimic the part of returns associated with the BM effect[5]. At the end of July of year *t*, all eligible stocks are split into 3 portfolios using the 30th and 70th percentile breakpoints (i.e. 30:40:30) based on their BM in June of the same year. The monthly value-weighted returns are rebalanced annually. The return differential between the top 30% BM stocks and the bottom 30% (i.e. HML) is used as a proxy for the BM factor. It is given by the following formula.

$$HML = Returns\ on\ High\ portfolio - Returns\ on\ Low\ portfolio \tag{2.6}$$

While there are different breakpoints used in the value anomaly literature, such as 40:20:40 (in Dimson, Nagel and Quigley 2003), rankings on BM using the 30:40:30 breakpoints are predominant in large markets. These were suggested by Fama and French (1993,1996, 2012) and followed by a large number of subsequent studies, such

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

[5] Although Prof.. French's database also provides calculations of HML and SMB factors for non-US markets, the data are limited to large geographic segments, of which the UK is part of the European segment. Given the size and economic diversity of the European market, it is more accurate to construct the UK factors rather than using the European proxies.

as Griffin and Lemmon (2002) for the UK, Ferguson and Shockley (2003), Zhang (2005) and Cooper (2006) for the US, to name a few. To avoid ambiguity, we use the 30:40:30 breakpoints in the HML calculation to ensure that the stocks in the High and Low portfolios are the most representative of their style.

(iii) Small-minus-Big

The Small-minus-Big (**SMB**) variable is a portfolio-based risk factor associated with the size effect (i.e. market capitalisation). The formula is presented below.

$$SMB = Returns\ on\ Small\ portfolio - \ Returns\ on\ Big\ portfolio \qquad (2.7)$$

Similar to the classification in Fama and French (1993), at the end of July of year *t*, stocks are split into 2 groups by the median. The 1 month allows the factor to capture underlying risks and also avoid possible biases caused by an asymmetric way of treating HML and SMB factors. The monthly portfolio returns are value weighted by the market value at the end of June, year *t*. The return differential between the small-cap stocks and the large-cap is meant to capture the size effect.

(iv) Winner-minus-Loser

The Winner-minus-Loser (**WML**) variable is meant to mimic the momentum factor of Jegadeesh and Titman (1993) in returns. 11-month past returns are used to classify the winners from the losers. The return differential between the top 30% stocks and the bottom 30% stocks means to capture the momentum effects. The monthly portfolio returns are calculated at July, year *t* with 1-month lag and value weighted by the market value at the end of June, year *t*.

$$WML = Returns\ on\ Winner\ portfolio - \ Returns\ on\ Loser\ portfolio \qquad (2.8)$$

It is worth mentioning that the WML factor is provided on Prof. French's website but only for large geographic segments, of which the UK is part of the European segment. Similar to the HML and SMB variables in section 2.4.1.A, the WML variable for the UK market is constructed exclusively on the UK FTSE350 instead of using the European factor as a proxy.

(v) Default risk

Among others, Pope (2010) supports the use of factor mimicking portfolios constructed from default risk and suggests that this would help build more robust factor models of estimating expected returns. This lends support to our approach to constructing default risk factors in this thesis.

Default factor (**DEF**) is constructed to mimic the part of returns associated with risk of bankruptcy.

$$DEF = Returns\ on\ High\ Default\ portfolio - Returns\ on\ Low\ Default\ portfolio \quad (2.9)$$

At the end of July of year *t*, stocks are split into 3 groups at the breakpoints of 30:40:30 based on their probability of bankruptcy, measured by O-scores at the end of December year *t-1*. The portfolio returns are value weighted and rebalanced annually. The monthly return differential between the top 30% O-score stocks and the bottom 30% O-score stocks means to capture the risk of default.

O-score was first proposed by Ohlson (1980), a method that intends to capture the likelihood of a company going bankrupt. The O-score method is entirely based on accounting data when predicting the financial health of a company. O-scores are calculated by the following formula:

$$\begin{aligned}\boldsymbol{O-score} = {} & -1.32 - 0.407\ log\ \frac{Total\ assets}{GNP\ price - level\ index} + 6.03\ \frac{Total\ liabilities}{Total\ assets} \\ & - 1.43\ \frac{Working\ capital}{Total\ assets} + 0.076\ \frac{Current\ liabilities}{Current\ assets} \\ & - 1.72\ (= 1\ if\ total\ liabilities > total\ assets, 0\ otherwise) \\ & - 2.37\ \frac{Net\ income}{Total\ assets} - 1.83\ \frac{Funds\ from\ operations}{Total\ liabilities} \\ & + 0.285\ (= 1\ if\ net\ loss\ for\ last\ two\ years, 0\ otherwise) \\ & - 0.521\ \frac{(Net\ income_t - Net\ income_{t-1})}{|Net\ income_t - Net\ income_{t-1}|} \qquad (2.10)\end{aligned}$$

Ohlson's (1980) O-score can take both positive and negative values, however firms with a negative O-score should simply be interpreted as having zero probability of default. As a general rule, any O-scores that are greater than 0.5 would suggest that the associated firm is likely to go bankrupt within 2 years. All input variables are greater than zero, except *Working capital* and *Net income* which can be negative. The method is useful for assessing a company's financial condition over time as well as benchmarking between companies.

Another default factor (**DEF'**) is constructed in the same way as the above DEF variable, and used for robustness check purposes. The DEF' uses Altman's (1968) Z-score instead of O-score as a proxy for default risks. Accordingly, at the end of July of year *t*, stocks are split into 3 groups based on their probability of bankruptcy, measured by Altman's (1968) Z-scores at the end of December year *t-1*. The portfolio returns are value weighted and rebalanced annually. DEF' is the monthly return differential between the top 30% Z-score stocks and the bottom 30% Z-score stocks. The Z-score is calculated using the formula below:

$$\boldsymbol{Z-score} = 0.012\ \frac{Working\ capital}{Total\ assets} + 0.014\frac{Retained\ earnings}{Total\ assets} + 0.033\frac{EBIT}{Total\ assets} + 0.006\ \frac{Market\ value\ equity}{Book\ value\ of\ total\ debt} + 0.999\ \frac{Sales}{Total\ assets} \tag{2.11}$$

Z-score can take both positive and negative values. Although there are different ways of interpreting Z-score, this thesis follows a useful rule of thumb, according to which companies with Z-scores below 1.8 are likely to go bankrupt while those with Z-scores above 3 have a low likelihood of bankruptcy. All input variables are greater than zero, except *Working capital*, *Retained earnings*, *EBIT,* and *Sales* which can take negative values.

2.5.1.B. Additional variables used in Chapter 4

(i) Campbell, Hilscher and Szilagyi's (2008) probability of corporate failure

From a range of default risk proxies discussed in the literature, the measure of corporate failure risk proposed by Campbell, Hilscher and Szilagyi (2008), henceforth **CHS score**, is a more accurate, complex but well represented empirical measure (Campbell, Hilscher and Szilagyi 2011, and Aretz, Florackis and Kostakis 2017). It includes not only accounting ratios but also market variables when forecasting the risk of bankruptcy. According to Charalambakis, Espenlaub and Garrett (2009), including both accounting and market information would lead to significant improvements in forecasting potential financial distress in UK companies. In their paper, Campbell et al. (2008) find that financially distressed firms generate anomalously low stock returns in the US. However, there have been a limited number of similar studies on the UK market, the area that this thesis aims to contribute to.

Based on CHS scores, the **CHS variable** is constructed to mimic the part of returns associated with risk of corporate failure. Similar to DEF and DEF' variables, at the end of July of year *t*, stocks are split into 3 groups at the breakpoints of 30:40:30 based on their probability of corporate failure, measured by Campbell, Hilscher and Szilagyi's (2008) CHS at the end of December year *t-1*. The portfolio returns are then rebalanced on an annual basis. The return differential between the top 30% CHS score stocks and the bottom 30% CHS score stocks means to capture the risk of corporate failure.

The rest of this sub-section presents a full description of the CHS proxy for corporate failure, how the input variables are collected and the algorithm used to calculate CHS scores. To calculate **CHS score**, we follow three main steps:

Step 1: Selecting predictive indicators

The CHS method first assumes that the probability of failure in month *t* has its marginal distribution, P_{t-1}, following a logistic distribution and being given by:

$$P_{t-1}(Y_{it} = 1) = \frac{1}{(1 + e^{-\alpha-\beta x_{i,t-1}})} \tag{2.12}$$

where Y_{it} equals 1 if the firm goes bankrupt in month *t* and $x_{i,t-1}$ is a vector of each explanatory variable *i* of the regression. We follow the study of Campbell et al. (2008) and include the following predictor variables in constructing the CHS probability of default[6].

NIMTA: Net Income over Market value of Total Asset,

TLMTA: Total Liabilities over Market value of Total Asset,

EXRET: Logarithm of gross excess return over value weighted FTSE350 return,

RSIZE: Logarithm of firm's market value over the total value of the FTSE350,

SIGMA: Standard deviation of firm daily stock returns over a period of three months,

CASHMTA: Cash and short-term investments over the market value of total assets,

MTBV: Firm's market to book value.

[6] See Appendix 3 for mathematical formulae of constructing each variable, proposed by Campbell, Hilscher and Szilagyi (2008).

All the above input variables are collected from the DataStream and Bloomberg databases. Details of the data source, variable definition and the DataStream Mnemonic code (DSMnemonic) are presented in Appendix 2 of the thesis.

In the CHS study, NIMTA and SIGMA aim to measure prospective profitability while EXPET and RSIZE are market-based versions of stock return and market value. A ratio of cash and short-term investments over the market value of the total assets of a firm (CASHMTA) means to proxy for the firm's liquidity position. Other ratios, namely TLMTA and MTBV, are widely used for the purpose of measuring firms' financial health. Table 2.5 summarises descriptive statistics of these variables.

It is worth noting that this chapter does not include the price-per-share variable as the original study did. This is because of the differences in the market index we examine. Unlike the NYSE and NASDAQ based on which Campbell, Hilscher and Szilagyi built their model, the London Stock Exchange does not have a minimum price-per-share requirement. Thus, UK firms are not likely to be de-listed for that reason[7]. Also, there is no reason to associate a low value of the share price with a distress situation. Therefore, price-per-share variable is not relevant in this analysis.

Step 2: Running logit regressions on predictive variables

$$Logit_{t-1} = \alpha_{t-1} + \sum_{i=1}^{n} \beta_i x_{i,t-1} \tag{2.13}$$

Where, $Logit_{t-1}$ is the logit probability of financial distress; and $x_{i,t-1}$ is a vector of the explanatory variable i listed in step 1.

The CHS probability of bankruptcy is estimated from a dynamic logit model (see equation 2.13) using the above range of accounting and equity-related variables. The logit model predicts the probability of an event occurring by estimating a logistic function using several predictor variables. The dependent variable is the bankruptcy indicator provided by DataStream for the UK market. Among delisted firms, firms that were delisted due to bankruptcy are identified by their dead-delisted status in DataStream.

[7] Campbell et al. (2008) explained that since NYSE and NASDAQ have a listing requirement of minimum $1 price per share, US firms with a low price per share would be at risk of being de-listed regardless of their performance. Thus, this variable could be one of the predictors of probability of failure in the US.

Campbell et al. (2008) predict the probability of bankruptcy in 1 month, 6 months, and 1, 2 and 3 years, and report the results in Table 4 (page 2913) of the paper[8]. They find that as they predict further into the future, the predictive power of CHS decreases. In this thesis, a 6-month lag is chosen because the method has a high predictive power and coincides with the way other explanatory variables, such as HML, SMB and WML, are built. This is also to allow for all company information being made available to investors before they make investment decisions.

Following the procedure suggested by Campbell et al. (2008), we also run logit regressions of failure indicators on 6-month lagged variables. This is to estimate the conditional probability of bankruptcy of FTSE350 firms in 6 months. Model (2.13) results in a linear vector of predictive variables. A higher level of the *Logit* implies a higher probability of bankruptcy of failure. The vector parameters are reported in Table 2.6.

The logit model generates a logit value (also called the logit probability of financial distress), and the estimation results in Table 2.6 show that the logit probability is given in the following formula.

$$Logit = -4.0127 - 2.6719\, NIMTA + 0.3361\, TLMTA - 1.8506\, EXRET - 0.2017\, RSIZE + 1.5289\, SIGMA - 2.0152\, CASHMTA + 0.4170\, MTBV \quad (2.14)$$

Where, *Logit* is the logit value or logit probability of financial distress; the definitions of explanatory variables in the equation, such as *NIMTA* and *TLMTA*, are provided earlier in Step 1.

Step 3: Calculating the CHS score

The conditional probability of failure, the CHS score, is computed as follows.

$$P_{t-1}(Y_{it} = 1|Logit_{i,t-1}) = \frac{1}{(1 + e^{-Logit_{t-1}})} \quad (2.15)$$

The CHS score, or $P_{t-1}(Y_{it=1} \mid Logit_{i,\,t-1})$, takes a value between 0 and 1. Companies that have CHS values of between 0 and 0.05 are considered to be relatively safe for investment while companies with a CHS score of between 0.9 and 1 are at risk of bankruptcy.

[8] See Campbell, J.Y., Hilscher, J. and Szilagyi, J. 2008. “In Search of Distress Risk”. *Journal of Finance* Vol. 63 for a complete set of predictive horizons.

CHS scores are computed for all 290 firms in the full sample. These individual company CHS scores are then used to form the CHS variable - a portfolio-based default factor. As mentioned earlier, CHS portfolios are built in the same way that other portfolio-based variables are constructed, which consists of three steps: (a) computing and ranking the CHS scores of each company on a monthly basis; (b) constructing CHS portfolios using the usual 30:40:30 breakpoint; and (c) rebalancing the portfolios annually.

As it is complex and time-consuming to compute company CHS score, this thesis supplies in Appendix 5 a set of source code that can be used to compute CHS variables quickly and correctly. Appendix 5 also explains step by step the role of each procedure, so it is possible to replicate and/or update this code to achieve other research objectives. The code is written in Visual Basic for Applications (VBA) programming language, but it is possible to use other programming languages to generate CHS values following the procedure described in the Appendix.

Despite recognising the advantages of CHS, we do not intend to engage in the debate on whether it is a better measure of default risk than its predecessors. As Hilscher and Wilson (2016) point out, due to the multidimensional nature of bankruptcy risk, one should not expect that one measure alone could capture all relevant factors.

(ii) Business cycle variables

Default spread - In this thesis, default spread (**DES**) is defined as the difference between the monthly average yields on corporate bonds and on long-term Government bonds (UK Gilt with a 15+ year maturity).

$$DES = Yields\ on\ Corporate\ bonds - UK\ Gilt\ 15 + years \tag{2.16}$$

Studies in the US may use different proxies for firm default spread as an indicator for the state of the economy. For example, Avramov and Chordia (2006) use the spread between yield to maturity on low-graded and high-graded corporate bonds, while Hahn and Lee (2006) define DES as the yield differential between a Baa corporate bond index and a 10-year Treasury constant maturity rate. However, when carrying out an analysis on systemic risk in the US and European markets, Giglio, Kelly and Pruitt (2016) note that these approaches are not suitable for most European markets, the UK in particular, due to lack of data.

By definition, default spread is meant to capture the hedging concerns of investors associated with variations in risk premiums (Jagannathan and Wang 1996). For the UK market, corporate bond and UK Gilts are usually used for such diversification purposes.

Term spread – (**TERM**) is the difference between monthly average returns on long-term and short-term Government bonds. In the case of the UK market, we use the return differential between 15+ year Gilt and 3-month yields. TERM and DES are widely used as proxies for the state of an economy since Merton (1973). Generally, TERM is used as an indicator of changes in market's expectation about future interest rates, and DES is to capture the effect of shifts in investment opportunities on investors.

$$TERM = UK\ Gilt\ 15 + year - LIBOR\ 3month \tag{2.17}$$

Dividend yield – (**DIV**) refers to the monthly average value-weighted dividend yield of all stocks in the sample. It is also one of business cycle variables widely used in the asset pricing literature.

$$DIV = \frac{\sum_{i=1}^{n} Dividend\ yield_i}{n} \tag{2.18}$$

Short-term Treasury Bill - The 3-month LIBOR rate of return is used to proxy for the short-term Treasury bill (**T-Bill**) for the UK market. As LIBOR is recorded on an annual basis, monthly T-Bill rates are calculated by converting the annual LIBOR to compound monthly rate of returns.

2.5.2. Descriptive statistics

This section starts with descriptive statistics for default risk indicators since they have not been reported explicitly for the UK in the literature. It then focuses on describing the key features of all regression explanatory variables used in the thesis analysis.

2.5.2.A. Default risk component

(i) CHS probability of corporate failure

This section will provide a description of the CHS score and its composite variables through three main stages.

Firstly, Table 2.5 summarises the key descriptive statistics of seven components that make up the CHS probability of bankruptcy as at 31st December 2012. In the table, there is evidence of a wide representation of firms with different sizes, operating performance (net income) and financial positions (e.g. cash and liabilities) in the FTSE350.

On average, net income over market value of total asset ratios across firms, NIMTA, is rather high at 68.25 with a median value of 65.56. The firm with the highest NIMTA in the FTSE350 is Polymetal International Plc. (at 2,712), a precious metals producer operating in Russia and Kazakhstan, and the firm with the greatest loss in comparison to its market value is Thomas Cook Group, a leisure travel group (at -1,356). In terms of liabilities, both the highest and the lowest TLMTA ratios are firms in the financial sector, Phoenix Group Holding and BH Marco, respectively. This is unsurprising because liability ratios in the financial industry tend to vary largely. They can signal but do not always reflect firms' financial positions as well as they do in the non-financial sector. In addition, the ratios between firms' cash and short-term investments over market value of total assets range from 0.08 to 0.67 with a mean of 0.23. The low ratios of these most liquid assets imply a high risk of default in the short run.

Regarding market-based variables, the large negative RSIZE shows that the size of the firms in our sample are considerably small in comparison to the total market value of the FTSE350 index. However, their market-to-book-value ratios differ greatly from each other, ranging from nearly -31 to +198. This suggests that our sample covers firms in various financial conditions. From the stock return standpoint, EXRET shows that on average the returns on individual stocks are slightly larger than those on the FTSE350 index. The return differentials are however insignificant. Low SIGMA values suggest a low stock return volatility over the most recent 3-month period. The absolute value of the FTSE350 stock average returns is 0.11 per month, ranging from 0.02 to 0.67, with a standard deviation of only 0.08.

Secondly, the next step is to run a logit regression on the above set of predictors and the results are summarised in Table 2.6. They show that out of 290 FTSE350 companies, there were 8 companies which were at high risk of default. In fact, 7 of them later went into financial distress, such as Northern Rock, being delisted in 2008, and the Royal Bank of Scotland, which was rescued by the government through a large bailout of £45bn in 2008. This shows an 87.5% accuracy, slightly lower than the 95.5% accuracy ratio reported by Campbell et al. (2008) for the US market.

As can be seen from the table, all predictive variables entering the logit regression with expected signs, and are statistically significant at a 1% or 5% level. The constant value is -4.0127 with a z-statistic of 18.22 in absolute terms. The estimated coefficient associated with NIMTA takes the value of -2.6719 (z-statistic is 4.12, statistically significant at a 1% level). The value of NIMTA is relatively high compared with other predictive indicators. This indicates that net income is one of the key indicators that could help investors to spot early signs of impending corporate failure. A company with lower net income over market value of total assets is more likely to experience financial distress, and a consecutive period of low or negative NIMTA signals default. Total liabilities over market value of total assets, TLMTA, can also contribute to identifying the risk of bankruptcy. The estimated TLMTA parameter takes the value of 0.3361 with a z-statistic of 8.53 (significant at a 1% level). Although having liabilities does not necessarily mean the company is under distress, a high ratio of liabilities over total assets means the company would struggle to repay its debts, and a long period of high TLMTA ratio could lead to default.

Beside the above accounting ratios, it is equally important to include market-related variables. For example, one of the key indicators predicting the probability of corporate failure is gross stock excess return over the market return. For the UK market, this thesis defines EXRET variable as the logarithm of gross excess return over the value weighted FTSE350 return. It shows how stocks of a company perform against the whole market. The coefficient associated with EXRET variable is estimated to be -1.8506, with z-statistic of 7.26 in absolute terms, which is statistically significant. A company whose stocks are being valued poorly by the market and/or is persistently underperforming the market tends to bear a higher level of diversifiable risk. The risk would be in the form of firm-specific reputational risk or operational risk. Since these risks can be mitigated through portfolio diversification, when investors are moving away from investing in these companies, they would then face further distress and even default if the problem persists.

Firm size in relation to the market size is also considered to be a relevant predictive indicator of financial distress. It means that smaller firms are more likely to experience difficulties in raising finance, securing favourable deals or attracting talent. However, in the UK market there is evidence suggesting that size plays a less significant role in predicting probability of bankruptcy. The estimated coefficient associated with the

RSIZE parameter is only -0.2017, slightly significant at a 10% level with a z-statistic of 2.48 in absolute terms. This finding is later confirmed in the subsequent chapters on the relationship between firm size and performance of individual stocks.

Similarly, market-to-book value ratio, MTBV, has been referred to as one of the key indicators explaining common stock returns in the asset pricing literature. According to the literature, companies with high market capitalisation in relation to their book value are considered to be overvalued by the market and would potentially be a less profitable investment. In the context of corporate failure prediction, assessment of firms' MTBV would shed light on how the market prices a company in the stock market. The coefficient associated with the MTBV variable is estimated to be 0.4170 (z-statistic is 3.56, statistically significant at a 1% level). A company with a high MTBV ratio is considered to be overpriced by the market, and therefore at higher risk of default as this situation is unlikely to be sustainable.

Another equity-related indicator that Campbell et al. (2008) proposed in the CHS regression relates to past stock returns. SIGMA is calculated by taking a square root of a sum of squared stock returns over a three-month period. Higher returns on equity may indicate that a company performs relatively well in comparison to their counterparts. The estimated coefficient associated with SIGMA takes the value of 1.5289 (z-statistic is 3.72, highly significant at a 1% level). The sign and magnitude of the coefficient suggests that the likelihood of failure is sensitive to past performance of stocks. However, the predictive ability is not as strong as many of the other indicators presented so far. One might relate SIGMA to momentum factor which is discussed later in Chapters 3 and 4. Although they are put in a different context, the findings in these chapters also suggest that past stock returns can contribute to predicting future stock performance, but the explanatory power is not consistently significant across the FTSE350 companies.

Campbell et al. (2008) also suggested the inclusion of the CASHMTA variable which captures a company's cash and short-term investment in relation to its market value of total assets. This is justifiable as CASHMTA is considered to be highly liquid assets which indicate the company's ability to cover short-term debt. Thus, the variable has been widely used in accounting and finance as a key indicator of immediate financial distress. The estimated coefficient associated with CASHMTA is negative (at -2.0152) and highly significant, indicating that companies with a low level of cash and short-term investment in relation to their total assets are more likely to face default.

Following Campbell et al. (2008), Table 2.6 reports McFadden's R^2 (also known as *Pseudo* R^2), a commonly used measure of model fit in the bankruptcy prediction literature. The *Pseudo* R^2 shows how a predictive model performs in relation to a model that only can capture the average default rate. According to McFadden (1974), a completely failed model would have a *Pseudo* R^2 of zero. In table 2.6, the *Pseudo* R^2 is equal to 21.35%, indicating a high level of predictive ability. It is lower than 31.6%, the *Pseudo* R^2 reported by Campbell et al. (2008) for the US market. This indicates that there is still room for further improvement through including country-specific variables. For example, there are some UK stocks experiencing thin trading or no trading at all for a considerable period of time. Thus, variables such as stock liquidity could be a potential predictive indicator.

Table 2.5: Descriptive Statistics for CHS composite variables

The table presents descriptive statistics of the key composite indicators making up the CHS proxy, including: Net income over market value of total assets (NIMTA), Total liabilities over market value of total assets (TLMTA), Logarithm of gross excess return over value weighted FTSE350 return (EXRET), Logarithm of firms' market value over the total value of FTSE350 (RSIZE), Square root of a sum of squared firm stock returns over a period of three months (SIGMA), Cash and short-term investments over the market value of total assets (CASHMTA), and Market-to-book value (MTBV).

As at 31st December 2012.

	Mean	**SD**	**Median**	**Max**	**Min**
NIMTA	68.25	198.73	65.56	2,712.32	-1,357.53
TLMTA	2,517	8,801	541	104,286	0
EXRET	0.01	0.07	0.01	0.46	-0.53
RSIZE	-6.83	1.26	-7.07	-2.74	-8.60
SIGMA	0.11	0.08	0.09	0.67	0.02
CASHMTA	0.23	1.34	0.25	0.67	0.08
MTBV	3.48	11.50	1.97	197.62	-30.89

Table 2.6: CHS predictions of default risk

The table summarises estimated parameters of logit regressions of Campbell, Hilscher and Szilagyi's (2008) bankruptcy indicator. The regression predictors are Net income over market value of total assets (NIMTA), Total liabilities over market value of total assets (TLMTA), Logarithm of gross excess return over value weighted FTSE350 return (EXRET), Logarithm of firms' market value over the total value of FTSE350 (RSIZE), Square root of a sum of squared firm stock returns over a period of three months (SIGMA), Cash and short-term investments over the market value of total assets (CASHMTA), and Market-to-book value (MTBV). Z-statistics are calculated based on the model standard errors. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

Variable	Coefficient	|z -statistic|
Constant	-4.0127	18.22***
NIMTA	-2.6719	4.12***
TLMTA	0.3361	8.53***
EXRET	-1.8506	7.26***
RSIZE	-0.2017	2.48**
SIGMA	1.5289	3.72***
CASHMTA	-2.0152	4.01***
MTBV	0.4170	3.56***
Number of defaults	7	
Firm-month observations	79246	
Number of firms in the sample	290	
Likelihood ratio $\chi 2$	1063.17***	
Pseudo R-squared	0.2135	

Thirdly, we computed CHS score using model (2.15) and its descriptive statistics are summarised in Table 2.7. The CHS score is reported alongside the O-score and Z-score. It is important, however, to note that these three default indicators are calculated using different methods, and therefore are not to be compared against each other. Interpretations of their score values are discussed in turn as follows.

CHS scores reported in Table 2.7 show that the majority of FTSE350 companies are in a healthy financial position. On average, the CHS scores are at approximately 42%. Given that companies with a CHS score of between 0.9 and 1 are considered to be at risk, the CHS mean of 0.42 is relatively low. The standard deviation of CHS scores is also low, being at 0.53. This shows that most of the FTSE350 companies bear low default risk and they are not experiencing volatile performance. The CHS score ranges from almost zero to 0.98 with a median value of 0.47. Among a total sample of 290 companies, there are 8 companies whose CHS scores are between 0.9 and 1. They are, therefore, classified as highly distressed companies. As mentioned earlier in this section, of those 8 highly distressed firms, 7 companies (87.5%) in fact went bankrupt or required rescue by the government within the period within a 12-month lag.

Table 2.7: Descriptive statistics for default risk indicators

This table summarises descriptive statistics of three proxies for default risk component, Ohlson's (1980) O-score, Altman's (1968) Z-score and Campbell, Hilscher and Szilagyi's (2008) CHS score. Section 2.5.1 provides a full description of how each default indicator is constructed.

	Mean	**SD**	**Median**	**Max**	**Min**
CHS score	0.42	0.53	0.47	0.98	0.00
O-score	0.16	1.81	0.09	1.05	-0.27
Z-score	3.35	6.10	3.47	4.11	-2.14

(ii) O-score

O-score is computed entirely based on accounting data when predicting the financial health of a company. As the method is useful for benchmarking between companies, in this thesis O-scores are used to rank companies for DEF variable formation. Although accounting information is traditionally regarded as a fundamental predictive indicator of a company's financial condition, the study finds that identifying high risk firms based on O-score is less accurate in comparison with using CHS. The O-score approach predicts 11 companies being in financial distress and likely to default within 2 years, but in fact only 7 of them later went bankrupt or were bailed out by the government. The accuracy ratio of the O-score method at a 2-year horizon is 63.6%, compared with 87.5% achieved using the CHS approach (at a 12-month horizon). One of the reasons would be that the predictive accuracy tends to decrease with longer horizons. However, Campbell et al. (2008), among others, did find that the CHS method achieves a better predictive power than the O-score method.

As can be seen from Table 2.7, on average O-scores across the sample are 0.16, with a standard deviation of 1.81. The relatively low standard deviation means that the financial conditions of FTSE350 companies are generally on a similar level. This confirms the previous observation by the CHS method. The O-scores range from -0.27 to 1.05, and the median is 0.09. However, firms with a negative O-score should simply be interpreted as having a close-to-zero probability of default. Since the majority of the companies have an O-score that is lower than 0.5, it can be said that the UK market was relatively stable over the testing period between 1990 and 2012.

(iii) Z-score

Another accounting model that is meant to predict default probability is the Z-score model first proposed by Altman (1968). As a rule of thumb, companies with Z-scores below 1.8 are likely to go bankrupt while those with Z-scores above 3 have a low likelihood of bankruptcy. The Z-score approach predicts 12 companies in distress, of which only 2 firms actually went into financial distress, while it misses 3 firms. The accuracy of the Z-score method is the lowest of the three predictive indicators. In Table 2.7, the mean of the Z-scores is approximately 3.35, suggesting that most companies in the sample have either average or low probability of going into default. The values of the Z-scores range between -2.14 and 4,11, around the median of 3.47. These show that the majority of companies in the FTSE350 have a Z-score that exceeds 3, implying a low probability of default.

There have been a number of studies suggesting that the Z-score approach was originally based on a small testing sample and the measure did not achieve a high predictive power (Amendola, Giordano, Parrella and Restaino 2017). However, Z-scores are still used as a supplementary indicator in identifying potential financial distress (see Hilscher and Wilson 2016, and Delis, Hasan and Mylonidis 2017 for examples). In this thesis, Z-scores are primarily used for robustness check purposes. It is used to form a Default variable (*DEF'*) by sorting stocks into portfolios based on their Z-score, and the DEF' is defined as the return differentials between the High and the Low Z-score portfolios.

2.5.2.B. Characteristics of the independent variables

This section will present descriptive statistics of all independent variables employed in the thesis. They include the FF three factors, Carhart's momentum element, default factors (based on CHS, O-score and Z-score), and business cycle variables. The descriptive statistics are summarised in Table 2.8. They are discussed in turn as follows.

The section starts by describing the main characteristics of the FF three factors. Firstly, the market variable, or market excess return $(R_m - R_f)$, has a mean value of 0.76% per month, and a standard deviation at 0.0417. This shows that in the long run, well diversified investment would generate positive returns and the returns would tend to be higher than the LIBOR 1-month rate. The excess returns on the market range from -12.64% to 11.30%. The period during which the market experienced particularly poor performance in comparison with the risk-free asset was during the 2008 financial crisis. Overall, the market portfolio performs consistently better than the risk-free asset, except during recessions. Secondly, the HML variable, which is formed from High and Low BM portfolios, is a time-series variable whose values range between -0.0894 and 0.1141 around a median of -0.0008. The mean of the HML variable is equal to 0.07% and standard deviation is at 0.0274. The positive value of the mean suggests that, in general, a BM effect exists among common stock returns in the UK. The last FF factor is SMB which is meant to mimic the risk factor associated with the size effect in common stock returns. The monthly average value of the SMB variable is 0.47%, ranging from -13.23% to 10.15%. It can be said that although there is a size effect in the market, the magnitude of the effect varies considerably over the 276-month testing period.

In Table 2.8, it is noted that momentum variable, WML, has a relatively high mean (0.89%) but a standard deviation (0.0405), suggesting that the variable deviates greatly from its mean. The momentum variable can reach a peak value of 41.15%, but can also plunge to -18.06%. The WML variable is meant to mimic the risk factor associated with momentum effect in average stock returns. Therefore, including a momentum variable would contribute to identifying any risk patterns associated with past performance but which has not been captured by other factors.

Table 2.8 also summarises the descriptive statistics of the default variable, proxied by 3 different measures of default likelihood: DEF (based on O-score), DEF' (based on Z-score), and CHS (based on CHS scores). From the table, it is worth noticing that although the three variables are proxies for the same risk element, their characteristics differ significantly from each other. These would therefore be particularly beneficial for robustness checks as the three variables tend not to be correlated. Therefore, they are more likely to be able to capture the risk element missed by the other proxies, if any, in a regression analysis. The DEF variable has a mean value of -0.39% with a standard deviation of only 0.0126. It ranges from -4.56% to 4.01% over the period between 31st January 1990 and 31st December 2012. In terms of the DEF' variable, the characteristics are largely similar. The DEF' averages -0.15% per month, with a maximum value of 3.36%, and a minimum value of -7.82%. The standard deviation of the variable is equal to 0.0123. One explanation would be that their based indicators, Z-score and O-score, are both accounting-based measures. In contrast, the CHS variable, which is constructed from accounting and market data, has a mean of 0.18%, ranging from a minimum value of -1.32% to a maximum value of 3.36%. The standard deviation of the variable is at 0.0237, higher than the previous default variables. This indicates that the risk element associated with the market tends to be more volatile and therefore more difficult to capture through accounting-only measures. Therefore, including the CHS variable would potentially improve the predictive power of the analysis in this thesis.

The last group of explanatory variables the thesis employed in value and momentum anomaly analyses is business cycle variables. They are meant to capture changes in investment opportunities and the risk associated with these changes. The first variable of this group is default spread, DES, which averages 2.25% per month. The variable ranges from a minimum value of -1.45% to a maximum of 7.22%. The variable standard deviation is 0.0424, the highest among the 11 independent variables considered in this thesis. This indicates that the return differentials between corporate bonds and long-term Government bonds varied considerably over the last 276 months. Term spread (*TERM*) is heavily dependent on the Government's decisions on Government bond rates (both long- and short-term). Over the sample period, TERM has an average of 1.10%, ranging between -0.19% and 6.54%. Dividend yield variable (DIV) averages 5.26%, which is relatively high, with a standard deviation of 0.0368. This reflects diverse dividend policies among UK firms. On the contrary, the short-term Treasury bill rate (T-Bill), is relatively stable over the same period. The variable has a low mean of 0.45%, and does not deviate significantly from the mean (a standard deviation of only 0.0026). Although T-Bill has not been set at negative rates, the returns of investing in T-Bill, one of the safest assets in the market, are significantly lower than on other types of investment.

Table 2.8: Descriptive statistics for explanatory variables

The table presents descriptive statistics of explanatory variables used in Chapters 3 and 4. The excess return on the market portfolio (also known as market premium), (R_m - R_f), is obtained from Prof Kenneth R. French's website for the UK market. HML and SMB variables are constructed similarly to the way Fama and French (1993) built these factors, which are meant to mimic BM and size effects in expected stock returns using the same breakpoints. The HML is the difference in monthly value-weighted returns of stocks in the top 30% BM and the bottom 30% BM ranking groups. The SMB is monthly return differentials between Small size stocks and Big size stocks by market capitalisation. The Small and Big companies are separated by the median. The WML variable is meant to mimic the momentum factor of Jegadeesh and Titman (1993) in returns. 11-month past returns are used to classify the Winners from the Losers. The WML is monthly return differentials between the top 30% stocks and the bottom 30% stocks by past returns. Default factor (DEF) is the difference in monthly value-weighted returns of stocks in the top 30% and the bottom 30% O-score ranking groups. For robustness check purposes, another default factor called DEF', is formed using Z-score instead of O-score as a proxy for firms' default risk. The DEF' is the monthly return differentials between the top 30% and the bottom 30% Z-score stocks.

In Chapter 4, instead of relying on the traditional O-score and Z-score, Campbell, Hilscher and Szilagyi (2008) proposed the use of CHS scores as a proxy for the probability of corporate failure. The formula for calculating CHS scores can be found in Section 2.5.1B earlier in this chapter. Next, the CHS variable is measured as monthly return differentials between the top 30% CHS score stocks and the bottom 30% CHS score stocks. DES is default spread, which is defined as the difference between the average yields on corporate bonds and long-term Government bonds. TERM is term spread, defined as return differentials between monthly average returns on long-term and short-term Government bonds. In the case of the UK market, we use the monthly return differential between 15+ year Gilt and 3-month yields. DIV is dividend yield, referring to the value-weighted average of dividend yields across the sample. T-Bill or short-term Treasury bill is the LIBOR 3-month. All variables are computed on a monthly basis.

Chapter 3	**Mean**	**SD**	**Median**	**Max**	**Min**
(R_m – R_f)	0.0076	0.0417	0.0113	0.1130	-0.1264
HML	0.0007	0.0274	-0.0008	0.1141	-0.0894
SMB	0.0047	0.0361	0.0049	0.1015	-0.1323
WML	0.0089	0.0405	0.0041	0.4115	-0.1806
DEF	-0.0039	0.0126	0.0017	0.0401	-0.0456
DEF'	-0.0015	0.0123	0.0081	0.0336	-0.0782
Chapter 4	**Mean**	**SD**	**Median**	**Max**	**Min**
CHS	0.0018	0.0237	0.0106	0.0614	-0.0132
DES	0.0225	0.0424	0.0117	0.0722	-0.0145
TERM	0.0110	0.0220	0.0007	0.0654	-0.0019
DIV	0.0526	0.0368	0.0623	0.1502	0.0063
T-Bill	0.0045	0.0026	0.0043	0.0109	0.0004

2.5.3. Graphing independent variables

This section provides visualisations of independent variables that are used in explaining value anomaly (in Chapter 3) and momentum (in Chapter 4). Together with variable descriptive statistics discussed earlier in Section 2.5.2, visualising the variables will provide a full picture of variables used in the thesis regression analysis.

As mentioned earlier in Section 2.4.1, this chapter uses line graphs to display independent variables instead of using scatter diagrams. The reason is that for independent variables, line charts could capture the *risk patterns* and *value changes over time* which potentially explain the dependent variables. Nevertheless, scatter diagrams would be more suitable for visualising dependent variables as they draw attention to the *magnitude* of abnormal returns generated by value and momentum strategies. This is only for presentation purposes and should not in any way affect the regression analysis in the rest of the thesis.

As can be seen from Panel A of Figure 2.5, the market, HML and SMB variables show characteristics of a stationary time-series. Their values over the period from 1990 to 2012 vary around the mean, and seem to be more volatile during the 2008 financial crisis. Among the three FF factors, the HML variable has the lowest mean (0.0007) and deviates less from its mean (standard deviation is only 0.0274). All three FF variables were highly negative during the period between 2008 and early 2010.

The WML factor is relatively volatile and unpredictable. It is noted that the WML was largely positive during the pre-1998 period, and turned to negative during the 1998-2001 period before fluctuating within a clear trend. In the late 1990s, when the momentum effect became widely documented, it could be the case that the generated abnormal profit was less likely to persist. The WML variable also experienced a negative shock during the 2008 financial crisis but returned to positive in 2011.

In regard to default variables, Chapter 3 includes two default factors, DEF and DEF', which are based on ranking firms' O-score and Z-score. Beside these proxies, Chapter 4 uses an additional default variable called CHS which is based on CHS score - a more recent and well-developed indicator of corporate failure. Figure 2.5 shows that firms with a high risk of default tend to perform poorly in the long run. They mostly generated negative premiums, and became profitable just before the 2008 financial crisis before returning to negative values.

Unlike the default variable, the default spreads variable (DES) is meant to capture firm distress risk associated with corporate bonds. Thus, this would potentially capture different risk elements. Default factor is associated with companies' accounting performance while default spreads are linked to performance of their corporate bonds. DES is defined as the yield differentials between corporate bonds and long-term Government bonds. In the UK, the Gilt 15+ year bonds are selected to be the proxy for long-term Government bonds. The DES factor is, therefore, heavily dependent on the Government's decisions on the Gilt 15+ year bond yields, such as 15-year, 20-year and 30-year bonds. The UK bond yield rates over 15+ year maturities were set at high rates during the period prior to 1994. They were between 98.2% and 124.7% per annum (or 5.7% to 7.0% per month). Since January 1994, the Gilt 15+ year bond yields were kept at a much lower level of between 2.1% and 8.8% per annum (or 0.2% and 0.7 per month). These explain the sharp increase in DES values in 1994. However, the large default spreads started to decline in 1998-1999 when corporate bond yields decreased while the Gilt bond yields remained low. The 2008 financial crisis saw companies lowering their bond yields as they were facing financial difficulties. The post-crisis period witnessed a strong recovery of corporate bonds against the Gilt 15+ year bonds.

Another business cycle variable is term spread, TERM, which refers to the return differentials between long-term and short-term Government bonds (i.e. between 15+ year Gilt and 3-month yields). As mentioned earlier, the Gilt 15+ year bond yields were set at a high rate before being cut by almost 85% to 0.53% per month in the beginning of 1994. Over that same period of time, the 3-month rates were relatively stable at around 0.44% per month. That explains the sudden drop in value of TERM in 1994.

Dividend yield, DIV, is defined as the value-weighted average of dividend yields that all companies in the sample paid over the sample period. As can be seen from Panel B of Figure 2.5, DIV decreased significantly over the sample period (1990-2012). This is because since 1990, there were an increasing number of UK companies paying no dividend. Especially during the dotcom boom of 2000-2001, the proportion of FTSE350 firms who did not pay any dividend was at a record high[9].

The last of 4 business cycle variables is the short-term Treasury bill, T-Bill, which refers to LIBOR 3-month rates. The diagram in Figure 2.5 shows that T-Bill was declining

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[9] "Many FTSE 350 companies paying no dividend", *The Financial Times*, 7th October, 2012.

during the sample period, but the most noticeable cutbacks were in August 1992 which saw T-Bill fall by 0.1%, November 2008 when the LIBOR 3-month dropped from 0.46% to 0.26% per month, and when it was cut further to 0.08% in March 2009. Since then, the T-Bill rates have been kept at a low level of between 0.04% and 0.07% per month.

Figure 2.5: Graphing independent variables

The figures below display visualisations of the independent variables used in Chapters 3 and 4. Line graphs are used to visualise independent variables because they could potentially show the risk patterns and changes in magnitude of independent variables. Independent variables are time series variables and constructed on a monthly basis. See notes in Table 2.8 for variable formation. The data covers a period between July 1990 and December 2012 (276 data points). The Y axis shows the values of the variable in question while the X axis represents time.

Panel A: Chapter 3 independent variables

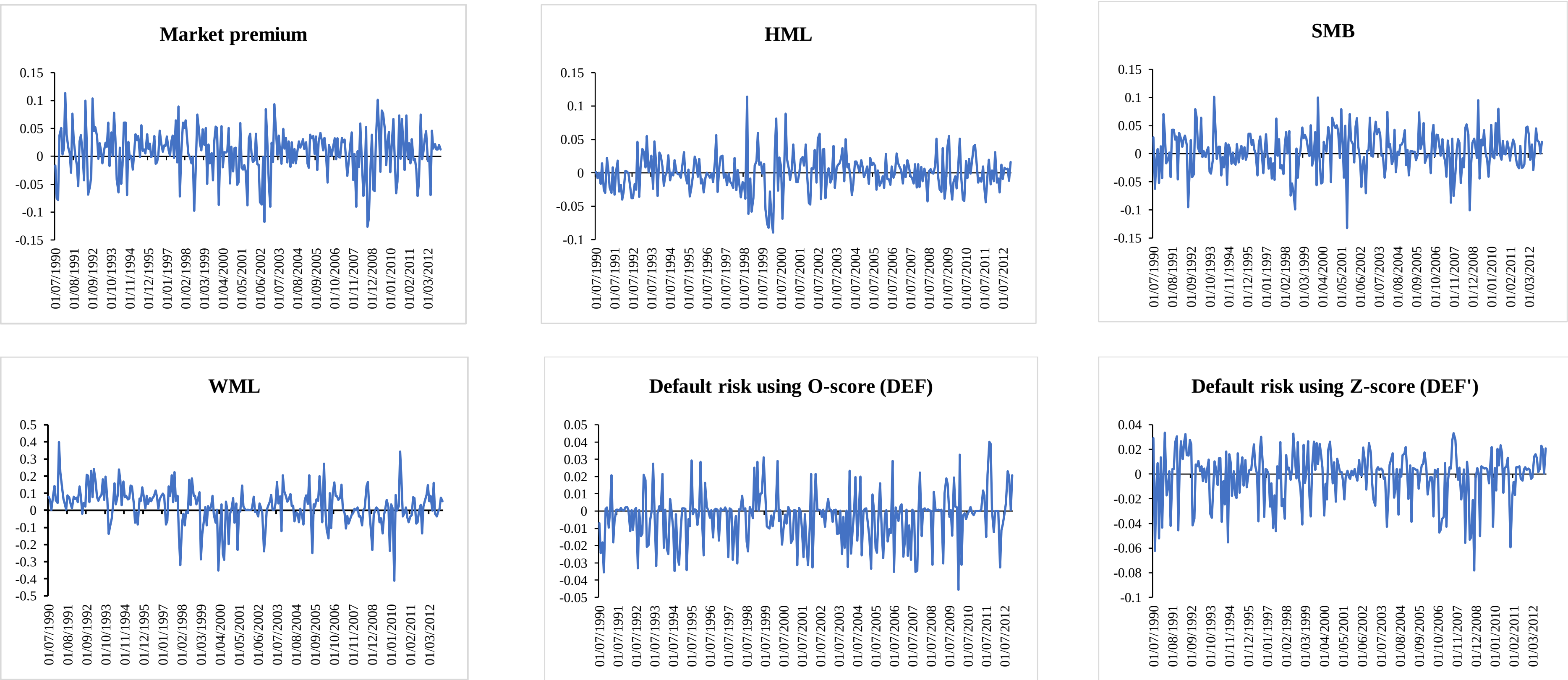
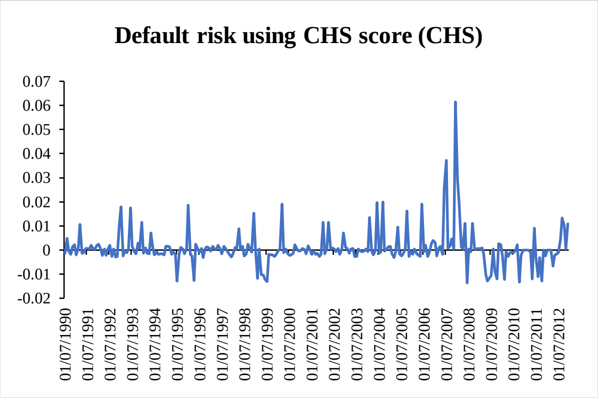
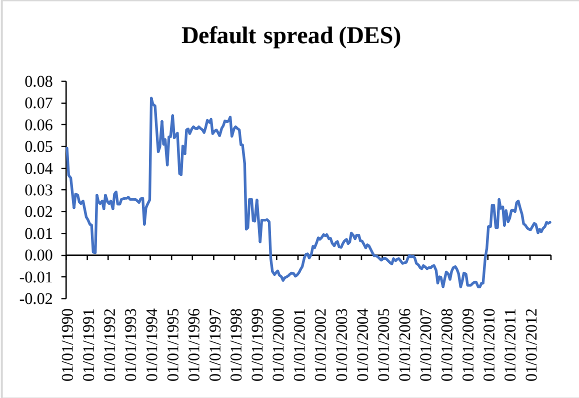
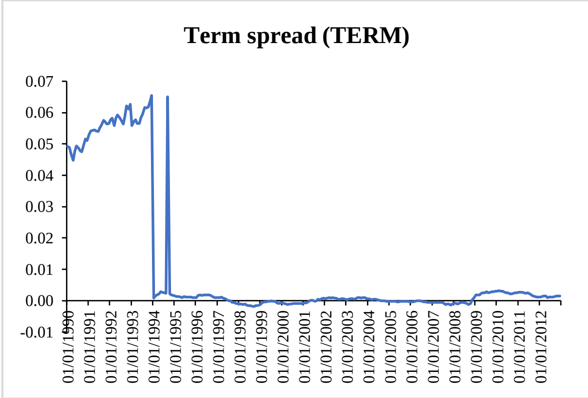


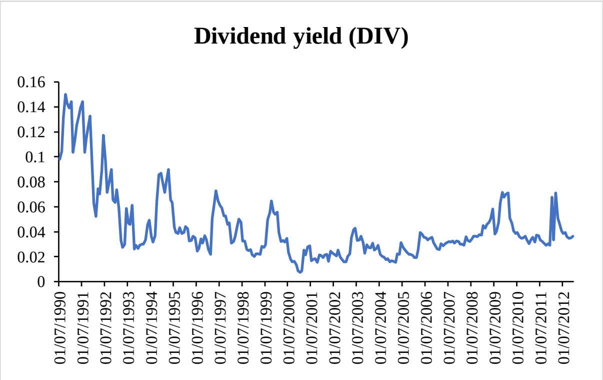
Figure 2.5 - Continued

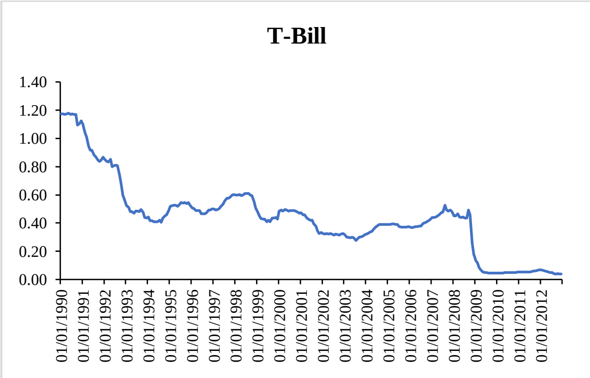
Panel B: Chapter 4 independent variables











2.5.4. Correlation matrix

This section summarises the correlation between explanatory variables used in each chapter. The correlation between each variable pair is computed using the longest coinciding sample available for the pair.

Panel A of Table 2.9 reports Pearson correlation coefficients between the independent variables used in Chapter 3. In the panel, there is no evidence that explanatory variables are correlated. The majority of correlation coefficients are low and less than 0.50 in absolute terms. The only exception is the relationship between two default variables, DEF and DEF'. Their correlation coefficient is 0.86, suggesting that if one variable increases, it is likely that the other variable will also increase. As both variables aim to capture the same type of risk, it is unsurprising that they are highly correlated. If DEF and DEF' indeed have the ability to identify firms with a high probability of default, they should report the same or largely similar conclusions as to which firms are likely to go bankrupt in the near future. In the thesis, DEF' is an alternative proxy for DEF, and only used in robustness checks of the results from analysis on the DEF variable. Thus, although they are highly correlated, this should not affect the accuracy of the analysis.

As can be seen from Panel A, the market variable has a positive correlation with BM and size effects, but is negatively correlated with momentum and default factors. The Pearson correlation coefficients between (R_m-R_f) and HML, and SMB are relatively low at 0.04 and 0.01, respectively. These show that BM and size effects have a positive correlation with movement of the market but the correlations are immaterial. The correlation coefficient between the market variable and WML is -0.16, suggesting that the momentum effect tends to be weaker during market upturns, and stronger during market downturns. Similarly, the correlation between default variables and the excess market returns are about -0.30. The weak and negative correlations indicate that the return differentials between High and Low default stocks tend to be larger during market downturns and smaller in market upturns.

Default variables DEF and DEF' are positively correlated with HML and SMB but negatively correlated with the WML variable. The correlation coefficient with the HML variable is slightly higher (at 0.25) than with the SMB variable (at 0.04). As explanatory variables used in each regression of Chapter 3 are not correlated with each other, there is no evidence of estimation biases in the analysis.

In terms of momentum anomaly, the results reported in Panel B of Table 2.9 show that the explanatory variables used in Chapter 4 analysis are not correlated. The correlation coefficients between the market factor and other variables are between 0.04 and 0.38 in absolute terms. The correlation is higher between business cycle variables and the market. This is because business cycle variables describe changes in investment choices in different market conditions. Therefore, there should be some market influence on changes in the business cycle variables. As the correlation coefficients are relatively low, there is no evidence of estimation errors caused by including business cycles in regressions on momentum premium.

Another default variable used in this thesis is CHS, which appears to be more correlated to DES than to other variables. Since they both aim to capture the risk of a company falling into a distress situation, it is possible that they are correlated. However, the correlation coefficient is only 0.36, lower than the threshold of 0.5, so it is unlikely that this would cause an estimation issue. In addition, CHS is a proxy for the risk of bankruptcy while DES is meant to capture the distress risk associated with corporate bonds. As not all companies issue bonds, it is unlikely that the two variables overlap and therefore they can be included in the same model.

It is worth noticing that WML variables are negatively correlated with the FF three factors and default variable but positively correlated with business cycle variables. Although the correlations are relatively weak, the sign of the correlation coefficients indicate that WML is likely to mirror the movement of the market. When the business cycle variables increase (typically during market upturns), WML tends to increase.

To summarise, explanatory variables used in the regressions in Chapters 3 and 4 are not strongly correlated, and therefore it is unlikely that there would be multicollinearity issues. However, a formal test will be carried out to test the problem where it is necessary.

Table 2.9: Correlation matrix between explanatory variables

The table reports Pearson correlation coefficients of explanatory variables in Chapter 3 (Panel A), as well as those in Chapter 4 (Panel B). See notes in Table 2.8 for variable definitions and formation. A student's *t*-test of a null hypothesis of zero correlation is also conducted. The results are reported if it rejects the null. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

Panel A: Chapter 3 variables

	$(R_m - R_f)$	**HML**	**SMB**	**WML**	**DEF**	**DEF'**
$(R_m - R_f)$	1.00					
HML	0.04	1.00				
SMB	0.01	-0.06	1.00			
WML	-0.16	-0.31	-0.09	1.00		
DEF	-0.30	0.25	0.04	-0.11	1.00	
DEF'	-0.27	0.18	0.13	-0.16	0.86***	1.00

Panel B: Chapter 4 variables

	$(R_m - R_f)$	**HML**	**SMB**	**WML**	**CHS**	**DES**	**TERM**	**DIV**	**T-Bill**
$(R_m - R_f)$	1.00								
HML	0.04	1.00							
SMB	0.01	-0.06	1.00						
WML	-0.16	-0.31	-0.09	1.00					
CHS	-0.22	0.19	0.12	-0.26	1.00				
DES	0.31	0.07	0.28	0.15	0.36	1.00			
TERM	0.24	0.25	0.16	0.23	0.17	0.35	1.00		
DIV	0.14	0.20	0.07	0.27	0.13	0.10	0.25	1.00	
T-Bill	-0.38	0.15	0.21	0.07	0.26	0.14	-0.33	0.04	1.00

2.6. CONCLUSION

Chapter 2 highlights the key methodology and data sample that this thesis's empirical analysis is based on. The chapter sets out a methodological framework including different approaches to the econometrics estimations of value premium (in Chapter 3) and momentum premium (in Chapter 4). It introduces and explains motivations behind the selection of each variable. The chapter also describes the sample statistics, such as descriptive statistics, correlation matrix and historical trends.

As described in section 2.2, the full sample consists of 290 companies in the FTSE350, covering a period between 31st January 1990 and 31st December 2012 (276 months). This forms a dataset of 79,246 firm-month observations. Firms are required to have at least 12 months of data in order to be included in the sample. In line with previous studies, Chapter 3, which concerns value anomaly, excludes stocks of financial firms to avoid misleading inferences about their financial health. As a result, the sample size is reduced to 269 firms in Chapter 3. Data is collected from various official sources, such as DataStream Thomson Reuters, Kenneth R. French's database, Bloomberg, the UK Debt Management Office database, and company financial statements.

In terms of methodology, the thesis employs two approaches to assessing the associations between distress risk and performance of two investment strategies – value and momentum investment. The two methods are regression analysis and a portfolios-based approach.

The regression approach aims to explain value premium (in Chapter 3) and momentum premium (in Chapter 4), using a range of explanatory variables which are meant to capture different risk elements in average stock returns. In the thesis, explanatory variables are constructed on the basis of the following criteria: competence as a proxy for the intended risk factor, consideration of country-specific characteristics, consistency, and the avoidance of potential biases. Although further diagnostic tests might be required to validate those qualities, the set of initial selection criteria would enable regression models to effectively test the hypotheses set out in subsequent chapters.

There are three CAPM-based models tested in this thesis. They are the FF three-factor model, the Carhart four-factor model and an augmented version of these two models which include a default risk variable. In Chapter 3, the dependent variables are the excess returns on 6 portfolios consisting of stocks with different sizes and BM characteristics. This is to explain the return differentials between value and growth portfolios, or value premium. The chapter also addresses potential distress risk associated with idiosyncratic volatility by undertaking a regression analysis on 9 portfolios, which are the intersections between 3 volatility portfolios and 3 BM portfolios. Additionally, 9 default/ BM portfolios are tested in order to assess the risk pattern associated with bankruptcy in average stock returns. The explanatory variables consist of the three FF factors, Carhart's momentum factor, and a default factor. The default variable is constructed using a number of indicators of a firm's probability of bankruptcy, including Ohlson's (1980) O-score and Altman's (1968) Z-score. The dependent variables in Chapter 4 are the excess returns on the Winners portfolio, and the excess returns on the Losers in relation to the risk-free asset. Beside the set of explanatory variables used in Chapter 3, Chapter 4 extends the list with 4 business cycle variables that have been recognised in the momentum literature for their ability to explain momentum to a certain degree. They are default spread, term spread, dividend yield and short-term Treasury Bill. The business cycle variables are meant to capture changes in investment choices in different market conditions.

In Chapter 4, the third default variable, the CHS variable, is introduced. It is based on CHS scores - a recently developed proxy for corporate failure proposed by Campbell et al. (2008). Although adding alternative proxies for a variable should not fundamentally change the estimation results, it may provide evidence as to whether the variable in question can capture the relevant risk element. The CHS approach incorporates both accounting and market information. It involves running dynamic logit models and calculating conditional probability of default. Theoretical explanation of the procedure can be found in section 2.5.1.B. Since computing CHS scores is a complex and time-consuming process, Appendix 5 of this chapter suggests a set of code written in VBA programming language to calculate CHS scores. They are the practical steps followed by this thesis, but it is also possible to use other programming languages to generate CHS values following the procedure described in this chapter.

The second method is a portfolio-based approach, according to which the sample is split into a number of portfolios based on the similarity of their characteristics. These portfolios then form dependent variables in the regression analysis. The portfolio grouping method captures a risk element by assessing the performance of two (or more) portfolios which react differently to this particular risk factor. The approach is also useful in comparing performance of stock with different characteristics, such as high versus low idiosyncratic volatility stocks.

It is worth noting that the portfolio grouping method is used more for value anomaly analysis than it is for momentum analysis. Following the portfolio-based approach, Chapter 3 builds 6 portfolios which are intersections between 3 size and 3 BM portfolios; and 9 volatility and BM portfolios. This provides valuable insight into the differences in performance between Value companies (i.e. having a high BM ratio) and Growth companies (i.e. Low BM) from various dimensions, such as firm size and idiosyncratic volatility. However, it is unprecedented in the momentum literature to use the portfolio-based system.

Sections 2.4 and 2.5 of Chapter 2 are devoted to describing the set of dependent and independent variables used in the thesis. They contain detailed descriptions of the construction of each variable, descriptive statistics and visualisation of all variables, and an analysis on the variable correlation coefficients. The initial analysis finds that:

(i) Amongst dependent variables, the excess returns on 6 size/BM portfolios differ mainly because of the difference in firm size. On average, the excess returns are positive for Small stocks but tend to be negative for Big stocks. The returns are slightly higher if companies are also value firms. When sorting stocks into 9 volatility/BM portfolios, it is noticed that highly volatile stocks have the highest excess returns but are highly unpredictable. They tend to be more sensitive to changes in the market, and perform particularly poorly during market downturns. In contrast, low volatility portfolios are less volatile, are less likely to be impacted by market shocks but do not generate positive excess returns in the long run. When looking at the risk pattern associated with default probability in excess returns on 9 default/BM portfolios, the descriptive statistics reveal that low DEF stocks perform better than high DEF ones in many aspects. They generate positive excess returns and are less volatile compared with the high DEF stocks. In the low DEF group, the value stocks portfolio produces higher returns but is more sensitive to changes in the market than their growth counterpart.

(ii) In regard to independent variables, some are highly sensitive to the market, for example SMB, WML and default factors which had particularly low excess returns during the recent 2008 financial crisis. However, other variables such as DES, TERM and T-Bill are more influenced by the Government's policy. Of the three proxies for default risk, the CHS variable, which is built from CHS score, exhibits higher predictive ability than DEF and DEF', which are formed based on O-score and Z-score, respectively. In terms of magnitude, all three variables have a negative mean and their values are particularly low during market downturns in relation to the risk-free rate of return.

(iii) Explanatory variables used in the thesis regression analysis are not correlated with each other. The only exception is the high correlation coefficient between two default variables, DEF and DEF'. This result is expected because both variables aim to capture the same type of risk. They are meant to proxy for firm probability of bankruptcy, so if DEF and DEF' indeed can predict firms that are at risk of default, they should report the same or largely similar conclusions. Since the two default variables do not present in the same regression, their correlation does not impact the estimations.

Chapter 2 sets out the methodological framework for the rest of this thesis, however, further explanations may be needed in each chapter to further explain how it is applied in testing specific hypotheses.

Chapter 3: Stock Volatility, Default risk and the Book-to-Market Equity Premium

3.1 INTRODUCTION

Value stocks refer to stocks of firms with high ratios of book-to-market equity (BM); in other words, these stocks are trading on the exchange at a low price compared to their book values. Portfolios can also be classified using other accounting variables, such as earnings to price (E/P), cash flow to price (C/P), leverage and dividend yield, see examples in studies by Davis (1994) and DeBondt and Thaler (1985).

Stocks, of which the above fundamental values are small, are characteristically known as *growth stocks* (Fama and French 1998). Bird and Whitaker (2003) and Bathala, Ma and Rao (2005) imply that normally growth stocks are expected to continue their outstanding performance and are unlikely to fall into distress over subsequent periods.

A large number of researchers have investigated the differences in returns between the two groups of stocks; they tend to support that firms with relatively high BM ratios have higher average stock returns than firms with low book-to-market value. These return differentials are called the book-to-market equity premium or *value premium*. For examples, Rosenberg, Reid and Lanstein (1985), and Davis, Fama and French (2000) find the book-to-market premium is robust in the US market, while Chan, Hamao and Lakonishok (1991) give evidence of the premium in Japan, and Fama and French (1998, 2012) confirm this in international markets. These positive return premiums have inspired both academia and practitioners to search for explanations.

The most dominant trend of argument is the risk-based reasoning. Supporters for neoclassical finance theory believe that the value premium is a compensation for bearing higher risk. Consistent with this view, Fama and French (1993) propose a three-factor model, henceforth the Fama-French three-factor model, consisting of the market risk, firms' size (stock price times number of shares outstanding) and BM factors as proxies for undiversifiable risks. Other studies argue that the value premium is not explained by the standard Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) and it therefore is known as an anomaly in stock markets. The existence and the reasons behind such an anomaly have been under debate for decades.

Black (1993) and MacKinlay (1995) suggest sample-specific explanation for value premiums, while DeBondt and Thaler (1987) and Lakonishok, Shleifer and Vishny (1994) propose overreaction and agency costs explanations. Fama and French (1992, 1995), Shumway (1996) and Chen and Zhang (1998) among others support risk-based reasons. Daniel and Titman (1997) argue that it is firms' characteristics rather than risk that explain the value premium. A valid question remaining is thus whether value premium is explained by risk-based models, such as the CAPM and the Fama-French three-factor model, or it is simply caused by sample biases, market overreaction, firms' characteristics or agency costs.

Therefore, this chapter will first revisit the question whether BM and default risks - being two of the dominant measures of distress situations - together with size effect have the capability to explain BM premium. It also tests this hypothesis in an extended model using a momentum component. Moreover, the chapter aims to test the hypothesis that firms with high stock volatility are riskier and that these risk loadings could explain the return differentials between value and growth securities.

Moreover, as little as the relationship between volatility and value premium is mentioned in existing literature, neither have the links between volatility and default risk been thoroughly established to explain value premium. Many researchers, including Chan and Lakonishok (2004), limit the scope of their studies at examining volatility at portfolio level for the purpose of finding which of the two BM stock groups is the riskier. However, the standard deviation of a population does not reflect the volatility level of individual BM stocks. A detailed motivation for explaining value premium through looking at volatility is discussed in section 3.2.3.

The chapter selects the FTSE350 to test its hypotheses for the following reasons. First, the UK is one of the most important and largest stock markets in Europe and the world, in the sense that it has a very high trading volume and liquidity – these two aspects are key drivers when volatility is concerned in the test. The market capitalisation is about Great British Pound (GBP) 1,733,343 million, ranked second in Europe and fifth in the world[10]. Secondly, the UK market has a wide range of advanced and complete financial instruments. Investors are well-informed and the majority of market participants are typically institutional; in addition, its private investors have a high exposure to financial

[10] World Federation of Exchanges, in December 2010

training and skills. As a result, these participants have the ability to look into the details in financial statements, from which they can extract information on the distress and volatility risk of firms. The UK's financial statements also tend to be more transparent, and are published at regular and pre-set intervals. Thirdly, only the FTSE350 is focused on, as, where volatility is concerned, it is the case that the small stocks at the bottom of the FTSE All-Share are not traded regularly and suffer zero or near-zero volatility over prolonged periods. These would hence bias the chapter's ability to test volatility's role in explaining the return differentials. Therefore, including only the FTSE350 would rule out this possibility and provide a more informative result regarding volatility's impact.

The rest of the chapter is organised as follows. Section 3.2 reviews the existing literature and research gaps that this chapter aims to bridge; the sample and the methodology are described in section 3.3. Section 3.4 examines the existence of value premium in relation to distress risk, and discusses four common explanations (i.e. the market risk, BM, size and momentum factors). Next, section 3.5 looks into whether historic volatility of stock returns can explain BM premium and, if so, does it reflect distress. The final section concludes the study and provides possible implications of the results.

3.2 LITERATURE REVIEW

This section will serve the following purposes. First, it discusses the vast literature on the BM premium, default risk and volatility. It then explores where the gaps lie within existing methodological and empirical aspects, which would potentially be of interest to study. Finally, the section explains the motivation and proposes the tests for three main hypotheses that will be thoroughly addressed later in the rest of the chapter.

3.2.1 The book-to-market value premium

One of the earliest studies on value premium was done by Graham and Dodd (1934). It indicates that the performance of high-growth firms is unlikely to be sustainable over time. This is found to be true also for firms that have done poorly in the recent past (Bird and Whitaker 2003, and Abhyankar, Ho and Zhao 2008). These studies further explain that in the long run, investors' views on the value of stocks would shift, and share prices would change accordingly. As a result, investors will aim to make a profit from a long position in value stocks and a short position in growth stocks to gain a *value premium,* also known as the BM premium.

Since then, many valuation indicators and markets have been examined in order to understand the existence of the BM premium. For example, Chan, Hamao and Lakonishok (1991) base their studies on Cash-Flow/Price ratio. However, later research shows that firms' cash flows are rather sensitive to an individual firm's policies, for instance depreciation policy. Hence, more recent studies, such as Teo and Woo (2004) and Chan and Lakonishok (2004) among others, focus on analysing Earnings/Price and Book-to-Market ratios. They also suggest combining several indicators for the purpose of better identifying undervalued stocks.

In developed markets, both Rosenberg, Reid and Lanstein (1985) and Davis, Fama and French (2000) find the book-to-market premium is consistently large and positive in the US market, while Chan, Hamao and Lakonishok (1991) give evidence of the premium in Japan being at the rate of 0.40% per month. Capaul, Rowley and Sharpe (1993) confirm the findings in six major security markets, including France, Germany, Switzerland, the United Kingdom, Japan and the United States during 11 years from 1981 to 1992.

Although testing in developed countries seems to be the main objective of researchers, value-premium researches in developing countries are also examined. For instance, a comprehensive study by Fama and French (1998) on 13 major markets finds a value premium of 7.68% per year on average. They further examine 16 emerging markets and show that value abnormal returns are more volatile in these markets but still remain high (16.91% annually). Another large study by Bird and Whitaker (2003) implements data of seven major European markets and finds that value strategies perform particularly well during the period of price correction following the booming periods. Once again, Fama and French (2012) update the findings in their previous study in 23 countries across four regions (North America, Europe, Japan and Asia Pacific) and confirm that, except for Japan, there is a value premium that decreases with firm size. They also rule out the possibility that these results are driven by the integration between the four regions. Although their finding for the Japanese market is inconsistent with those in Chan et al. (1994), it is due to their sample excluding non-financial firms while the prior work covered all sectors. Generally, most studies tend to document the success of value strategies in their respective markets.

However, the reliability of value-based strategies is far from certain. Contrary to the above studies, the study by Jegadeesh and Titman (1993) indicates that although stocks with low returns in the last 12 months tend to continue such poor performance in the short-term, in the long-term the opposite trend is followed. Other researchers, such as Asness, Krail and Liew (2000) and Yen, Sun and Yan (2004), support this view that although high BM firms generate higher returns than low BM firms over some periods, such value premium disappears in others. They attribute these results to country-specific reasons, such as short-selling restrictions, and testing methods. Thus, it is worthwhile to search for the reasons behind the existence (or the absence) of BM premium.

Fama and French (1992, 1993, 1996) support the explanatory power of the CAPM and document that value stocks fundamentally outperform growth stocks. The explanation is that the excess returns on value strategies are a reward for bearing such an extra risk. Consistent with this view, Chen and Zhang (1998) give evidence that high BM stocks are associated with poor recent performance, high financial leverage and uncertain future earnings. Also, Lettau and Ludvigson (2001) provide evidence that value firms are riskier than growth firms, especially during recessions. It is because their returns are highly correlated with consumption growth in "bad" times when this correlation is least desirable. Consistent with this view, Petkova and Zhang (2005) show that conditional beta of value stocks[11] is positively correlated with the market premium and they are, therefore, riskier in market downturn periods. However, they argue that besides the market risk factor, other fundamental variables of firms, such as BM and size, do explain value premium in a multifactor model. Section 3.3 of the chapter will go in-depth into the validity of this argument.

There are a number of well-discussed explanations for this anomaly that are summarised as follows.

In the literature, there have been many models built upon a fundamental presumption that a higher return on assets is the compensation for taking extra risk. The value premium is, therefore, a form of risk-compensation and not an abnormality or market inefficiency. Hence, most naturally, models incorporating risks are considered – for example, the CAPM, Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM), the Arbitrage Pricing Theory (Ross 1976), and Breeden's (1979) Consumption-based Capital Asset Pricing Model (CCAPM) are all risk-based theories supporting risk explanations. Based upon the efficient market hypothesis in which the

[11] In the paper, the conditional beta is defined as a ratio of the covariance between return on stock *i* and return on the market portfolio, divided by variance of the market portfolio.

market is efficient and should reflect a fair price for the securities, there are higher risks in taking these opportunities presented by the known value investing strategy. Fama and French (1993) support risk reasons for the BM and size effects; but despite the success of this model across international markets, they admit that there has not been any theoretical background behind the choice of those two factors. Nonetheless, Ferguson and Shockley (2003) find a theoretical rationale for Fama and French's factors. They suggest that explanatory variables that are equity-only constructed and related to leverage and financial distress such as High-minus-Low (HML) and Small-minus-Big (SMB) should capture in part the risk missed by the CAPM beta.

On the contrary, Daniel and Titman (1997) argue that it is firms' characteristics, not risk, that explain value premium. They believe that the BM effect captured by the HML factor is indeed only part of firms' characteristics. In other words, the value and growth *characteristics* of firms are mostly responsible for the value premium. It is, additionally, because firms sharing the same characteristics tend to fall into distress at the same time. Also, these low and high BM characteristics are associated with stock returns. Hence, the difference in returns between portfolios formed based on B/M ratio has been mistakenly attributed to risk while it is in fact due to distress and growth prospect characteristics.

However, Davis, Fama and French (2000) point out that Daniel and Titman's results seem to be biased as they used a rather short sample period. Extending Daniel and Titman's 20.5-year sample, Davis et al (2000) find that the test on 68 years from 1929 to 1997 yields statistically insignificant intercepts, while excluding that 20.5-year period, the estimation results in a significant intercept value. This implies that the Fama and French three-factor model might not seem to perform as well in a short period as it does in a longer period. Therefore, Daniel and Titman's preference toward firm characteristics might be a result of a short sample testing rather than a failure of the risk-based explanation.

In related arguments, Black (1993) and MacKinlay (1995) also suggest a sample specific explanation. Their main argument implies that the abnormal return on value over growth stocks that has been observed in the US market is unlikely to occur in other markets. Nevertheless, a vast amount of subsequent studies find evidence of value premium in out-of-sample testing across the globe. Some of the largest scale researches are Capaul, Rowley and Sharpe (1993) and Fama and French (1998, 2012) to name but a few. They find evidence that value premium exists not only in the US but also in more than 30 other countries.

On the other hand, Kothari, Shanken and Sloan (1995) claim that data-selection bias is the explanation for value premium. This study gives evidence that the value premium is merely due to sources error. In particular, *Compustat*, which was used by many notable researches at the time, is a common data provider which back-fills its data prior to 1978, its founding year. Firms added into the Compustat database before 1978 were back-filled all the way from 1946, but firms added in 1978 were backfilled only from 1973. Hence, firms that were delisted or did not meet Compustat's criteria were not included in its database, while firms overcoming distressed conditions were accepted. The practice was documented to be in favour of high performing value stocks and, consequently, the success of the value premium strategies. On the contrary, Chan, Jegadeesh and Lakonishok (1995) and Barber and Lyon (1997) noted the problem caused by Compustat is unlikely to generate biases, especially over a long period of time. They tested other samples, free from such a problem, and found that selection bias was not the reason behind the presence of the value premium anomaly.

Lastly, DeBondt and Thaler (1987) and Lakonishok, Shleifer and Vishny (1994) propose overreaction and agency costs explanations. They document the psychological sentiment in which investors tend to undervalue low market value stocks. Similarly, investors overvalue stocks with high market value in relation to their book value. Typical examples of this preference still continue today when the highly-demanded stocks of technology firms, such as Facebook, Google, and Microsoft, have low BM values, i.e. growth stocks with high market values.

3.2.2 Probability of bankruptcy explanations

Although this work is not the first to study the relationship between default probability and equity returns, it differs from previous studies in exploring the possibility that default probability can explain the movement of stock returns and value premium. In order to test that possibility, default probability is used as a proxy for firms' default risk and tested alongside other risk factors in a risk-based regression. Moreover, the chapter uses only portfolio-based factors to capture risk patterns in capital asset pricing. This approach is strongly supported by recent research such as Ferguson and Shockley (2003), Simlai (2014) and Gubellini (2014). They explain further that if the asset pricing model uses portfolio-based proxies only, it can explain the market anomalies well while other approaches of estimating equity risk will lead to estimation errors.

Two of the most popular measures for the likelihood of bankruptcy in the literature are O-score suggested by Ohlson (1980) and Z-score proposed by Altman (1968). Using both of these measures, Dichev (1998) finds no evidence to support that firms with either high BM or high probability of bankruptcy provide high return opportunities as compensation for distress risk. The study documents that investing in firms with higher default probability even results in lower average returns. In addition, the results imply that default risk is a separate distress component and unlikely to relate to the distress pattern captured by size and BM factors.

Also analysing O-score and Z-score of US firms, Griffin and Lemmon (2002), however, find that among value stocks, firms with a higher probability of bankruptcy yield higher returns on average while the opposite is true for growth firms. More importantly, the value premium is much larger in the group with highest default risk in comparison with the other groups (14.44% per annum compared to, for example, 3.87% in the group with lowest probability of default). The large difference between Dichev's (1998) and Griffin and Lemmon's (2002) findings is perhaps due to the sample size as the latter analyses a 32-year period while the former looks at a much shorter sample of 15 years. In addition, Griffin and Lemmon point out that the findings in the previous study are mainly driven by the extremely poor performance of high O-score and low BM firms.

Nevertheless, Garlappi and Yan (2011) predict that the relationship between value premium and probability of bankruptcy might be a hump shape. While constructing a model testing the role of shareholders' ability to help distressed firms to recover, they notice that value premium increases as probability of bankruptcy increases until the default probability reaches a certain point. Their observation is however drawn on US-based firms only. Moreover, the proxy for default risk, the Expected Default Frequency (EDF) index provided by Moody, is a forward-looking measure. Hence, the actual relationship between equity returns and firm default likelihood is still under debate.

More importantly, one question that many researches seem to be concerned about is what the main reasons behind the return differential between high and low O-score firms are. Some conclude that the risk-based models are unable to capture the anomaly and suggest that overreaction theory can. For example, Griffin and Lemmon (2002) argue that high O-score firms tend be small firms which attract less attention from analysts and they are therefore more likely to be mispriced. Garlappi, Shu and Yan (2008) argue that firms where shareholders can gain a greater benefit from renegotiation while the firm is in distress (i.e. high probability of bankruptcy) should generate lower returns. However, the opposite is true when this shareholder advantage is limited.

Both O-score and Z-score are based on firms' accounting and economic variables while some studies use indirect approaches to compute default probabilities. Examples are Shumway (1996) who chooses delisting due to distress reasons, Vassalou and Xing (2004) who employ Merton's option pricing model (Merton 1974) and Garlappi et al. (2008) who use the EDF measure of Moody's KMV by Merton (1974). Although academics and practitioners are far from agreeing which method is superior, O-score and Z-score are more popular to academics due to their simplicity and consistency while Merton's approaches are more favourable among traders.

Non-accounting information also joins with accounting data in some studies but the reliability of their approaches appears to be questionable. Whittred and Zimmer (1984, p.295) consider if delays in financial reporting can add predictive ability to accounting data in identifying distress firms and conclude that the results "depend on strong assumptions". Anginer and Yildizhan (2010) use corporate credit spreads as a proxy for probability of default and argue that their proxy outperforms other measurements, such as bond ratings, accounting related variables and estimated variables, in terms of capturing systematic risk. However, it could be worthwhile noticing that bankruptcies are not caused only by market judgment on firms' bonds but mainly by their ability to meet debt obligations. More importantly, the paper did not consider cases when firms do not issue bonds or have less frequently traded bonds. These studies considered accounting data but they have their limitations.

Hence, one contribution of this chapter lies within the comprehensive methodologies implementing probability of default into the conventional distress risk. The foundation of this method comes from a study by Griffin and Lemmon (2002) who reported that probability of bankruptcy sometimes contains information about distress risk. In this chapter, both forming factors and the portfolio grouping approaches will be included. Additionally, in order to check the robustness of results, we use Ohlson's (1980) O-score as well as Z-score ranking to construct those factors and portfolios. The factors are formed using different measurements for default risk. As both current business performance and past income of firms are linked to the likelihood of bankruptcy, the measures are, therefore, expected to be able to capture the majority of firms' default risk. This forms the chapter's first hypothesis which examines the explanatory ability of default risk in asset pricing.

Although the chapter aims to analyse default risk in relation to value premium in a more constructive way, it has a more ambitious goal which is to uncover another possible type of risk, volatility risk, as well as to bridge the gap in its literature. The next section will present the discussion on volatility, and the areas in volatility literature that need to be explored in a deeper level.

3.2.3 The role of volatility in explaining value anomaly

This section looks into the motivation for using volatility by reviewing the existing discussions in the literature on volatility and the research gaps that need to be explored further.

A. Discussion on volatility and value premium

It has long been observed that prices of financial assets fluctuate stochastically (Tauchen 2011), and this is often linked with the level of risk involved. According to Fama and French (1992), higher returns must imply some source of risk. Supporting this view, Fama and French (1993, 1995, 1996) continue to document that the value premium compensates for risks that haven't been explained by the CAPM. An early research refers risk in the stock market as capital loss possibility and volatility of stock returns (McDonald 1975). The risk of capital loss has been widely proxied by probability of bankruptcy, while volatility gains only a little attention.

Among the first studies mentioning the need of discussing volatility risk, Lorie (1968) explains that variability in rates of return on assets implies the lack of predictability which creates greater risk associated with these assets. He observes that in a particular group of pension fund assets, there is a strong correlation between historic variability and the future rate of return. Although volatility is not the only type of risk involved to financial assets, Lorie points out that it captures enough of the risk and should be a good place to start in analysing the risk and return relation.

Regarding value anomaly, a study done by Arisoy (2010) exxamines the difference in volatility factors between value and growth stocks in France. On an international scale, Fama and French (1998) briefly examine standard deviations of stock returns (as a proxy for volatility) and establish a link between volatility and BM premium. Nevertheless, their work only focuses on testing the relationship between volatility and value anomaly at a portfolio level. This chapter expands the test to the firm level and expects to produce more informative results[12].

Taking a closer look at the relation, a vast body of literature has found that there is a significant negative correlation between stock market return and stock volatility. Perhaps the first empirical research noticing that link was Black (1976). The underlying reason behind that negative correlation was later investigated further by Christie (1982) who attributed it to changing financial leverage caused by equity price changes. This is thus called the *leverage effect*. Since these early articles, different econometric techniques and volatility measurements have been adopted to check the validity of those findings. For example, Nelson (1991) built the Exponential General AutoRegressive Conditional Heteroskedastic model (E-GARCH) model to test the effect. Glosten, Jagannathan and Runkle (1993) use the variance of excess return as a stock volatility measurement. More recently, Kim, Morley and Nelson (2004) employ Markov-switching with market volatility to capture the effect: they first develop a partial equilibrium model to estimate volatility feedback and by using the Markov-switching specification, they then construct a model explaining stock returns with the volatility feedback variable estimated in the first stage.

However, some opponents argue that the relation does not persist. For instance, Brandt and Kang (2004) document that although there is a negative relation between conditional expected return and stock volatility, the unconditional mean appears to be positively correlated to the volatility. More damningly, Fink, Fink and He (2012) find no evidence of any significant correlation between expected stock returns and the idiosyncratic volatility. They argue that the correlation found in the previous studies is a result of using information that was not available for investors at the time of trading (i.e. forward-looking information) and that individual volatility should not be used to forecast future returns.

Schwert (1990) finds that during the October 1989 stock market crash, high market volatility was associated with low stock returns. However, apart from this brief period,

[12] Avramov and Chordia (2006) document that using a firm-level approach, their test avoids data biases and loss of information displayed in a portfolio-level testing method.

the percentage changes in market volatility was not the main reason behind other huge drops in stock prices as it was normally believed. The link between market volatility and stock return is still under debate. Re-examining this over a longer and more serious crisis will provide a stronger conclusion and shed light into future research.

The first reason for a negative relationship between stock returns and volatility level is attributed to risk-based theory. Bekaert and Harvey (1997) and Ang, Hodrick, Xing and Zhang (2006), to name but a few, suggest that the changes in volatility of stock returns lead to changes in the expectation of future market returns or in the risk-return balance (i.e. higher risk, higher returns), which will induce changes in the investment opportunity as a result. They argue that if volatility of market return is a systematic risk (undiversifiable), its effects should present in returns of stocks. They found that stocks with high sensitivities to volatility (either aggregate volatility or idiosyncratic volatility) have lower average returns and the lower returns cannot be explained by aggregate volatility risk, size, BM, momentum and liquidity effects. Hence, in this chapter a different measurement – firm default risk – is used to see if it can explain the phenomenon. Section 3.3 will discuss the variable construction and testing methodology in detail.

Additionally, from the macroeconomic point of view, Bansal, Kiku, Shaliastovich and Yaron (2014) find that volatility in the macroeconomy plays a significant role in explaining expected equity return and consumption return. Similarly, Campbell, Lettau, Malkiel and Xu (2010) imply that market return volatility may be an indicator which could be used to forecast GDP growth rate. Moreover, in the presence of volatility, the role of stock index returns in forecasting GDP is significantly reduced, suggesting that volatility outperforms and subsumes stock returns' predictive ability.

The second reason for the lower returns on highly volatile stocks comes from the behaviour theory. It is believed that investors in a market that experiences low stock volatility tend to be more optimistic about future stock returns. Supporting this view, Campbell and Taksler (2003) show that equity volatility contributes to explaining corporate bond yields, they argue it is because investors become more optimistic when stock price increases. It appears that a relationship exists between market volatility and the equity premium.

Lastly, the CAPM-type models usually have a common presumption that higher volatility is associated with higher returns. This risk-based explanation has been receiving significant support from both scholars and practitioners. According to Huang, Yang and Zhang (2013), as highly volatile stocks are more likely to be under financial distress, they are riskier than less volatile stocks and therefore carry a positive value premium. The relation is documented by many researchers to be especially significant during recessions. For example, Schwert (1989, 1990) shows that during the Great Depression (1929-1939), stock volatility level was unusually high, and he explains that it is because at the time, investors did not know if the market could survive. In addition, Hamilton and Lin (1996) indicate that it is economic recessions that drive fluctuations in stock return volatility and that volatility and market conditions are highly correlated. More recently, Gulen, Xing and Zhang (2011) provide further evidence of a strong relationship between stock return volatility, the level of risk taking and market downturns in international markets. Also, Wachter (2013) and Choi (2013) explain that during "bad" times, the possibility of poor outcomes causes high stock market volatility and significantly increases equity premium.

A subject that has attracted even more attention in volatility literature is the volatility measurements and their possible connection with value premium. Some examples are Lakonishok et al (1994) who compare simple standard deviation of portfolios, and Arisoy (2010) who employs at-the-money straddles as a proxy for stock volatility risk. However, the more complicated at-the-money straddles can only serve as a volatility proxy in well-developed derivative markets. In terms of method, Campbell et al (2001) use a disaggregated approach on market, industry and firm-level volatility while Brandt and Kang (2004) employ Vector AutoRegression (VAR) which has the advantage of incorporating time-varying volatility without the requirement of exogenous predictors in testing the relationship between volatility and returns. Also, Tauchen (2011) proposes a two-factor structure in a general equilibrium in which stochastic discount factor (SDF) and stochastic volatility in consumption are the driving factors. The approach, however, requires certain assumptions to be held, such as the conditional lognormal distribution assumption.

B. Gaps in volatility and value anomaly literature

The chapter aims to bridge the gaps in literature on value premium and volatility in the following aspects.

(i) Analysing from a comprehensive economic approach

As mentioned earlier, the existing literature on volatility is great in number but rather limited in scope. It is worth noticing that most of the studies have not gone any further than observing and explaining the correlation between stock return and stock volatility. Few have attempted to test the potential explanatory relationship between them. Indeed, Campbell et al (2011) have admitted there is a limitation in the existing research on volatility in the sense that volatility tends to be examined from description statistics rather than an economic model approach. In order to bridge this gap, this chapter therefore aims to capture the risk pattern in stock price volatility in its econometric models using individual volatility in a portfolio approach.

(ii) The risk pattern in stock volatility in explaining value premium

Additionally, the majority of studies on volatility focus on how historical volatility could forecast future index volatility and derivatives trading. The question whether variability of stock returns as a proxy for risk could explain value premium still remains.

Furthermore, the risk pattern in stock volatility so far has not been distinguished from other types of risk when explaining expected stock returns. As discussed in the literature on volatility section, it is long accepted that highly volatile stocks are considered to be risky. However, existing studies tend to explain the return differential caused by volatility risk by measuring distress risk with a presumption that volatile firms are financially distressed firms rather than to attempt to capture volatility risk separately.

For these reasons, besides common factors such as the market factor, BM, firm size, past returns and probability of bankruptcy, this study aims to examine the relationship between volatility level and value premium.

(iii) The potential relation between volatility and default risk

Although some studies have documented the difference in default probability among value versus growth stocks and observed the correlation between stock volatility and expected stock return, the question whether firms with high default probability will experience high levels of price changes and vice versa still remains. Naturally, concerns over a firm default likelihood could potentially make the the market expectation on its stock returns more volatile while highly volatile stocks might signal default risk.

This study will be one of the first studies to look at the potential relationship between stock volatility and its distress conditions. A recent working paper by Chen and Chollete (2006) began to analyse this aspect, however the work looks at the relationship between O-score and volatility in only one dimension, which uses the explanatory ability of default risk on portfolio sort by volatility. They also only consider default factors and the market beta in their regression on volatility portfolios. The present chapter will examine two dimensions. It first analyses the risk aspect of volatility and that of default risk in explaining value premium separately. The second dimension is exploring the explanatory power of the default factor together with the Fama and French (1993) three factors and Jegadeesh and Titman's (1997) momentum component in capturing the movement in the return of inter-section portfolios between idiosyncratic volatility and B/M ratio. This will not only put all three related elements, default risk, volatility and value premium, under the same lens – but will also be able to consider BM, size and momentum effects at the same time.

This will be discussed in detail in section 3.5.2 under Hypothesis 3.

3.2.4 Hypotheses

The main objectives of Chapter 3 are to answer three key questions on the presence of value phenomenon in the UK, what explains it and the role of each explanatory factor. In order to answer these questions, we set out three hypotheses as follows.

Hypothesis 1: Value premium is associated to the market risk, default risk or a firm's fundamental variables, such as size, B/M ratio and past returns.

The first hypothesis ties with the fundamental question that many dominant studies still debate: Is the value investing strategy profitable? If it is, do the four factors – namely the CAPM's beta, the Fama and French's size and BM, and Jegadeesh and Titman's momentum factor – have a significant explanatory power in capturing the value premium?

The chapter also brings the debate a step further by examining the explanatory power of default risk in a more constructive and comprehensive way. It looks at default effect from two dimensions, which are the effect in portfolios and in risk factors. In particular, the former approach looks at the risk patterns in portfolios and the latter focuses on building explanatory variables which can explain returns on the portfolios.

Hypothesis 2: The historic volatility of stock returns explains the book-to-market premium.

The second hypothesis bridges the gap in the value premium's literature. While there is a need documented to examine volatility impact in asset pricing, the explanatory power of volatility risk, if any, in capturing expected stock returns empirically has not attracted much attention. Moreover, measures and approaches to volatility in the literature tend to be indirect, such as using option price changes. Thus, this chapter's approach will be to examine directly stock price volatility when aiming to understand stock returns. Furthermore, this hypothesis looks at the risk pattern of volatility specifically for the purpose of explaining the return differential between High and Low BM stocks. In short, testing this hypothesis would provide an answer for the long-existing question of whether stock volatility could contribute to explaining value premium in a direct and more comprehensive approach.

Hypothesis 3: Volatility and default risk are correlated.

If there is a link between volatility and the premium, and also between default risk and the premium, one question that might arise is whether there is any relation between the two. This is because the economic meaning of volatility and distress conditions are somewhat related. Once a firm is in distress, investors expect their stocks to be more volatile than usual and at the same time, volatile stocks tend to signal a distress condition. Hence, if it is found that they are strongly correlated, further tests are still required to determine whether one of the two factors is redundant and can be omitted. However, if they are weakly correlated, it is not likely that one can substitute for the other. The examination method in testing this alone should provide insights into the validity of each factor in explaining expected equity returns.

Since volatility and default risk are presented in different forms, risk patterns in portfolios and in factor loading respectively, identifying the link between them through simple correlation matrix analysis does not seem to be feasible. As an alternative, their relation is addressed by looking how much variation in return of stocks with different degrees of volatility is explained by their default risk.

3.3. CHAPTER CONTRIBUTION

Chapter 3 examines the validity of value strategies in the UK market in a more recent set of data. More importantly, it focuses on seeking the underlying reasons for value premium and the role of distress risk in explaining the anomaly. Chapter 3 contributes to the value anomaly literature from both methodological and empirical aspects.

Firstly, Chapter 3 employs a comprehensive range of approaches. There are two analysis approaches used in the chapter which are regression analysis based on constructing factor variables, and a portfolio-based system which assesses risk patterns that stocks in the same portfolio would share. These approaches can be used separately or to complement each other in one model, depending on the research objectives. In Chapter 3, a combination of these methods allows distress risk to be assessed from multiple dimensions. Therefore, this enables more underlying risk factors, which can explain value anomaly, to be identified.

The chapter also uses a number of asset pricing models in the value anomaly literature to explain value premium. The testing models include the traditional CAPM, the FF three-factor model, the Carhart four-factor model and their augmented versions with a default factor added. This will allow a direct comparison between models in regard to variable explanatory power and the model goodness of fit.

Secondly, the role of default risk in capturing value premium is investigated in more constructive ways. The first and more commonly used method is in constructing the default risk factor. The second approach is a portfolio-based method which identifies the risk pattern associated with default probability in the returns on inter-sectional portfolios. The description and advantages of these approaches are discussed in detail in Section 2.3 of Chapter 2. In terms of proxies for default risk, the chapter uses two well-established indicators for firm default risk, namely O-score proposed by Ohlson (1980) and Z-score by Altman (1968).

It is worth noticing that the thesis differs from previous studies in the way that it constructs default factor from default probability indicators that are more suitable for the UK market. Unlike studies undertaken in the US market[13], the thesis does not support the use of corporate bond spread (i.e. yield spread between Moody’s Baa and

[13] For examples, Petkova and Zhang (2005), Petkova (2006), and Shah and Kebewar (2013).

Aaa corporate bonds) and changes in credit rating as proxies for the default risk of UK firms. It is because the UK corporate credit rating system is not as well developed as the system in the US. Therefore, it may not be accurate to rely on corporate credit ratings to identify firms that are likely to be bankrupt in the future. Instead, we measure default risk based on firm probability of default, which is a relatively more indicative and reliable proxy in the UK.

Thirdly, contributing to the extant literature on value anomaly, the study analyses the risk pattern associated with stock idiosyncratic volatility as another indicator of distress risk. Although volatility has long been documented as a relevant risk to stock returns, it has not been incorporated into the existing literature on value anomaly. Unlike previous studies on volatility, the present chapter employs a portfolio-based method that would allow the idiosyncratic risk pattern in stock volatility to be examined separately from other types of distress risk in average stock returns. This approach enables the chapter to capture potential distress risk at a firm level that has not been covered in the regression approach by default risk, as stock prices can be influenced by many factors other than the firm's financial performance.

Last but not least, for the first time, the empirical aspects of the volatility–default risk relation are analysed and their potential roles in explaining value premium are also carefully addressed. While both factors are separately documented to link to value anomaly, they have yet to be analysed in the same context. If a company is in a distress condition, one of the possible signals would be that their stock prices experience a number of highly volatile periods. At the same time, it is also possible that the stock volatility is caused by non-financial factors, such as changes in management or political announcements. These may in time put firms in distress situations but the risk has not been captured in accounting-based indicators. It is, therefore, beneficial to consider volatility risk and default risk in one analysis, and to test their relation in order to better understand value anomaly from the risk perspective.

The next section will explain the data and methodological framework designed to test the chapter's hypotheses. It also discusses initial findings on the presence of value premium in the UK, which motivates the study to seek for the underlying reasons behind the anomaly.

3.4. DATA AND METHODOLOGY

3.4.1 Data

Section 2.2 of Chapter 2 provides a description of the sample and data used in Chapter 3 as well as in the whole thesis. This section aims to summarise key elements of the data that are particularly relevant to the analysis in Chapter 3. The sample covers the period from 31st January, 1990 to 31st December, 2012 (276 months). The return for each month is the difference between the natural logarithm returns of stock prices of that month compared with the previous month. Monthly data of the FTSE350 are obtained from the DataStream Thomson Reuters database.

The chapter focuses on the FTSE350 instead of the FTSE All share for particular reasons as follow. Since one of the main objectives of this chapter is to examine the explanatory ability of firm-level volatility risk on average stock returns, where the high volatility stocks (High Vo) are considered to be riskier than the low volatility stocks (Low Vo). The FTSE350 index excludes the FTSE SmallCap which consists of very low varying stocks, or ones that don't vary at all for a long period of time due to thin trading. Those stocks would have very low volatility but without necessarily being a safer option. Excluding these ensures the results are not biased toward thin trading stocks. They also do not contribute to the explanatory factors this chapter is looking for in term of volatility.

Firms must satisfy the following criteria to be included in the sample for year *t*. First they must have sufficient historical information for 6 months before the portfolio formation date (i.e. July of year *t*) to ensure that the accounting variables are identified before they are used to explain excess returns. In this case it is December of year *t-1*, also because it normally coincides with the fiscal year end of firms. However, firms need to be at least one year old as of December, 2012 to be considered.

Fama and French (1992) show that a minimum of a 6-month lag is likely to be appropriate to ensure that investors have time to consider the financial reports, even where there are delays. In line with previous studies[14], this study focuses on analysing non-negative B/M ratios and non-zero dividend firms.

[14] See studies by Chan et al. (1991), Fama and French (1992, 1996), Drew and Veeraraghvan (2002) for examples.

Financial firms are also excluded from the sample[15] because their capital structures seem to reflect a different meaning from those of non-financial companies. For example, the high leverage of financial firms might not imply a distress condition, which is otherwise the case for non-financial firms (Fama and French 1992). As this thesis focuses on distress risks, it is important that distress conditions are captured correctly.

The firm sectors are classified based on FTSE ICB system (Financial Times Stock Exchange Industry Classification Benchmark, which used to be known as FTSE Global Classification System)[16]. The classification consists of 10 economic groups, 39 industrial sectors and 102 industry sub-sectors.

The screening process reduces the initial sample from 290 to 269 firms (the excluded firms are 17 financial firms, and 2 firms with no BM data). Section 2.2 of Chapter 2 – Research methodology – explains the sample collection, formation and characteristics in detail.

The market factor is obtained from Prof. Kenneth R. French's website[17] and the LIBOR 1-month middle rate is used as a proxy for the risk-free asset. The two Fama and French factors, HML and SMB, are constructed in accordance to Fama and French (1993). The WML component is built following Jegadeesh and Titman's (1997) approach. Although beside BM, the chapter also performs the test on E/P and DY for robustness check purposes, firms do not have to have data on all the three indicators to be included in the sample. As nearly half of the firms on the FTSE350 index do not have C/P data in DataStream, the robustness checks using C/P are omitted to avoid misleading results.

3.4.2 Portfolio formation

Although Sections 2.4 and 2.5 of Chapter 2 have described in detail the methods with which dependent and independent variables are constructed, this section briefly

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[15] A considerable number of studies have focused on non-financial companies, for instance Fama and French (1992), Akdeniz, Altay-Salih and Aydogan (2000), and (Yen et al. 2004). However, Barber and Lyon (1997 cited in Yen et al. 2004 p.21) have revealed that it is also appropriate to apply value strategies for financial firms.

[16] The ICB industry/sector codes are obtained from the Datastream database under the DSMnemonic code WC07040

[17] The author thanks Professor Kenneth R. French for making the data available on his website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

summarises them to provide an introduction to the empirical analysis that uses those variables.

Dependent variables: Portfolio and dependent variable constructions are formed in a similar way to Davis, Fama and French (2000). In their study they form 25 portfolios (i.e. 5 size x 5 BM portfolios) for the purpose of identifying the difference in returns of stocks with very similar characteristics. We also apply this approach in this study but construct fewer portfolios due to the large difference in the number of firms listed in the US and the UK.

Six portfolios – Small/Low, Small/Medium, Small/High, Big/Low, Big/Medium and Big/High – are constructed from the intersections between two Size and three BM portfolios. For example, the Small/Low portfolio consists of stocks that are in the Small size group and also in the Low BM group. More specifically, small and big firms are separated by the median at the end of June, year *t*. Also, firms' B/M ratio at the end of December of year *t-1* is used to sort stocks into high, middle and low book-to-market portfolios for the following year using the breakpoints of the top 40%, the middle 20% and the bottom 40%. It is worth noticing that non-US markets have significantly fewer listed firms in comparison with the US market. Thus, following Dimson et al. (2003), our test uses the 40:20:40 breakpoint for the UK market *instead* of the usual 30:40:30 in order to select all stocks that can be representative of the value and growth portfolios. However, this line of explanation does not apply to the risk factor constructions later in this section.

Separately, another 9 portfolios are formed based on individual firm volatility and B/M ratio. They are again intersections between three firm volatility and three BM portfolios. Firm-level volatility at the end of June year *t-1* for one year beginning July year *t-1* is ranked separately into three portfolios with similar deciles (40:20:40). The breakpoints for BM are also at the 40^{th} and 60^{th} percentiles. The decision to break volatility/BM into many smaller groups (9 instead of 6 portfolios) is driven from an idea of examining extreme effects. Value-weighted portfolio returns are calculated monthly from July year *t* until June of year *t+1*. The portfolios are rebalanced every year.

It is worth noticing that in this chapter all explanatory variables will be constructed using the usual 30:40:30 breakpoint as they are meant to proxy for the risk patterns that have not been captured by the CAPM rather than to measure the actual returns. They are, therefore, expected to capture the most extreme positions which are the riskiest and the safest options associated with their corresponding type of risk in the market.

Unlike other variables, volatility portfolios are formed without lags given the fact that stock prices are accessible without long delays. In addition, under normal business conditions, it appears to be more practical for investors to rely on one-year stock volatility to make their portfolio allocation decisions rather than on a longer horizon. Therefore, one-year volatility is used to rank volatility portfolios. It is also possible to use less-than-a-year analysis for more frequent portfolio rebalancing. Considering the fact that transaction costs would make frequent rebalancing too costly, this chapter limits its study to a one-year buy-and-hold strategy.

Independent variables: From a range of independent variables listed in Section 2.5 of Chapter 2, the explanatory variables used to test the relationship between value premium and distress risk in Chapter 3 include the following: the FF three factors (i.e. the market, HML, SMB), the Carhart momentum factor (WML), and default factors (DEF which is based on O-score, and DEF' which is based on the Z-score indicator).

As described earlier in Section 2.5 of Chapter 2, the three FF factors are constructed as described in Fama and French (1993). The market variable (R_m - R_f) is the market excess returns on all UK firms with BM data. The data is obtained from Kenneth R. French's database. The High-minus-Low (HML) factor is meant to mimic the risk patterns associated with the BM in asset returns. HML is computed as the difference between the monthly returns on the simple average return on the two High BM stock portfolios and those on the simple average return of the two Low BM stock portfolios. The Small-minus-Big (SMB) variable is computed as the size effect representative, mimicking the risk factor associated to size in asset returns. SMB is the difference between the monthly returns on the simple average return on the three small stock portfolios and those on the simple average return of the three big stock portfolios.

Winner-minus-Loser (WML) is constructed based on the stock's 11-month past returns, following Jegadeesh and Titman's (1993) approach. The monthly portfolio returns are calculated at July, year *t* with a 1-month lag and value weighted by the market value at the end of June, year *t.* The WML is the return differential between the top 30% and the bottom 30% stocks.

Lastly, the default risk (DEF) factor is constructed as the return differentials between the highest 30% and the lowest 30% default probability groups ranked by O-score. For robustness check purposes, the chapter also employs the DEF' variable which is based on Z-score, an alternative indicator of default probability. Throughout the chapter, this breakpoint is used consistently when forming factors on a portfolio basis. More specifically, similar to Fama and French's (1993) method of constructing the HML factor, each year's value-weighted returns of each group are computed from July, year *t-1* to June, year *t* and rebalanced annually. The difference in their monthly returns then forms the risk factors for that given period.

3.4.3 Designing the tests

The chapter aims to examine the above three hypotheses in section 3.2.4 using both time-series and cross-sectional approaches. The Ordinary Least Squares (OLS) method is used to estimate the parameters in all regressions.

The chapter first examines the validity of value strategies and the explanatory power of Fama and French's three factors in capturing the value premium, if any, in the UK. Next, it tests the first hypothesis on the role of default risk and conventional risk factors (e.g. market risk, size, B/M ratio, and momentum effect) in explaining value anomaly. In order to test the role of default risk in explaining the abnormal value premium phenomenon, the chapter studies this from two dimensions: i) it constructs default factors (DEF) using default probability as the proxy; (ii) it uses Griffin and Lemmon's (2002) portfolio approach to further check the robustness of the results.

In terms of proxies, when considering default probability, besides using O-score as proposed by Ohlson (1980), another commonly used proxy, Z-score as proposed by Altman (1968) is used to ensure the findings are not driven by the choice of indicator. If the robustness check confirms the findings, the rest of the chapter will base its analysis on O-score for its wider application. Details of the formulae, construction and discussion will be detailed in section 3.4.5.

It is worth noticing that in the literature, corporate bond yield is usually used as default risk proxies. While this approach is equally valid, this chapter is pioneering the use of the probability of bankruptcy to proxy for default risk in value anomaly literature. This approach includes an extensive and comprehensive range of firm's accounting information. Furthermore, not every firm issues corporate bonds, hence our approach will be expected to provide a more comprehensive picture of firms' default risk. The DEF factor is constructed on the basis of portfolio return differentials between the highest and the lowest default probability stocks.

In the second approach, Griffin and Lemmon's (2002) 9 default risk/BM portfolios can be formed similarly to the way we built the volatility/BM portfolios described earlier in section 3.4.2. It is worth noticing that, unlike Griffin and Lemmon, this chapter constructs 9 intersection portfolios from the FTSE350 as this appears to be more suitable for non-US markets. In Griffin and Lemmon's study, for each of the two size groups they sort 15 separate portfolios formed between three BM portfolios and five O-score portfolios. This results a set of 30 intersection portfolios. However, this portfolio formation has the potential to cause econometric issues which may arise from the small size of regressed portfolios.

Regarding hypothesis 2, as stock return volatility is not normally considered as a risk factor on its own, this chapter does not aim to construct a separate factor but rather to capture the risk pattern in return volatility in their intersection portfolios.

To separately examine the relationship between value premium and volatility risk, the chapter constructs 9 intersection portfolios from three independent BM portfolios (High, Medium and Low BM) and three rankings on volatility (also High, Medium and Low volatility). This will enable to answer the question whether the risk pattern in BM and default likelihood conditions is reflected in stock returns. See section 3.3.2 for details of the intersection portfolio construction. Additionally, a number of asset pricing models, including the CAPM, the Fama and French three-factor model and an augmented Fama and French's model with default risk, are used to estimate the stock returns of the 9 portfolios cross-sectionally.

Although there are several more complicated asset pricing models than the classical CAPM and Fama and French three-factor model, these two provide at least a useful starting point. Specifically, derived from the CAPM, there are, for example, several augmented models: ICAPM, CCAPM and their conditional versions. Among them, Merton (1973) documents that the CAPM can still explain a significant fraction of the movement of asset returns. For more details, Appendix 4 provides a summary of some alternative asset pricing models that are frequently used in the literature. Since the chapter does not intend to engage in the debate on the best possible asset pricing model, it starts with the simple but long-standing CAPM and Fama and French's model. Subsequently, for the purpose of testing a new candidate – default risk – the Fama and French three-factor model is augmented with this factor.

Finally, to further examine hypothesis 3 of whether default risk and volatility are both related to characteristics that imply a distress risk in stock returns, the chapter seeks to capture their risk pattern by using O-score and volatility ranking that is reflected in stock returns. It also checks the robustness of the findings by employing other proxies for default probability, such as Altman's (1968) Z-score.

3.4.4 The Asset pricing models

- The CAPM

In order to explain value premium, there are two main asset-pricing models, namely the CAPM of Sharpe (1964) and Lintner (1965), and the three-factor regressions proposed by Fama and French (1993).

According to the CAPM, systematic risk is related to expected returns, while unsystematic risk and firms' characteristics are irrelevant. The basic form of the CAPM is:

$$E(R_i) = R_f + \beta_{im} [E(R_m) - R_f] \qquad (3.1)$$

Where, $E(R_i)$, $E(R_m)$ are expected returns on asset i and the market, respectively;

R_f is the risk-free rate of returns, and β_{im} is the slope in the time-series regression:

$$\beta_{im} = \frac{Cov\ (Ri,Rm)}{Var\,(Rm)} \qquad (3.2)$$

Where, $cov(R_i, R_m)$ is covariance between returns on asset i and returns on the market; and $var(R_m)$ is variance of returns on the market portfolio.

In the study, the estimates of the CAPM time-series regression are reported as follows:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i (R_{m,t} - R_{f,t}) + \varepsilon_{it} \qquad (3.3)$$

Where, $R_{i,t}$ is returns on asset i at time t; R_{ft} is returns on the risk-free asset at time t; $R_{m,t}$ is returns on the market portfolio; and ε_{it} is an error term.

The null hypothesis is that all intercepts are equal to zero.

- The Fama and French three-factor models

$$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + h_i HML_t + s_i SMB_t + \varepsilon_{it} \quad (3.4)$$

Where, High-minus-Low (HML) and Small-minus-Big (SMB) are the excess returns of high BM over low BM portfolios, and small over large portfolios, respectively; and ε_{it} is an error term.

- The Carhart (1997) four-factor models

$$R_{it} - R_{ft} = \acute{\alpha}_i + \beta'_i (R_{mt} - R_{ft}) + h'_i HML_t + s'_i SMB_t + w'_i WML_t + \varepsilon_{it} \quad (3.5)$$

Where, the WML proxy for momentum component is measured by the difference in returns between stocks of firms in the highest 30% past 11-month group and those in the lowest 30% past-11-month performers; and ε_{it} is an error term.

- The Augmented models

$$R_{it} - R_{ft} = \theta_i + \delta_{mi} (R_{mt} - R_{ft}) + \delta_{HMLi} HML_t + \delta_{SMBi} SMB_t + \delta_{DEFi} DEF_t + \nu_{it} \quad (3.6)$$

and,

$$R_{it} - R_{ft} = \theta'_i + \delta'_{mi} (R_{mt} - R_{ft}) + \delta'_{HMLi} HML_t + \delta'_{SMBi} SMB_t + \delta'_{WMLi} WML_t + \delta'_{DEFi} DEF_t + \nu'_{it} \quad (3.7)$$

Where, DEF stands for default risk measured by the difference in returns between stocks of firms with a high probability of bankruptcy and those with a low probability of defaulting, and ν_{it} is an error term.

3.4.5 O-score and Z-score

Developing from the conditional logit model, Ohlson (1980) uses maximum likelihood methodology to estimate the logarithm of probability of outcomes in equation (3.8) and build an O-score based on nine dependent variables, including six main accounting ratios, $log\,\frac{Total\ assets}{GNP\ price-level\ index}$ and two dummy variables in formula (3.9) [18].

$$Log(\beta) = \sum_{i \in S_1} \log P(X_i, \beta) + \sum_{i \in S_2} \log(1 - P(X_i, \beta)) \quad (3.8)$$

Where, X_i = vector of predictors for i^{th} observation

[18] See Griffin and Lemmon (2002, p.2320) for a mathematical form of the Ohlson's (1980) O-score calculation.

β = vector of unknown parameters

P(X_i, β) = probability of bankruptcy for any given X_i and β

S_1 and S_2 are the sets of bankruptcy and non-bankruptcy firms.

$$\boldsymbol{O-score} = -1.32 - 0.407\, log\, \frac{Total\ assets}{GNP\ price - level\ index} + 6.03\, \frac{Total\ liabilities}{Total\ assets} - 1.43\, \frac{Working\ capital}{Total\ assets} + 0.076\, \frac{Current\ liabilities}{Current\ assets} - 1.72\, (= 1\ if\ total\ liabilities > total\ assets, 0\ otherwise) - 2.37\, \frac{Net\ income}{Total\ assets} - 1.83\, \frac{Funds\ from\ operations}{Total\ liabilities} + 0.285\, (= 1\ if\ net\ loss\ for\ last\ two\ years, 0\ otherwise) - 0.521\, \frac{(Net\ income_t - Net\ income_{t-1})}{|Net\ income_t - Net\ income_{t-1}|} \quad (3.9)$$

Unlike Ohlson, Altman (1968, p.594) proposes the use of Z-score with fewer independent variables and including only accounting ratios; the formula is as follows.

$$\boldsymbol{Z-score} = 0.012X1 + 0.014X2 + 0.033X3 + 0.006X4 + 0.999X5 \quad (3.10)$$

Where, $X_1 = \frac{Working\ capital}{Total\ assets}$

$$X_2 = \frac{Retained\ earnings}{Total\ assets}$$

$$X_3 = \frac{Earnings\ before\ interest\ and\ taxes\ (EBIT)}{Total\ assets}$$

$$X_4 = \frac{Market\ value\ equity}{Book\ value\ of\ total\ debt}$$

$$X_5 = \frac{Sales}{Total\ assets}$$

3.4.6 Volatility measurement of stock returns

The chapter computes an individual firm's share price standard deviation as proxy for its volatility. Standard deviation (σ_X) measures the variability of X, in other words, it measures how much X_i is deviated from the mean. The formula of the sample standard deviation is as follows.

$$\sigma_X = \sqrt{\frac{\sum_{i=1}^{N}(X_i - \bar{X})^2}{(N-1)}} \tag{3.11}$$

Where, σ_X is the standard deviation of variable X over a period of N; $\bar{X}$ is the mean of variable X over the whole period.

Volatility is subtly computed. First, for a 1-year buy-and-hold strategy, historical volatility is considered for the 1 month straight before portfolio formation. This allows for investors to have the most up-to-date information and provides enough time for the information to be widely known. Within that month, monthly volatility is calculated based on daily stock returns over a 1-month period from 1st June to 31st June year *t*.

3.4.7 Data descriptive statistics

The sample consists of 269 non-financial FTSE350 firms that have been listed for at least one year and have sufficient data on market capitalisation, and at least one of the four key ratios (BM, E/P, DY or C/P). Table 3.1 summarises some of the main features of the sample. It shows that the sample covers a wide range of firm sizes. While the largest firm reaches more than GBP 81 billion in value, the market value of the smallest firm is only about GBP 0.377 billion. However, their market value is nearly GBP 6.5 billion on average with a median of GBP 1.6 billion, which is equivalent to a medium sized business. This indicates that the majority of firms in the sample are large- and medium-sized businesses.

In terms of market value ratios, the BM ranges from -0.06 to 3.84 while the median is at 0.37, showing that there are a greater number of growth stocks (i.e. low BM) than value stocks (high BM) in the FTSE350. Moreover, on average, firms in the sample have a BM ratio of about 0.5 suggesting that growth firms in the UK have a relatively low book value, only about half of their market value. Furthermore, summary statistics of the other key market value ratios, E/P, DY and C/P, confirm these observations.

Table 3.1: Summary statistics

The table presents the summary statistics of the sample as of 31st December 2012. It reports firm size, BM, E/P, DY and C/P ratios of the 269 firms in the sample. The statistics include the mean, standard deviation (SD), median, maximum and minimum values of these measures across the sample.

	Market value (£million)	BM	E/P	DY	C/P
Mean	6,495.28	0.50	0.08	2.74	0.13
SD	13584	0.48	0.04	1.82	0.11
Median	1,636.01	0.37	0.08	2.62	0.10
Max.	81,310.19	3.84	0.29	11.95	0.69
Min.	377.38	-0.06	0.001	0	-0.22

3.4.8 Value premium and robustness checks

The chapter first checks if the value anomaly exists in the UK market in recent times. Besides the commonly used BM indicator, it also uses E/P and DY to rank stocks into value and growth portfolios for robustness check purposes. The results are reported in Table 3.2.

As can be seen from the table, value stocks do generate a higher return than growth. On average, the value premium is about 0.09% a month when using BM as the indicator and it is 0.06% in the case of E/P and DY ratios. More importantly, the results show that although there is value premium in the UK, it is statistically insignificant. The findings are consistent with those found by Dimson et al. (2003) for the UK market. The robustness checks also indicate that using different indicators does not affect our results.

Table 3.2: Value premium and Robustness checks

Table 3.2 reports the performance of value strategies using three commonly-used indicators for value and growth stocks, namely BM, E/P and DY. The less-popular ratio, C/P, is omitted due to insufficient data. The table summarises average monthly value-weighted returns on value and growth portfolios (in percentage). Value consists of the highest 40% BM (E/P or DY) stocks, Medium are the middle 20% and Growth includes the lowest 40% BM (E/P or DY) stocks. The *t-statistics* test the significance level of the portfolio rate of return in question.

	BM	**E/P**	**DY**
Value	0.59	0.52	0.47
Growth	0.40	0.46	0.41
Value-Growth	0.09	0.06	0.06
[*t*-statistics]	[0.49]	[0.47]	[0.42]

3.5 DISTRESS RISK EXPLANATIONS

3.5.1 Book-to-market equity and size premium

This section considers the presence of the value premium and size premium. Table 3.3 reports the average monthly 1-year buy-and-hold returns for each size and book-to-market portfolio.

The value premium exists more in the small portfolios than in the big ones. On average, the results indicate a 0.11%/month of return differential for small stocks, and -0.25 for big stocks. This makes sense economically because small value firms are more likely to be distressed firms, and therefore bearing higher risks. Thus, any small firms that have survived for 20 years could have a higher returns rate. Clearly, big growth firms are more profitable than big value firms. The return differentials between value and growth stocks are, however, statistically insignificant in both size-groups. The finding is not the same as one documented in Dimson et al. (2003) which reports a strong value premium in the UK from 1955-2001. The difference in sampling could largely explain this difference. While Dimson et al. (2003) look at all firms traded in the London Stock Exchange, including financial firms and SmallCap stocks, this chapter sees the need to exclude them in its sample (discussed earlier in section 3.4.1).

Table 3.3: Six Size/BM portfolios

Table 3.3 summarises the monthly value-weighted returns of 6 intersection portfolios (in percentage) formed by 3 book-to-market value and 2 size rankings, and value and size premiums. In particular, Value consists of the highest 40% BM stocks, Medium are the middle 20% and Growth includes the lowest 40% BM stocks. Small and Big stocks are separated by the medium. *t*-statistics show the mean significance of corresponding abnormal returns. *, **, and *** denote the significance levels at 10%, 5% and 1%.

	Size			
BM group	Small	Big	Small-Big	*t*-statistic
Value	0.75	0.10	0.65	1.96*
Medium	0.64	0.16	0.48	1.51
Growth	0.64	0.35	0.29	1.27
Value Premium	0.11	-0.25		
[*t*-statistic]	[0.48]	[-1.00]		

Regarding size premium, it is much higher among the value stocks than growth stocks, i.e. 0.65% and 0.29%, respectively. Obviously by definition, small value firms have a lot more potential for growth than big cap value firms. Also, the size effect is only slightly significant among value stocks (*t*-statistic value of 1.96, significance at 10% level). Both value and size premiums are mostly insignificant, implying that investors correctly price stocks in the UK market; in other words, the market is fairly efficient.

Table 3.4 now investigates the value premium and whether the differences in firm level volatility risk captured by BM and volatility are reflected in stock returns. There are 9 portfolio returns calculated as the intersection of three volatility groups by three BM portfolios. The three volatility groups are high volatility (High Vo), medium volatility (Med Vo), and low volatility (Lo Vo). Within the low volatility group (considered to be the safer group) there does not exist a value premium. The returns on the Value/Low Vo portfolio is 0.43%, being lower than Growth/Low Vo stocks by 6 basis points (at 0.49%). In contrast, among the High Vo group, the positive premium exists although it is relatively small at 0.01% per month.

More volatile risky choices do not perform better than the lower volatility portfolio. This result is consistent for both the value and the growth group (0.16% and 0.15% versus 0.43% and 0.49%, respectively). As a preliminary check, this study found no evidence suggesting that high volatility stocks generate a higher return than low volatility stocks. Within the low volatility group, investing in the value stocks, which are more likely to be in distress, brings lower returns than growth firms. The opposite is true for high volatility portfolios. In short, the safer the choice is, made by volatility grouping, the more profits growth and value stocks bring (the tendencies are 0.15% – 0.24% – 0.49% and 0.16% - 0.27% - 0.43%).

Table 3.4: Nine Volatility/BM portfolios

This table presents the monthly value-weighted returns of 9 intersection portfolios (in percentage) formed by 3 book-to-market values and 3 volatility rankings, and the potential abnormal returns. In particular, Value consists of the highest 40% BM stocks, Medium are the middle 20% and Growth includes the lowest 40% BM stocks. Low Vo, Medium Vo and High Vo stand for low, medium and high volatility stocks using the same breakpoints. *t*-statistics test the mean significance of corresponding abnormal returns. *, **, and *** denote the significance levels at 10%, 5% and 1%.

		Volatility risk			
BM group	Low Vo	Medium Vo	High Vo	Low Vo-High Vo	*t*-statistic
Value	0.43	0.27	0.16	0.27	0.71
Medium	0.78	0.24	0.31	0.47	1.18
Growth	0.49	0.24	0.15	0.34	0.97
Value Premium	-0.06	0.03	0.01		
[*t*-statistic]	[-0.24]	[0.09]	[0.02]		

3.5.2 The Fama and French three-factor model

Table 3.5 reports time series estimations on the returns on six portfolios ranked by size and BM from 1990 to 2012. The Fama and French (1993) three factor model is employed to examine whether it has any ability to capture the size and BM patterns in stock returns. The factor loadings are calculated from monthly value weighted portfolios by regressing excess returns on the market portfolio (R_M), book-to-market (HML) and size (SMB) effects.

As can be seen from Table 3.5, the coefficients of the market factor (Beta) are found to be significant at a 1% confidence level with the exception of the Big stocks with a high BM value portfolio. Perhaps the market factor does not affect the big stocks as much as the smaller ones, even though they are value stocks too. Overall, the CAPM betas appear to remain important in explaining stock returns. When the model captures variations in returns well, the intercept should be indistinguishable from zero. In our case the big stock portfolio has statistically insignificant intercepts; that implies that the pricing errors are low. However, for small portfolios, pricing errors are negatively more significant as they move across BM groups. The results of negative regression intercepts are consistent with those in the Fama and French study (1993).

The HML factor is important for value stocks at a 1% level and not for growth stocks. This indicates the significant explanatory power of the book-to-market effects in explaining high BM stock returns while it is not the case for growth groups. The positive signs of coefficients associated with the book-to-market factor loading reaffirm the results of previous studies, such as Dimson et al. (2003) and Phalippou (2007).

The coefficient associated with the size factor is -0.230, significant at a 5% level, for small growth stocks but not for the big ones of the same group (-0.006 with *t*-statistic at -0.06). Similar results are observed within the high BM group. This factor is often hard to find an economic interpretation for, as even Fama and French admitted the short-fall of the factor bearing no link with economic theories. They also found size effects have a negative relation to the average returns of stocks.

From Table 3.5, *Adjusted* R^2s are relatively low and tend to be lower as they move toward big and low BM groups. This confirms the results discussed earlier that the Fama and French three-factor model seems to capture better the movement of small-cap stocks and high BM stocks.

Table 3.5: Three-factor regressions for six portfolios sorted by size and BM

The table presents time-series estimation results of Fama and French's (1993) three-factor model on 6 intersection portfolios formed by 3 book-to-market and 2 size rankings. In particular, HBM, M and LBM denote the highest 40%, the middle 20% and lowest 40% book-to-market value stocks while Small and Big stocks are separated by the medium. The excess return on the market, $R_m - R_f$, is obtained from Prof. Kenneth R. French's website for the UK market. HML and SMB are constructed similarly to the way Fama and French (1993) built their factors, which are meant to mimic BM and size effects in expected stock returns using the same breakpoints. The table reports estimated coefficients and their *t*-statistics. *, **, and *** denote the significance levels at 10%, 5% and 1%. The goodness of fit R^2s are adjusted for the degree of freedom.

	Small	Big	Small	Big
	α		t(α)	
HBM	-0.002	0.002	-0.51	0.68
M	-0.007	-0.003	-1.77*	-0.68
LBM	-0.008	-0.002	-2.16**	-0.56
	β		t(β)	
HBM	0.480	0.059	5.60***	0.78
M	0.723	0.517	8.05***	5.62***
LBM	0.596	0.400	6.61***	4.29***
	h		t(h)	
HBM	0.442	0.591	3.42***	5.13***
M	-0.179	-0.256	-1.31	-1.84*
LBM	0.028	0.098	0.21	0.69
	s		t(s)	
HBM	-0.176	-0.120	-1.83*	-1.39
M	-0.029	-0.225	-0.29	-2.17**
LBM	-0.230	-0.006	-2.26**	-0.06
	Adj R^2			
HBM	0.16	0.10		
M	0.19	0.11		
LBM	0.15	0.06		

3.5.3 Carhart four-factor model

Carhart's (1997) four-factor model is an extension of the FF three-factor model, including a momentum factor. Following Jegadeesh and Titman's (1993) approach to building the momentum component, the WML is constructed based on stocks' 11-month past returns. The monthly portfolio returns are calculated at July, year *t* with a 1-month lag and value weighted by the market value at the end of June, year *t*. The WML is the return differential between the top 30% and the bottom 30% stocks. The estimation results on the four-factor model are reported in Table 3.6.

Using the Carhart (1007) four-factor model on size/BM excess returns, the estimation results show that the explanatory power of the FF model has been improved slightly. The intercepts are lower in terms of magnitude and significance. For the value stock (i.e. high BM equity), the constant terms are about 0.001 (*t*-statistics are -0.37 for Small stocks and -0.42 for Big stocks). Similarly, regressions on the excess returns on Big stocks (including value, growth and medium BM companies) produce insignificant constant terms. They range from -0.002 to -0.001 (*t*-statistics are between -0.71 and -0.42). On the contrary, the constant in regression on the Small/Low BM portfolio excess returns remains high at -0.010 (*t*- statistic is -2.58, statistically significant at 5% level). Unlike in the FF three-factor model, regression on the Small/Medium BM excess returns produces an intercept that is no longer statistically significant. This implies that perhaps some risk elements missed in the three-factor model have been priced in the four-factor model.

With regard to model explanatory variables, the magnitude of coefficients associated with these decreases slightly. The sign and significance of market beta, HML and SMB coefficients largely remain unchanged in the presence of the momentum component. The market betas are positive and statistically significant in most cases. Also, the coefficients are larger within small stocks than big stocks. The estimated market beta is 0.479 (significant with a *t*-statistic of 5.54) for the Small/High BM portfolio and is 0.591 (highly significant with a *t*-statistic of 6.56) for the Small/Low BM portfolio. However, these coefficients are only 0.061 (statistically insignificant) and 0.397 (significant at 1%) for Big/High BM and Big/Low BM, respectively.

Coefficients associated with the BM effect are positive and highly significant in regressions on value portfolios but insignificant for growth stocks. In regressions on the value stocks, the estimated coefficients *h'* take the value of 0.445 (*t*-statistic is 3.43) and 0.588 (*t*-statistic is 5.10) for Small/High BM and Big/High BM, respectively. For growth portfolios, the BM variable is positively correlated to excess returns on both the Small and Big portfolios. The BM effect is however not dominant among these groups of stocks. The coefficients associated with BM factor are statistically insignificant, being at only 0.029 and 0.099 for Small growth and Big growth portfolios, respectively. Among Medium BM stocks, there is some BM effect shown in Big/Medium BM stocks but it has a limited effect on Small/Medium BM portfolio returns.

Similar to what was observed in the above BM effect testing, the size effect is more noticeable among Small stocks but less in the Big portfolio. The estimated coefficients associated with the SMB variable are negative and statistically significant in regressions on Small/High BM and Small/Low BM excess returns. In these regressions, they take the values of -0.179 (*t*-statistic of -1.85) and -0.227 (*t*-statistic of -2.4). The results suggest that it is important to take into account differences in market values when explaining the movement in average returns of small size companies. Also, investing in smaller stocks could gain a higher size premium while returns on big stocks are less sensitive to the size effect. In the original study, Fama and French (1992, 1993) have noticed this relationship in the US, and the findings in this chapter confirm that their conclusions on the roles of BM and size effects are also valid in the UK market.

In terms of the momentum factor, the results in Table 3.6 indicate that there is a momentum effect among Small/Low BM stocks but the explanatory power of the momentum variable is less significant in explaining excess returns on other portfolios. In the table, the estimated coefficients *w'* are largely positive (negative) in regressions on excess returns on the Small (Big) portfolios. This suggests that investing in big companies is less likely to lead to a large momentum premium whilst investing in smaller firms would do so.

The higher *Adjusted* R^2s in the Carhart regressions imply that the momentum variable has contributed to capturing more of the movement in average stock returns. The *Adjusted* R^2s are between 0.17 and 0.26 in comparison with under 0.06 and 0.19 in the FF three-factor model. The low goodness of fit of both models suggests that there are potentially risk elements that have not been captured by these classic models.

Table 3.6: Four-Factor Regressions for Six Portfolios Sorted by Size and BM

The table presents time-series estimation results of Carhart's (1997) four-factor model on 6 intersection portfolios formed by 3 book-to-market value and 2 size rankings. In particular, HBM, M and LBM denote the highest 40%, the middle 20% and lowest 40% book-to-market value stocks while Small and Big stocks are separated by the medium. The excess return on the market, $R_m - R_f$, is obtained from Prof. Kenneth R. French's website for the UK market. HML and SMB are constructed similarly to the way Fama and French (1993) built their factors, which are meant to mimic BM and size effects in expected stock returns using the same breakpoints. The WML component is built based on stocks' 11-month past returns, according to which WML is the return differential between the top 30% and the bottom 30% stocks. The table reports estimated coefficients and their *t*-statistics. *, **, and *** denote the significance levels at 10%, 5% and 1%.

	Small	Big	Small	Big
	$\acute{\alpha}$		t($\acute{\alpha}$)	
HBM	-0.001	-0.001	-0.37	-0.42
M	-0.006	-0.002	-1.26	-0.71
LBM	-0.010	-0.001	-2.58**	-0.43
	β'		t(β')	
HBM	0.479	0.061	5.54***	0.82
M	0.731	0.519	8.07***	5.65***
LBM	0.591	0.397	6.56***	4.20***
	h'		t(h')	
HBM	0.445	0.588	3.43***	5.10***
M	-0.173	-0.254	-1.29	-1.81*
LBM	0.029	0.099	0.24	0.69
	s'		t(s')	
HBM	-0.179	-0.122	-1.85*	-1.41
M	-0.028	-0.222	-0.26	-2.13**
LBM	-0.227	-0.006	-2.24**	-0.05
	w'		t(w')	
HBM	-0.010	-0.063	-0.50	-0.98
M	0.085	-0.073	1.31	-1.02
LBM	0.108	-0.084	1.98*	-1.26
	Adj R^2			
HBM	0.25	0.20		
M	0.26	0.24		
LBM	0.21	0.17		

3.5.4 SMB, HML, WML and factor loading on default risk

In this section, the Fama and French (FF) three-factor model and Carhart four-factor model also control for the risk of a firm going bankrupt measured by O-score as suggested by Ohlson (1980). First of all, default risk is added in the conventional FF three-factor model and the findings are discussed in section 3.5.4.A. In order to have a direct comparison of the default risk for the three- and four-factor models, we also control for the DEF factor in a regression on Carhart's four factors in section 3.5.4.B. The results of these sections are reported in Panels A and B of Table 3.7, respectively.

3.5.4.A. Default risk and the FF three-factor model

In this section, an augmented model is formed by adding a default component to the FF model. The default factor, DEF, is meant to mimic the risk patterns in stock returns that have not been captured by Fama and French's three factors. Panel A of Table 3.7 summarises the estimated coefficients of time-series regressions on 6 intersection portfolios formed between 2 size portfolios (Small and Big) and 3 BM portfolios (High, Medium and Low).

As can be seen from the table, the regression intercepts are negative and insignificant in most cases. Exceptions are in the regression on the Big/High BM portfolio which results in a positive intercept, and the regression on the Small/Low BM group which produces a statistically significant intercept. These confirm findings reported earlier in this chapter that value and size premiums do not exist in all groups of stocks. In particular, the value premium is more noticeable within Small stocks while the size effect is more dominant in value stocks.

The coefficients associated with the market factor are positive and statistically significant at a 1% level in most cases, except for the Big/High BM portfolio. The market beta in regression on the Big/High BM stock returns is only 0.041 (*t*-statistic is 0.62, statistically insignificant). This indicates that unlike other portfolio groups, the Big and Growth companies among the FTSE350 are less likely to be affected by the overall movement of the market. For other portfolios, the coefficients δ_m are highly significant, for example the market beta in regression on Small/Low BM is as high as 0.622 with a *t*-statistic of 6.55, which is of a 1% statistical significance.

In line with Griffin and Lemmon's (2002) findings, the results in Panel A show that HML and SMB variables are important in explaining the movement of average stock returns in the UK. The coefficients associated with the HML factor are positive and highly significant in regressions on High BM portfolios. The estimated coefficients are 0.339 (*t*-statistic is 3.31) for Small/High BM stocks and 0.715 (*t*-statistic is 5.21) for Big/High BM groups. The magnitude and significance of the HML coefficients, δ_{HML}, decrease in the Medium BM portfolio and become statistically insignificant in the Low BM group. These indicate that the BM effect is more noticeable among High and Medium BM stocks.

In terms of the size effect, the estimated coefficients δ_{SMB} show that the SMB variable plays an important role in explaining returns on the Small/Low BM and the Big/Medium BM stocks but less important in regression on the Big/Low BM and High BM portfolio returns. The values of δ_{SMB} in the regressions on the Small/Low BM and Big/Medium BM portfolio returns are -0.221 (*t*-statistic of -2.18, significant at a 5% level), and 0.249 (*t*-statistic of 1.98, significant at a 10% level), respectively. However, the coefficients are only between 0.002 and 0.140 in absolute terms and statistically insignificant in the case of other portfolios.

From Panel A, it can be said that beside the Fama and French three factors, the default risk proxied by O-score does play an important role in explaining expected stock returns. Generally, firms with a high probability of bankruptcy or under distress would be less likely to yield a high stock return. The results in Panel A indeed confirm that default risk has a negative relationship with expected stock returns in the UK market. Additionally, most of the coefficients associated with DEF are statistically significant, especially among small stocks. The coefficients range from -0.092 (*t*-statistic equal to -0.93) to -0.210 (*t*-statistic is -2.37, significant at a 5% level). Furthermore, when comparing with the FF regressions, the constant terms from the regressions are less significant. The *Adjusted* R^2s in models augmented with the default variable are also higher. In Table 3.5, the highest *Adjusted* R^2 is 19%. However, the highest *Adjusted* R^2 in Table 3.7 is 39%. The results suggest that the presence of the DEF factor in the FF three-factor model contributes to capturing more of the movement in average stock returns in the UK.

Table 3.7: Time-series regressions with default risk on 6 size/BM portfolios

Panel A: Augmented Fama and French (1993) three-factor model (model 3.6)

$$R_{it} - R_{ft} = \theta_i + \delta_{mi}(R_{mt} - R_{ft}) + \delta_{HMLi} HML_t + \delta_{SMBi} SMB_t + \delta_{DEFi} DEF_t + v_i$$

The table presents time-series estimation results of the above regression on 6 intersection portfolios formed by 3 book-to-market and 2 size rankings. In particular, HBM, M and LBM denote the highest 40%, the middle 20% and lowest 40% book-to-market value stocks while Small and Big stocks are separated by the medium. The excess return on the market, $R_m - R_f$, is obtained from Prof.. Kenneth R. French's website for the UK market. HML and SMB are constructed similarly to the way Fama and French (1993) built their factors, which are meant to mimic BM and size effects in expected stock returns using the same breakpoints. Distress factor (DEF) is the difference in value-weighted returns of stocks in the top 30% O-score and the bottom 30% O-score ranking groups. It is worth noticing that while these 6 portfolios are formed using the breakpoint 40:20:40 to adapt to the smaller size of non-US markets, portfolio-based factors use the usual 30:40:30 breakpoint instead because they proxy for risk factors rather than measuring actual returns. The panel reports estimated coefficients and their *t*-statistics. *, **, and *** denote the significance levels at 10%, 5% and 1%. The goodness of fit R^2s are adjusted for the degree of freedom.

	Small	Big	Small	Big
	θ		t(θ)	
HBM	-0.001	0.004	-0.39	0.82
M	-0.007	-0.002	-1.05	-0.55
LBM	-0.006	-0.002	-2.01**	-0.51
	δ_m		t(δ_m)	
HBM	0.356	0.044	5.52***	0.67
M	0.617	0.545	7.68***	5.71***
LBM	0.622	0.389	6.55***	4.10***
	δ_{HML}		t(δ_{HML})	
HBM	0.339	0.715	3.31***	5.21***
M	-0.220	-0.278	-1.89*	-1.92*
LBM	0.031	0.111	0.25	0.88
	δ_{SMB}		t(δ_{SMB})	
HBM	-0.106	-0.140	-1.66	-1.44
M	0.002	0.249	0.09	1.98*
LBM	-0.221	-0.015	-2.18**	-0.10
	δ_{DEF}		t(δ_{DEF})	
HBM	-0.114	-0.108	-2.34**	-1.88
M	-0.100	-0.092	-1.04	-0.93
LBM	-0.210	-0.203	-2.37**	-2.01*
	Adj R^2			
HBM	0.45	0.39		
M	0.39	0.36		
LBM	0.42	0.41		

Table 3.7 – Continued

Panel B: Augmented Carhart (1997) four-factor model (model 3.7)

$R_{it} - R_{ft} = \theta'_i + \delta'_{mi}(R_{mt} - R_{ft}) + \delta'_{HMLi}HML_t + \delta'_{SMBi}SMB_t + \delta'_{WMLi}WML_t + \delta'_{DEFi}DEF_t + \nu'_i$

The table presents time-series estimation results of the above regression on 6 intersection portfolios formed by 3 book-to-market value and 2 size rankings. In particular, HBM, M and LBM denote the highest 40%, the middle 20% and lowest 40% book-to-market value stocks while Small and Big stocks are separated by the medium. The excess return on the market, $R_m - R_f$, is obtained from Prof. Kenneth R. French's website for the UK market. HML and SMB are constructed similarly to the way Fama and French (1993) built their factors, which are meant to mimic BM and size effects in expected stock returns using the same breakpoints. Following Jegadeesh and Titman's (1993) approach, Winner-minus-Loser (WML) is constructed based on stocks' 11-month past returns. The monthly portfolio returns are calculated at July, year *t* with a 1-month lag and value weighted by the market value at the end of June, year *t*. WML is the return differential between the top 30% and the bottom 30% stocks. The distress factor (DEF) is the difference in value-weighted returns of stocks in the top 30% O-score and the bottom 30% O-score ranking groups. It is worth noticing that while these 6 portfolios are formed using the breakpoint 40:20:40 to adapt to the smaller size of non-US markets, the portfolio-based factors use the usual 30:40:30 breakpoint instead because they proxy for risk factors rather than measure actual returns. The panel reports estimated coefficients and their *t*-statistics. *, **, and *** denote the significance levels at 10%, 5% and 1%. The goodness of fit R^2s are adjusted for the degree of freedom.

	Small	Big	Small	Big
	θ'		t(θ')	
HBM	-0.001	0.005	-0.41	0.85
M	-0.005	-0.003	-1.00	-0.61
LBM	-0.004	-0.004	-1.87*	-0.65
	δ'_m		t(δ'_m)	
HBM	0.351	0.041	5.46***	0.62
M	0.610	0.543	7.62***	5.68***
LBM	0.619	0.386	6.41***	4.03***
	δ'_{HML}		t(δ'_{HML})	
HBM	0.335	0.712	3.29***	5.20***
M	-0.218	-0.273	-1.86*	-1.87*
LBM	0.030	0.111	0.22	1.38
	δ'_{SMB}		t(δ'_{SMB})	
HBM	-0.109	-0.143	-1.68	-1.47
M	0.003	0.251	0.12	2.01*
LBM	-0.225	-0.016	-2.21**	-0.12
	δ'_{WML}		t(δ'_{WML})	
HBM	-0.021	-0.056	-0.24	-0.33
M	0.113	-0.102	1.71	-1.25
LBM	0.216	-0.103	1.98*	-1.27
	δ'_{DEF}		t(δ'_{DEF})	
HBM	-0.112	-0.102	-2.30**	-1.71
M	-0.089	-0.091	-1.01	-0.90
LBM	-0.205	-0.200	-2.32**	-1.97*
	Adj R^2			
HBM	0.46	0.41		
M	0.42	0.38		
LBM	0.44	0.43		

3.5.4.B. Default risk and the Carhart (1997) four-factor model

The augmented Carhart model includes all the FF three factors, a momentum component and an additional default factor. In Panel B of Table 3.7, the estimated results are largely similar to those reported in Panel A for the augmented FF three-factor model. However, the magnitude of estimated coefficients are reduced in the presence of the momentum variable. The momentum factor also shows an ability to improve the overall performance of the model, especially contributing to explain the movement of the Small/Low BM portfolio.

As can be seen from the table, the constant terms remain negative and insignificant in most cases. The magnitude of the intercepts are however slightly smaller in absolute terms than those in the augmented FF three-factor model. Although the constant term in regression on Small/Low BM remains statistically significant, its magnitude and significance decrease to a 10% significant level.

In the presence of the momentum variable, the coefficients associated with other explanatory variables keep both their sign and significance. The magnitude is again marginally smaller than previously observed in the three-factor model. The market betas are positive and statistically significant at a 1% level, except for Big/High BM (δ'_m is equal to 0.041, *t*-statistic is 0.62). In other cases, the market betas range from 0.351 for Small/High BM to 0.619 for Small/Low BM, and *t*-statistics are between 4.03 to 7.62. Similar to the results in Panel A, the BM variable shows the ability to explain more movement of High BM and Medium BM stocks whilst it is not the case for Low BM stocks. In contrast, the size effect is more noticeable among Small/Low BM and Big/Medium BM portfolios. In terms of the distress factor, the results in Panel B confirm that default risk plays an important role in explaining the movement of Small portfolios, mainly within value and growth stocks. Among the Big stocks, the default variable however can only capture the default risk pattern in average returns on the Big/Low BM portfolio.

In comparison with the augmented FF three-factor model, the results in Panel B indicate that the momentum variable does contribute to explaining the movement of Small/Low BM stock returns. In the regression on the Small/Low BM portfolio returns, the coefficient associated with the WML variable, δ'_{WML}, is equal to 0.216 (*t*-statistic is just under 1.98, statistically significant at a 10% level). This means that small and growing companies, such as start-ups, tend to continue their good performance and are therefore a profitable investment in the long run. This tendency is however less observable in other groups of companies. For these groups, the momentum effect is less significant in capturing the risk patterns in portfolio returns. The estimated coefficients δ'_{WML} for those portfolios range between -0.021 and 0.216, statistically insignificant, with *t*-statistics of between -0.24 and 1.71. Although adding the WML variable does improve the estimation quality, the improvement is not substantial. The *Adjusted* R^2s increase to around 2 percent, comparable to those reported for the augmented Fama-French three-factor model.

Overall, the results in Panels A and B show that default risk plays an important role in explaining the movement of average stock returns. Its explanatory power is particularly noticeable in regressions on returns on Small stocks. This implies that small companies are more likely to suffer default risk than their big counterpart. Among Big stocks, it is Low BM stocks that bear a higher distress risk than High BM stocks. This indicates that big and over-priced companies have a higher probability of going bankrupt than big and growing firms.

The next section will discuss the robustness tests which aim to ensure that these findings are not sensitive to the choice of indicator or methodological approach.

3.5.5 Robustness checks

This section uses two approaches to check the robustness of the findings reported in section 3.5.4. Firstly, regressions are re-run on another commonly used proxy for default risk, which is Z-score. Secondly, an additional analysis is carried out using the portfolio-based approach to capturing default risk. This method was suggested by Griffin and Lemmon (2002) for the UK market, and will be implemented alongside the first approach in order to check the validity of findings in this chapter.

The results from the first approach are summarised in Table 3.8, of which Panel A reports the results of robustness checks using the FF three-factor model and the results of the test using the Carhart four-factor model are summarised in Panel B. In the table, the results indicate that when using Z-score instead of O-score as a proxy for a corporation's probability of bankruptcy the overall outcome is largely unchanged.

As can be seen from Panel A of Table 3.8, the constant terms are statistically insignificant. They range from -0.005 to -0.001 with *t*-statistics of between -0.93 and -

0.40. These once again confirm the findings that value and size premiums in the UK market are insignificant. The market factor remains the key explanatory variable in explaining the average stock returns. The coefficients associated with the excess market return variable, δ'_m, are positive and highly significant. It is worth noticing that in the regression on Big/High BM stocks, the estimated market beta is higher and becomes statistically significant when Z-score is used as an indicator for default risk. This may be due to the way Z-score is calculated. Besides the accounting information that O-score relies on, Z-score also includes firm size in measuring the probability of corporate failure. Therefore, the market risk elements become perhaps more important in explaining the movement of Big/High BM portfolio returns than they are when O-score is employed.

The results in Panel A also show that when Z-score is used as an alternative indicator of bankruptcy probability, the BM effect remains a key factor in capturing the movement of returns on the High BM and Medium BM portfolios but less significant among the Low BM stocks. Compared with the results reported previously in Table 3.7, most of the coefficients associated with the HML variable are lower in absolute terms but the differences are immaterial. Similarly, the size effect becomes slightly less noticeable in the regressions that use Z-score to measure default likelihood among FTSE350 companies. Despite these changes in magnitude, the significance of the coefficients associated with the size factor is unchanged. The coefficients δ'_{SMB} are statistically significant at a 10% level in regressions on the Small/Low BM and Big/Medium BM portfolios. They are -0.189 (*t*-statistic is -1.97) and 0.214 (*t*-statistic is 1.87), respectively.

Consistent with the previous results, default probability is negatively related to the expected stock returns. This indicates that in the long run companies with a higher likelihood of going bankrupt tend to have lower average stocks returns. In addition, Small and High BM firms and Big stocks with Low BM are among those most sensitive to default risk. In regressions on the excess returns on the two portfolios, the estimated coefficients associated with default risk, $\delta'_{Z\text{-}score}$, are -0.213 and -0.221 (*t*-statistic values of -2.10 and -2.17, and significant at a 10% level), respectively. However, the constant term from the regression on the Small/Low BM stocks is no longer significant, suggesting that the regression model is able to explain more of the differentials in stock returns.

In summary, the three factors in the FF model together with the default factor continue to play an important role in pricing expected stock returns of FTSE350 companies. Although using an alternative default factor results in sign changes for some coefficients, the magnitude and significance of explanatory variables do not change substantially.

As reported in Panel B of Table 3.8, a similar robustness check is carried out on the augmented Carhart four-factor model. It is to test whether the findings reported in Panel B of Table 3.7 are robust. In this test, Z-score (instead of O-score) is used as an indicator of bankruptcy probability.

Overall, the estimated coefficients in the augmented Carhart model are consistent regardless of which default indicator is used. In the regressions on excess returns on 6 size/BM portfolios, the intercepts range from -0.006 to -0.002, with *t*-statistics being between -0.97 and -0.31 (statistically insignificant). The market factor remains an important variable in explaining the returns on these 6 portfolios. The market betas (δ'_m) are slightly higher in the model using Z-score, and statistically significant across all portfolios. One improvement observed in the estimations is that using a different proxy for default risk leads to an improvement in the market factor ability to explain Big/High BM excess returns. In the regression, the coefficient associated with the market variable is equal to 0.117 (*t*-statistic is 2.21, significant at a 10% level) in comparison with just 0.041 (*t*-statistic is 0.62, statistically insignificant) in the model using O-score (reported in Panel B of Table 3.7). It may be due to the fact that besides accounting information Z-score also takes into account company market value. Therefore, this slight improvement may imply that incorporating market information in measuring default risk could enhance distress risk analysis. This lends support to the thesis's approach which aims to incorporate both accounting and market information in measuring distress risk in average stock returns.

In terms of BM and size effects, the coefficients associated with these factors keep the same sign and magnitude in models using different default probability indicators. The δ'_{HML} are about 0.3 to 0.5 in regressions on the High BM portfolio excess returns. Their *t*-statistics range between 3.07 and 3.78 (highly significant at a 1% level). For Medium BM stocks, the coefficients are lower in absolute terms and only statistically significant at a 5% level. The magnitude and significance of the BM effects are much smaller in the Low BM portfolios (i.e. the Growth portfolio) than in the above portfolios. The coefficients δ'_{HML} are 0.043 (t-statistic is 1.36) in the regression on Small/Low BM stocks, and 0.074 (t-statistic is only 0.89) in the case of the Big/Low BM portfolio. In the two regressions, the estimated δ'_{HML} are statistically insignificant, indicating that the BM effect is less noticeable among growth companies. The robustness check also confirms that the size factor can explain more of the movement in Small/Low BM and Big/Medium BM stock returns, but less for other portfolios. The estimated coefficients δ'_{SMB} remain significant in regressions on these two portfolio returns (t-statistics are about 2.80, significant at a 5% level). The coefficient values are, however, just under 0.090 and not significant for other portfolios.

Similar to the results in Panel B of Table 3.7, the results in Table 3.8 show that the momentum factor could capture some risk elements in the Small/Low BM portfolio but less in other groups of stocks. The coefficient δ'_{WML} associated with the momentum variable is estimated to be highly positive at 0.174 with a t-statistic of 2.77 (significant at a 10% level) for small and growth stocks. This indicates that small and fast-growing companies are likely to continue their past performance whilst this tendency is less noticeable in other company types.

In terms of the distress factor, using Z-score instead of O-score to form default variables does not change the results of the analysis. As can be seen from Panel B of Table 3.8, the coefficients associated with the default factor are negative and significant in regressions on both High BM and Low BM excess returns. Unsurprisingly, the results confirm that companies in financial distress generate lower excess returns. Moreover, the default risk does play an important role in explaining their long-term average returns. The coefficients $\delta'_{Z\text{-}score}$ are -0.201 for Small/High BM stocks and -0.169 for Big/High BM. These values are slightly lower, at -0.122 and -0.148, for Small/Low BM and Big/Low BM, respectively. All estimated default coefficients are statistically significant irrespective of the choice of default indicators.

The results in Panel B also confirm that adding the WML variable to the FF three-factor model marginally improves the explanatory power of the FF model. The regression *Adj-*R^2s increases slightly from nearly 0.50 in the augmented FF model to around 0.52 in the model including a momentum variable.

In summary, results from the first approach indicate that using a different proxy for default risk does not materially change the chapter findings that the default factor plays an important role in explaining return differentials responsible for value anomaly.

Table 3.8: Time-series regressions with default risk measured by Z-score on 6 size/BM portfolios

Panel A: Augmented Fama and French (1993) three-factor model.

$$R_{it} - R_{ft} = \theta_i + \delta_{mi} (R_{mt} - R_{ft}) + \delta_{HMLi} HML_t + \delta_{SMBi} SMB_t + \delta_{Z\text{-}scorei} Z\text{-}score_t + v_i$$

The panel checks the robustness of the outcome in Table 3.7 using an alternative indicator of firms' default probability: Z-score, proposed by Altman (1968). It presents time-series estimation results of the above regression on 6 intersection portfolios formed by 3 book-to-market value and 2 size rankings. In particular, HBM, M and LBM denote the highest 40%, the middle 20% and lowest 40% book-to-market value stocks while Small and Big stocks are separated by the medium. The excess return on the market, R_m - R_f, is obtained from Prof Kenneth R. French's website for the UK market. HML and SMB are constructed similarly to the way Fama and French (1993) built their factors, which are meant to mimic BM and size effects in expected stock returns. The distress factor (Z-score) is the difference in value-weighted returns of stocks in the top 30% Z-score and the bottom 30% Z-score ranking groups. It is worth noticing that while these 6 portfolios are formed using the breakpoint 40:20:40 to adapt to the smaller size of non-US markets, portfolio-based factors use the usual 30:40:30 breakpoint instead because they proxy for risk factors rather than measure actual returns. The panel reports estimated coefficients and their *t*-statistics. *, **, and *** denote the significance levels at 10%, 5% and 1%. The goodness of fit R^2s are adjusted for the degree of freedom.

	Small	Big	Small	Big
	θ		$t(\theta)$	
HBM	-0.003	-0.001	-0.43	-0.40
M	-0.002	-0.002	-0.51	-0.56
LBM	-0.005	-0.001	-0.93	-0.42
	δ_m		$t(\delta_m)$	
HBM	0.434	0.215	3.21***	1.99*
M	0.412	0.533	3.02***	4.11***
LBM	0.388	0.501	2.89***	3.72***
	δ_{HML}		$t(\delta_{HML})$	
HBM	0.301	0.423	3.13***	3.21***
M	0.200	0.157	2.02**	2.01**
LBM	0.085	0.099	0.56	0.58
	δ_{SML}		$t(\delta_{SMB})$	
HBM	0.097	0.135	0.72	1.07
M	0.102	0.214	1.37	1.87*
LBM	-0.189	-0.072	-1.97*	-0.81
	$\delta_{Z\text{-}score}$		$t(\delta_{Z\text{-}score})$	
HBM	-0.213	-0.221	-2.10*	-2.17*
M	-0.154	-0.101	-1.37	-1.36
LBM	-0.176	-0.214	-1.22	-2.32*
	Adj R^2			
HBM	0.47	0.41		
M	0.40	0.51		
LBM	0.52	0.39		

Table 3.8 - Continued

Panel B: Augmented Carhart (1997) four-factor model.

$$R_{it} - R_{ft} = \theta'_i + \delta'_{mi} (R_{mt} - R_{ft}) + \delta'_{HMLi} HML_t + \delta'_{SMBi} SMB_t + \delta'_{WMLi} WML_t + \delta'_{Z\text{-}scorei} Z\text{-}score_t + \nu'_i$$

Panel B checks the robustness of the outcome in Table 3.7 using an alternative indicator of firms' default probability: Z-score, proposed by Altman (1968). It presents time-series estimation results of the above regression on 6 intersection portfolios formed by 3 book-to-market value and 2 size rankings. In particular, HBM, M and LBM denote the highest 40%, the middle 20% and lowest 40% book-to-market value stocks while Small and Big stocks are separated by the medium. The excess return on the market, R_m - R_f, is obtained from Prof Kenneth R. French's website for the UK market. HML and SMB are constructed similarly to the way Fama and French (1993) built their factors, which are meant to mimic BM and size effects in expected stock returns. The WML component is built based on stocks' 11-month past returns, according to which WML is the return differential between the top 30% and the bottom 30% stocks. The distress factor (Z-score) is the difference in value-weighted returns of stocks in the top 30% Z-score and the bottom 30% Z-score ranking groups. It is worth noticing that while these 6 portfolios are formed using the breakpoint 40:20:40 to adapt to the smaller size of non-US markets, portfolio-based factors use the usual 30:40:30 breakpoint instead because they proxy for risk factors rather than measure actual returns. The panel reports estimated coefficients and their *t*-statistics. *, **, and *** denote the significance levels at 10%, 5% and 1%. The goodness of fit R^2s are adjusted for the degree of freedom.

	Small	Big	Small	Big
	θ'		$t(\theta')$	
HBM	-0.002	-0.003	-0.31	-0.40
M	-0.003	-0.004	-0.62	-0.66
LBM	-0.006	-0.004	-0.97	-0.65
	δ'_m		$t(\delta'_m)$	
HBM	0.462	0.117	3.18***	2.21*
M	0.524	0.350	3.15***	4.36***
LBM	0.551	0.442	3.20***	4.74***
	δ'_{HML}		$t(\delta'_{HML})$	
HBM	0.321	0.548	3.07***	3.78***
M	-0.200	-0.191	-2.83**	2.70**
LBM	0.043	0.074	1.36	0.89
	δ'_{SMB}		$t(\delta'_{SMB})$	
HBM	-0.062	-0.083	-1.45	-1.93
M	0.074	0.212	1.85	2.88**
LBM	-0.194	-0.086	-2.79**	-1.96
	δ'_{WML}		$t(\delta'_{WML})$	
HBM	-0.025	-0.076	-1.23	-1.62
M	0.096	-0.102	1.98	-1.96
LBM	0.174	-0.107	2.77*	-1.98
	$\delta'_{Z\text{-}score}$		$t(\delta'_{Z\text{-}score})$	
HBM	-0.201	-0.169	-2.85**	-2.46*
M	-0.056	-0.074	-1.38	-1.86
LBM	-0.122	-0.148	-2.16*	-2.41*
	Adj R^2			
HBM	0.52	0.55		
M	0.47	0.58		
LBM	0.50	0.49		

The *second approach* to identifying the risk patterns associated with default likelihood is the portfolio-based approach using the default variable as base portfolios. The general approach was described in Chapter 2, and it has also been used particularly in the UK context by Griffin and Lemmon (2002). In this section, the chapter utilises the portfolio-based approach in value anomaly testing, aiming to capture default risk in average returns on 9 intersection DEF/BM portfolios. The 9 portfolios are the intersections between 3 default portfolios and 3 BM portfolios. According to Griffin and Lemmon (2002), any potential risk patterns in expected stock returns of going into default are meant to be captured in separate groups of stocks with similar distress characteristics.

The robustness check in this section uses a combination of both portfolio-based and regression approaches. The regression estimations will be carried out on the FF three-factor model as well as the Carhart four-factor model and the results are shown in Panels A and B of Table 3.9, respectively.

From Panel A of the table, it is found that the FF model can explain more of the value premium in the High DEF/Low BM portfolio than in other groups. The regression intercept is equal to -0.121 (*t*-statistic is -2.31, significant at a 10% level). The market factor also shows a strong and consistent explanatory ability in explaining the movement of stock returns. The estimated market betas are positive and highly significant across all 9 portfolio groups. They range from 0.359 (for Low DEF/High BM stocks) to 0.534 (for High DEF/Low BM stocks). These suggest that companies which are overpriced by the market but in severe financial distress are the group that is most sensitive to changes in the market. On the contrary, value firms with a low risk of default are more resilient and their performance is less likely to be affected by the market factor.

Additionally, the results in Panel A confirm that other explanatory factors, including BM, size, and default probability, are also important risk characteristics in explaining the value premium. The majority of the coefficients associated with these variables are statistically significant. Similar to the findings in section 3.4.4, estimation results of the robustness check show that the coefficients associated with the HML variable δ'_{HML} are highly significant in regressions on the excess returns on High DEF portfolios, and those on High BM portfolios. The coefficients take the values of between 0.166 and 0.205 (*t*-statistics are 2.52 and 3.12, respectively) for the former group of portfolios, and between 0.174 and 0.205 (*t*-statistics are 3.01 and 3.12, respectively) for the latter. The BM effect is less significant for other portfolios and becomes statistically insignificant among Low DEF/Low BM stocks.

In the panel, there is evidence that the risk patterns associated with the size effect contribute to explaining return differentials between value versus growth stocks as well as those between High and Low default risk stocks. The size factor is more noticeable among Low BM stocks. The coefficients δ'_{SMB} are negative and statistically significant in regressions on the excess returns on the High DEF/Low BM and Medium DEF/Low BM portfolios. They take the values of -0.134 (*t*-statistic is -2.45, and significant at 5%) and -0.112 (*t*-statistic is -2.23, significant at a 10% level), respectively. This may be due to the fact that in the FTSE350, the majority of Low BM (or growth) companies have a high market capitalisation value. Thus, the size premium reduces among growth stocks. In terms of the risk patterns associated with firm default probability, the results in Panel A indicate that the return on Low DEF stocks is more sensitive to the size effect than High and Medium DEF portfolios. The coefficient associated with the SMB variable is estimated to be 0.112, statistically significant at a 10% level for the stocks that are less likely to be in financial distress, but the coefficient takes the value of only 0.078 (*t*-statistic of 0.52, insignificant) in regressions on excess returns on stocks of medium and high distress companies. The results suggest that default risk would contribute to explaining average stock returns.

Next, Panel B of Table 3.9 reports the estimated coefficients of Carhart four-factor regressions on excess returns on the 9 DEF/BM portfolios tested above. Similar to the findings reported in Table 3.7, the market, BM and size effects, together with the distress factor play an important role in capturing the risk patterns in average stock returns while the momentum effect is only observable in some growth stocks. Additionally, by sorting portfolios based on default risk, the analysis in this section finds that the momentum factor could also capture the movement of returns on stocks where there is less distress. Moreover, the results in Panel B confirm that adding the momentum variable could marginally improve the model's goodness of fit in comparison with the three-factor model.

As can be seen from Panel B, the value of constant terms varies from 0.002 to 0.098, with *t*-statistics being between 0.13 and 1.42, statistically insignificant. The traditional market factor remains highly significant across the estimations. In addition, the estimated market betas are higher in the regressions on the High DEF and/or Low BM portfolios than these on the Low DEF and/or High BM groups. Thus, it seems that companies in high financial distress, especially those that have low BM, are more sensitive to the movement of the market than firms that are financially stable and/or have a high B/M ratio.

Moreover, the coefficients associated with BM effect are highly significant across regressions on stocks sorted by DEF and BM. The only exception is in the regression on Low DEF/Low BM portfolio, where the coefficient δ'_{HML} is equal to 0.068 (*t*-statistic is only 1.35 and statistically insignificant). This shows that there is little evidence of any BM effect among growth firms which are financially successful. Earlier in Section 3.4.4, the results in Panel B of Table 3.7 also suggest that the BM effect is less noticeable in growth stocks. In regressions on other portfolios, the coefficients associated with the HML variable take the value of between 0.125 and 0.234. *t*-statistics are between 2.61 and 2.92, and statistically significant at the levels 1% to 5%.

On the other hand, the size effect is less significant among stocks sorted by DEF and B/M ratio. The coefficients δ'_{SMB} are relatively low in absolute terms and only significant at a 10% level in regressions on excess returns on the High DEF/Low BM and Medium DEF/Low BM portfolios. Their estimated values are -0.102 (*t*-statistic of -1.88) and -0.109 (*t*-statistic of -2.01) in these 2 regressions, respectively. This implies that the size effect plays a less important role in capturing default risk in average stock returns. It can however contribute to explaining movement in returns of growth stocks.

Using the Carhart four-factor model in explaining returns on the intersection DEF/BM portfolios could improve the estimations. The additional momentum variable shows some ability to explain more of the movement in Low DEF stock returns. The coefficients associated with the WML variable are estimated to be between 0.111 and 0.163, statistically significant, in regressions on the returns on low default probability companies. To some extent, adding a momentum factor also improves the model goodness of fit, and contributes to achieving slightly higher *Adjusted* R^2s.

Overall, the findings reported in Table 3.9 are consistent with previous studies which pointed out that stocks with different default probabilities behave differently. The results once again confirm the findings discussed so far in this chapter that besides size, BM and momentum effects, probability of bankruptcy does play an important part in explaining expected stock returns in general and the return differentials between high and low BM stocks in particular.

Table 3.9: Time-series regressions on 9 DEF/BM portfolios

Panel A: Fama and French (1993) three-factor model

$$R_{it} - R_{ft} = \theta_i + \delta_{mi}(R_{mt} - R_{ft}) + \delta_{HMLi} HML_t + \delta_{SMBi} SMB_t + \nu_i$$

Panel A presents time-series estimation results of Fama-French regressions on 9 intersection portfolios formed by 3 default probability and 3 book-to-market value rankings using breakpoints of 40%, 20% and 40%. In particular, HBM, M and LBM denote the highest 40%, the middle 20% and lowest 40% book-to-market value stocks while High DEF, Medium DEF and Low DEF stand for high, medium and low O-score stocks. The excess return on the market, $R_m - R_f$, is obtained from Prof. Kenneth R. French's website for the UK market. HML and SMB are constructed similarly to the way Fama and French (1993) built their factors, which are meant to mimic BM and size effects in expected stock returns. The panel summarises estimated coefficients and their *t*-statistics. *, **, and *** denote the significance levels at 10%, 5% and 1%. The goodness of fit R^2s are adjusted for the degree of freedom.

	High DEF	Medium DEF	Low DEF	High DEF	Medium DEF	Low DEF
		θ			$t(\theta)$	
HBM	0.052	0.077	0.101	1.26	1.35	1.98
M	-0.014	-0.011	0.004	-0.68	-0.62	0.02
LBM	-0.121	-0.078	-0.031	-2.31*	-1.82	-0.41
		δ_m			$t(\delta_m)$	
HBM	0.462	0.459	0.359	3.52***	3.02***	2.98***
M	0.511	0.505	0.405	3.61***	3.60***	3.46***
LBM	0.534	0.507	0.436	4.28***	3.78***	3.15***
		δ_{HML}			$t(\delta_{HML})$	
HBM	0.205	0.202	0.174	3.12***	3.08***	3.01**
M	0.178	0.139	0.133	2.87**	2.77**	2.49*
LBM	0.166	0.121	0.092	2.52**	2.21*	1.78
		δ_{SMB}			$t(\delta_{SMB})$	
HBM	0.078	0.108	0.112	0.52	1.59	2.12*
M	-0.021	0.101	0.109	-0.31	1.77	2.07
LBM	-0.134	-0.112	-0.101	-2.45**	-2.23*	-1.89
		Adj R^2				
HBM	0.50	0.62	0.60			
M	0.48	0.51	0.49			
LBM	0.51	0.45	0.42			

Table 3.9 - Continued

Panel B: Carhart (1997) four-factor model

$$R_{it} - R_{ft} = \theta'_i + \delta_{mi}(R_{mt} - R_{ft}) + \delta_{HMLi} HML_t + \delta_{SMBi} SMB_t + \delta_{WMLi} WML_t + \nu'_i$$

Panel B presents time-series estimation results of Carhart regressions on 9 intersection portfolios formed by 3 default probability and 3 book-to-market value rankings using breakpoints of 40%, 20% and 40%. In particular, HBM, M and LBM denote the highest 40%, the middle 20% and lowest 40% book-to-market value stocks while High DEF, Medium DEF and Low DEF stand for high, medium and low O-score stocks. The excess return on the market, $R_m - R_f$, is obtained from Prof. Kenneth R. French's website for the UK market. HML and SMB are constructed similarly to the way Fama and French (1993) built their factors, which are meant to mimic BM and size effects in expected stock returns. The WML component is built based on stocks' 11-month past returns, according to which the WML is the return differential between the top 30% and the bottom 30% stocks. The panel summarises estimated coefficients and their *t*-statistics. *, **, and *** denote the significance levels at 10%, 5% and 1%. The goodness of fit R^2s are adjusted for the degree of freedom.

	High DEF	Medium DEF	Low DEF	High DEF	Medium DEF	Low DEF
		θ'			$t(\theta')$	
HBM	-0.055	0.062	0.098	-1.22	1.43	1.42
M	-0.012	-0.031	0.002	-0.51	-0.72	0.13
LBM	-0.072	-0.068	-0.043	-1.30	-1.35	-0.77
		δ_m			$t(\delta_m)$	
HBM	0.456	0.461	0.342	3.45***	3.33***	2.98***
M	0.542	0.502	0.403	4.52***	4.02***	3.21***
LBM	0.533	0.511	0.434	4.37***	3.87***	3.41***
		δ_{HML}			$t(\delta_{HML})$	
HBM	0.234	0.163	0.157	2.92***	2.81**	2.79**
M	0.207	0.125	0.137	2.88**	2.75**	2.78**
LBM	0.132	0.136	0.068	2.61**	2.78**	1.35
		δ_{SMB}			$t(\delta_{SMB})$	
HBM	0.022	0.096	0.056	0.63	1.65	1.25
M	-0.019	0.098	0.052	-0.42	1.67	1.23
LBM	-0.102	-0.109	-0.101	-1.88*	-2.01*	-1.85
		δ_{WML}			$t(\delta_{WML})$	
HBM	-0.022	-0.047	0.163	-0.57	-1.01	2.82**
M	-0.026	-0.066	0.111	-0.64	-1.23	2.05*
LBM	-0.043	-0.010	0.156	-0.71	-0.72	2.73**
		Adj R^2				
HBM	0.61	0.65	0.63			
M	0.52	0.55	0.53			
LBM	0.64	0.66	0.51			

3.5.6 Conclusion

Testing on the FTSE350 index over a 23-year period from 1990 to 2012, the chapter finds evidence that the default probability is an important factor beside size, BM and momentum effects in explaining value premium and should be considered in asset pricing modelling. Additionally, the results suggest that small and growth companies are among the more profitable investment in the long run as they tend to continue their good performance. Furthermore, in the presence of a default factor, the Carhart four-factor model performs only slightly better than FF three-factor model. In the Carhart model, the additional momentum variable contributes to explaining more of the movement of Small/Low BM portfolio returns but this is less noticeable for other portfolios.

Using a comprehensive set of proxies including Ohlson's (1980) O-score and Altman's (1968) Z-score, the chapter confirms that the default risk measured by probability of bankruptcy has a negative relationship with expected stock returns. It also exhibits a significant explanatory power in capturing well the movement of stock returns. More specifically, default risk plays an important role in explaining the movement in returns of smaller stocks. The distress factor has a negative and significant impact on average returns on the Small portfolio. This suggests that small companies are more likely to suffer default risk than their Big counterpart. Among Big companies, Big/Low BM companies tend to bear a higher distress risk than Big/High BM firms. Hence, large and over-priced companies are more likely to be at a higher risk of going into default than large and growing firms.

The results in this section are found to be robust and are not driven by the choice of default risk proxies (O-score or Z-score), or analysis approaches (a regression approach or a portfolio sorting method). Although the estimation results can vary slightly, they keep the same sign and magnitude in the large majority of cases.

The next section will extend the analysis to including individual stock volatility in the list of risk factors that would potentially explain return differentials generated by value investment strategies.

3.6 THE VOLATILITY EXPLANATIONS

3.6.1 Volatility and value premium

Table 3.10 reports time series estimations on the returns on 9 portfolios ranked by three volatility and three BM portfolios over the 23-year sample period up to December 2012. Firstly, the time-series analysis relies on the Fama and French (1993) three-factor model to capture the performance of extreme high and low volatility (Vo) groups. The explanatory factors are calculated from monthly value weighted portfolios by regressing excess returns on the market portfolio, book-to-market and size effects. The results are summarised in Panel A of Table 3.10. Next, similar estimations are carried out using the Carhart four-factor model in order to establish a direct comparison of volatility risk in time-series three- and four-factor regressions. The four-factor model results are reported in Panel B of the table. Finally, since the idiosyncratic volatility factor only concerns firm-level risk, this section also reports cross-sectional estimation results of the above tests in order to identify the relationship between firm-level volatility risk and the rest of the market. These results are summarised in Table 3.11.

In Panel A of Table 3.10, stocks are sorted into 3 BM portfolios and 3 idiosyncratic volatility portfolios. The estimation regressions on the 9 intersection portfolios show that the market variable has an important effect on stock returns. This is similar to what has been previously reported in Section 3.5.2 which was based on size/BM ranking. The coefficients associated with market factor are all significant at a 1% level, confirming the importance of the market beta in explaining the movement of average stock returns. In other words, the CAPM beta remains a well-performing factor. The beta negative sign, however, differs from what was found in the Fama and French (1993) regressions. It could be interpreted in the way that the higher the market systematic risk is, the lower expected returns on volatility/BM portfolios are. Also, there is a possibility that the more diversified our portfolios are, the fewer firm-level volatility effects these portfolios suffer.

The HML factor is now seen to play a more significant role in capturing the risk patterns in returns on both value and growth portfolios. The coefficients associated with the factor, δ_{HML}, are statistically significant at a 1% level. It is worth noting that unlike the estimations on size and BM portfolios in previous studies done in major markets including the UK, such as Fama and French (1998), the FF three-factor model run on volatility and BM portfolios results in negative δ_{HML} for the High BM portfolios and positive coefficients for the Low BM portfolios. In addition, the estimated coefficients δ_{HML} in regressions on the High Vo portfolio returns have higher absolute values than those on Low Vo portfolios. These suggest that highly volatile stocks are more sensitive to the HML variable than low volatile stocks.

As can be seen in Panel A, SMB effects show a stronger impact on the average returns of Medium and Low volatility groups. The estimated coefficients associated with the SMB variable δ_{SMB} are -0.148 (*t*-statistic is -2.42, statistically significant at a 5% level) in the regression on Medium Vo/High BM stocks and -0.099 (*t*-statistic is -1.75, statistically significant at 10% level) in the Medium Vo/Low BM portfolio regression. However, among Low Vo portfolios, only the regression on Low Vo/Medium BM portfolio generates a significant δ_{SMB} which takes the value of -0.153 (*t*-statistics is -2.35, significant at a 5% level). Nevertheless, for High volatility portfolios the size effect is not noticeable. In regressions on these stock returns, the δ_{SMB} takes values of between -0.65 and 0.89, which are statistically insignificant. It is also worth noting that the sign of coefficients δ_{SMB} is largely negative for Low BM stocks.

In terms of model performance, using the portfolio-based formation approach significantly improves the regression *Adjusted* R^2s. Within the High volatility portfolios, the FF three-factor model captures the most variation in excess returns on value stocks, followed by the growth group. The *Adjusted* R^2s are lower toward the lower volatility groups. Overall, the approach using Vo/BM ranking shows a higher explanatory ability in capturing BM effects than the traditional size/BM portfolio formation system.

In Panel B of Table 3.10, the estimation results of the Carhart four-factor model show that when stocks are split into 9 Vo/BM portfolios, the three FF factors remain important in explaining the average stock returns, whilst the additional momentum effect is less noticeable. The constant terms in the time-series regressions are small and statistically insignificant across the board. Their estimated values are between 0.48 and 0.74 in the regressions on the High Vo and Medium Vo portfolios, and between -0.92 and -0.50 in the regressions on Low Vo stocks. On the other hand, the coefficients associated with the market variable, R_m, are negative and highly significant in all 9 regressions. Their estimated values range from 0.521 to 1.216 in absolute terms, with *t*-statistics being between 11.07 and 18.26, statistically significant at a 1% level. This once again confirms the important role of the market beta in capturing the risk patterns associated with default and BM risk in common stock returns.

Similar to the results from the FF three-factor model, the HML variable has significant explanatory power in explaining value anomaly as well as the return differentials between the High and Low volatility stocks. In Panel B, the estimated coefficients associated with the BM factor, $\delta'_{HML,}$ take the values of between -0.425 and -0.372 (*t*-statistics of between -4.15 and -3.06, statistically significant at a 1% level) in regression on the Value portfolio excess returns. For the Growth stocks, the coefficient δ'_{HML} is 0.357 (*t*-statistic is 4.21, significant at 1% level) in the regression on the High Vo/Low BM portfolio returns, while it is higher at 0.427 (*t*-statistic is 4.82, also highly significant at 1% level) in the Low Vo/Low BM portfolio estimations. The BM effect is however not significant among Medium BM stocks.

In terms of the size effect, the results in Panel B of the table show that Medium Vo/High BM, Medium Vo/Low BM and Low Vo/Medium BM are the three groups of stocks that are more exposed to the size effect than the other portfolios. This implies that firm size is not necessarily a key predictor of highly volatile stocks. The value of coefficients associated with the size variable, $\delta'_{SMB,}$ is between only -0.008 and 0.031 (*t*-statistics are from -0.37 to 0.75, statistically insignificant) in regressions on excess returns on the High Vo portfolios. The size effect is most noticeable among Medium Vo/High BM companies. The coefficient takes the value of -0.178 (the *t*-statistic is -2.68, significant at a 5% level). This suggests that value and less volatile stocks are more sensitive to the size effect than other groups. Also, among those companies, stocks of smaller firms tend to generate higher average excess returns.

On the contrary, the momentum variable does not display significant explanatory power in capturing the movement in average returns on portfolios sorted by Vo/BM. The coefficients associated with the WML variable are estimated to be between -0.1 and -0.061 for High Vo stocks, and slightly higher ranging between -0.103 and 0.117 for the Low Vo portfolios. The *t*-statistic values show that they are statistically insignificant in all 9 regressions.

The regression *Adjusted* R^2s are to some extent similar to those reported in the FF three-factor model, suggesting that when explaining return differentials between High and Low Vo stocks, the momentum factor is not one of the key elements in the estimations.

Table 3.10: Time-series regressions on 9 portfolios sorted by volatility and BM

Panel A: Fama and French (1993) three-factor model

$$R_{it} - R_{ft} = \theta_i + \delta_{mi}(R_{mt} - R_{ft}) + \delta_{HMLi} HML_t + \delta_{SMBi} SMB_t + v_i$$

Panel A presents time-series estimation results of Fama-French regressions on 9 intersection portfolios formed by 3 book-to-market and 3 volatility ranking breakpoints of 40:20:40. In particular, HBM, M and LBM denote the highest 40%, the middle 20% and lowest 40% book-to-market value stocks while High Vo, Med Vo and Low Vo stand for high, medium and low volatility stocks. The excess return on the market, $R_m - R_f$, is obtained from Prof. Kenneth R. French's website for the UK market. HML and SMB are constructed similarly to the way Fama and French (1993) built their factors, which are meant to mimic BM and size effects in expected stock returns. The panel reports estimated coefficients and their *t*-statistics in parentheses. *, **, and *** denote the significance levels at 10%, 5% and 1%. The goodness of fit R^2s are adjusted for the degree of freedom.

	High Vo	Med Vo	Low Vo	High Vo	Med Vo	Low Vo
		θ			t(θ)	
HBM	0.002	0.000	-0.004	0.97	0.12	-1.92*
M	0.003	0.001	-0.005	0.89	0.23	-2.19**
LBM	0.005	0.001	-0.003	2.08**	0.51	-1.80*
		δ_m			t(δ_m)	
HBM	-1.154	-0.887	-0.681	-20.91***	-16.33***	-14.53***
M	-1.404	-1.004	-0.807	-18.23***	-13.94***	-14.00***
LBM	-1.344	-0.924	-0.712	-23.27***	-18.49***	-16.45***
		δ_{HML}			t(δ_{HML})	
HBM	-0.848	-0.427	-0.350	-10.12***	-5.19***	-4.92***
M	-0.171	-0.073	-0.143	-1.46	-0.67	-1.63
LBM	0.420	0.271	0.298	4.79***	3.57***	4.54***
		δ_{SMB}			t(δ_{SMB})	
HBM	0.041	-0.148	0.048	0.65	-2.42**	0.90
M	0.077	0.071	-0.153	0.89	0.87	-2.35**
LBM	-0.043	-0.099	-0.048	-0.65	-1.75*	-0.98
		Adj R^2				
HBM	0.71	0.57	0.50			
M	0.57	0.43	0.46			
LBM	0.67	0.56	0.51			

Table 3.10 - Continued

Panel B: Carhart (1997) four-factor model

$$R_{it} - R_{ft} = \theta'_i + \delta'_{mi}(R_{mt} - R_{ft}) + \delta'_{HMLi}HML_t + \delta'_{SMBi}SMB_t + \delta'_{WMLi}WML_t + v'_i$$

Panel B presents time-series estimation results of Carhart (1997) regressions on 9 intersection portfolios formed by 3 book-to-market and 3 volatility ranking breakpoints of 40:20:40. In particular, HBM, M and LBM denote the highest 40%, the middle 20% and lowest 40% book-to-market value stocks while High Vo, Med Vo and Low Vo stand for high, medium and low volatility stocks. In terms of explanatory variables, see Panel A for the description of ($R_m - R_f$), HML and SMB. The WML component is built based on the stocks' 11-month past returns, according to which the WML is the return differential between the top 30% and the bottom 30% stocks. This panel reports estimated coefficients and their *t*-statistics in parentheses. *, **, and *** denote the significance levels at 10%, 5% and 1%. The goodness of fit R^2s are adjusted for the degree of freedom.

	High Vo	Med Vo	Low Vo	High Vo	Med Vo	Low Vo
		θ'			$t(\theta')$	
HBM	0.001	0.001	-0.003	0.49	0.50	-0.92
M	0.002	0.001	-0.002	0.72	0.49	-0.51
LBM	0.002	0.002	-0.004	0.73	0.48	-0.50
		δ'_m			$t(\delta'_m)$	
HBM	-1.020	-0.621	-0.521	-17.42***	-12.16***	-11.07***
M	-1.216	-0.872	-0.545	-18.26***	-14.52***	-11.12***
LBM	-1.202	-0.714	-0.564	-18.01***	-14.01***	-11.38***
		δ'_{HML}			$t(\delta'_{HML})$	
HBM	-0.425	-0.215	-0.372	-4.72***	-3.06***	-4.15***
M	-0.112	-0.096	-0.101	-1.71	-0.89	-1.36
LBM	0.357	0.212	0.427	4.21***	3.02***	4.82***
		δ'_{SMB}			$t(\delta'_{SMB})$	
HBM	0.018	-0.178	0.031	0.51	-2.68**	0.86
M	0.031	0.027	-0.162	0.75	0.72	-2.21*
LBM	-0.008	-0.164	-0.076	-0.37	-2.27*	-1.10
		δ'_{WML}			$t(\delta'_{WML})$	
HBM	-0.061	-0.081	-0.103	-0.62	-0.71	-1.23
M	-0.066	-0.007	0.000	-0.68	-0.36	0.15
LBM	-0.100	0.108	0.117	-1.15	1.42	1.56
		Adj R^2				
HBM	0.75	0.61	0.52			
M	0.58	0.50	0.63			
LBM	0.69	0.62	0.65			

Next, Table 3.11 reports cross-sectional regression results from the CAPM, the FF model, the Carhart model and the augmented models controlling for default risk for both approaches. The estimation results are reported in turn in Panels A to D of the table. In contrast to the CAPM, the FF model seems to be able to capture the majority of the risk patterns in returns of stocks sorted by size and BM. As can be seen from Panel B, the three FF factors are highly significant in regressions on the 6 size/ BM portfolio returns. The regressions on the FF model result in higher *Adjusted* R^2s (increasing from 0.60 in the CAPM to 0.65). F-test results also show that the explanatory variables are jointly significant.

However, in regressions on 9 volatility/BM portfolio returns the size factor appears to lose its explanatory power while the market and BM effects remain significant. The coefficients γ_m and γ_{HML} are estimated to be -0.99 (t-statistic of -48.04) and -0.11 (t-statistic of -3.63), respectively. Both variables are highly significant at a 1% level in the regressions explaining the value premium in 9 portfolios sorted by idiosyncratic volatility and B/M ratios. However, the coefficient associated with size effect, γ_{SMB}, is estimated to be 0.34 (t-statistic is 15.3, statistically significant at a 1% level) in regressions on 6 size/BM portfolio excess returns, while taking the value of only -0.03 (t-statistic is -1.21, statistically insignificant) in estimations from 9 volatility/BM portfolio regressions.

Although sorting stocks into 6 size/BM portfolios seems to result in higher *Adjusted* R^2s than using volatility and BM, the regression intercept is only statistically significant different from zero at a 1% level in the size/BM approach. This indicates that there is some level of estimation error remaining in the equation. Similar results are found in the CAPM regressions on excess returns on portfolios sorted by size and BM. In regressions on 6 size/BM portfolio returns, the *Adjusted* R^2s increase from 0.60 (in the CAPM model) to 0.65 in the FF three-factor model, while *Adjusted* R^2s remain at 0.51 in regressions on 9 volatility/BM portfolio returns. These suggest that although the two pricing models can capture more of the movement in excess returns on stocks sorted by size and BM, the estimation errors associated with these models are lower in regressions on stocks sorted based on volatility and B/M ratios.

Estimation results from augmented models of the FF model and the Carhart model are summarised in Panels C and D of Table 3.11. The results show signs of model improvement in explaining average stock returns. As can be seen from Panel C of the table, when including the DEF factor, the regression results in less significant constant terms and higher *Adjusted* R^2s. In size/BM regressions, the intercept decreases from -0.009 (*t*-statistic is -10.7, significant at a 1% level) in the FF model to just -0.001 (*t*-statistic is -2.2, significant at a 5% level) in the augmented FF model. A similar result is observed in the volatility/BM portfolio regressions. In both cases, the model goodness of fit increases, and the improvement in estimating the volatility/BM portfolio returns is more noticeable. The resulted *Adjusted* R^2 in the volatility/BM estimation is 0.68 in the augmented FF model, in comparison with only 0.51 in the traditional FF model. These indicate that stocks with similar volatility and BM characteristics tend to behave more similarly, and their return anomaly is likely to be captured more easily than those sorted by size and BM. In addition, the augmented model shows an improvement in capturing the movement of volatility/BM stock returns.

In terms of the default factor, the results in Panel C show that there is evidence supporting that default risk plays an important role in explaining cross-sectional stock returns, especially in explaining value anomaly. The estimated coefficients associated with the DEF variable take negative values and are highly significant in cross-sectional regressions on stocks formed by both size/BM and volatility/BM criteria. The coefficients γ_{DEF} are estimated to be -0.20 (*t*-statistic is -6.1) and -0.31 (*t*-statistic is -10.9) in regressions on 6 size/BM and on 9 volatility/BM portfolio returns, respectively. Both are statistically significant at a 1% level. These indicate that the default variable can contribute to capturing the risk patterns associated with firm default likelihood in stock returns. The variable also plays an important role in explaining the return differentials between value and growth portfolios, small and big, as well as high and low volatile stocks.

The augmented Carhart model with an additional DEF variable displays a slightly stronger ability to capture the risk elements missed by the CAPM and the FF model. The results in Panel D of Table 3.11 show that besides the traditional three FF factors which remain the key drivers of value anomaly, the default factor also plays an important role in explaining cross-sectional stock returns. Similar to the results reported earlier for the augmented FF model, estimations using the Carhart model result in highly significant coefficients associated with the market and BM factors. The market beta takes the values of 0.82 (*t*-statistic of 27.0, highly significant at a 1% level) in regressions on size/BM portfolio returns and -1.17 (*t*-statistic is -32.1, significant at a 1% level) in volatility/BM portfolio estimations.

However, the size effect is significant only in size/BM regressions but less noticeable in volatility/BM portfolio regressions. The estimated coefficient γ_{SMB} takes the value of 0.01 (*t*-statistic is 2.0, significant at a 10% level) in the former, and a value of 0.02 (*t*-statistic is only 1.5, statistically insignificant) in the latter. This suggests that firm size does contribute to explaining the difference in returns between the 6 size/BM portfolios. In other words, there is a link between firm size, size premium and value premium. However, this relationship is not observed among stocks of different idiosyncratic volatility.

In contrast, adding a momentum factor does not significantly improve model performance in the cross-sectional context. As can be seen from the results in Panel D, there is little evidence suggesting that the momentum variable, WML, could explain the difference in cross-sectional returns on common stocks. The coefficients associated with the variable are less than -0.01 (*t*-statistic is -1.6) in regressions on 6 size/BM portfolio excess returns, and are 0.03 (*t*-statistic is 1.8) in the 9 volatility/BM regressions. In both cases, the coefficients γ_{WML} are statistically insignificant.

Although the model goodness of fit is slightly highly for the augmented Carhart four-factor model, the improvement is marginal in comparison with the augmented FF model. The *Adjusted* R^2 increases from 0.67 to 0.69 in regressions on the 6 size/BM portfolio returns, and from 0.68 to 0.72 in the case of volatility/BM portfolios. In summary, together with the FF three factor model, the default risk variable shows a high explanatory power in explaining value premium, size premium and return differentials between High and Low idiosyncratic volatility stocks. The results confirm the findings reported earlier in Table 3.10 for the time-series analysis. In other words, the findings concluded in this section are robust in both time-series and cross-sectional analyses.

Table 3.11: Cross-sectional regressions

Panels A and B present the FF and CAPM cross-sectional regressions using the excess returns on 6 intersections of size/BM portfolios formed by 3 BM and 2 size rankings, and on 9 Vo/BM portfolios sorted by 3 volatility and 3 BM portfolios. Panel C (and D) reports the estimation results of a model consisting of the three (and four) factors and default risk on 6 size/BM and 9 Vo/BM portfolios. The excess return on the market, $R_m - R_f$, is obtained from Prof Kenneth R. French's website for the UK market. HML and SMB are constructed similarly to the way Fama and French (1993) proposed, which are meant to mimic BM and size effects in expected stock returns. The WML component is built based on the stocks' 11-month past returns, according to which the WML is the return differential between the top 30% and the bottom 30% stocks. DEF is the difference in value-weighted returns of stocks in the top 30% O-score and the bottom 30% O-score groups. The table reports estimated coefficients and their *t*-statistics in parentheses. *, **, and *** denote the significance levels at 10%, 5% and 1%. The goodness of fit measure R^2s are adjusted for the degree of freedom. *F*-statistics test the joint significance of the explanatory variables.

Panel A: The CAPM: $R_{it} - R_{ft} = \gamma_{0,i} + \gamma_{m,i}(R_{mt} - R_{ft}) + \varepsilon_{i,t}$

	γ_0	γ_m	$t(\gamma_0)$	$t(\gamma_m)$	*Adj-R^2*	*F-statistic*
6 Size/BM	-0.008	1.01	-8.6***	49.1***	0.60	2410
9 Vo/BM	0.001	-1.01	0.06	-49.80***	0.51	2480

Panel B: The Fama and French three factor models: $R_{it} - R_{ft} = \gamma_{0,i} + \gamma_{m,i}(R_{mt} - R_{ft}) + \gamma_{HML,i} HML + \gamma_{SMB,i} SMB + \varepsilon_{it}$

	γ_0	γ_m	γ_{HML}	γ_{SMB}	$t(\gamma_0)$	$t(\gamma_m)$	$t(\gamma_{HML})$	$t(\gamma_{SMB})$	*Adj-R^2*	*F-statistic*
6 Size/BM	-0.009	0.97	0.16	0.34	-10.7***	49.5***	5.5***	15.3***	0.65	1018
9 Vo/BM	-0.000	-0.99	-0.11	-0.03	-0.02	-48.04***	-3.63***	-1.21	0.51	836

Panel C: Regressions on 3 factors and Factor loadings on Default risk: $R_{it} - R_{ft} = \gamma_{0,i} + \gamma_{M,i}(R_{mt} - R_{ft}) + \gamma_{HML,i} HML + \gamma_{SMB,i} SMB + \gamma_{DEF,i} DEF + \varepsilon_{it}$

	γ_0	γ_m	γ_{HML}	γ_{SMB}	γ_{DEF}	$t(\gamma_0)$	$t(\gamma_m)$	$t(\gamma_{HML})$	$t(\gamma_{SMB})$	$t(\gamma_{DEF})$	*Adj-R^2*	*F-statistic*
6 Size/BM	-0.001	0.88	0.27	0.01	-0.20	-2.2**	36.2***	6.1***	2.1*	-6.1***	0.67	2515
9 Vo/BM	0.001	-1.02	-0.32	0.02	-0.31	0.01	-49.0***	-11.5***	1.0	-10.9***	0.68	2106

Panel D: Regressions on 4 factors and Factor loadings on Default risk: $R_{it} - R_{ft} = \gamma_{0,i} + \gamma_{m,i}(R_{Mt} - R_{ft}) + \gamma_{HML,i} HML + \gamma_{SMB,i} SMB + \gamma_{WML,i} WML + \gamma_{DEF,i} DEF + \varepsilon_{it}$

	γ_0	γ_m	γ_{HML}	γ_{SMB}	γ_{WML}	γ_{DEF}	$t(\gamma_0)$	$t(\gamma_m)$	$t(\gamma_{HML})$	$t(\gamma_{SMB})$	$t(\gamma_{WML})$	$t(\gamma_{DEF})$	*Adj-R^2*	*F-stats*
6 Size/BM	-0.001	0.82	0.34	0.01	-0.00	-0.19	-1.1	27.0***	8.3***	2.0*	-1.6	-5.4***	0.69	2601
9 Vo/BM	0.002	-1.17	-0.41	0.02	0.03	-0.24	1.3	-32.1***	-9.1***	1.5	1.8	-6.7***	0.72	2315

<u>*Note*</u>*:* For presentation purposes, in this table coefficients associated with *one* explanatory variable are denoted by *the same* symbol across 4 models even though they take different values in different models.

3.6.2 The relation between stock volatility and default risk

This section aims to test hypothesis 3 that there is a relationship between the change in volatility of stocks and their distress conditions. There are two approaches used to test the hypothesis: time-series and cross-sectional regressions. Section 3.6.1 has collectively discussed cross-sectional regression results, thus this section will dedicate to the time-series analysis.

To investigate whether default risk can explain the risk pattern reflected in the level of stock volatility, the chapter estimates time-series regressions on 9 intersection portfolios formed by three BM portfolios and three volatility rankings using an augmented model consisting of the three FF factors and default probability. The estimation results are reported in Panel A of Table 3.12. A further analysis is carried out on these portfolios using an augmented Carhart four-factor model. The model consists of the three FF factors, a momentum variable WML, and a default factor DEF. The results of this analysis are presented in Panel B of Table 3.12.

In Panel A of Table 3.12, the majority of the constant terms are insignificant, except in regressions on low BM portfolios. The intercepts are 0.004 and 0.003 (both being statistically significant at a 10% level) in regressions on High Vo/Low BM and Medium Vo/Low BM, respectively. This suggests that the augmented FF model could describe more of the return differentials between stocks with different idiosyncratic volatility levels in Growth groups. In line with the findings in the cross-sectional analysis, the market and BM factors consistently play an important role in explaining average stock returns, while a size effect is only noticeable in some Growth and/or Low volatility stocks. The market betas range from -1.330 to -0.771 (*t*-statistics of between 10.12 and 18.01, highly significant at a 1% level). Similarly, the coefficients associated with the BM variable, δ'_{HML}, are statistically significant in regressions on the excess returns on both High and Low volatility portfolios. The BM effect is less but remains significant among Medium volatility stocks. These indicate that the market and BM effects contribute considerably to capturing the risk patterns associated with idiosyncratic volatility risk and BM risk in average stock returns. In terms of the size factor, the explanatory ability of the SMB variable is more noticeable in the Medium Vo/Medium BM, Low Vo/Medium BM, and Medium Vo/Low BM portfolios. The coefficients, δ'_{SMB}, are statistically significant at a 10% level and take the values of 0.098, 0.121 and

-0.100, respectively. The weaker size effect on other portfolios suggests that firm size does not necessarily lead to stock volatility, and that the size effect is less noticeable among stocks of growth companies.

The coefficients associated with the DEF factor are, however, statistically significant in most cases. Particularly, high volatility portfolio returns tend to be more sensitive to the default factor. Their coefficients are positive and range from 0.512 to 0.719 (*t*-statistics are 3.57 to 4.03, significant at a 1% level). This suggests that highly volatile stocks are more likely to go bankrupt than low volatility groups. Medium volatility portfolios are also relatively sensitive to company default likelihood. For example, the coefficient, δ'_{DEF}, takes the value of -0.201 (*t*-statistic is -2.01, significant at a 10% level) in the regression on excess returns on Value and Medium volatility stocks. Nevertheless, the size effect does not contribute to explaining the average returns on stocks with Low idiosyncratic volatility.

In addition, higher estimated *Adjusted* R^2s in regressions on the High and Medium volatility portfolios indicate that the augmented FF model that controls for default risk has the ability to capture more of the movement in returns of high and medium volatility stocks than those of the low volatility stocks.

Next, Panel B of Table 3.11 will summarise the results of a similar time-series analysis which uses an augmented Carhart model instead of the augmented FF model. Similar to the findings reported in the cross-sectional analysis, adding a momentum factor does not lead to a significant improvement in model performance. The WML variable also does not have a strong explanatory power in explaining return differentials between value versus growth companies nor between High and Low volatility stocks.

As can be seen from Panel B, market effect remains important in regressions on excess returns on all 9 volatility/BM portfolios. The value of market betas ranges from -1.255 to -0.748, with *t*-statistics being between -17.08 and -8.69, statistically significant at a 1% level. The coefficients associated with the BM factor δ'_{HML} are also highly significant. The BM effect is particularly strong among value stocks. When sorting stocks by firm-level volatility, both High and Low volatility portfolios are highly affected by the BM factor. This means the HML variable could contribute to capturing the risk patterns associated with the BM effect in stocks with different idiosyncratic volatility levels.

Similar to the results reported in the cross-sectional analysis and those seen in the augmented FF model, the size factor plays a less important role in explaining the time-series average returns on portfolios sorted by idiosyncratic volatility and B/M ratio. The estimated coefficients associated with the SMB variable are low and statistically insignificant in regressions on High and Low volatility stocks. Their absolute values are between 0.026 and 0.034 in the regressions on the former, and between 0.027 and 0.041 in the regressions on the latter portfolio. Medium volatility stocks are, however, more sensitive to changes in firm size than other groups. The coefficient δ'_{SMB} is estimated to be 0.060 (*t*-statistic of 2.44, statistically significant at a 10% level) for the Medium Vo/Medium BM portfolio. It takes the value of -0.071 (*t*-statistic of -2.52, also significant at a 10% level) in the regression on the Medium Vo/Low BM portfolio returns. It is worth noting that the negative sign of δ'_{SMB} in regressions on Low BM portfolios suggests that among growth companies, smaller firms tend to generate higher excess returns in the long run.

In terms of default risk, the time-series regressions on 9 volatility/BM portfolio returns show that High volatility stocks exhibit a higher risk of going into default and the opposite is true for Low volatility stocks. The coefficients associated with the default factor δ'_{DEF} are positive and highly significant in regressions on the High volatility portfolios. They take the values of 0.501, 0.427 and 0.703 (*t*-statistics of 5.12, 4.83 and 6.72, and all are statistically significant at a 1% level) in regressions on excess returns on Value, Medium BM and Growth stocks, respectively. On the contrary, in regressions on Low volatility portfolios, the estimated parameters δ'_{DEF} are negative and smaller in absolute terms than those seen in the regressions on the High volatility stocks. This suggests that Low volatility stocks are likely to bear a lower risk of going bankrupt. However, the tendency is less noticeable among the Low volatility stocks.

Overall, the three FF factors and the default variable are important explanatory variables in capturing the risk patterns associated with the BM and idiosyncratic volatility effects in average stock returns. Among those variables, though, the explanatory power of the size factor is less consistent. The results are confirmed in both time-series and cross-sectional estimations. In addition, the momentum variable might contribute to improving the goodness of fit of the traditional FF model and its augmented version, but the improvement is immaterial.

Table 3.12: Factor loading on Default risk in 9 Volatility/BM portfolios

Panel A: Augmented Fama and French (1993) three-factor model

$$R_{it} - R_{ft} = \theta_i + \delta_{mi}(R_{mt} - R_{ft}) + \delta_{HMLi} HML_t + \delta_{SMBi} SMB_t + \delta_{DEFi} DEF_t + \nu_i$$

The panel presents time-series estimation results of the above regression on 9 intersection portfolios formed by 3 volatility and 3 book-to-market rankings using breakpoints of 40:20:40. In particular, HBM, M and LBM denote the highest 40%, the middle 20% and lowest 40% book-to-market value stocks while High Vo, Med Vo and Low Vo stand for high, medium and low volatility stocks. The excess return on the market, $R_m - R_f$, is obtained from Prof. Kenneth R. French's website for the UK market. HML and SMB are constructed similarly to the way Fama and French (1993) built their factors, which are meant to mimic BM and size effects in expected stock returns. The default factor (DEF) is the difference in value-weighted returns of stocks in the top 30% O-score and the bottom 30% O-score ranking groups. It is worth noticing that while these 9 portfolios are formed using the breakpoint 40:20:40 to adapt to the smaller size of non-US markets, the portfolio-based factors use the usual 30:40:30 breakpoint instead because they proxy for risk factors rather than measuring actual returns. The panel summarises estimated coefficients and their *t*-statistics. *, **, and *** denote the significance levels at 10%, 5% and 1%. The goodness of fit R^2s are adjusted for the degree of freedom.

	HBM	M	LBM	HBM	M	LBM
		θ			t(θ)	
High Vo	0.001	0.003	0.004	0.52	0.76	1.92*
Med Vo	0.001	0.002	0.003	0.51	0.54	1.91*
Low Vo	0.000	-0.001	-0.002	0.33	-0.48	-1.51
		δ_m			t(δ_m)	
High Vo	-1.330	-1.278	-1.175	-18.01***	-17.15***	-15.01***
Med Vo	-1.153	-1.016	-0.862	-16.41***	-13.94***	-10.76***
Low Vo	-1.042	-0.859	-0.771	-12.56***	-11.73***	-10.12***
		δ_{HML}			t(δ_{HML})	
High Vo	-0.752	-0.597	-0.084	-9.54***	-5.20***	-2.92*
Med Vo	-0.112	-0.093	0.076	-3.06**	-2.17	2.11*
Low Vo	-0.656	-0.476	0.185	-6.17***	-4.01***	3.54***
		δ_{SMB}			t(δ_{SMB})	
High Vo	0.039	0.071	-0.051	0.71	1.02	-0.91
Med Vo	-0.056	0.098	-0.100	-0.88	2.34*	-2.42*
Low Vo	0.040	0.121	-0.039	0.82	2.78*	-0.67
		δ_{DEF}			t(δ_{DEF})	
High Vo	0.512	0.515	0.719	3.57***	3.74***	4.03***
Med Vo	-0.201	-0.204	0.010	-2.01**	-2.12**	0.21
Low Vo	-0.056	-0.031	-0.038	-1.01	-0.50	-0.52
		Adj R^2				
High Vo	0.62	0.58	0.60			
Med Vo	0.57	0.55	0.52			
Low Vo	0.34	0.42	0.31			

Table 3.12 - Continued

Panel B: Augmented Carhart (1997) four-factor model

$$R_{it} - R_{ft} = \theta'_i + \delta_{mi}(R_{mt} - R_{ft}) + \delta_{HMLi} HML_t + \delta_{SMBi} SMB_t + \delta_{WMLi} WML_t + \delta_{DEFi} DEF_t + \nu'_i$$

Panel B presents time-series estimation results of the above regression on 9 intersection portfolios formed by 3 volatility and 3 book-to-market rankings using breakpoints of 40:20:40. In particular, HBM, M and LBM denote the highest 40%, the middle 20% and lowest 40% book-to-market value stocks while High Vo, Med Vo and Low Vo stand for high, medium and low volatility stocks. In terms of explanatory variables, see Panel A for the description of (R_m – R_f), HML, SMB and DEF. The WML component is built based on stocks' 11-month past returns, according to which the WML is the return differential between the top 30% and the bottom 30% stocks. The panel summarises estimated coefficients and their *t*-statistics. *, **, and *** denote the significance levels at 10%, 5% and 1%. The goodness of fit R^2s are adjusted for the degree of freedom.

	HBM	M	LBM	HBM	M	LBM
		θ'			t(θ')	
High Vo	0.000	0.001	0.002	0.23	0.44	0.63
Med Vo	0.001	0.002	0.002	0.43	0.59	0.62
Low Vo	0.002	-0.002	-0.001	0.61	-0.60	-0.42
		δ_m			t(δ_m)	
High Vo	-1.216	-1.255	-1.160	-15.42***	-17.08***	-13.54***
Med Vo	-1.103	-1.012	-0.782	-13.27***	-11.45***	-9.34***
Low Vo	-1.015	-0.748	-0.761	-11.44***	-8.69***	-8.77***
		δ_{HML}			t(δ_{HML})	
High Vo	-0.543	-0.423	-0.083	-6.25***	-5.14***	-2.68*
Med Vo	-0.102	-0.025	0.068	-2.88**	-1.78	2.66*
Low Vo	-0.541	-0.317	0.174	-6.20***	-4.68***	3.08***
		δ_{SMB}			t(δ_{SMB})	
High Vo	0.026	0.032	-0.034	1.56	1.61	-1.66
Med Vo	-0.048	0.060	-0.071	-1.92	2.44*	-2.52*
Low Vo	0.027	0.030	-0.041	1.52	1.72	-1.87
		δ_{WML}			t(δ_{WML})	
High Vo	-0.015	-0.038	-0.070	-1.23	-1.66	-2.50*
Med Vo	0.027	0.023	0.051	1.50	1.46	1.93
Low Vo	0.042	0.036	0.063	1.89	1.64	1.98
		δ_{DEF}			t(δ_{DEF})	
High Vo	0.501	0.427	0.703	5.12***	4.83***	6.72***
Med Vo	-0.200	-0.195	0.008	-3.79**	-3.54**	0.16
Low Vo	-0.034	-0.021	-0.025	-1.65	-1.42	-1.23
		Adj R^2				
High Vo	0.71	0.72	0.75			
Med Vo	0.60	0.64	0.70			
Low Vo	0.53	0.50	0.49			

3.7 CONCLUSION AND IMPLICATION

The results in Chapter 3 confirm findings from previous studies in the UK that value stocks outperform their growth counterpart. However, the value premium is statistically insignificant, at approximately 0.06% - 0.09% per month. The finding remains largely unchanged when using alternative indicators to BM (for example, E/P and DY) to classify stocks as value or growth. A size effect also exists in the UK market although the size premium is much higher among value stocks than it is in growth stocks (0.65% versus 0.29%, respectively). Perhaps it is because small value firms tend to have more room for growth than big cap value firms.

Additionally, the chapter explores certain areas in the literature that are of interest to study by taking individual stock volatility into account in explaining value premium anomaly. The volatility has long been documented as a relevant risk to stock returns, yet not incorporated into the study of the value premium. Chapter 3 finds no evidence supporting investment in highly volatile stocks. Even within the low volatility group, investing in value stocks, considered to be more likely to face financial distress, would bring lower returns than investing in growth firms.

The first conclusion from the chapter regression estimations is that, unlike commercial marketing reasoning, the safer an investment is in the FTSE350 the better profit it would generate. Over the course of an examination period from 31st January 1990 to 31st December 2012, although the value premium is statistically insignificant, value stocks outperform growth stocks in the long run. This result is consistent when looking at both the BM rank of risk, where value stocks are considered to be riskier than growth stocks, and looking at the volatility measure. In this index, the big stocks with a high BM value are much less prone to being affected by the market factor, while this factor plays an important role for other stocks. This could imply a diversifying option during market downturn periods.

Secondly, the chapter finds that the three FF factors play important roles in explaining return differentials between the value and growth portfolios. The market beta is statistically significant at a high level consistently across all regressions in the thesis. This confirms the central role of the market factor in asset pricing. On the other hand, the HML factor has a significant explanatory power in explaining high BM stock returns while it is not the case for the growth portfolio returns. The results in Chapter 3 show that the size effect can contribute to explaining returns on both the value and growth portfolios but the effect is more noticeable among the small stocks. The results suggest that it is important to take into account differences in companies' market capitalisation with the average stock returns of small sized companies. In addition, investing in smaller stocks could gain a higher size premium, which might not be the case for big stocks because their returns are less sensitive to the size effect. The findings in Chapter 3 confirm those in Fama and French (1992, 1993) which recognised the roles of BM and size effects in explaining common stock returns in the US.

In regard to the momentum factor, the chapter finds that the momentum variable WML has a significant explanatory power in regressions on Small/Low BM stock returns while the momentum effect is less noticeable for other portfolios. The sign of estimated coefficients associated with the WML parameter indicates that investing in smaller companies is more likely to lead to a high momentum premium which may not be the case when investing in big firms.

Thirdly, using both methods of factor constructing and portfolio formation and a range of default risk measures, the chapter finds that the default factor plays an important role in explaining the risk pattern in stock returns. Using the portfolio-based system, the analysis finds evidence suggesting that companies with a high default probability tend to have a negative effect on the expected stock returns. These are typically under distress and less likely to generate high stock returns. The results from regression approaches confirm that default risk has a negative relationship with expected stock returns in the UK market. Most of the coefficients associated with default variables are statistically significant, and more noticeable among small stocks. The result indicates that small companies are more likely to suffer default risk than the big firms. Within the big stocks, low BM stocks tend to suffer a higher distress risk than high BM stocks. This means big and over-priced companies are more likely to go bankrupt than big and growing firms. More importantly, in the presence of the default factor, other explanatory variables remain important in the models. Alternative measures of default risk do not seem to affect the empirical findings.

In summary, the above findings show that there is no evidence to reject the null hypothesis 1 that value premium in the UK can be explained by the market risk, default risk and firms' fundamental variables, such as size, B/M ratio and past returns.

To test hypothesis 2, Chapter 3 uses both regression and portfolio-based approaches to assess the role of idiosyncratic volatility in explaining average stock returns. The estimations on 9 volatility/BM portfolio returns are also undertaken from time-series as well as cross-sectional dimensions. The results indicate that while the market and HML factors show an ability to capture the risk patterns associated with firm-level volatility in stock returns, size and momentum factors have a lower explanatory power. While the HML factor is significant both statistically and in absolute terms, the SMB effect is noticeable only among Medium and Low volatility stocks and the WML factor is not significant in all estimations.

Lastly, in the test of hypothesis 3 on the relation between volatility and default, it is confirmed that the link between them is positive in the highly volatile group of stocks. In other words, stocks that are highly volatile tend to suffer a statistically significant higher default probability. The opposite is true for low volatility stocks. In the presence of the default factor, both time-series and cross-sectional analyses reveal that the market and BM factors continue to play an important role in explaining common stock returns, while the size effect is only noticeable in some growth and/or low volatility stocks. Once again, Carhart's WML factor does not contribute to explaining the return differentials between stocks with different BM and volatility levels. The default variable is statistically significant in most cases. More specifically, the high volatility portfolio returns tend to be more sensitive to the default factor. The findings are not affected by the choice of default proxies.

One of the most important observations in Chapter 3 is the relative improvement of the pricing models used in this chapter in explaining value premium. In comparison with the traditional FF model, adding a WML variable has contributed to capturing more of the movement in average stock returns. The improvement is however immaterial. The *Adjusted* R^2s in Carhart four-factor regressions are between 17% and 26%, slightly higher than those in the FF three-factor model (which are between 6% and 19%). In the presence of the default risk factor, both the FF and Carhart models achieve much better goodness of fit measures. The FF augmented model with an additional default variable has higher *Adjusted* R^2s, increasing from between 6% and 19% to between 39% and 45%. Adding a default variable to the Carhart model also considerably enhances the model as *Adjusted* R^2s increase from the range of 17% and 26% to between 38% and 46%. This suggests that there is room for further model enhancement in future research.

Chapter 4: Firm Distress Condition and Momentum Investment Strategies

4.1 INTRODUCTION

Although the idea of momentum trading strategy is dated back to Levy (1967), it has been developed and tested empirically by Jegadeesh and Titman (1993), according to whose theory investors could earn significant abnormal returns from buying past well performing stocks (winners) and selling past poorly performing stocks (losers). Over more than two decades, the abnormal returns have been observed in many markets; however, the question of what has driven momentum profits in those markets is still unresolved. Among others, Fama and French (1996) show that momentum profitability cannot be explained by either the standard CAPM or the Fama and French (1993) three-factor model. Since then, both scholars and practitioners have been seeking for the underlying reasons behind this intriguing anomaly. If the investment method of following the winners actually works, a question raised is whether this implies market inefficiency.

Another branch of market efficiency literature concerns the role of firms' financial distress risk in explaining momentum anomaly. This arises from both behavioural finance and risk-based theories. The former suggests investors' misvaluation of distressed firms while the latter considers financial distress conditions as extra risks which could potentially explain the anomaly. Also, a risk-based study by Agarwal and Taffler (2008) shows that, similar to the US, there is no link between financial distress risk and size and BM effects in the UK. In other words, there is no evidence that default risk has already been captured by the Fama and French's three factors. This leaves open a possibility that if momentum is driven by risk, distress risk could add value to the classical Fama and French's model in explaining the anomaly.

Therefore, the roles of business cycles and default risk in explaining momentum profitability are jointly tested for the first time in this study. Whereas there are vast studies on the links between momentum and business cycles and a few on momentum and default risk, there have yet to be any efforts testing the explanatory relationship of the two factors in explaining momentum anomaly. Perhaps this is due to a possibility that some risk patterns in default risk may vary with business cycles. Rather than going around the problem, the thesis aims to find out whether business cycles and firm default risk reinforce or subsume each other in explaining momentum.

This chapter makes the following main contributions. Firstly, the chapter contributes to fulfilling the need for more research in the UK, focusing on the link between momentum and firm distress conditions. The last empirical study addressing momentum in the UK was on a dataset up to 2002, before the 2008 financial crisis when distress risk might be more visible. Secondly, unlike previous studies, the chapter proposes the use of a more recent and reliable proxy of firm's default probability generated from Campbell, Hilscher and Szilagyi's (2008) probability model, henceforth the CHS model, which uses not only accounting but also equity market variables. Lastly, although there is evidence that momentum strategies perform differently over business cycles and that momentum anomaly could be explained by firm distress risk, there have not been any attempts to collectively examine the explanatory ability of the two elements in capturing momentum. This chapter aims to bridge this particular gap in the literature.

The results in the present study confirm that there is a significant momentum premium in the UK for up to 12-month investments. The results hold even when different investment horizons and seasonality have been taken into account. This confirms the findings of previous studies in the UK that momentum strategies generate positive returns if investing for less than one year but the returns were only significant for holding periods of up to 6 months. In addition, the chapter finds that the momentum abnormal returns are large and statistically significant in market upturns, particularly noticeable during economic expansions. In contrast, the strategies perform poorly during market downturns and lead to large losses during recessions.

In search for reasons behind the momentum anomaly in the UK, we find that default risk plays an important role in explaining the anomaly. The variable could capture much of the movement in returns on the past poorly performing stocks but become less significant in explaining the winner returns. When business cycles are taken into account, the role of the distress variable remains important for loser stocks but insignificant for the winner group.

In terms of other explanatory variables, traditional variables such as the market beta and HML consistently show a significant explanatory power, whereas size and momentum variables seem to capture more movement of the winners' returns but become less important in explaining the losers' returns. Moreover, business cycle variables such as default spread and dividend yield could explain more of the returns on the winners but not the returns on the losers, while term spread and short-term T-Bill do not play a significant role in the models. Robustness check results show that the chapter findings are not sensitive to the choice of proxies and are relatively free from multicollinearity biases.

The rest of this chapter is organised as follows. Section 4.2 presents the literature review, the research gaps and the chapter's main hypotheses. Section 4.3 describes the data and methodology. Section 4.4 reports and discusses the main findings, and section 4.5 concludes the chapter.

4.2 LITERATURE

This section does not try to review the vast discussion on momentum investment strategy. It focuses rather on the main arguments on the possible relationship between firm distress condition and the performance of momentum strategies. Section 4.2 starts by presenting the theoretical framework motivating momentum trading, it then briefly discusses the performance of the strategy especially during "bad" states of the economy. The main objective of this section is to understand the potential link between momentum profitability and firms' financial distress and to identify the gaps in the literature that deserve further attention.

4.2.1 Momentum investment strategies

4.2.1.A. Theoretical background

On the one hand, there are a large number of economists and statisticians supporting the theory of random walk, which emphasises that historical security prices cannot predict future price changes, thus attempts to construct trading rules based on past stock returns are "mechanical" and will not lead to profitability (Jensen 1967, p.77). On the other hand, numerous investment strategies have been proposed and tested, for example value strategies (Graham and Dodd 1934) and contrarian strategies (De Bondt and Thaler (1985, 1987), to name but a few, which pursue the past poor performers. Debate on the long-standing presence of these trading strategies has received a lot of attention from both theoretical and practical standpoints. More importantly, it raises the question of whether the random walk theory and trading rules can compromise.

In the early literature on investment strategies, Levy (1967), notably, empirically documented a new set of trading rules, of which the most discussed ones were momentum strategies. He observed a significant profitability when buying past winners and selling past losers over a period of 27 weeks. However, studies by Jensen (1967) and Jensen and Benington (1970) soon pointed out a number of methodological issues in Levy's work that made it not replicable, such as sample selection bias and a strong assumption of no lag trading. They found that, after correcting the errors, momentum trading was not as profitable as a simple buy-and-hold strategy. The validity of the momentum strategies was therefore questioned until Jegadeesh and Titman (1993) developed a more practical method, that unlike Levy's approach allows the test to be replicable. They constructed portfolios based on ranking stock returns with lag intervals rather than price ratios of individual stocks with no lag. Their research showed that the momentum trading did generate significant positive returns. In the long run, however, the profitability tends to disappear, suggesting the presence of return reversal effects. The phenomenon is interesting because if information about stock prices in the past can be used to beat the market and generate excess returns, this implies a violation of the weak form market efficiency which claims that all past stock prices are reflected in current prices. Hence, the success of momentum strategies is also referred to as an anomaly in the market.

In explaining the momentum anomaly, Fama (1998) reviews several competing explanations, among which the two theories that gain the most support are risk-based explanation and mispricing theory. According to the first theory, there is a strong relationship between risk and return, in which a higher return is expected as a compensation for bearing higher risk (Avramov and Chordia 2006). As a result, the abnormal return is likely to be a result of taking extra risk that has not been captured by the market beta. Whereas, behavioural finance suggests that investors tend to delay price reactions to relevant information and misprice stocks as a result (Barberis, Shleifer and Vishny 1998). In other words, the success of momentum strategies is attributed to these investors' psychological biases. Let us review in detail discussions on each of the two explanations.

(i) Risk-based theory

The argument that the risk unobserved by the CAPM can be a source of abnormal return has gained much support from market efficiency theorists. For example, in a book chapter published in 2010, Lai, Li, Conover and Wu (2010) provide comprehensive analysis on risk asset pricing and find strong support for common risk factors, such as BM, size and financial distress in asset modelling. Regarding momentum, under the efficient market hypothesis, momentum-reversal effects are consistent with time-varying risk premium[19]. The common approach is constructing explanatory variables from mimic portfolios that aim to capture certain types of risk that can potentially explain the return differentials between the winner and the loser stocks. For example, Ball and Kothari (1989) and Conrad and Kaul (1998) suggest that cross-sectional variation can explain momentum profits while Chordia and Shivakumar (2002) show strong support for the explanatory power of macroeconomic variables, including dividend yield, default spread, term spread and yield on the three-month Treasury bill. They also indicate that the momentum payoffs disappear once the market adjusts for the information proxied by the variables. On the contrary, Griffin, Ji and Martin (2003) find no evidence that those macroeconomic variables can explain the significant and consistent momentum profits both in and outside the US. The return reversal over one- to five-year periods observed in their sample is not in line with the risk-based explanations.

Some studies question whether momentum can be explained by firm investment policy. For example, Johnson (2002) proposes a risk-based model of partial equilibrium that shows that stochastic dividend growth rate can account for momentum abnormal return. In Liu and Zhang's (2008) study, most of the momentum profits are explained by the expected growth rate of industrial production, while Titman, Wei and Xie (2004) find that stocks of firms that invest more have lower returns. Concerning the 2003 US proposal cutting taxes on dividends, Dong and Goss (2011) show that both BM and momentum effects were not driven by changes in shareholders' dividend income.

Explaining momentum anomaly using the risk-based theory can be challenging because (a) naturally well-performing stocks do not appear to be riskier; and (b) the abnormal returns so far have not been explained by the risk proxies in standard asset pricing models like the CAPM and Fama-French three-factor model. Regarding systematic risk, Jegadeesh and Titman (1993) find that the market beta of the past losers is higher than that of the winners. Additionally, there is no evidence of positive serial correlation of factor portfolio return that could lead to favour high beta stocks. Hence, pursuing the

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[19] See Berk, Green and Nail (1999), Johnson (2002), Liu and Zhang (2008) for more examples.

past winners is not riskier under the CAPM. Also, Fama and French (1996) indicate that their model cannot explain the momentum anomaly. Moreover, in a study on single securities, Avramov and Chordia (2006) confirm that none of the examined asset pricing models, including conditional and unconditional versions of the CAPM, Consumption-based CAPM (CCAPM) and the Fama and French model, can capture momentum effects.

However, one risk element that some researchers found to have played a crucial role in explaining those challenges is business cycle risk. The idea has its root in Cochrane (1991) which provides evidence that some variables reflecting the upturn or downturn characteristics of the economy can forecast aggregate stock return, which in turn has the ability to predict future economic activities. Hence, it is natural to expect an explanatory relationship between business cycle risk and expected stock market return. Section 4.2.2 will present more detailed evidence of this relationship in the literature.

(ii) Mispricing theory

Early studies by DeBondt and Thaler (1985, 1987) document that investors in financial markets tend to overreact to information, especially "bad" news. Based on behavioural theories, they suggest that not only does investors' overreaction affect stock prices, it also can explain the large difference in returns between the losers and the winners in the long run. Additionally, their results which show a lower risk associated with higher returns among the losers indirectly imply a rejection of the risk-based theory.

Lo and MacKinlay (1990), among others, however, argue that most of the abnormal returns observed in previous studies are due to the delay of stock price reactions rather than to investors' overreaction. They indicate that the continuation of short-term returns is the fundamental reason for the success of past well performing stocks over past poor performers. Accordingly, mispricing theory attributes momentum profitability to investors' psychological biases. Lee and Swaminathan (2000) also find that past trading volume, which reflects investors' interest in a stock, plays an important role in predicting the magnitude and persistence of momentum profitability. The study suggests that investors are indeed slow in modifying their view in accordance with new information. Supporting these views, Grinblatt and Han (2005) show that momentum profit is caused by investors' tendency to hold on to their positions regardless of their potential gains/losses and, when this factor is controlled for, past stock returns can no longer explain the anomaly.

The mispricing explanation gains much support among momentum researchers. For example, Daniel, Hirshleifer and Subrahmanyam (1998) classify investors' psychological biases into two groups: overconfidence in private information, and self-attribution asymmetrically. According to their research, the former issue is likely to lead to mispricing, especially when the information is in the form of public announcements that have strong effects on return. More interestingly, the latter bias is documented to be the underlying reason of the short-term success of momentum strategies as investors shift from overconfidence to underconfidence once the biases are found.

Consistent with the mispricing arguments, Griffin and Lemmon's (2002) study points out that small and distressed firms are those mostly likely to be mispriced by investors, and this is the underlying reason behind the large return differentials between high and low BM stocks observed in the US, especially among the group with highest probability of bankruptcy.

Analysing at a more detailed level, Jegadeesh and Titman (1993) find no evidence that either systematic risk or delays in price reactions to common factors could explain the high abnormal returns generated from momentum trading strategies but delayed price reactions to firm specific information can. This theory is supported by Hong, Lim and Stein (2000) who demonstrate that when firm size is kept fixed, momentum strategies are more prominent among firms with low analyst coverage, especially in the past loser group. They, therefore, conclude that it takes time for investors to react to firm specific information and that negative information travels more slowly in the market.

Besides the main two arguments that risk-based and mispricing theories could explain momentum, some people think momentum premium is caused by data mining. However, the robust success of momentum strategies across markets and over time shows that data mining is unlikely to be a valid explanation. Besides the evidence in the US shown in Jegadeesh and Titman (1993) and their updated paper in 2001, momentum return is also found in many non-US markets. Some examples are Foerster, Prihar and Schmitz (1995) providing evidence of large momentum profitability in Canada, Rouwenhorst (1998, 1999) confirming the result in 12 European markets and 20 emerging countries, while Chui, Titman and Wei (2000) find similar results in Asian markets.

The following sections will review more recent evidence of momentum strategies across different markets, and especially their performance in the UK.

4.2.1.B. Performance of momentum investment strategies

This section does not ambitiously aim to review the vast discussion on momentum strategies. It rather focuses on presenting the main arguments that have shaped the momentum literature of the present time, and from which further explorations are based on.

Since Jegadeesh and Titman (1993) documented large momentum profitability in the US, there has been an enormous amount of studies on the performance of these investment strategies both inside and outside the US. On one hand, among others, Grundy and Martin (2001) find consistent momentum abnormal returns in the US over the entire post-1926 period. Also, an extensive study by Griffin et al. (2003) on a large sample of 40 markets across continents shows strong support for momentum trading both abroad and in the US. On the other hand, Schewert (2003) argues that profit-related market anomalies, such as the size and value anomalies, typically weaken, disappear or even reverse after the investment strategies become known. Nevertheless, recent studies by Jegadeesh and Titman (2001, 2002) continue to confirm findings in many researches on the validity of momentum investing which was first documented in their earlier paper in 1993. Moreover, a more recent study by Fama and French (2008, p.1662) even concludes that the abnormal returns from momentum trading continue to be "pervasive". Their updated study, Fama and French (2012), confirms the presence of momentum profitability across the globe, except in Japan. They explain that the failure of momentum strategies in Japan is a chance result.

It is worth noticing that momentum strategies which take into account stock prices should not be mistaken for earnings momentum which is based on firm earnings. While Cohen, Gompers and Vuolteenaho (2002) point out that more profitable firms have superior average stock returns, Chan, Jegadeesh and Lakonishok (1996) show that although the two anomalies coexist, they still find significant momentum profits after adjusting for momentum in firm earnings.

The strategies of buying (selling) the highest (lowest) past return stocks have been popular not only among researchers but also among traders. It is natural for both professional and non-professional investors to choose the currently successful stocks over the rest. Interestingly, quantitative trading managers as well as non-quantitative mutual fund managers also show interest in at least some form of price momentum strategies (Daniel, Jagannathan and Kim 2012).

One interesting observation about momentum strategies which is unlike any other anomalies, is that momentum profitability is sensitive to the holding period and to investment horizons. The early study of Jegadeesh and Titman (1993) has shown that momentum profit is large and significant over holding periods of 3 to 12 months. In the following year the profit partly disappears and no longer exists in the subsequent two years. In addition, an updated work by Jegadeesh and Titman (2001) also finds momentum investment turns from large positive strategies in the first year to negative-return investment during months 13 to 60 following the formation period. Later, Griffin et al. (2003) document that there are some periods when momentum investors may suffer losses if they exercise their stocks. Additionally, George and Hwang (2004) provide empirical support for momentum strategies based on a flexible rather than a fixed horizon. However, Daniel et al. (2012) propose “dynamic” momentum strategies that incorporate the hidden Markov’s model of Hamilton (1989) to predict those periods of negative returns, and document that these strategies are superior to the traditional static momentum. This is because the dynamic approach can help momentum investors avoid periodic losses. As a result, momentum-oriented investors could benefit from a more consistent return premium.

4.2.1.C. Momentum strategies in the European markets

It is perhaps worth reporting the findings of some key papers on momentum in the European markets - the economic area that the UK operates in. Generally, momentum profitability is documented in majority of European markets. For example, Griffin et al. (2005) report positive momentum returns in 14 out of 17 European countries. The exceptions are Portugal, Norway and Greece. Similarly, Nijman, Swinkels and Verbeek (2002) find a momentum effect in the stock returns of 13 European countries, in which the returns are statistically significant in the UK, Denmark and France.

In terms of investment periods, Rouwenhorst (1998) found that momentum profit is large and significant in their sample of 12 European countries in the medium term (3- to 12-month holding periods). Similarly, Mengoli (2004) observes significant momentum return over less-than-12-month periods in the Italian Stock Exchange. The profitability, however, disappears after one year. These findings are consistent with the US results documented earlier by Jegadeesh and Titman (1993). More recently, Lam (2007) also documents significantly positive returns generated by 6-month momentum strategies in three major European countries, France, Germany and the UK, between 1977 and 2002.

In contrast, Franck, Walter and Witt (2013) do not find evidence that German mutual funds employing momentum strategies outperform other funds. They further explain that it is because German funds largely use the strategies in trading European and Asian stocks but less on domestic stocks. Also, the mutual funds with such global equity focus account for just half of the number of funds in Germany. So this perhaps explains their different findings.

Although momentum effect is documented in many markets in Europe, it is important to study the underlying reasons behind the anomaly on a country level. On the one hand, Chui, Titman and Wei (2010) argue that a national culture effect could explain the differences in performance of momentum strategies between countries. On the other hand, Nijman et al. (2002) and Fama and French (2012) among others indicate that it is individual stock performance that determines the presence of momentum, not countries' or industries' characteristics. The next section will focus on discussions on momentum in UK firms, and the aim is to identify potential gaps, if any, in the momentum literature in the UK.

4.2.1.D. Momentum strategies in the UK

Research on momentum investing in the UK market is relatively underdeveloped considering the position of the London Stock Exchange in the world's financial centres. Most studies have the UK as a subset in their international-scale research. Rouwenhorst's (1998) work, for example, admits that more than half of firms in his sample of twelve international markets are those in three major countries, namely the UK (23%), France (20%) and Germany (10%)[20], and among which, he finds the UK exhibits a 0.9% monthly return on average from momentum strategies. More recently, examining a sample of 40 countries, Griffin et al. (2003) also notice the presence of abnormal return in most markets and report that momentum-oriented investors in the UK can gain a return of 1.03% per month on average for a 3-month holding period. This excess return is statistically significant (*t*-value of 6.14) and among the highest rates in their sample. However, this abnormal return decreased to only 0.20% if investors held their portfolios for 12 months and disappeared afterward. In their updated study, Griffin et al. (2005) confirm these findings but do not attempt to research further. This is perhaps due to the fact that most investment strategies were originally discovered in the US. However, thorough examination in non-US markets would provide out-of-sample evidence about what truly drives these anomalies[21].

[20] Calculation is based on the details given in Rouwenhorst (1998, p.272-273) showing that among 2,190 stocks in his sample, the UK contributes 494, France: 427 and Germany: 228 firms.

[21] As pointed out in Griffin et al.'s (2003) international study, if momentum is explained by risk, it is largely country-specific risk.

Realising this gap, some researchers have recently begun to explore the subject in the UK. A study by Chabot, Ghysels and Jagannathan (2009) shows that momentum strategies generated significant abnormal returns even during the Victorian era with an exemption of the January reversal, which they attribute to the tax-free system on capital gains at the time. However, they find a period of no momentum profit for 3.8 months once every 1.4 years. Also, Agarwal and Taffler (2008) find evidence that during a more recent period between 1979 and 2002 past winners outperform past losers among distressed stocks but it is not the case within the non-distress group[22]. Figures in Table 3 of their paper indicate that the return differentials between the winners and the losers are not statistically significant. However, since their work does not focus on testing the performance of momentum strategies, no further analysis is carried out.

Therefore, there is still a need for more in-depth analysis on the performance and the driving factors behind momentum trading in the UK, and this thesis aims to contribute to that segment of the existing literature.

4.2.2 Momentum and business cycles

From a theoretical standpoint, many theorists predict that changes in credit market conditions could affect a firm's risk bearing and their expected stock returns[23]. In particular, Berk, Green and Naik (1999) estimate a firm's value to be based on the value of its assets plus growth options. Their theoretical model predicts that economic conditions can directly affect expected stock return through interest rate changes.

Regarding momentum anomaly, whether it is driven by risk-based or behavioural factors, there are perhaps still reasons to expect that business cycles and market conditions could have an effect on its profitability. More specifically, the risk levels have long been serving as the first point of concern in investment decision making whenever there are changes in the market conditions. These are grounds for concern because Ahmed and Lockwood (1998) and Howton and Peterson (1998), for example, find evidence of a significant difference in systematic risks in upturn and downturn markets. Also, it is widely documented that well performing stocks and poorly performing stocks react to good and bad market conditions differently (Ang and Chen 2002, and Li, Miffre and Brooks 2006 among others). Hence, one could expect changes in the expected return of the winners and the losers as a result of changes in risk levels.

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[22] In Agarwal and Taffler's (2008) study, distressed stocks are defined as securities of firms that have a negative Z-score, and therefore are at risk of bankruptcy.

[23] See Bernanke and Gertler (1989), Kiyotaki and Moore (1997) for examples.

On the other hand, it is also possible to relate the differing states of the economy to investors' sentiment and to the possibility of investors' misvaluation. The behavioural finance theory implies that investors are more positive (negative) when good (bad) news comes along and as a result, they tend to under-react (over-react) to the news (DeBondt and Thaler 1985). That is the foundation of the misvaluation arguments. In contrast, Antoniou, Lam and Paudyal (2007) find that although business cycles contribute significantly in capturing momentum returns, behavioural biases are not the underlying reason behind that explanatory ability. They further explain that it is risk factors that are attributable to business cycles that drive momentum abnormal returns.

Empirically, there have been a large number of studies showing a strong link between momentum profitability and the states of the economy. According to Chordia and Shivakumar (2002), poor business conditions, especially recessions, have been shown to have negative impacts on momentum performance. They find momentum strategies result in negative returns during these periods, yet which are statistically insignificant. The trading strategies, however, generate considerably larger profits in the US during economic booms. Similarly, Cooper, Gutierrez and Hameed (2004) find that returns from momentum strategies are only positive and significant during economic expansion. They attribute this result to changes in investor sentiment which is reflected by stock market conditions. However, Griffin et al. (2003) point out that market upturns or downturns can reflect other measurable variables. In particular, they list a range of macroeconomic variables that are more related to the market states, such as changes in industrial production and in inflation. More importantly, the study provides strong evidence of significant momentum profitability across 4 continents, in both "good" and "bad" economic conditions.

4.2.3 The relationship between firm distress condition and momentum

From the asset pricing viewpoint, there has been evidence of distress-risk explanatory power in predicting equity returns. Early studies by Chan and Chen (1991) and Fama and French (1992) show that higher returns generated by small and value stocks are a compensation for their higher distress risk. Additionally, Fama and French (2008) find evidence that small and unprofitable firms experience unusually low stock returns, whereas equity returns increase with profitability among profitable firms.

Momentum investing, a sub-branch of the asset pricing literature, further suggests that the higher return of the winner stocks over the losers is associated with firm size and financial conditions. More specifically, Eisdorfer, Goyal and Zhdanov (2011) provide evidence that size, value and momentum anomalies are most noticeable among stocks that are under great financial pressure. They explain that investors tend to greatly misvalue those stocks. These findings are consistent with Hong et al.'s (2000) research which shows that momentum profitability is much higher among stocks with low analyst coverage (usually associated with a higher likelihood of being mispriced). In addition, Grinblatt and Moskowitz (2004) find higher momentum profits among consistent winners.

Connecting the two concepts, there is a growing body of research studying whether firms' financial distress risk can explain the long-standing momentum anomaly. For instance, a study by Avramov, Chordia, Jostova and Philipov (2007) reports a strong link between momentum profits and firm distress conditions in the US. They find that momentum strategies yield significant abnormal profits among firms with low credit ratings while there is no such premium found among high-grade firms. Their study further documents that stock volatility and firm characteristics, such as size, age and leverage, do not seem to have the ability to capture the return differential between the high and low credit rating groups.

Similarly, Agarwal and Taffler (2008) confirm the important role of default risk in explaining momentum profitability in the UK market. Using a different proxy for firm financial distress, they argue that momentum anomaly in the UK is explained only by Z-score (i.e. Altman's (1968) measure of probability of bankruptcy). They document that the market tends to underreact to firms' distress conditions, and momentum profits are in fact driven by a very slow response to the poor performance of firms with a positive Z-score (i.e. having similar characteristics of previous bankrupt firms). As a result, momentum is a proxy for financial distress risk and the Z-score-based factor should act as an alternative to momentum factor in the traditional Carhart (1997) four-factor asset pricing model.

A more recent study by Abinzano, Muga and Santamaria (2014) in four EU countries (UK, France, Germany and Spain) finds that default risk could explain the returns on loser portfolios but not the returns on winner portfolios. This is because the characterisation of the winner stocks is more complex and therefore it is difficult to explain their returns.

From a theoretical perspective, Campbell et al. (2008) point out that if firm distress risk has not been captured by the CAPM, it may contribute to explaining market anomalies, such as size and value premiums. This implies that the abnormal returns may be a compensation for bearing a higher default risk.

However, the question of whether or not these arguments are valid empirically is still under debate and this chapter devotes sub-section (ii) of section 4.2.4 to discussing this concern.

The next section will discuss in detail the gaps in the momentum and financial distress literature, from which this chapter's research questions emerged.

4.2.4 Gaps in momentum literature

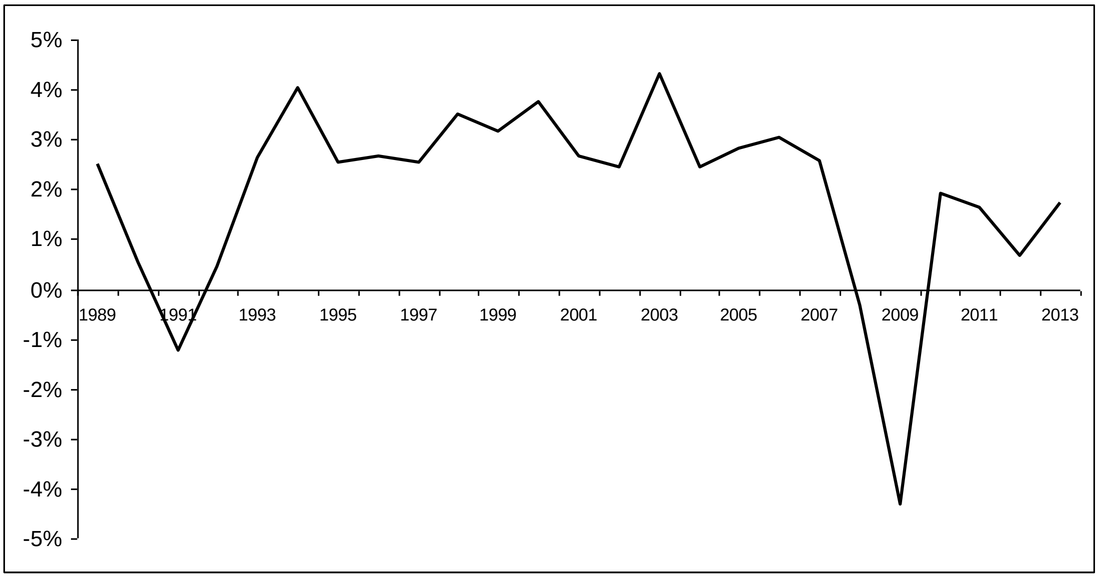
There are a number of areas in the literature that can potentially be developed further in order to meet the growing demand for fully understanding the underlying reasons behind the well-recognised momentum anomaly.

(i) Under-developed research in the UK

As discussed in the previous section, there is evidence supporting the link between firms' financial distress condition and the performance of momentum strategies, though it is mostly found in the US market. Research outside the US would provide the necessary out-of-sample evidence of momentum and the sources of the anomaly. However, among a limited number of works concerning momentum in the UK, there have not been any attempts to study the role of default risk in explaining momentum anomaly. Also, the most recent empirical works on momentum in the UK are on a dataset up to 2002. Thus, this chapter aims to explore this under-developed area in the literature.

Additionally, a large-scale research by Griffin et al. (2003) points out that if business cycle risk drives momentum, it is not global risk but country-specific risk factors that are responsible for the momentum profits. They, therefore, strongly suggest for future researchers to look at momentum anomaly on a country-by-country basis. Figure 4.1 shows that from 1989 to 2013 the UK economy has experienced both sides of the business cycle with a long period of growth and stability found between two market downturns in 1990-1992 and 2007-2010. It is, therefore, worth testing whether momentum profitability in the UK is explained by business cycles.

Figure 4.1: UK GDP Growth rate (1989-2013)



(ii) Measures of financial distress risk

Previous studies have set up a link between momentum and firm distress risk but there are some concerns over the proxies for distress risk used in their tests. For example, Avramov et al. (2007) propose using credit rating as a proxy for firms' bankruptcy risk. It is not only a familiar and straightforward measure but also the only measure that takes into consideration both quantitative and qualitative firm-related information. However, as Griffin et al. (2003) observed, bond markets and corporate credit ratings outside the US are not developed well enough to provide a reliable measure of firm's creditability. Thus, despite the promising benefits of the proxy, it is difficult to apply this approach in non-US markets without causing some forms of data bias.

Alternatively, using Altman's (1968) Z-score to measure default risk, Agarwal and Taffler (2008) find that, unlike Fama and French's (1992) results, in the UK market firm size and BM factors do not capture distress risk but that momentum does. They go further, making a rather strong statement that a risk factor built from Z-score portfolios should replace the winner-minus-loser factor in Carhart's (1997) four-factor model as the Z-score-based factor is superior in representing the same type of risk.

There are a number of reasons suggesting that Agarwal and Taffler (2008) might have overstated the role of Z-score in explaining asset return in general and momentum profit in particular. First of all, by considering only whether Z-score is positive or negative (which is appropriate when relying on this measure, as they pointed out that the actual value of Z-score is meaningless), they automatically disregard the fact that some firms can experience a more serious financial distress than others, and so do the associated stock prices. Thus, instead of only two groups, a more detailed ranking of their risk level is needed and the return on their stocks should be weighted accordingly. Secondly, Z-score is well recognised as an easily-calculated measure of default probability, originally built from a sample of only 66 firms in the manufacturing sector. Applying this score on firms in the financial sector is not advisable while the Winner-minus-Loser factor is not limited in any particular sectors. This perhaps prevents Agarwal and Taffler (2008) from generalising their findings. Finally, although being a popular measure of default risk, Z-score is constructed purely based on accounting variables while momentum strategies are based on past stock market prices.

In this thesis, we therefore propose using Campbell-Hilscher-Szilagy's (2008) proxy for default probability which covers a large set of both accounting and equity market variables. More details on the proxy construction and its advantages over the previous measurements are provided earlier in section 2.5.1 of Chapter 2.

(iii) Controlling for thin trading issues

Moreover, it is worth noticing that most UK-based studies look at the FTSE All-share index, which includes a large number of small and medium stocks which experience long periods of irregular trading activities. Their past returns, therefore, do not provide reliable evidence of their actual performance. Irregular trading stocks would therefore unsurprisingly be classified as losers. There are two issues with including them in loser portfolios: (a) In theory, momentum investors should sell the losers to gain profit, while in practice, there is little chance that the ask offers (or sell offers) can actually been exercised due to the thin trading experience. (b) While momentum profit is documented to be driven by the poor performance of small and distressed stocks[24], the thin trading issue associating with stocks within this category will potentially bias toward accepting this hypothesis. To reduce these possible biases, the chapter, therefore, proposes the use of FTSE350 stocks when explaining momentum anomaly in the UK. The exclusion of extremely small and irregular trading stocks has also been strongly recommended for the US market by Jegadeesh and Titman (2001) among others in order to reduce standard errors.

[24] Hong et al. (2000) and Lesmond, Schill and Zhou (2004) find that most momentum profit comes from the return continuation of past poor performing stocks and small and distressed firms are more likely to fall into this group.

(iv) The possibility that firm default risk and business cycle risk can explain momentum.

Whereas there is an extensive literature on momentum and a growing literature on its relationship with business cycles, as well as with firms' financial distress conditions, there have not been any efforts connecting these three related phenomena. This is possibly because there is a possible link between business cycles and firm default risk while there is no clear-cut measure of the effect of the former on the latter. Putting default risk and business cycle effects in one context may allow their role, if any, in explaining momentum anomaly to be distinguished and quantified.

This thesis therefore aims to bridge these gaps in the literature by testing the following three main hypotheses.

4.2.5 Hypotheses

Hypothesis 1: Momentum strategies are profitable in the UK.

The chapter revisits the anomaly in the UK market and updates the validity of momentum strategies. Hypothesis 1 is to find out if the strategies of buying the past winners and selling the past losers generate a positive abnormal return in the UK. Testing the hypothesis also provides an answer for the question of whether or not these trading strategies outperform a simple buy-and-hold policy.

In addition, the chapter also addresses the performance of momentum investing in different states of the economy. Many researches in non-UK markets show a large momentum profit during economic expansion but not during downturns while others find significant momentum returns in both states of the economy. The objective of this hypothesis is to contribute to this debate with UK evidence.

Hypothesis 2: Momentum profitability varies over business cycles.

There is evidence in the literature of a link between momentum profitability and business cycles. In order to better understand whether business cycles can contribute to explaining momentum in the UK, this chapter also looks at how momentum strategies perform over different business cycles. It compares momentum returns over periods of negative versus positive GDP growth rates, and between these during two extreme states of the economy: economic recessions and expansions.

Hypothesis 3: Momentum profitability can be explained by default risk.

If there are momentum profits in the UK, testing Hypothesis 3 will fulfil the need for researching the explanatory power of firms' default risk in explaining momentum anomaly in the UK. As studies in this subject were carried out only recently and mostly in the US, it is important, especially for practitioners, to ensure that their trading strategies are based on research findings that have been tested both in- and out-of-sample.

Hypothesis 4: Firm distress condition and business cycle risk contribute to explaining momentum profitability.

There is evidence that firm financial distress conditions can explain momentum anomaly and that momentum profits vary with economic conditions. Therefore, it is natural to ask if the two factors contribute to capturing momentum profitability. Examining this link provides new evidence of the explanatory abilities of firms' default probability and business cycles collectively. Additionally, the test can also help us answer an important question of whether momentum anomaly in the UK is driven by risk or investor irrationality.

4.3 CHAPTER CONTRIBUTION

Momentum investment strategies have been documented widely in the literature. Most studies, however, focused on the US market or on certain groups of countries as a whole. Studies focusing exclusively on the UK market were dated back in the 1990s and early 2000s. Given the important role of the UK in the global economy and a number of recessions which have occurred recently, it is worth revisiting the question of whether there are abnormal momentum returns in the UK market and, if so, what are the factors explaining the anomaly.

Chapter 4 contributes to the existing literature firstly by incorporating effects of the recent shocks in the market together with firms' default risk in capturing momentum premium in the UK. There have been numerous studies[25] reporting a strong link between the presence of momentum premium and states of the economy. However, this is the first empirical study that examines the impact of economic shocks in more recent years, most notably the financial crisis in 2008, on momentum investors in the UK.

[25] For example, Chordia and Shivakumar (2002) and Cooper et al. (2004) for the US, and Griffin et al. (2003) for the UK market.

Section 4.5.1 of this chapter will report the performance of momentum strategies in the UK in various market conditions, such as market downturns versus upturns, or recessions versus expansions. More importantly, the chapter provides an assessment on the role of risk associated with these changes in the economy in explaining momentum anomaly. While there is not a single proxy for states of the economy, the analysis is based on a set of business cycle factors that are collectively meant to mimic the risk elements associated with changes in the state of the economy.

Secondly, when taking firm distress conditions into account, unlike previous studies the chapter employs a range of distress variables to ensure more risk elements associated with distress conditions in common stock returns are captured. These include default risk, BM, size and past return effects, together with business cycle components such as term spread and default spread. While some variables have been mentioned in the momentum literature, such as BM, size and past return effects, the role of the others has not been tested in the same context.

In regard to default risk, the analysis is based on a more accurate proxy for firms' default probability calculated from Campbell, Hilscher and Szilagyi's (2008) dynamic probability model. The measure includes not only accounting but also equity market variables. Before Campbell et al. (2008), models predicting the probability of corporate failure were developed nearly four decades ago. Additionally, the default indicator proposed by Campbell et al. (2008) has been documented to have a higher accuracy than the earlier indicators. Campbell et al.'s (2008) proxy, however, has not been used in the momentum studies. For the first time, Campbell et al.'s (2008) corporate failure indicator is used as the main proxy for default risk in explaining momentum anomaly. Other measures of default probability, such as O-score and Z-score, are also employed for robustness check purposes.

Finally, although there is already evidence of momentum anomaly being explained by firm default risk while also associating this with business cycles, the chapter is the first work linking the three elements in the same context. This approach enables the study to report on whether the risk component associated with one variable has been captured by the other, and whether these risk elements can collectively explain momentum anomaly in the UK. If they do, this would contribute to enhancing the performance of momentum modelling going forward.

4.4. DATA AND METHODOLOGY

4.4.1 Data

Data used in this chapter are the FTSE350 stocks, covering a period from 31st January 1990 to 31st December 2012. As discussed earlier, the use of the FTSE350 rather than the FTSE All share is more suitable for asset pricing in the UK market. This is also in line with Jegadeesh and Titman (2001) among others who exclude small and illiquid stocks from their sample to reduce standard errors. The stock returns for each month are the natural logarithm returns of stock prices. Firms must at least have data on stock returns from 6 months prior to the portfolio formation date until the end of the holding period to be included in the related portfolios. For example, 6-month-holding portfolios in month *t* include firms that have data at least from month *t-6* to month *t+6*. In line with previous studies on momentum strategies, this chapter includes financial firms and firms with no BM data. In short, 10 portfolios (described in Section 4.4.2 B) are formed from a full sample of 290 firms (see Appendix 1 for the constituent list).

Data are obtained from the DataStream database unless stated otherwise. There is some accounting data that is not available in DataStream for some firms, for instance Earnings Before Interest and Taxes (EBIT). EBIT is obtained from Bloomberg and in some cases hand-collected from the firms' annual reports published on their official websites. The UK Gilt rates are obtained from the UK Debt Management Office database. Details of data sources and data collection process are described in Appendix 2 of this thesis. Among input variables, only the market excess return is obtained from Prof. Kenneth R. French's website. Other variables are constructed as described the in next section (a summary can also be found in Appendix 3).

4.4.2 Methodology

4.4.2. A Default risk proxies

There are number of proxies for default probability discussed in the literature, the most commonly used measures are Altman's (1968) Z-score, Merton's (1974) distant-to-default, Ohlson's (1980) O-score, and Campbell-Hilscher-Szilagy's (2008) model (CHS hereafter). To measure firms' default risk, the chapter employs the last and also the latest measure – the CHS dynamic hazard model – for the following reasons. Firstly, the distinct merit of this method is that it is by far the only measure considering a large set of both accounting and equity market variables, and thus can potentially possess a higher predictive ability on bankruptcy risk[26]. Moreover, unlike value and size anomalies, momentum is based on past equity returns; the CHS is therefore a more appropriate measure in momentum analysis than accounting-based measures, such as Z-score and O-score. Furthermore, some studies such as Aretz, Florackis and Kostakis (2017) show that for non-US markets, the CHS measure appears to be more suitable due to its ability to incorporate country-specific characteristics. Lastly, Bharath and Shumway (2008) and Campbell et al. (2008) find evidence that the CHS model outperforms Merton's (1974) model, which was based on bond pricing, in forecasting bankruptcy in their sample. They find that over a long period of time, the volatility in many variables such as firm characteristics, market value and equity prices become significant in predicting bankruptcy rate and the CHS has the ability to capture that time variance. Nevertheless, the chapter will later utilise other proxies for robustness check purposes.

We follow Campbell, Hilscher and Szilagyi's (2008) study to compute the CHS value of each company[27]. CHS values are made up of a number of accounting and equity ratios as described in section 2.5.1.B of Chapter 2. Accounting ratios forming the CHS variable have been widely used in previous studies such as Altman (1968) and Ohlson (1980) to forecast the risk of bankruptcy. By also including equity information, Campbell et al. (2008) allow the market view on firms' default probability to be captured in the CHS. More details on the procedure for computing the CHS score can be found in Appendix 5 of the thesis.

4.4.2. B Portfolio formation

Following Jegadeesh and Titman (2001), we first form 10 portfolios based on ranking past 6-month lagged return and hold for 6 months. At the end of each month *t*, stocks are classified into portfolios by ranking in ascending order their monthly returns from month *t-5* to month *t* and then forming 10 equally weighted portfolios, in which the lowest past return is P1 and the highest past return is P10. That means P1 (P10) consists of 10% of the stocks with the lowest (highest) returns over the previous 6 months. The

[26] Franzen, Rodger and Simin (2006) raise the concern that measures of distress risk based solely on accounting variables are losing their accuracy in recent times. Market-based measures, however, are not subject to this criticism.

[27] See Appendix 3 for the mathematical formula of constructing each variable, proposed by Campbell, Hilscher and Szilagyi's (2008).

portfolios are held from month *t+1* to month *t+6* following the formation month. The momentum profits are defined as the return differentials between P10 and P1.

In addition, to examine momentum profitability in the periods following portfolio formation as considered in previous studies, the chapter also separately constructs 10 portfolios based on 6-month lagged return with 3-, 9-, 12- and 60-month holding periods. The main reason for choosing these timelines is to check if there is a momentum reversal over 12+ month investments, which previous studies, for example Griffin et al. (2003), have documented in several countries, including the UK and the US. Portfolios are equally weighted and rebalanced monthly. In this chapter, we consider only 6-month lagged returns as Jegadeesh and Titman (1993) find that trading strategies based on returns of the last 1, 2, 3 and 4 quarters do not yield significantly different results. Moreover, since this chapter is particularly interested in the default probability variable which is constructed using information from firms' financial statements, it is important that the requirement of a minimum of 6-month lag is met to ensure that outside investors have time to fully consider the financial reports.

4.4.2. C Explanatory variable construction

Variable construction has been discussed earlier in Section 2.5 of Chapter 2 and more details can be found in Appendix 3 of this thesis. Beside Fama and French's (1993) three factors, in Chapter 4 there are a number of explanatory variables employed to proxy for business cycles, including default spread (DES), term spread (TERM), dividend yield (DIV) and the 3-month London Interbank Offered Rate LIBOR (a proxy for the short-term Treasury Bill, T-Bill). A large number of early studies, such as Fama (1981) and Fama and French (1988), have shown that these variables are closely related to short-term and long-term business cycles. They found that these variables experienced mean reversion across different economic cycles.

DES is defined as the difference between the average yields on corporate bonds and on long-term Government bonds (UK Gilt with a 15+ year maturity). DIV refers to the average value-weighted dividend yield of all stocks in the sample. TERM is the difference between average returns on long-term and short-term Government bonds (15+ year Gilt and 3-month rate, respectively) and T-Bill is the rate of return of the 3-month LIBOR.

In addition, the chapter also uses a portfolio-based approach to form the distress factor, in which stocks are also sorted into three portfolios: high, medium and low distress groups, based on their probability of default. It is worth noticing that, unlike the way distress portfolios were constructed in the previous section, CHS portfolios are formed using the usual 30:40:30 breakpoint. This is because portfolio-based explanatory variables aim to proxy for the associated risk factors rather than measure actual stock returns.

In the four-factor model, there is a potential simultaneity bias concerning the dependant variable (R_i-R_f) and the Winner-minus-Loser (WML) variable as both variables aim to capture certain aspects of the momentum effects. To reduce this possibility, this chapter constructs two variables using different intervals with a lag in formation date. As described earlier, the winner and loser portfolios are formed every month based on their past 6-month returns and rebalanced every 6 months. On the other hand, following Jegadeesh and Titman (1993), WML is constructed based on stocks' 11-month past returns. The monthly portfolio returns are calculated at July, year *t* with a 1-month lag and value weighted by the market value at the end of June, year *t*. The WML is the return differential between the top 30% and the bottom 30% stocks.

4.4.2. D Valuation models

(i) Estimation methods

The chapter will start with the traditional FF three-factor model. Although Fama and French (1996) find that the FF model fails to capture momentum patterns in average returns in the US, we look to test whether an augmented FF model, enhanced with a default factor – CHS – can explain momentum in the UK market. The augmented FF model is given by:

$$\boldsymbol{R_{i,t}} - \boldsymbol{R_{f,t}} = \alpha + \beta_m (R_{m,t} - R_{f,t}) + \beta_{HML} HML_t + \beta_{SMB} SMB_t + \beta_{CHS} CHS_t \quad (4.1)$$

Where, R_{it} is returns on asset *i* at time *t*; R_{mt} is returns on the market at time *t*; HML_t is the High-minus-Low variable at time *t*; SMB_t is the Small-minus-Big variable at time *t;* and CHS_t is the CHS variable. These explanatory variables are described in detail in Section 2.5 of Chapter 2.

Following Fama and French (2012), we will also use the four-factor model proposed by Carhart (1997) to capture momentum returns. The Carhart classical risk-based model is also documented to perform well in capturing momentum effects in the UK. Gregory, Tharyan and Christidis (2013) show that after removing illiquidity stocks from the FTSE All share index, which are mostly non-FTSE350 stocks, stock cross-sectional returns can be explained by Carhart's (1997) four-factor model, including market beta, HML, SMB and WML variables. In addition, for the UK market, they strongly support the use of risk factor models, in which factors are constructed based on portfolios with similar characteristics. For instance, the factor HML is formed from the return differentials between high and low BM portfolios. They find evidence that these models can explain abnormal returns in general and momentum anomaly in particular.

This empirical study will consider an augmented Carhart model given in the below equation to explain momentum in the FTSE350:

$$\boldsymbol{R_{i,t}} - \boldsymbol{R_{f,t}} = \alpha' + \beta'_{m}\,(R_{m,t} - R_{f,t}) + \beta'_{HML}HML_t + \beta'_{SMB}SMB_t + \beta'_{WML}WML_t + \beta'_{CHS}CHS_t \qquad (4.2)$$

Where, R_{it} is returns on asset i at time t; R_{mt} is returns on the market at time t; HML_t is the High-minus-Low variable at time t; SMB_t is the Small-minus-Big variable at time t; WML_t is the Winner-minus-Loser variable at time t; and CHS_t is the CHS variable at time t. These explanatory variables are described in detail in Section 2.5 of Chapter 2.

To ensure the results are not sensitive to the choice of proxy, we employ a number of most commonly used variables, including CHS's (2008) estimated variable, Altman's (1968) Z-score, and Ohlson's (1980) O-score.

The chapter then considers if adding business cycles could contribute to explaining momentum returns. Section 4.5.2 provides analysis on how momentum profitability changes over different business cycles by looking at the potential effects of changes in investment opportunities during economic cycles. To proxy for the changes in investment opportunities, this chapter uses a range of variables that have been widely reported in the literature, namely DES, TERM, DIV and T-Bill. Next, section 4.5.3 addresses the possible explanatory power of firms' distress conditions in explaining momentum in the UK. In addition, the section aims to find out if adding business cycles can contribute to explaining momentum profitability. One concern raised is the possibility of multicollinearity issues between distressed firms and market conditions. This concern will be addressed later in section 4.5.4 to ensure the robustness of the results.

The regression models are given as follows.

$$\boldsymbol{R_{i,t}} - \boldsymbol{R_{f,t}} = \sigma + \gamma_m (R_{m,t} - R_{f,t}) + \gamma_{HML} HML_t + \gamma_{SMB} SMB_t + \gamma_{CHS} CHS_t + \gamma_{DES} DES_t + \gamma_{TERM} TERM_t + \gamma_{DIV} DIV_t + \gamma_{T-Bill} T-Bill_t \tag{4.3}$$

and,

$$\boldsymbol{R_{i,t}} - \boldsymbol{R_{f,t}} = \sigma' + \gamma'_m (R_{m,t} - R_{f,t}) + \gamma'_{HML} HML_t + \gamma'_{SMB} SMB_t + \gamma'_{WML} WML_t + \gamma'_{CHS} CHS_t + \gamma'_{DES} DES_t + \gamma'_{TERM} TERM_t + \gamma'_{DIV} DIV_t + \gamma'_{T-Bill} T-Bill_t \tag{4.4}$$

Where, R_{it} is returns on asset *i* at time *t*;

R_{mt} is returns on the market at time *t*;

HML_t is the High-minus-Low variable at time *t*;

SMB_t is the Small-minus-Big variable at time *t;*

WML_t is the Winner-minus-Loser variable at time *t;*

CHS_t is the CHS variable at time *t*;

DES_t is the Default spread variable at time *t*;

$TERM_t$ is the Term spread variable at time *t*;

DIV_t is the Dividend yield variable at time *t*; and

$T\text{-}Bill_t$ is the Short-term Treasury Bill variable at time *t*.

These explanatory variables are described in detail in Section 2.5 of Chapter 2.

(ii) Seasonal effects

Jegadeesh and Titman (1993) notice an unusual seasonality in momentum behaviour. Unlike any other calendar month, January sees a sudden shift in momentum profits from largely positive to significantly negative returns. Although there is nothing to suggest that January differs from any other months, Jegadeesh and Titman (2001) revisit this phenomenon and find that it is small-size and low-priced stocks that drive the seasonality. However, the seasonality is still not fully explained when excluding those stocks. Thus, this chapter also examines the performance of momentum strategies in January and in non-January months to see whether the January effect in momentum profit exists in the UK. If it does, the analysis will be adjusted accordingly.

In addition, as mentioned in previous sections, there has been evidence that market conditions can affect momentum profitability. It shows that momentum anomaly exhibits large positive abnormal returns during economic expansions and may shift to losses during recessions. At the same time, during the testing period the UK experienced a long period of recession following the 2008 global financial crisis. Hence, it is also crucial to check if these events have had effects on momentum strategies in the UK market.

4.5 EMPIRICAL RESULTS

4.5.1 Performance of momentum strategies

4.5.1. A Momentum anomaly

Several studies have documented the presence of momentum profitability in the UK[28]. However, given the important position of the UK in the global economy, the number of studies done on this market is relatively modest. Also, it is worth mentioning that most of the works were performed on the 1990s and early 2000s data. Since then, there have been a number of significant events that could change the cost of investment opportunity, such as the recent financial crisis in 2008 and the Bank of England's decision to keep interest rates at a record low of 0.5% since March 2009. Thus, it is important to incorporate these changes and to update momentum-oriented investors with more recent findings.

Table 4.1 reports the average monthly returns of momentum strategies across investment horizons. Most studies have documented the results for 6-month investment periods or longer. In this section, we first look at the less commonly reported strategies which involve buying the past 6-month winners, sell the past 6-month losers and rebalancing every 3 months.

The results in Table 4.1 further confirm that in the UK market the winner stocks also outperform the losers for a shorter investment period of 3 months. On average, momentum investing generates 1.24% per month. The average excess return is both statistically and economically significant (*t*-statistic value of 4.12). It is also worth noticing that the return differentials between the top winners are larger in comparison with those at the bottom groups. For instance, stocks in the loser group (P1) and the

[28] See Griffin, Ji and Martin (2003) and Antoniou, Lam and Paudyal (2007) for examples.

second lowest past return stocks (P2) is 0.03% (i.e. 0.61% minus 0.58%). This is much smaller than the return differential between P10 and P9 (0.25% per month). Thus, it is likely that the momentum effect is stronger among the winners. The explanation for this result perhaps ties with Fama and French's (1992) observation that firms tend to continue their performance over a period of less than 6 months.

Additionally, in comparison with buy-and-hold strategies, which buy securities at the beginning and hold until the end of the investment period, all of the momentum strategies tested in this chapter outperform these simple strategies. The result reinforces the view that frequent trading does generate profit for UK investors.

The next section will verify the performance of momentum investing over different investment horizons in order to ensure the robustness of the results. The most commonly reported holding periods are 6 months, 9 months and 12 months. We also look at a 60-month investment as there has been a concern about a reversal momentum effect over a long holding period.

4.5.1. B Momentum premium checks

(i) Different investment horizons

In this section, the chapter checks if the difference in holding periods affects its findings. As can be seen from Table 4.1, there are momentum abnormal returns in the UK for up-to-one-year holding periods. Statistically, the returns are largely significant only in 3- and 6-month investment periods. The average abnormal returns range from 1.01% to 1.24% per month with *t*-statistic values of 3.23 and 4.12, respectively. These results are slightly lower than those documented in previous studies. Some examples are Rouwenhorst (1998) and Antoniou et al. (2007) which found momentum profitability at about 2.10%. The slight difference is perhaps due to the fact that their samples also cover small and illiquid stocks which are shown to yield higher momentum but not likely to be exercised in reality.

From the table, one observation drawn is that the return from momentum strategies is squeezed more quickly as investors extend their holding period. For example, keeping their position for 9 to 12 months is still profitable but the rates of return were much lower than those for 6 months. More specifically, on average the 9-month (12-month) strategies generate returns of 0.67% (0.25%) monthly, decreasing by a half (a quarter), compared with 1.01% previously. Additionally, returns from both strategies are statistically insignificant. This confirms the results documented in the literature that momentum profitability tends to last for one year. To cap it all, holding the winners for a long period of 60 months even leads to a loss of 0.37% per month on average.

(ii) Seasonality

This section examines the possible seasonal effects on the performance of momentum strategies in Januaries as have been noticed by Jegadeesh and Titman (1993). It is worth noticing that in order to identify seasonality, analysing portfolios that have been held for more than a year may not be very meaningful. Thus, this section only looks at momentum profits over 3-, 6-, 9- and 12-month holding periods.

In Panel A of Table 4.2, overall the UK momentum strategies experience a slightly worse performance during Januaries compared with other months. Although the average momentum returns are still positive, they become less significant. The 3-month holding strategies yield a return of 1% per month, statistically significant at a 1% level. Apart from the 3-month investing horizon, other strategies (6-, 9- and 12-month holding periods) generate statistically insignificant returns of 0.83%, 0.39% and 0.11% a month on average. On the other hand, excluding Januaries sees higher returns for momentum investors across all holding periods. However, the difference is relatively small suggesting that the January effects, if any, in the UK do not have a significant impact on momentum strategies. The returns are also statistically significant for 3- and 6-month investment periods. The results are largely similar to those for the whole testing period.

Table 4.1: Momentum strategies

At the end of each month *t*, stocks are classified into 10 equally weighted portfolios, P1 to P10. The portfolio P1 (P10) consists of 10% of the stocks with the lowest (highest) returns over the previous 6 months. The first column reports average returns of simple buy-and-hold strategies on each portfolio. Separately, the portfolios are held for a *K*-month period, including 3-, 6-, 9-, 12- and 60-month holding periods. For example, when K= 6-months, the portfolios are held from month *t+1* to month *t+6* and rebalanced at the end of month *t+6*. The momentum profits are defined as the return differentials between P10 and P1. The time-series means are presented in percentage. *t*-statistics (in parentheses) report the results of the test for a zero mean. *, ** and *** denote significance at a 10%, 5% and 1% level.

	Buy and	**K = 3-month**		**6-month**		**9-month**		**12-month**		**60-month**	
	Hold	Mean	*t*-stat.	Mean	*t*-stat.	Mean	*t*-stat.	Mean	*t*-stat.	Mean	*t*-stat.
P1	0.07	0.58	(1.74)	0.52	(1.60)	0.23	(1.01)	0.15	(1.01)	0.08	(1.11)
P2	0.05	0.61	(1.98)	0.55	(1.62)	0.28	(1.03)	0.16	(1.04)	0.07	(1.09)
P3	0.04	0.66	(2.11)	0.60	(2.01)	0.30	(1.03)	0.14	(1.00)	0.03	(1.02)
P4	0.02	0.65	(2.29)	0.64	(2.15)	0.45	(1.06)	0.18	(1.06)	0.01	(1.01)
P5	0.01	0.69	(2.32)*	0.69	(2.20)	0.62	(1.10)	0.20	(1.07)	-0.01	(-0.98)
P6	0.01	0.76	(2.76)**	0.73	(2.48)**	0.66	(1.12)	0.24	(1.08)	-0.02	(-1.00)
P7	-0.03	0.98	(3.17)***	0.87	(3.15)***	0.74	(1.45)	0.27	(1.18)	-0.07	(-1.01)
P8	-0.05	1.42	(4.32)***	0.94	(3.19)***	0.73	(1.30)	0.33	(1.51)	-0.16	(-1.02)
P9	-0.14	1.57	(4.74)***	1.20	(4.15)***	0.78	(2.08)	0.35	(1.78)	-0.24	(-1.05)
P10	-0.22	1.82	(5.37)***	1.53	(4.31)***	0.90	(2.14)	0.40	(2.02)	-0.29	(-1.08)
Momentum (P10-P1)	**-0.29**	**1.24**	**(4.12)*** **	**1.01**	**(3.23)*** **	**0.67**	**(1.14)**	**0.25**	**(1.09)**	**-0.37**	**(-1.10)**

4.5.2 Momentum and states of the economy

As mentioned earlier in section 4.2.1.A, there are some concerns about the performance of momentum strategies over business cycles documented in Chordia and Shivakumar (2002). Hence, in this section, we look at how momentum strategies performed over different states of the economy. In this chapter, GDP real growth rates are used as a proxy for the state of the UK economy. They include market upturns and downturns (i.e. positive and negative GDP growth rates) and extreme market conditions (economic recessions and expansions). Regarding the extreme states, two consecutive quarters of negative GDP growth rate indicates a recession and a period of rapid growth in GDP of more than the trend rate of economic growth (i.e. 2.5% annually for the UK) is defined as an economic expansion. Accordingly, over the period from January 1990 to December 2012, there were two main periods of economic expansions (1993Q1 - 2000Q4 and 2002Q4 - 2007Q4) and two periods of economic recessions (1991Q1 - 1991Q4 and 2008Q3 - 2009Q4) in the UK. Among those periods, the second recession period from 2008Q3 to 2009Q4 appears to be the most serious. It is associated with the recent financial crisis which started around September 2008 when Lehman Brothers went bankrupt. Although the precise starting date of this financial crisis is subject to discussion, this chapter does not intend to engage in this debate.

From Panel B of Table 4.2, it can be said that momentum profitability is most significant over 3- to 6-month investment periods and in “good” economic conditions. During periods of GDP growth, the return differentials between the winners and the losers are between 1.10% and 1.28% (statistically significant at a 1% level) for these two strategies. Momentum strategies weaken as the investment horizon expands. Nonetheless, they still generate between 0.23% and 0.64% returns over 9- and 12-month investment periods. Expansion periods see even higher momentum abnormal returns. On average, momentum investors receive 1.34% per month if they hold their portfolios for 3 months; 1.23%, 1.02% and 0.72% for 6-, 9- and 12-month holding periods, respectively. The average returns are also statistically significant for all investment horizons, except for the 12-month investment.

On the contrary, momentum strategies do not seem to generate profits during market downturns and perform especially poorly during recessions. During negative GDP growth periods, there is not much difference in returns between the past winners and the past losers. The return differentials range from almost zero to 0.91% and are statistically insignificant. Unsurprisingly, the momentum strategies even lead to losses during recessions.

In short, the results in this chapter confirm that momentum strategies only generate positive and significant abnormal returns during “good” economic conditions but perform particularly poorly during recessions. The next section will explore these links from a dynamic approach that perhaps will offer a better picture of the relationship between momentum profitability and business cycles.

Table 4.2: January effects and states of the economy

The table reports monthly momentum premium in January versus non-January (in Panel A), and over different economic conditions (in Panel B). An economic expansion is defined as a period of more than 2.5% annual growth. Two consecutive quarters of negative GDP growth rate indicates a recession. Portfolios are also held for 3-month, 6-month, 9-month and 12-month periods. See notes in Table 4.1 for details of portfolio formation. M is the sample length (in months). The means are presented in percentage and *t*-statistics are shown in parentheses. *** denotes significance at a 1% level.

		K = 3-month		**6-month**		**9-month**		**12-month**	
	M	Mean	*t*-stat.	Mean	*t*-stat.	Mean	*t*-stat.	Mean	*t*-stat.
Panel A: January effects									
January	23	1.00	(3.21)***	0.83	(2.67)	0.39	(1.01)	0.11	(0.97)
Non-January	253	1.29	(3.93)***	1.08	(3.22)***	0.74	(1.15)	0.32	(1.05)
Panel B: Macroeconomic states									
GDP < 0	30	0.91	(2.75)	0.68	(1.98)	0.38	(1.00)	-0.01	(-0.68)
GDP >0	246	1.28	(4.07)***	1.10	(3.14)***	0.64	(1.12)	0.23	(0.10)
Recessions	28	0.77	(2.05)	-0.09	(-0.75)	-0.21	(-0.99)	-0.41	(-1.24)
Expansions	147	1.34	(4.43)***	1.23	(4.05)***	1.02	(3.38)***	0.72	(1.12)

4.5.3 Firm distress condition and business cycles in explaining momentum

4.5.3. Momentum and default risk

Similar to the Griffin et al. (2003) approach, regression analysis in this section will focus on portfolios held for 6 months only. This is because (i) it is more common to use the 6-month horizon in momentum return estimations, (ii) only up-to-6-month momentum returns are statistically significant in our sample, and (iii) there has not been any evidence of estimation biases caused by differences in portfolio holding periods.

The role of firms' default risk in capturing momentum returns will be addressed by incorporating a default risk factor into the FF three-factor model and Carhart's (1997) four-factor model. The augmented model is given by equations 4.1 and 4.2 as described in section 4.4.2.D. In this section, we focus on estimating the average returns of the top winners (P10) and the bottom losers (P1). The estimation results are shown in Tables 4.3 and 4.4.

The results in Table 4.3 show that default risk plays an important role in improving the FF three-factor model in capturing momentum effect. The coefficients associated with the CHS variable are statistically significant for both the P1 and P10 portfolios. The coefficient values are -0.122 (*t*-statistic is -2.07, significant at 5%) and -0.108 (*t*-statistic is -1.79, significant at 10%) for the losers and the winners, respectively.

In line with Fama and French's (1993) conclusions, we find that market beta and HML are the key explanatory variables in explaining average stock returns. The market beta is higher in the regression on winner excess returns and the value is 0.727, compared to 0.308 for the loser excess returns. Both coefficients are positively and statistically significant at a 1% level. On the contrary, the coefficient associated with HML shows a negative relationship between the BM effect and excess returns on the winners but a positive relationship with the excess returns on the losers. The β_{HML} are -0.124 (*t*-statistic is -2.14, significant at 5%) for the winners and 0.220 (*t*-statistic is 2.71, significant at 1%) for the losers.

Size effect however is not statistically significant in explaining excess returns on the losers, P1, and only significant at 10% level in the case of P10, the winners. It may be because a majority of the winner companies in the FTSE350 are big firms while the pattern is not clearly evident among the loser group.

From Table 4.3, it can be said that default risk plays an important role in capturing momentum effects. The coefficients associated with the CHS variable are statistically significant in regressions on the loser and the winner excess returns. The distress factor is also negatively associated with the average excess returns on both portfolios. β_{CHS} values are -0.122 (statistically significant at 5%) and -0.108 (statistically significant at 10%), respectively.

F-statistics shows that all explanatory variables in the regressions are jointly significant. The estimated *Adjusted* R^2*s* are 61% for the winner group and 59% for the losers. These results mean the estimations are relatively good but can be improved further.

Overall, the results in this table suggest that default risk can contribute to explaining momentum anomaly and that default risk proxies for the risk element that has not been captured by the three FF factors.

Next, we will look at an augmented Carhart (1997) model which differs from the previous model (mode 4.1) by the addition of a momentum effect, WML. A full formula of the augmented Carhart model is given by model 4.2 presented in section 4.4.2.D. Estimation results of model 4.2 are reported in Table 4.4.

The findings in Table 4.4 are consistent with those in previous studies including Carhart's factors (i.e. market beta, HML, SMB and WML) in explaining momentum in the UK, such as Lam (2007), which shows that the four factors play a relatively important role in explaining the anomaly. Betas associated with the market factor (R_m-R_f) are both significant at a 1% level (0.311 and 0.740 for P1 and P10 respectively). The explanatory power of HML is slightly more significant within the loser group. The HML coefficient is 0.201, statistically significant at a 1% level (*t*-statistic of 2.58) in the estimation explaining the movement in return on stocks with poor past performance. It is, however, negative and slightly less significant (-0.086, *t*-statistic of -1.78, 10% significance) for the group of stocks with high past returns. The opposite observation is seen for the SMB and WML factors. The estimated coefficients associated with these two variables are statistically significant at a 10% level in the estimations explaining momentum returns on the past winners (β'_{SMB} and β'_{WML} are -0.102 and 0.106, respectively). They are, however, only -0.011 and -0.023 (statistically insignificant) in the estimations on the past loser returns.

Since one of this chapter's main objectives is to look at the role of default risk, it hereby focuses more on analysing this factor in the estimations. As can be seen from Table 4.4, default risk does contribute to explaining momentum profitability for the losers but less so for the winners. The coefficient associated with the CHS default risk is -0.054 (significant at a 5% level, *t*-statistic of -1.89) for P1, the bottom group, indicating that the return on firms with low profitability in the past is more sensitive to the distress factor. In other words, the CHS default risk could explain more movement of excess return on the past losers. It is, however, not the case in P10, the top past return firms. A β'_{CHS} value of -0.013 (*t*-statistic -1.14) in the estimation on P10 excess returns is statistically insignificant. It indicates that the CHS default risk does not seem to be an important factor in explaining stock returns of the winner portfolio. Perhaps, the past poorly performing firms are more sensitive and therefore more likely to suffer from potential distress than the past top performers.

In addition, *F*-statistics values of the regressions reported in Table 4.4 show that there is evidence of joint significance between explanatory variables. There are also potential areas for model improvement as *Adjusted* R^2 ranges between 64% and 68%, slightly higher than those in the augmented FF model. Next, sub-section 4.5.3.B which considers more possible explanatory variables will touch on possible areas for model improvement. It is, however, worth mentioning again that this chapter does not aim to engage in the discussion of the best fit models and thus only compares the *Adjusted* R^2 to see if there are any significant differences between estimated regressions.

Regarding robustness checks, one concern is whether the choice of CHS as an indicator for default risk would lead to biased results compared with the results that would have been found if using traditional proxies, such as O-score and Z-score. The robustness check on findings in Table 4.4 is reported in Table 4.8 and it will be collectively analysed in detail in section 4.5.4 at the end of this chapter.

In the next section, we continue testing the potential role of default risk in explaining the expected returns on the top winners and on the losers but with business cycle variables also included.

Table 4.3: Momentum and Default risk

The table reports the estimated results of the below regressions on momentum returns (model 4.1)

$$R_i - R_f = \alpha + \beta_m (R_m - R_f) + \beta_{HML} HML + \beta_{SMB} SMB + \beta_{CHS} CHS$$

The winners (P10) and losers (P1) are classified based on their 6-month past returns and held for 6 months before being rebalanced. Portfolio P1 (P10) consists of the 10% of stocks with the lowest (highest) returns over the previous 6 months. See notes in Table 4.1 for construction of the dependent variables, and notes in Table 2.8 of Chapter 2 for explanatory variables. The table shows estimated coefficients and their *t*-statistics. *, **, and *** denote the significance levels at 10%, 5% and 1%. *F*-statistics show results of the test on the joint significance of explanatory variables and *Adjusted* R^2 measures the goodness of fit of the model.

	Constant		$R_m - R_f$		HML	
	α	t(α)	β_m	t(β_m)	β_{HML}	t(β_{HML})
P1	0.001	0.03	0.308***	2.95	0.220***	2.71
P10	0.002	0.05	0.727***	2.93	-0.124**	-2.14
	SMB		CHS		*F*-statistics	*Adj.* R^2
	β_{SMB}	t(β_{SMB})	β_{CHS}	t(β_{CHS})		
P1	-0.099	-0.26	-0.122**	-2.07	2278	0.59
P10	-0.110*	-1.84	-0.108*	-1.79	2154	0.61

Table 4.4: Momentum, WML and Default risk

The table reports the estimated results of the following regressions on momentum returns (model 4.2)

$$R_i - R_f = \alpha' + \beta'_m (R_m - R_f) + \beta'_{HML} HML + \beta'_{SMB} SMB + \beta'_{WML} WML + \beta'_{CHS} CHS$$

The winners (P10) and losers (P1) are classified based on their 6-month past returns and held for 6 months before being rebalanced. Portfolio P1 (P10) consists of the 10% of stocks with the lowest (highest) returns over the previous 6 months. See notes in Table 4.1 for construction of the dependent variables, and notes in Table 2.8 of Chapter 2 for explanatory variables. The table shows estimated coefficients and their *t*-statistics. *, **, and *** denote the significance levels at 10%, 5% and 1%. *F*-statistics show results of the test on the joint significance of explanatory variables and *Adjusted* R^2 measures the goodness of fit of the model.

	Constant		$R_m - R_f$		HML	
	α'	$t(\alpha')$	β'_m	$t(\beta'_m)$	β'_{HML}	$t(\beta'_{HML})$
P1	0.001	0.04	0.311***	2.98	0.201***	2.58
P10	0.003	0.05	0.740***	3.11	-0.086*	-1.78
	SMB		WML		CHS	
	β'_{SMB}	$t(\beta'_{SMB})$	β'_{WML}	$t(\beta'_{WML})$	β'_{CHS}	$t(\beta'_{CHS})$
P1	-0.011	-0.14	-0.023	-1.56	-0.054**	-1.89
P10	-0.102*	-1.59	0.106*	1.82	-0.013	-1.14
	F-statistics	*Adj. R^2*				
P1	2304	0.64				
P10	2210	0.68				

4.5.3. B Momentum, Default risk and Business cycles

As documented earlier, there is evidence that some variables which are attributable to business cycles could explain momentum. Also, some studies show that there is a link between momentum profits and firm financial conditions. These observations motivate this section to put all three elements together in order to test if distress risk together with default risk and business cycles can contribute to explaining momentum returns from a risk-based approach. The augmented FF model with CHS and business cycle variables is given by equation 4.3 in section 4.4.2. The augmented Carhart model with CHS and business cycle variables is given by equation 4.4. The results are reported in Tables 4.5 and 4.6, respectively.

When considering firms' default risk and business cycles in one regression, there are potential biases caused by a correlation between these two groups of explanatory variables. This is when firms go bankrupt due to poor economic conditions without respect to their operating performance. This is known as a multicollinearity problem. Multicollinearity can be identified via the variance inflation factor (VIF) and tolerance values of the estimation in question. The VIF and tolerance values of model 4.3 (and 4.4) can be found in Tables 4.5 (and 4.6), and detailed discussions will follow in section 4.5.4.B.

According to Table 4.5 (reporting results from model 4.3), in the presence of business cycle variables, there are not significant changes in sign and magnitude of the coefficients associated with explanatory variables in the augmented FF model (model 4.1). While the signs are unchanged compared with model 4.1, the coefficients are slightly lower when adding business cycle variables.

The intercepts are between 0.001 and 0.002 (*t*-statistics are 0.02 and 0.03) in regressions on excess returns on the loser and winner portfolios. The market beta (γ_m) and BM effect (γ_{HML}) remain important explanatory variables in capturing momentum abnormal returns. For the loser (winner) portfolio, the coefficient associated with the market factor is 0.254 (0.769) and the *t*-statistic value is 2.52 (3.61). These are slightly lower compared with those in model 4.1 but still statistically significant at a 1% level. Similar results are observed for the HML variable. The estimated value of γ_{HML} is 0.205 (*t*-statistic of 2.84, 1% significance) in regression on the excess returns on the losers. The coefficient is estimated to be -0.110 (*t*-statistic of -2.15, 5% significance) in regression on the winner excess returns. Size effects are, however, statistically insignificant in the loser regression and significant in the winner regression. This pattern has been observed previously in model 4.1 when a default variable was added to the FF three-factor model. These show that size effects are more dominant among the winner stocks but less evident in the loser portfolio.

With the presence of business cycles, the default variable still plays an important role in explaining momentum. However, the coefficient associated with default risk (γ_{CHS}) becomes slightly less significant in statistical terms. In regression on the excess returns on P1 (the losers), the estimated coefficient associated with the CHS variable is -0.115, still negative and statistically significant at a 5% level. However, for P10 (the winners) the estimated coefficient is -0.069, statistically insignificant, compared with -0.108 (statistically significant at a 10% level) that was previously seen in Table 4.3 for model 4.1 – the augmented FF model.

In regard to business cycle variables, default spread (DES) and dividend yield (DIV) could explain more of the risk patterns in average stocks returns than term spread (TERM) and short-term Treasury bill (T-Bill). The coefficients associated with the DES variable are negative and statistically significant at a 10% level in regressions on the loser and winner excess returns. The values are -0.122 (*t*-statistic of -2.13) and -0.110 (*t*-statistic of -2.11), respectively. The estimated DIV coefficient is 0.118 in the regression on the loser excess returns, but has a negative value of -0.103 in the winner regression. In both cases, the coefficients are statistically significant at a 10% level. This reflects the common practice in which the winner companies are less likely to pay high dividends while still being able to keep shareholders' interest. Unlike the winners, the loser companies are expected to pay a high dividend in order to demonstrate that they are worth the shareholders' investment. Therefore, the losers tend to have lower retained earnings to reinvest in their business.

Unlike findings in previous studies[29], TERM and T-Bill do not seem to play as important a role as the other business cycle variables in explaining average stock returns. This is because, unlike the US market, the UK interest rates and Treasury Bill rates are not changed as frequently. Therefore, they are less attractive to investors looking to profit from the rate differentials. In this chapter, the estimated coefficients

[29] See Chordia and Shivakumar (2002) and Petkova (2006).

associated with these variables are statistically insignificant. The value of γ_{TERM} is 0.073 (-0.068) in regression on the loser (winner) excess returns while the $\gamma_{T\text{-}Bill}$ value is 0.034 (0.051) in regression on the loser (winner) excess returns. In both cases, the coefficients are statistically insignificant.

In terms of *F*-statistics, regression on the loser and the winner excess returns provides *F*-statistics values of 2412 and 2256, respectively. These indicate a high level of joint significance between explanatory variables in the regressions. *Adjusted* R^2*s* are also higher in the presence of business cycle variables. They increase from 59% (losers) and 61% (winners) in model 4.1 to 65% (losers) and 68% (winners) in model 4.3. Although, it is not this chapter's objectives to assess the goodness of fit of the regressions, it is worth recognising the role of business cycles variables in improving these estimation models.

In order to establish a comparison between models with and without WML variables, the rest of this section also reports the estimation results of a model that consists of Carhart's (1997) four factors (including the FF three-factor model and WML), default risk and business cycle variables (i.e. model 4.4).

Table 4.5: Momentum, Default risk and Business cycles

The table reports the estimated results of the following regressions on momentum returns (model 4.3):

$$R_i - R_f = \sigma + \gamma_m (R_m - R_f) + \gamma_{HML} HML + \gamma_{SMB} SMB + \gamma_{CHS} CHS + \gamma_{DES} DES + \gamma_{TERM} TERM + \gamma_{DIV} DIV + \gamma_{T\text{-}Bill} T\text{-}Bill$$

See notes in Table 4.1 for P1 and P10 portfolio formation. Explanatory variables are defined in the notes in Table 2.8 of Chapter 2. *F*-statistics show the results of the test on the joint significance of explanatory variables and *Adjusted* R^2 measures the goodness of fit of the model. The variance inflation factor (VIF) and tolerance values of multicollinearity tests are also reported.

	Constant		$R_m - R_f$		HML	
	σ	t(σ)	γ_m	t(γ_m)	γ_{HML}	t(γ_{HML})
P1	0.001	0.02	0.254***	2.52	0.205***	2.84
P10	0.002	0.03	0.769***	3.61	-0.110**	-2.15
	SMB		CHS		DES	
	γ_{SMB}	t(γ_{SMB})	γ_{CHS}	t(γ_{CHS})	γ_{DES}	t(γ_{DES})
P1	-0.058	-0.34	-0.115**	-2.23	-0.122*	-2.13
P10	-0.097*	-2.11	-0.069	-1.34	-0.110*	-2.11
	TERM		DIV		T-Bill	
	γ_{TERM}	t(γ_{TERM})	γ_{DIV}	t(γ_{DIV})	$\gamma_{T\text{-}Bill}$	t($\gamma_{T\text{-}Bill}$)
P1	0.073	1.72	0.118*	2.03	0.034	1.29
P10	-0.068	-1.62	-0.103*	-1.97	0.051	1.47
			F-statistics	*Adj.* R^2	VIF	Tolerance
P1			2412	0.65	1.22	0.82
P10			2256	0.68	1.21	0.83

In Table 4.6, which reports regressions on Carhart's four factors, CHS and business cycle variables, we note that the magnitude and significance of explanatory variables decrease in the presence of WML. This is particularly noticeable in the case of the dividend yield (DIV) variable which is no longer statistically significant.

As can be seen from the table, the (R_m-R_f) and HML variables remain important in capturing returns on the UK top winners and top losers. Estimated coefficients associated with the two variables are relatively high at 0.232 and 0.193, respectively, for the past poorly performing stocks (both statistically significant at a 1% level). The coefficient γ'_m is 0.771 (1% significance) and γ'_{HML} is -0.097 (10% significance) for the past top performers. Similar to findings in the previous section for model 4.2, two variables, SMB and WML, show the ability to explain more of the movement in returns on the past top performing portfolio (P10) than on the last poorly performing group (P1). However, the magnitude of the SMB variable in regression 4.4 on the P10 returns is slightly higher than that of model 4.2 before including business cycles (γ_{SMB} equals -0.109, significant at 10% in model 4.4, compared to -0.102, significant at 10% in model 4.2).

The distress variable, CHS, still plays an important role in explaining returns on the loser P1 but is less important in capturing returns on the winners P10. The estimated coefficient stands at -0.124 (5% significance) for the former and at only -0.027 (insignificant) for the latter. Compared with regression 4.3 which does not include the WML variable, the coefficients associated with the default risk CHS are slightly higher (lower) in absolute terms for the losers (winners). These confirm the earlier findings in the previous section that the past poorly performing firms seem to be more sensitive to potential distress than the past top performers.

Regarding business cycle variables, there is only the market default indicator (DES), which is measured as the difference between the average yields on corporate bonds and on long-term Government bonds, showing some degree of explanatory ability in explaining the movement in returns on both the losers and the winners. The estimated coefficients, γ'_{DES}, are -0.105 and -0.108, respectively, and they are both statistically significant at a 10% level. The negative values signal that returns on both portfolios are likely to decrease as corporate bonds across the market become riskier with poorer bond ratings. The dividend yield variable (DIV), which is the average value-weighted dividend yield of all stocks in the FTSE350, could capture the movement in returns on the past poor performers but becomes less important when explaining returns on the past winners. The estimated coefficients associated with the dividend yield, γ'_{DIV}, are 0.102 (significant at a 10% level) and -0.057 (statistically insignificant). Note that in regression on the winner excess returns, the coefficient associated with the DIV variable is no longer significant in the presence of the WML variable. However, there is no evidence that other variables such as term spread (TERM) and short-term Treasury bill (T-Bill) play a significant role in explaining the returns on the winners and the losers.

F-statistics indicate a high level of joint significance between explanatory variables in regressions on returns in the winner and loser groups. *Adjusted R^2s* range from 67% to 69%, which are slightly higher than they were before adding business cycle variables. The difference, however, provide little insight into the role of these variables in explaining returns on the two portfolios.

Table 4.6: Momentum, WML, Default risk and Business cycles

The table reports the estimated results of the following regressions on momentum returns (model 4.4):

$$R_i - R_f = \sigma' + \gamma'_m (R_m - R_f) + \gamma'_{HML} HML + \gamma'_{SMB} SMB + \gamma'_{WML} WML + \gamma'_{CHS} CHS + \gamma'_{DES} DES + \gamma'_{TERM} TERM + \gamma'_{DIV} DIV + \gamma'_{T\text{-}Bill}\, T\text{-}Bill$$

See notes in Table 4.1 for P1 and P10 portfolio formation. The explanatory variables are defined in the notes in Table 2.8 of Chapter 2. *F*-statistics show the results of the test on the joint significance of explanatory variables and *Adjusted* R^2 measures the goodness of fit of the model. The variance inflation factor (VIF) and tolerance values of multicollinearity tests are also reported.

	Constant		$R_m - R_f$		HML	
	σ'	t(σ')	γ'_m	t(γ'_m)	γ'_{HML}	t(γ'_{HML})
P1	0.001	0.03	0.232***	2.71	0.193***	2.86
P10	0.004	0.05	0.771***	3.53	-0.097*	-1.92
	SMB		WML		CHS	
	γ'_{SMB}	t(γ'_{SMB})	γ'_{WML}	t(γ'_{WML})	γ'_{CHS}	t(γ'_{CHS})
P1	-0.010	-0.13	-0.021	-1.43	-0.124**	-2.15
P10	-0.109*	-1.97	0.103*	1.96	-0.027	-1.23
	DES		TERM		DIV	
	γ'_{DES}	t(γ'_{DES})	γ'_{TERM}	t(γ'_{TERM})	γ'_{DIV}	t(γ'_{DIV})
P1	-0.105*	-1.91	0.051	1.63	0.102*	1.89
P10	-0.108*	-1.98	-0.046	-1.47	-0.057	-1.62
	T-Bill		*F*-statistics	*Adj.* R^2	VIF	Tolerance
P1	0.020	1.33	2457	0.67	1.27	0.79
P10	0.045	1.44	2315	0.69	1.16	0.86

4.5.4 Robustness and diagnostic tests

4.5.4. A Robustness checks

The main objective of this section is to check the robustness of the results in section 4.5.3 using different proxies for default risk. Other commonly used proxies for firms' default probability, Z-score and O-score, will be used to ensure results are not sensitive to the choice of default risk proxy. In these tests, portfolios are constructed based on 6-month past returns and 6-month holding periods, similarly to the way they were formed in the CHS approach for comparison purposes. The estimation results from model 4.1 to model 4.4 are summarised in four tables, sequentially numbered Table 4.3 to Table 4.6; and the robustness checks on these models are reported in Tables 4.7 to 4.10. These test outcomes will be discussed in turn below.

Robustness check on model 4.1:

$$\boldsymbol{R_{i,t}} - \boldsymbol{R_{f,t}} = \alpha + \beta_m (R_{m,t} - R_{f,t}) + \beta_{HML} HML_t + \beta_{SMB} SMB_t + \beta_{CHS} CHS_t$$

Firstly, to ensure that the results reported in Table 4.3 (model 4.1: augmented FF model including a CHS variable) are not driven by the choice of default risk proxies, we use O-score and Z-score as alternative proxies for firms' distress situations. The results of using O-score are summarised in Panel A and these of using Z-score are shown in Panel B of Table 4.7.

In Panel A of Table 4.7, the estimated coefficients of regressions given by model 4.1 using O-score are slightly lower in absolute terms than those using CHS. However, the levels of significance are not affected by the choice of default proxies. The market beta from a regression on the loser excess returns is 0.235 (significant at a 1% level) and the estimated beta for the winner portfolio is much higher, at 0.416 (significant at a 1% level). This indicates that the market factor could explain more of the movement of the winner returns that it does for the losers.

The opposite is true in the case of HML. Whilst the BM effect is important in explaining momentum, it tends to capture more of the movement in the loser stock returns than that of the winners. In regression on the loser excess returns, the coefficient associated with the HML variable is positive and statistically significant (β''_{HML} is 0.214, *t*-statistic is 2.62). However, the β''_{HML} takes a negative value of -0.145 (*t*-statistic is -2.10) in regression on the winner excess returns. This is because in the FTSE350 index, there are more value firms (i.e. High BM) that fall into the loser category than into the winner category. As a result, the loser average returns are more likely to be positively correlated with the High-minus-Low effect.

Similar to the findings reported in Table 4.3, the results in Table 4.7 show that the size effect is more noticeable in the winner average returns. The estimated coefficient associated with the SMB variable is -0.121 (statistically significant at a 10% level) in the regression on the winner excess returns while it is only -0.076 (statistically insignificant) in the case of the losers.

In this robustness check, the results also confirm that when O-score is used as a proxy for default probability, default risk remains an important variable in explaining momentum anomaly. The coefficient associated with the O-score variable, $\beta_{O\text{-}score}$, is -0.124 (-0.105) in regression on the loser (winner) excess returns. In both regressions, the coefficients are negatively and statistically significant. When firms suffer a higher default risk, they have lower expected returns.

Panel B of Table 4.7 shows that using Z-score rather than CHS as a proxy for default risk does not affect the findings documented earlier. Intercepts from all estimations are positive and statistically insignificant. In terms of explanatory variables, the results confirm that besides (R_m-R_f), HML is an important factor that could explain the returns on both the losers and the winners. The coefficients associated with these explanatory variables are largely significant for both the loser and the winner portfolios. Similar to what has been reported previously, the size effect is only evident in the winner excess returns and less in the loser excess returns. The coefficient associated with the size effect is -0.122 (statistically significant at a 10% level) in regression on the winner excess returns. It is, however, only -0.091 (statistically insignificant) in the case of the losers.

When Z-score is employed as a proxy for default risk, the coefficients associated with the variable are slightly more significant than using other proxies. In regression on the loser excess returns, $\beta_{Z\text{-}score}$ is -0.156 (*t*-statistic is -2.09, significant at a 5% level) while it is -0.174 (*t*-statistic increases to -2.13, significant at 5% instead of 10%) in the regression on the winner excess returns.

In summary, estimations reported for model 4.1 are robust and not driven by the choice of default risk proxies.

Table 4.7: Robustness check on model 4.1

Panel A: Estimated results of model 4.1 using O-score as a proxy for default risk, given by the following formula:

$$R_i - R_f = \alpha'' + \beta''_m (R_m - R_f) + \beta''_{HML} HML + \beta''_{SMB} SMB + \beta_{O\text{-}score} O\text{-}score$$

See notes in Table 4.1 for P1 and P10 portfolio formation. The explanatory variables are defined in the notes in Table 2.8 of Chapter 2. The table shows the estimated coefficients and their *t*-statistics. *, **, and *** denote the significance levels at 10%, 5% and 1%. *F*-statistics show the results of the test on the joint significance of explanatory variables and *Adjusted* R^2 measures the goodness of fit of the model.

	Constant		$R_m - R_f$		HML	
	α''	$t(\alpha'')$	β''_m	$t(\beta''_m)$	β''_{HML}	$t(\beta''_{HML})$
P1	0.002	0.04	0.235***	2.86	0.214***	2.62
P10	0.002	0.03	0.416***	3.04	-0.145**	-2.10
	SMB		O-score			
	β''_{SMB}	$t(\beta''_{SMB})$	$\beta_{O\text{-}score}$	$t(\beta_{O\text{-}score})$		
P1	-0.076	-0.42	-0.124**	-2.02		
P10	-0.121*	-1.88	-0.105*	-1.79		
	F-statistics	*Adj.* R^2				
P1	2257	0.58				
P10	2048	0.59				

Table 4.7 - Continued

Panel B: Estimated results of model 4.1 using Z-score as a proxy for default risk, given by the following formula:

$$R_i - R_f = \alpha'' + \beta''_m (R_m - R_f) + \beta''_{HML} HML + \beta''_{SMB} SMB + \beta_{Z\text{-}score} Z\text{-}score$$

See notes in Table 4.1 for P1 and P10 portfolio formation. The explanatory variables are defined in the notes in Table 2.8 of Chapter 2. The table shows the estimated coefficients and their *t*-statistics. *, **, and *** denote the significance levels at 10%, 5% and 1%. *F*-statistics show results of the test on the joint significance of explanatory variables and *Adjusted* R^2 measures the goodness of fit of the model.

	Constant		$R_m - R_f$		HML	
	α"	t(α")	β''_m	$t(\beta''_m)$	β''_{HML}	$t(\beta''_{HML})$
P1	0.003	0.04	0.420***	3.01	0.215***	2.92
P10	0.002	0.03	0.615***	3.12	-0.201***	-2.86
	SMB		Z-score			
	β''_{SMB}	$t(\beta''_{SMB})$	$\beta_{Z\text{-}score}$	$t(\beta_{Z\text{-}score})$		
P1	-0.091	-0.56	-0.156**	-2.09		
P10	-0.122*	-1.87	-0.174**	-2.33		
	F-statistics	*Adj.* R^2				
P1	2784	0.60				
P10	3061	0.63				

Robustness check on model 4.2:

$$\boldsymbol{R_{i,t}} - \boldsymbol{R_{f,t}} = \alpha' + \beta'_m (R_{m,t} - R_{f,t}) + \beta'_{HML} HML_t + \beta'_{SMB} SMB_t + \beta'_{WML} WML_t + \beta'_{CHS} CHS_t$$

The second robustness test is carried out on results in Table 4.4 (model 4.2: an extension of the Carhart model including a CHS variable) and the results are reported in Panels A and B of Table 4.8. From the two panels, it can be said that the findings are largely similar to those found when using CHS as a proxy. The market beta, BM and default risk factors still remain significant explanatory variables in explaining the movement in returns on both the winners and the losers in the UK. Whereas, the size and momentum variables seem to be able to capture more movement of the winners' returns but become less important in explaining the losers' returns. In addition, the absolute values of the estimated coefficients are slightly higher using these two proxies. This is perhaps due to the different approach in calculating these proxies, which is mainly by adding up accounting ratios, while the CHS variable is generated from estimating the Campbell et al. (2008) dynamic model.

The results in Panel A of Table 4.8 also show that when using O-score as a proxy for default risk, the estimations tend to result in a slightly higher *t*-statistic for some variables, namely SMB and O-score. For example, the coefficient associated with SMB is statistically significant at a 5% level in estimating P10 returns (comparing with a 10% level in Table 4.4). Coefficients associated with momentum variables remain statistically significant (insignificant) for the past top (poor) performance stocks. Other independent variables, (R_m-R_f) and HML, also present a strong explanatory power in explaining stock returns. The market betas are 0.526 and 0.742, both significant at a 1% level, in the estimations on P1 and P10 returns, respectively. The coefficients are 0.231 (1% significance) and 0.092 (10% significance) for the HML variable.

In Panel B, the results indicate that there is no evidence of significant differences caused by using Z-score instead of CHS as a proxy for distress situations. (R_m-R_f) and HML remain statistically significant in estimations on both portfolios while the SMB and WML coefficients are only slightly significant (at a 10% level) in the winner portfolio. The distress variable, in contrast, explains more the movement in returns on the loser portfolio. In other words, the past poorly performing stocks appear to be more sensitive to the distress factor that the past top performing stocks.

Table 4.8: Robustness check on model 4.2

Panel A: Estimated results of model 4.2 using O-score as a proxy for default risk, given by the following formula:

$$R_i - R_f = \alpha'' + \beta''_m (R_m - R_f) + \beta''_{HML} HML + \beta''_{SMB} SMB + \beta''_{WML} WML + \beta''_{O\text{-}score} O\text{-}score$$

See notes in Table 4.1 for P1 and P10 portfolio formation. The explanatory variables are defined in the notes in Table 2.8 of Chapter 2. The table shows the estimated coefficients and their *t*-statistics. *, **, and *** denote the significance levels at 10%, 5% and 1%. *F*-statistics show the results of the test on the joint significance of explanatory variables and *Adjusted* R^2 measures the goodness of fit of the model.

	Constant		$R_m - R_f$		HML	
	α''	$t(\alpha'')$	β''_m	$t(\beta''_m)$	β''_{HML}	$t(\beta''_{HML})$
P1	0.004	0.23	0.526***	3.01	0.231***	2.15
P10	0.015	0.54	0.742***	3.23	0.092*	1.97
	SMB		WML		O-score	
	β''_{SMB}	$t(\beta''_{SMB})$	β''_{WML}	$t(\beta''_{WML})$	$\beta''_{O\text{-}score}$	$t(\beta''_{O\text{-}score})$
P1	-0.015	-0.63	-0.101	-1.72	-0.207***	-2.13
P10	-0.198**	-2.07	0.124*	1.98	-0.101*	-1.82
	F-statistics	*Adj.* R^2				
P1	2410	0.65				
P10	2305	0.66				

Table 4.8 - Continued

Panel B: Estimated results of model 4.2 using Z-score as a proxy for default risk, given by the following formula:

$$R_i - R_f = \alpha'' + \beta''_m (R_m - R_f) + \beta''_{HML} HML + \beta''_{SMB} SMB + \beta''_{WML} WML + \beta''_{Z\text{-}score} Z\text{-}score$$

See notes in Table 4.1 for the P1 and P10 portfolio formation. The explanatory variables are defined in the notes in Table 2.8 of Chapter 2. The table shows the estimated coefficients and their *t*-statistics. *, **, and *** denote the significance levels at 10%, 5% and 1%. *F*-statistics show the results of the test on the joint significance of explanatory variables and *Adjusted* R^2 measures the goodness of fit of the model.

	Constant		$R_m - R_f$		HML	
	α"	t(α")	β''_m	$t(\beta''_m)$	β''_{HML}	$t(\beta''_{HML})$
P1	0.001	0.17	0.372***	2.96	0.216***	2.52
P10	0.010	0.23	0.629***	3.22	-0.172*	-2.11
	SMB		**WML**		**Z-score**	
	β''_{SMB}	$t(\beta''_{SMB})$	β''_{WML}	$t(\beta''_{WML})$	$\beta''_{Z\text{-}score}$	$t(\beta''_{Z\text{-}score})$
P1	-0.027	-0.54	-0.075	-0.79	-0.176**	-2.12
P10	-0.162*	-1.92	0.131*	1.91	-0.083	-0.87
	F-statistics	*Adj.* R^2				
P1	2311	0.63				
P10	2212	0.67				

Robustness check on model 4.3:

$$\boldsymbol{R_{i,t}} - \boldsymbol{R_{f,t}} = \sigma + \gamma_m (R_{m,t} - R_{f,t}) + \gamma_{HML} HML_t + \gamma_{SMB} SMB_t + \gamma_{CHS} CHS_t + \gamma_{DES} DES_t + \gamma_{TERM} TERM_t + \gamma_{DIV} DIV_t + \gamma_{T-Bill} T - Bill_t$$

The third robustness check is on model 4.3 of which the estimations are shown earlier in Table 4.5 of section 4.5.3 B, and the results of the check are reported in Table 4.9.

As can be seen from Panel A of Table 4.9, using O-score rather than CHS as a proxy for default risk does not affect the results. In this robustness test, an O-score variable is added to the augmented Carhart (1998) four-factor model. Although the intercepts of the regression are higher, the differentials are insignificant in both absolute terms and statistical terms. The regression constants from estimations on the loser and winner excess returns are 0.003 and 0.002 with *t*-statistic values of 0.05 and 0.02, respectively. These values were only 0.001 and 0.002 (*t*-statistic values of 0.04 and 0.03) in the previous estimations and none was statistically significant.

In terms of independent variables, their explanatory power is largely unchanged in the robustness check. The market factor, (R_m - R_f), is still the key variable in capturing the movement of stock excess returns. The market beta is 0.310 (0.797) and the *t*-statistic is 2.67 (3.56), which is statistically significant at 1% in the regression on the loser (winner) excess returns.

Similarly, the results in Panel A confirm that BM and size effects are important explanatory variables in explaining the momentum anomaly. The coefficients associated with HML are 0.214 (*t*-statistic value is 2.54) and -0.175 (*t*-statistic is -2.10) in regressions on the loser and winner excess returns, respectively. Both coefficients are statistically significant. The difference in sign between these coefficients could be because there are more high BM companies in the loser portfolio than there are in the winner portfolio.

In contrast, the size effect only plays an important role in explaining the winner returns but not in the loser returns. In particular, the coefficient associated with the SML variable is -0.114 with a *t*-statistic value of -2.02 (statistically significant at a 10% level) in the regression on the winner excess returns, but it is only -0.031 (*t*-statistic is -1.23, statistically insignificant) in the case of the losers.

In addition, the robustness check results once again confirm that the choice of proxies for default risk does not significantly affect the role of the default factor in capturing the return differentials between the winner and the loser portfolios. For the loser stocks, capturing default patterns in their average returns is particularly vital. The O-score coefficient takes the value of -0.147 (*t*-statistic of -2.09) in a regression on the loser excess returns. Nevertheless, the role of the default variable in explaining the winner returns is less significant. Similar to the findings summarised in Table 4.5, in this estimation the coefficient associated with default probability is statistically insignificant. It has a value of -0.056 with a *t*-statistic value of -1.62, just slightly higher than those reported for the estimations using the CHS proxy.

When O-score is used instead of CHS as a default risk proxy, the estimated coefficients associated with business cycle variables show that default spread and dividend yield remain important in explaining excess returns both on the losers and on the winners. Compared with the results reported for regressions using CHS, the coefficients associated with DES and DIV are marginally lower but remain statistically significant at a 10% level. On the other hand, the term spread and T-Bill variables are insignificant in regressions explaining the excess returns on the loser and the winner portfolios. The coefficients γ''_{TERM} and $\gamma''_{T\text{-}Bill}$ take the values of 0.032 and 0.042 in the loser regressions, and values of -0.041 and 0.055 in the winner regressions. Also, the VIF and tolerance indicators confirm that there are no multicollinearity issues in these estimations.

Next, Panel B of Table 4.9 summarises the robustness check results on model 4.3, employing Altman’s (1968) Z-score, another widely-used bankruptcy indicator, as a proxy for default probability. It can be said that the findings are not materially changed following this modification. The regression intercepts and coefficients remain at a similar level to those observed in regressions using CHS and O-score.

The estimated constant terms are insignificant, being at 0.002 in regressions on the loser excess returns and slightly higher at 0.004 in the case of the winner excess returns. In terms of explanatory variables, there are no significant changes in sign and magnitude, compared with those previously recorded. The market beta is 0.215 (*t*-statistic is 2.74) for the losers, P1, and is 0.578 (*t*-statistic is 3.34) for the winners, P10. Both coefficients are statistically significant at a 1% level. The coefficients associated with the HML variable are also relatively high in absolute terms, at 0.187 and -0.123 for P1 and P10, respectively. The size effect is more significant in regressions on the winner excess returns than it is in the loser regressions. The estimated γ''_{SMB} is -0.102 with a *t*-statistic value of -2.13 for the former and being only -0.032 (*t*-statistic is -0.21) for the latter.

Default risk, which is proxied by Z-score, remains statistically significant in explaining the loser excess returns but insignificant in capturing the movement of the winner excess returns. Similar to what has been documented in Table 4.5, the robustness check finds that among business cycle variables, default spread and dividend yield contribute to explaining momentum but there is no evidence that term spread and T-Bill variables have the same explanatory power. The regression on VIF and tolerance show that there is no multicollinearity problem in this robustness test.

Overall, the results in Table 4.9 indicate that there is no empirical evidence that the findings reported in Table 4.5 for model 4.3 are biased and driven by the choice of default risk proxies.

Table 4.9: Robustness check on model 4.3

Panel A: Estimated results of model 4.3 using O-score as a proxy for default risk, given by the following formula:

$$R_i - R_f = \sigma'' + \gamma''_m (R_m - R_f) + \gamma''_{HML} HML + \gamma''_{SMB} SMB + \gamma''_{O\text{-}score} O\text{-}score + \gamma''_{DES} DES + \gamma''_{TERM} TERM + \gamma''_{DIV} DIV + \gamma''_{T\text{-}Bill} T\text{-}Bill$$

See notes in Table 4.1 for P1 and P10 portfolio formation. The explanatory variables are defined in notes in Table 2.8 of Chapter 2. *F*-statistics show the results of the test on the joint significance of explanatory variables and *Adjusted* R^2 measures the goodness of fit of the model. The variance inflation factor (VIF) and tolerance values are also reported from multicollinearity tests.

	Constant		$R_m - R_f$		HML	
	σ''	$t(\sigma'')$	γ''_m	$t(\gamma''_m)$	γ''_{HML}	$t(\gamma''_{HML})$
P1	0.003	0.05	0.310***	2.67	0.214***	2.54
P10	0.002	0.02	0.797***	3.56	-0.175**	-2.10
	SMB		O-score		DES	
	γ''_{SMB}	$t(\gamma''_{SMB})$	$\gamma''_{O\text{-}score}$	$t(\gamma''_{O\text{-}score})$	γ''_{DES}	$t(\gamma''_{DES})$
P1	-0.031	-1.23	-0.147**	-2.09	-0.111*	-2.01
P10	-0.114*	-2.02	-0.056	-1.62	-0.105*	-1.97
	TERM		DIV		T-Bill	
	γ''_{TERM}	$t(\gamma''_{TERM})$	γ''_{DIV}	$t(\gamma''_{DIV})$	$\gamma''_{T\text{-}Bill}$	$t(\gamma''_{T\text{-}Bill})$
P1	0.032	1.33	0.106*	1.99	0.042	1.36
P10	-0.041	-1.34	-0.110*	-2.00	0.055	1.46
			F-statistics	*Adj.* R^2	VIF	Tolerance
P1			2742	0.62	1.51	0.66
P10			2301	0.65	1.32	0.76

Table 4.9- Continued

Panel B: Estimated results of model 4.3 using Z-score as a proxy for default risk, given by the following formula:

$$R_i - R_f = \sigma'' + \gamma''_m (R_m - R_f) + \gamma''_{HML} HML + \gamma''_{SMB} SMB + \gamma''_{Z\text{-}score} Z\text{-}score + \gamma''_{DES} DES + \gamma''_{TERM} TERM + \gamma''_{DIV} DIV + \gamma''_{T\text{-}Bill} T\text{-}Bill$$

See notes in Table 4.1 for P1 and P10 portfolio formation. The explanatory variables are defined in notes in Table 2.8 of Chapter 2. *F*-statistics show the results of the test on the joint significance of explanatory variables and *Adjusted* R^2 measures the goodness of fit of the model. The variance inflation factor (VIF) and tolerance values are also reported from multicollinearity tests.

	Constant		$R_m - R_f$		HML	
	σ''	t(σ'')	γ''_m	t(γ''_m)	γ''_{HML}	t(γ''_{HML})
P1	0.002	0.01	0.215***	2.74	0.187***	2.53
P10	0.004	0.02	0.578***	3.34	-0.123**	-2.32
	SMB		Z-score		DES	
	γ''_{SMB}	t(γ''_{SMB})	$\gamma''_{Z\text{-}score}$	t($\gamma''_{Z\text{-}score}$)	γ''_{DES}	t(γ''_{DES})
P1	-0.032	-0.21	-0.153**	-2.34	-0.172**	-2.36
P10	-0.102*	-2.13	-0.056	-1.15	-0.106*	-2.17
	TERM		DIV		T-Bill	
	γ''_{TERM}	t(γ''_{TERM})	γ''_{DIV}	t(γ''_{DIV})	$\gamma''_{T\text{-}Bill}$	t($\gamma''_{T\text{-}Bill}$)
P1	0.052	1.12	0.113*	2.21	0.028	0.72
P10	-0.066	-1.37	-0.098*	-1.98	0.062	1.25
			F-statistics	*Adj.* R^2	VIF	Tolerance
P1			2542	0.66	1.15	0.87
P10			2782	0.67	1.36	0.74

Robustness check on model 4.4:

$$\boldsymbol{R_{i,t}} - \boldsymbol{R_{f,t}} = \sigma' + \gamma'_m (R_{m,t} - R_{f,t}) + \gamma'_{HML} HML_t + \gamma'_{SMB} SMB_t$$
$$+ \gamma'_{WML} WML_t + \gamma'_{CHS} CHS_t + \gamma'_{DES} DES_t + \gamma'_{TERM} TERM_t$$
$$+ \gamma'_{DIV} DIV_t + \gamma'_{T-Bill} T - Bill_t$$

Finally, we perform a similar check on the results reported in Table 4.6 for estimations using model 4.4. The robustness check results are summarised in Table 4.10, in which Panel A reports the estimation using O-score while Panel B is the results of the estimation using Z-score as a proxy for distress conditions.

As can be seen from Panel A, the findings are largely similar to those in Table 4.6. Using O-score instead of CHS as a proxy for default risk does not change the dominant roles of the market and BM factors in explaining stock returns in the UK. The market betas stand at 0.321 for the loser stocks (P1) and at 0.561 for the winner stocks (P10), both significant at a 1% level. The coefficients associated with the HML variable are also high, at 0.128 (*t*-statistic is 2.82) and -0.101 (*t*-statistic is 2.41) when estimating returns on the losers and on the winners, respectively.

Additionally, the momentum variable (WML) still plays a role in explaining returns on the winner group but is less important in capturing the loser returns. The β_{WML} for P10 is 0.096 (*t*-statistic value of 1.94, significant at a 10% level) and -0.032 for P1 (*t*-statistic is -0.45, statistically insignificant). The opposite is true for the dividend yield variable, DIV, which could explain more movement in returns on the P1 portfolio (β_{DIV} is 0.105, significant at a 5% level) but does not show a significant explanatory power on P10 returns.

In terms of the term spread and T-Bill variables, the results in Panel A confirm that they are not able to explain much the returns on both the winner and loser portfolios. Their estimated coefficients range from -0.041 to 0.063, which are statistically insignificant with *t*-statistic values being from -1.04 to 1.07, respectively.

However, in this regression the size factor does not seem to capture movement in returns on either of the portfolios. The estimated coefficients range from -0.026 to -0.073, and both are statistically insignificant. In contrast, compared with the estimation results in Table 4.6, default risk (O-score) and default spread (DES) show a higher explanatory ability in explaining returns on the winner stocks. Their associated coefficients are -0.085 (*t*-statistic is -1.92) and -0.112 (*t*-statistic is -2.14), respectively.

Panel B of Table 4.10 shows the estimation results on model 4.4, using Z-score as a proxy for default risk. They confirm most of the findings reported earlier in Table 4.6. The market, HML and DES variables remain strong factors in explaining the movement in returns on both the top performing and poorly performing groups. The HML coefficient is even more significant for the winners P10 (-0.116, significant at a 5% level compared to -0.097, significant at a 10% level).

The explanatory power of the SMB and WML factors is more significant for the winners but becomes insignificant for the loser stocks. The coefficients are -0.214 and 0.072 for the winners but only -0.031 and -0.041 for the losers. The SMB variable, -0.214, is also slightly more significant (*t*-statistic at -2.55, significant at a 5% level) compared with a SMB coefficient of -0.110 (*t*-statistic at -2.07, significant at a 10% level) in Table 4.6, when CHS is used as a proxy for default risk. In contrast, dividend yield (DIV) could explain more movement in returns on the loser stocks but less on the winners. The coefficient, β_{DIV}, estimated from the regression on the losers' returns, is slightly significant (-0.124, significant at 10%) while it stays at -0.051 (insignificant) for the winner group.

Similar to the findings in Table 4.6, the default variable remains important in capturing movement in returns on the past poorly performing stocks (P1) while it loses this explanatory ability in the regression on returns on the top performing stocks (P10). For the P1 group, the coefficient associated with the default variable is -0.147 (*t*-statistic is -2.20, significant at a 5% level) but being only -0.036 (*t*-statistic is -0.77, statistically insignificant) in the case of P10.

For the last two explanatory variables in the regression, TERM and T-Bill, again there is no evidence that they are able to capture the movement in returns on either the losers or the winners in the FTSE350. This result confirms a conclusion documented in section 4.5.3 B.

Table 4.10: Robustness check on model 4.4

Panel A: Estimated results of model 4.4 using O-score as a proxy for default risk, given by the following formula:

$$R_i - R_f = \sigma'' + \gamma''_m (R_m - R_f) + \gamma''_{HML} HML + \gamma''_{SMB} SMB + \gamma''_{WML} WML + \gamma''_{O\text{-}score} O\text{-}score + \gamma''_{DES} DES + \gamma''_{TERM} TERM + \gamma''_{DIV} DIV + \gamma''_{T\text{-}Bill} T\text{-}Bill$$

See notes in Table 4.1 for P1 and P10 portfolio formation. The explanatory variables are defined in the notes in Table 2.8 of Chapter 2. *F*-statistics show the results of the test on the joint significance of the explanatory variables and *Adjusted* R^2 measures the goodness of fit of the model. The variance inflation factor (VIF) and tolerance values are also reported from multicollinearity tests.

	Constant		R_m - R_f		HML	
	σ''	t(σ'')	γ''_m	t(γ''_m)	γ''_{HML}	t(γ''_{HML})
P1	0.001	0.06	0.321***	3.10	0.128***	2.82
P10	0.003	0.07	0.561***	3.36	-0.101**	2.41
	SMB		WML		O-score	
	γ''_{SMB}	t(γ''_{SMB})	γ''_{WML}	t(γ''_{WML})	$\gamma''_{O\text{-}score}$	t($\gamma''_{O\text{-}score}$)
P1	-0.026	-0.31	-0.032	-0.45	-0.207***	-3.07
P10	-0.073	-1.18	0.096*	1.94	-0.085*	-1.92
	DES		TERM		DIV	
	γ''_{DES}	t(γ''_{DES})	γ''_{TERM}	t(γ''_{TERM})	γ''_{DIV}	t(γ''_{DIV})
P1	-0.081*	-1.90	0.036	0.52	0.105**	2.14
P10	-0.112**	-2.14	-0.041	-1.04	-0.071	-1.65
	T-Bill		*F*-statistics	*Adj.* R^2	VIF	Tolerance
P1	0.014	0.26	2535	0.66	1.32	0.76
P10	0.063	1.07	2412	0.69	1.17	0.85

Table 4.10- Continued

Panel B: Estimated results of model 4.4 using Z-score as a proxy for default risk, given by the following formula:

$$R_i - R_f = \sigma'' + \gamma''_m (R_m - R_f) + \gamma''_{HML} HML + \gamma''_{SMB} SMB + \gamma''_{WML} WML + \gamma''_{Z\text{-}score} Z\text{-}score + \gamma''_{DES} DES + \gamma''_{TERM} TERM + \gamma''_{DIV} DIV + \gamma''_{T\text{-}Bill} T\text{-}Bill$$

See notes in Table 4.1 for P1 and P10 portfolio formation. The explanatory variables are defined in the notes in Table 2.8 of Chapter 2. *F*-statistics show the results of the test on the joint significance of explanatory variables and *Adjusted* R^2 measures the goodness of fit of the model. The variance inflation factor (VIF) and tolerance values are also reported from multicollinearity tests.

	Constant		$R_m - R_f$		HML	
	σ''	t(σ'')	γ''_m	t(γ''_m)	γ''_{HML}	t(γ''_{HML})
P1	0.002	0.10	0.312***	3.25	0.083**	2.26
P10	0.001	0.04	0.537***	3.47	-0.116**	-2.43
	SMB		WML		Z-score	
	γ''_{SMB}	t(γ''_{SMB})	γ''_{WML}	t(γ''_{WML})	$\gamma''_{Z\text{-}score}$	t($\gamma''_{Z\text{-}score}$)
P1	-0.031	-0.74	-0.041	-0.77	-0.147**	-2.20
P10	-0.084*	-1.95	0.072*	1.81	-0.036	-0.77
	DES		TERM		DIV	
	γ''_{DES}	t(γ''_{DES})	γ''_{TERM}	t(γ''_{TERM})	γ''_{DIV}	t(γ''_{DIV})
P1	-0.112*	-2.02	0.033	0.75	0.124*	2.14
P10	-0.100*	-2.13	-0.062	-1.03	-0.051	-1.00
	T-Bill		*F*-statistics	*Adj.* R^2	VIF	Tolerance
P1	0.026	0.54	2412	0.65	1.23	0.81
P10	0.066	1.28	2368	0.69	1.21	0.83

4.5.4. B Multicollinearity tests

As briefly mentioned earlier, when considering the roles of firms' default risk and business cycles in capturing the movements of momentum returns in one regression (e.g. model 4.3 and model 4.4), it is possible that there is a correlation between these two groups of explanatory variables. It would be that regardless of firm operating performance, they are more likely to go into default during poor economic conditions and less likely during market expansions. If this multicollinearity issue does exist, the explanatory power of individual variables will not be identified. The problem of multicollinearity could be detected by looking at the VIF and tolerance values of the estimation in question.

It is worth noticing that the multicollinearity issue is less likely to materially bias models 4.1 and 4.2 because there are yet to be any economic reasons suggesting a linear correlation between the explanatory variables in the model. Therefore, this chapter will perform multicollinearity test on models 4.3 and 4.4 only. The VIF and tolerance values of the estimations on these models are reported at the end of Tables 4.5 and 4.6.

From the tables, it can be seen that there is no evidence of any multicollinearity problems in the estimations. As can be seen from Table 4.5, the VIF values are 1.22 and 1.21 for the loser (P1) and the winner (P10) portfolios, respectively. All values are less than 5 and the tolerances are greater than 0.20. These indicate either a weak correlation or none at all between the proxies for firms' default risk and business cycle variables in mode 4.3. That means the estimation of their individual explanatory power is not biased.

Similarly, the results in Table 4.6 show that the VIF value is 1.27 (tolerance value of 0.79) for the regression on the loser portfolio and it is 1.16 (tolerance value of 0.86) for the regression on the winner portfolio. As the VIF values are less than 5 and the tolerances are greater than 0.20, we can safely conclude that there is no multicollinearity problem in model 4.4.

To sum up, the findings reported in this chapter on momentum and firm distress condition are not sensitive to the choice of proxies and are relatively free from multicollinearity biases.

4.6 CONCLUSION

Chapter 4 addresses momentum anomaly in the UK, seeks the underlying risk factors that would potentially explain the momentum premium, and focuses particularly on the role of distress risk in this assessment. In the chapter, distress risk is examined through a number of indicators, such as the risk of corporate failure, business cycle risk in changes in the bond market and interest rates. The main findings of this chapter are as follows.

Firstly, in testing hypothesis 1 the chapter finds evidence of momentum profitability in the UK market between 1990 and 2012. The abnormal returns are statistically significant for 3- and 6-month holding periods (the monthly rates of return are 1.24% and 1.01%, respectively). However, momentum strategies weaken as the investment horizon is widened and disappear after 12 months. The chapter also finds that the simple buy-and-hold strategies underperform all of the tested momentum strategies. On average, the buy-and-hold approach leads to a loss in returns. However, overall the return losses as a result of holding the past winners for a long term (i.e. up to 5 years) are relatively small and statistically insignificant. In addition, results in this chapter show that although momentum investors might see small differences in stock returns between Januaries and other months, there is no evidence of a significant January effect in the UK stock market.

Secondly, from an assessment on how momentum strategies perform over different states of the economy, the chapter finds that the momentum abnormal returns are large in absolute terms. Also, there is no evidence to reject the null hypothesis 2 that states of the economy affect momentum premium. The momentum premium is found to be statistically significant in "good" market conditions, and particularly noticeable during economic expansions. Over a 3-month investment period, the return differentials between the winners and the losers increase from 1.24% per month in normal circumstances to 1.28% during market upturns, and to 1.34% in booming periods. However, momentum strategies perform poorly during market downturns and even lead to huge losses during recession periods. Momentum investors might start to experience losses as early as 6 months after the investment.

Thirdly, regarding hypothesis 3, the results in the chapter reveal that the default risk factor plays a significant role in explaining the movement in returns on the loser portfolio in the UK but is less important in explaining the winners. The past poorly performing firms are more likely to suffer from potential distress than the past top performers. The results also show that default risk could indeed contribute to explaining momentum profitability. Using alternative proxies for default risk, such as O-score, Z-score and CHS score, does not significantly affect the findings.

Finally, in explaining momentum anomaly, the results in Chapter 4 show that the traditional explanatory variables, such as the market and HML variables, consistently show significant explanatory power whereas size and momentum variables seem to capture more movement of the returns on the winners but become less important in explaining the losers' returns. One possible explanation is that the majority of the winner companies in the FTSE350 are actually big firms while the pattern is not as clear in the loser portfolio.

The chapter also finds that business cycle factors may contribute to explaining momentum premium. Among four business cycle variables, only market default spread (DES) plays a significant role in explaining the movement in returns on both the loser and the winner portfolios. The dividend yield variable (DIV), however, could only capture the movement in excess returns on the past poor performers but becomes less important in explaining excess returns on the past winners. In addition, Chapter 4 finds no evidence that other business cycle variables, including term spread (TERM) and short-term Treasury Bill (T-Bill), could explain the movement in returns on the winners or the losers. The results are largely similar regardless of the choice of proxies for default risk, whether DEF, DEF' or CHS. As there are a number of distress risk variables presented in the model, such as default risk and default spread, it is necessary to test whether they are correlated, which would lead to biased estimations. The tests confirm that the results in this chapter do not suffer from multicollinearity biases. These mean the results in Chapter 4 do not support rejection of the null hypothesis 4.

When comparing the performance of all models used in the chapter, it is found that the model goodness of fit does improve in the presence of default factor and business cycle variables. In the augmented FF model, the *Adjusted* R^2s are 59% and 61% in regressions on the excess returns on loser and winner portfolios, respectively. The measures of model goodness of fit increase to 64% and 68% when adding a momentum variable (WML), and to 65% and 68% when adding business cycle variables. In the presence of all explanatory variables, including the three FF factors, the Carhart WML element, a default variable and business cycle variables, the *Adjusted* R^2s are 67% in the regression on the loser portfolio returns and 69% in the estimation on the winner portfolio returns. Although the *Adjusted* R^2s are relatively high, they show that there is still potential for further improvement in modelling momentum-based trading strategies. It is worth noting that the *Adjusted* R^2 measure has made the necessary adjustment for the number of predictors in the model. Therefore, the newly added explanatory variables contributed to the above improvement in model performance by more than what would be expected by chance. In conclusion, it can be said that distress risk could contribute to enhancing model performance in capturing momentum premium; however, the improvement is not substantial and more needs to be done in order to better explain momentum anomaly.

It is recognised that the chapter has a number of limitations that could potentially be an area for further research. For example, the chapter's conclusions were only drawn from the UK sample using linear regressions. Testing on a larger sample and using a more dynamic form of asset pricing models would perhaps improve the robustness of the results. Also, more indicators could be used as a proxy for firms' distress conditions, such as analyst coverage and distance to default, in the robustness checks. These might be of interest for future research on distress risk and asset pricing.

Chapter 5: Conclusion and Future Research

The thesis brings together analyses of two dominant investment strategies, namely value investing (buying shares in value firms and selling shares in growth firms) and momentum strategies (buying best past performing stocks and selling worst past performing stocks). Although the market and firm-level distress risks have been documented to be important factors in explaining movement of stock returns, this thesis is one of the first studies researching the link between these distress conditions collectively and outcomes of the above investment strategies.

The thesis contributes to the extant literature from both methodological and empirical aspects. First of all, it addresses the questions in value premium (chapter 3), and momentum premium (chapter 4) in a more recent dataset – taking into account substantial changes in the market post-2008 and changes in investors' strategies to respond to the recent financial crisis. This is particularly relevant when default risk is the main focus of the thesis. Further contributions and empirical findings of each chapter will be summarised as follows.

Chapter 3 contributes to the value anomaly literature in a number of ways.

(i) In terms of methodology, the chapter uses collectively a number of different measures and approaches to explaining value premium, some of which have been incorporated for the first time in the value anomaly literature. There are 2 analysis approaches used in the chapter. The first method is a regression system which estimates the relationships among risk factor variables. This approach allows us to measure the explanatory ability of each factor in explaining the dependent variables, which are the excess returns on value and growth portfolios. The regression analysis provides a direct comparison between the roles of different explanatory variables in one model as well as across different estimation models. The second approach is a portfolio-based analysis which aims to capture the risk patterns that stocks in the same portfolio would share. Used in conjunction with the regression analysis method, the portfolio-based approach provides some valuable insight into how stocks with different risk characteristics might behave and what factors could explain these differences. In addition, the present study is one of the first analyses looking at the return differentials between stocks that bear different default and BM risks. It also seeks to explain the underlying reasons behind the return premium.

(ii) Another contribution of Chapter 3 is capturing the link between default risk and value premium in a constructive and direct way. The chapter measures default risk using a relatively more indicative proxy, namely firm probability of bankruptcy. While previous studies tend to use indirect measures of default risk, such as corporate credit ratings and analyst coverage – the use of an indicator for company default probability would eliminate the possibility of capturing a different risk element to what was initially intended. For example, small companies might receive a low level of analyst coverage but it does not necessarily mean they are under financial distress. In addition, the chapter analyses default risk from two dimensions, which are the risk patterns associated with average stock returns on 9 default/BM intersectional portfolios, and the default risk factor in explaining common stock returns.

(iii) Considering an additional proxy for distress conditions, the chapter also uses stock volatility. More specifically, it provides an analysis on the risk pattern associated with idiosyncratic volatility in explaining average stock returns. The analysis aims to capture firm distress risk that has not been covered by default risk. It occurs when stock prices are influenced by factors other than the firm's financial performance.

(iv) The empirical aspects of volatility and default risk relation are analysed, and their potential roles in explaining value premium are carefully addressed for the first time. While idiosyncratic volatility and default risk have been analysed separately in the value anomaly literature, it is important to test their roles individually as well as collectively in the same context. From an investor's view, these two risk components are somewhat related; the present study provides an assessment on whether they measure the same type of risk and, if not, whether one can contribute to explaining the other.

To summarise the findings of Chapter 3, there is evidence of positive but insignificant value premium in the FTSE350 over 276 months from 31st January 1990 to 31st December 2012. The results in the UK also show stocks with low BM and/or low idiosyncratic volatility, considered to be a safer investment, generate slightly higher returns than the riskier stocks. On average, the value premium is about 0.09% a month when using BM as the indicator and it is 0.06% in the case of E/P and DY ratios. In terms of firm-level volatility, there is a premium in high volatility stocks and in small stocks, while there is no evidence of a value premium within low volatility and big groups.

In addition, Chapter 3 finds evidence indicating that default probability contributes to explaining the risk pattern in stock returns. Equities of firms with a high probability of bankruptcy tend to have lower returns on average. Moreover, considering stock volatility in conjunction with Fama and French's (1993) three factors does increase the explanatory power of the model significantly. Furthermore, in examining the relation between stock volatility and default risk, the thesis finds that highly volatile stocks tend to ultimately suffer a higher bankruptcy probability. The levels of firm default probability are shown to have the ability to explain the return differentials between high and low volatility stocks.

In terms of model goodness of fit, the results in Chapter 3 show that the Carhart four-factor model performs slightly better than the traditional FF three-factor model in explaining value premium. The improvement from adding a momentum factor is immaterial. However, in the presence of the default risk factor, both the FF and Carhart models achieve much higher *Adjusted* R^2s. The measures increase by 21% to 33% depending on the model. This lends further support to the above conclusion that default risk plays an important role in capturing the risk patterns associated with company financial distress conditions in common stock returns.

Chapter 4 studies the role of firms' probability of bankruptcy and business cycles in explaining momentum premium. The main contributions of the chapter are as follows.

(i) In the chapter, different proxies for default risk are incorporated with the changes in economic conditions before, during and after the recent 2008 crisis to capture momentum returns in the UK. Although it has been documented in the literature that distress risk at a firm level and at the market level has an impact on the performance of momentum strategies, there has not been any effort to test the explanatory power of both components in the momentum context. The chapter has provided a more comprehensive view of how distress risk might affect momentum premium through these various channels.

(ii) When taking firms' distress conditions into account, unlike previous studies the chapter uses a well-developed proxy for a firm's default probability. The indicator was first proposed by Campbell, Hilscher and Szilagyi (2008), and incorporates both accounting and market information in a dynamic probability model. So far, the momentum literature that considers bankruptcy risk has been based purely on accounting-based proxies, such as O-score. They were designed nearly four decades ago when the stock market might not have been as complex as it is now. Since being put into use, Campbell et al.'s (2008) default measure has been regarded as being more accurate than previously developed predictors. In the chapter, other measures of default probability, such as O-score and Z-score, are utilised for robustness check purposes. Thus, it is unlikely for there to be default risk elements missed when drawing the chapter conclusion.

(iii) Previously, there has been evidence in the literature that momentum anomaly could be explained by firm default risk, and that momentum is also associated with business cycles. The chapter is the first work linking the three elements in the same context. Linking all three variables could potentially show whether one's effect has been captured by another, and whether the explanatory power of each variable is robust. Also, this would potentially contribute to improving the predictive ability of models used in the present study.

The results in Chapter 4 indicate that there is significant momentum premium in the UK for up to a 12-month investment period. The returns are more significant for any holding periods of up to 6 months. This confirms the findings from previous studies in the UK that momentum strategies generate positive returns for investments of less than one year. The results hold even when different investment horizons and seasonality have been taken into account. The chapter does not find evidence of any January effects in the UK. In addition, results of the analysis suggest that the momentum abnormal returns are large and statistically significant in market upturns, these are particularly noticeable during economic expansions. However, the strategies underperform during market downturns. More damagingly, they would lead to large losses during recessions.

When explaining momentum, the analysis confirms that the market beta and BM variables remain important factors. Size and momentum variables could better explain returns on the past winners; yet they become less important in capturing returns on the past losers. Among four business cycle variables, default spread and dividend yield could contribute to explaining stock returns while term spread and the short-term Treasury bill could not. Including default risk factor in the regressions significantly improves the joint explanatory power of the independent variables in capturing returns on the losers. However, the impact is less significant in explaining the movement of returns on the winners. It is also worth noting that the past poorly performing firms are more likely to suffer from potential distress than the past top performers.

In the thesis, there is evidence that the FF and Carhart models could explain more of the return differentials between winners and losers than between value and growth stocks. In comparison with the results in the chapter on value anomaly (Chapter 3), the *Adjusted* R^2s in Chapter 4 are higher. Moreover, the model goodness of fit shows signs of improvement in the presence of the default factor and business cycle variables. However, the improvement is not substantial and more needs to be done in order to better explain momentum anomaly. When adding WML and business cycle variables to the augmented FF three-factor model, the *Adjusted* R^2s increase from between 59% and 61% to about 65% and 68%. Although the *Adjusted* R^2s are relatively high, these nonetheless show that there is still potential for further improvement in modelling momentum-based trading strategies.

Across the above investment themes, there are some areas and issues that this thesis has not been able to address and would be the limitations of this study. For example, the thesis focuses on the UK market over the last 22 years, using the linear regression approach. It may be that testing on more markets over a longer period and using a more dynamic form of asset pricing models would improve the robustness of the results. Also, more indicators could potentially be used as a proxy for firms' distress conditions, such as analyst coverage and credit rating, especially for robustness check purposes. These might be of interest for our future research on distress risk and asset pricing.

Finally, as the UK voted to leave the EU in June 2016, a new arrangement between the UK and the rest of the EU could have a significant impact on UK stock prices. Following the vote, the FTSE350 has been relatively volatile and many investors are showing hesitation in investing in UK assets. The topics of market downturns, business cycles and firm default risk become even more relevant in this time of uncertainty.

Since it is unclear what arrangement the UK will achieve after triggering Article 50, the new arrangement will provide a new breakpoint for future research on FTSE350 companies. The new terms and agreements would provide materials to expand the discussion on the investment strategies in this thesis, for both the pre-negotiation and post-negotiation periods. When the UK leaves the EU, it is expected that the membership withdrawal could have a great impact on firms' ability to apply for EU funding and to attract foreign investment. These in turn would have significant effects on default probability, especially on the ability to repay debts of FTSE350 firms. These would cause investors to adjust their investment strategies in general and the two investment strategies addressed in this thesis in particular. As such, the UK's case would become particularly interesting and one hopes future research would look into the impact of this event and the UK investment environment.

Appendices

Appendix 1: Sample

Appendix 1 lists name of the companies that are included in the sample, company ticker, sector and IPO date. In Chapter 3 which looks at value anomaly, the sample consists of 269 non-financial firms[30]. Chapter 4 regarding momentum anomaly is based on a full sample of 290 firms because unlike value studies, momentum analysis does not differentiate financial firms from non-financial firms.

Source: Thomson Reuters.

	Company	Ticker	Sector	IPO[31]
1.	3i Group PLC	III	Capital Markets	18/07/1994
2.	3I Infrastructure PLC	3IN	Capital Markets	08/03/2007
3.	A.G.Barr PLC	BAG	Beverages	n/a
4.	Aberdeen Asset Management PLC	ADN	Capital Markets	28/03/1991
5.	Aberforth Smaller Companies Trust PLC	ASL	Investment Trusts	n/a
6.	Acacia Mining PLC	ACAA	Metals & Mining	24/03/2010
7.	Admiral Group PLC	ADML	Insurance	23/09/2004
8.	Aggreko PLC	AGGK	Commercial Services & Supplies	29/09/1997
9.	Alliance Trust PLC	ATST	Capital Markets	n/a
10.	Amec Foster Wheeler PLC	AMFW	Energy Equipment & Services	23/12/1982
11.	Anglo American PLC	AAL	Metals & Mining	24/05/1999
12.	Antofagasta PLC	ANTO	Metals & Mining	05/07/1982
13.	Ashmore Group PLC	ASHM	Capital Markets	12/10/2006
14.	Ashtead Group PLC	AHT	Trading Companies & Distributors	n/a
15.	Associated British Foods PLC	ABF	Food Products	01/08/1994
16.	Assura PLC	AGRP	Equity Real Estate Investment Trusts (REITs)	n/a

[30] In this thesis, financial firms are Banks and Capital Markets.
[31] n/a indicates the information is not available.

17.	AstraZeneca PLC	AZN	Pharmaceuticals	21/09/2007
18.	AVEVA Group PLC	AVV	Software	28/11/1996
19.	Aviva PLC	AV	Insurance	04/06/1990
20.	Babcock International Group PLC	BAB	Commercial Services & Supplies	14/08/1989
21.	BAE Systems PLC	BAES	Aerospace & Defense	11/02/1981
22.	Balfour Beatty PLC	BALF	Construction & Engineering	28/06/1945
23.	Bankers Investment Trust PLC	BNKR	Investment Trusts	n/a
24.	Barclays PLC	BARC	Banks	31/12/1953
25.	Barratt Developments PLC	BDEV	Household Durables	n/a
26.	BBA Aviation PLC	BBA	Transportation Infrastructure	11/11/1960
27.	Bellway PLC	BWY	Household Durables	n/a
28.	Berendsen PLC	BRSN	Commercial Services & Supplies	30/03/1981
29.	Berkeley Group Holdings PLC	BKGH	Household Durables	n/a
30.	BGEO Group PLC	BGEO	Banks	14/10/2011
31.	BH Macro Ltd	BHMG		08/03/2007
32.	BHP Billiton PLC	BLT	Metals & Mining	28/07/1997
33.	Big Yellow Group PLC	BYG	Equity Real Estate Investment Trusts (REITs)	08/05/2000
34.	Bodycote PLC	BOY	Machinery	n/a
35.	Booker Group PLC	BOK	Food & Staples Retailing	20/07/2004
36.	Bovis Homes Group PLC	BVS	Household Durables	09/12/1997
37.	BP PLC	BP	Oil, Gas & Consumable Fuels	29/03/1954
38.	Brewin Dolphin Holdings PLC	BRW	Capital Markets	26/05/1994
39.	British American Tobacco PLC	BATS	Tobacco	29/01/1962
40.	British Empire Trust PLC	BTEM	Diversified Financial Services	n/a

41.	British Land Company PLC	BLND	Equity Real Estate Investment Trusts (REITs)	20/03/1951
42.	Britvic PLC	BVIC	Beverages	08/12/2005
43.	BT Group PLC	BT	Diversified Telecommunication Services	03/12/1984
44.	BTG PLC	BTG	Pharmaceuticals	28/06/1995
45.	Bunzl plc	BNZL	Trading Companies & Distributors	20/06/1957
46.	Burberry Group PLC	BRBY	Textiles, Apparel & Luxury Goods	18/07/2002
47.	Cairn Energy PLC	CNE	Oil, Gas & Consumable Fuels	22/12/1988
48	Caledonia Investments PLC	CLDN	Diversified Financial Services	n/a
49.	Capita PLC	CPI	Professional Services	21/08/1991
50.	Capital & Counties Properties PLC	CAPCC	Real Estate Management & Development	17/05/2010
51.	Carillion PLC	CLLN	Construction & Engineering	n/a
52.	Carnival PLC	CCL	Hotels, Restaurants & Leisure	23/10/2000
53.	Centamin PLC	CEY	Metals & Mining	n/a
54.	Centrica PLC	CNA	Multi-Utilities	17/02/1997
55.	Cineworld Group PLC	CINE	Media	27/04/2007
56.	City of London Investment Trust PLC	CTY	Diversified Financial Services	n/a
57.	Clarkson PLC	CKN	Marine	n/a
58.	Close Brothers Group PLC	CBRO	Capital Markets	n/a
59.	CLS Holdings PLC	CLSH	Real Estate Management & Development	12/05/1994
60.	Cobham PLC	COB	Aerospace & Defense	20/12/1954
61.	Compass Group PLC	CPG	Hotels, Restaurants & Leisure	02/02/2001
62.	Cranswick PLC	CWK	Food Products	n/a
63.	CRH PLC	CRH	Construction Materials	05/02/1973
64.	Croda International PLC	CRDA	Chemicals	10/06/1964

65.	Daejan Holdings PLC	DJAN	Real Estate Management & Development	n/a
66.	Dairy Crest Group PLC	DCG	Food Products	31/07/1996
67.	DCC PLC	DCC	Industrial Conglomerates	n/a
68.	Debenhams PLC	DEB	Multiline Retail	04/05/2006
69.	Dechra Pharmaceuticals PLC	DPH	Pharmaceuticals	21/09/2000
70.	Derwent London PLC	DLN	Equity Real Estate Investment Trusts (REITs)	n/a
71.	Diageo PLC	DGE	Beverages	06/05/1952
72.	Dignity PLC	DTY	Diversified Consumer Services	02/04/2004
73.	Diploma PLC	DPLM	Trading Companies & Distributors	n/a
74.	Domino's Pizza Group PLC	DOM	Hotels, Restaurants & Leisure	24/11/1999
75.	Drax Group PLC	DRX	Independent Power and Renewable Electricity	20/12/2005
76.	DS Smith PLC	SMDS	Containers & Packaging	02/01/1986
77.	Dunelm Group PLC	DNLM	Specialty Retail	19/10/2006
78.	easyJet plc	EZJ	Airlines	22/11/2000
79.	Edinburgh Investment Trust PLC	EDIN	Diversified Financial Services	n/a
80.	Electra Private Equity PLC	ELTA	Capital Markets	20/08/2001
81.	Electrocomponents PLC	ECM	Electronic Equipment, Instruments & Components	n/a
82.	Elementis PLC	ELM	Chemicals	01/04/1964
83.	Entertainment One Ltd	ETO	Media	29/03/2007
84.	Essentra PLC	ESNT	Chemicals	06/06/2005
85.	Euromoney Institutional Investor PLC	ERM	Media	11/06/1986
86.	EVRAZ plc	EVRE	Metals & Mining	08/06/2005
87.	Experian PLC	EXPN	Professional Services	11/10/2006
88.	F&C Commercial Property Trust Ltd	FCPTL	Real Estate Management & Development	17/07/2009

89	Ferrexpo PLC	FXPO	Metals & Mining	20/06/2007
90.	Fidelity China Special Situations PLC	FCSS		19/04/2010
91.	Fidelity European Values PLC	FEV	Diversified Financial Services	n/a
92.	Fidessa Group PLC	FDSA	Software	09/06/1997
93.	Finsbury Growth & Income Trust PLC	FGT	Capital Markets	24/12/1953
94.	FirstGroup PLC	FGP	Road & Rail	n/a
95	Foreign & Colonial Investment Trust PLC	FRCL		n/a
96.	Fresnillo PLC	FRES	Metals & Mining	14/05/2008
97.	G4S PLC	GFS	Commercial Services & Supplies	20/07/2004
98.	Galliford Try PLC	GFRD	Construction & Engineering	16/12/1997
99.	GCP Infrastructure Investments Ltd	GCPI	Investment	22/07/2010
100.	Genesis Emerging Markets Fund Ltd	GSS	Diversified Financial Services	n/a
101.	Genus PLC	GNS	Biotechnology	06/07/2000
102.	GKN PLC	GKN	Auto Components	14/06/1946
103.	GlaxoSmithKline PLC	GSK	Pharmaceuticals	22/05/1972
104.	Glencore PLC	GLEN	Metals & Mining	24/05/2011
105.	Go-Ahead Group PLC	GOG	Road & Rail	28/04/1994
106.	Grafton Group PLC	GFTU_u	Trading Companies & Distributors	n/a
107.	Grainger PLC	GRI	Real Estate Management & Development	n/a
108.	Greencore Group PLC	GNC	Food Products	18/04/1991
109.	Greene King PLC	GNK	Hotels, Restaurants & Leisure	n/a
110.	Greggs PLC	GRG	Hotels, Restaurants & Leisure	n/a
111.	GVC Holdings PLC	GVC	Hotels, Restaurants & Leisure	n/a
112.	Halfords Group PLC	HFD	Specialty Retail	03/06/2004

113.	Halma PLC	HLMA	Electronic Equipment, Instruments & Components	Halma PLC
114.	Hammerson PLC	HMSO	Equity Real Estate Investment Trusts (REITs)	31/05/1945
115.	Hansteen Holdings PLC	HSTN	Equity Real Estate Investment Trusts (REITs)	29/11/2005
116.	HarbourVest Global Private Equity Ltd	HVPEa		05/12/2007
117.	Hargreaves Lansdown PLC	HRGV	Capital Markets	18/05/2007
118.	Hays PLC	HAYS	Professional Services	n/a
119.	HICL Infrastructure Company Ltd	HICL	Capital Markets	29/03/2006
120.	Hikma Pharmaceuticals PLC	HIK	Pharmaceuticals	01/11/2005
121.	Hill & Smith Holdings PLC	HILS	Metals & Mining	n/a
122.	Hiscox Ltd	HSX	Insurance	15/11/2006
123.	Hochschild Mining PLC	HOCM	Metals & Mining	03/11/2006
124.	HomeServe PLC	HSV	Commercial Services & Supplies	n/a
125.	Howden Joinery Group PLC	HWDN	Trading Companies & Distributors	n/a
126.	HSBC Holdings PLC	HSBA	Banks	n/a
127.	Hunting PLC	HTG	Energy Equipment & Services	n/a
128.	IG Group Holdings PLC	IGG	Capital Markets	28/04/2005
129.	IMI PLC	IMI	Machinery	09/03/1996
130.	Imperial Brands PLC	IMB	Tobacco	01/10/1996
131.	Inchcape PLC	INCH	Distributors	02/01/1986
132.	Inmarsat PLC	ISA	Diversified Telecommunication Services	17/06/2005
133.	Intermediate Capital Group PLC	ICP	Capital Markets	19/05/1994
134.	International Consolidated Airlines Group SA	ICAG	Airlines	10/01/2011
135.	International Public Partnerships Ltd	INPP		09/11/2006
136.	Intertek Group PLC	ITRK	Professional Services	29/05/2002

137.	Intu Properties PLC	INTUP	Equity Real Estate Investment Trusts (REITs)	02/06/1905
138.	Investec PLC	INVP	Capital Markets	29/07/2002
139.	IP Group PLC	IPO	Capital Markets	15/10/2003
140.	ITV PLC	ITV	Media	02/02/2004
141.	IWG Plc	IWG	Commercial Services & Supplies	n/a
142.	J D Wetherspoon PLC	JDW	Hotels, Restaurants & Leisure	n/a
143.	J Sainsbury PLC	SBRY	Food & Staples Retailing	11/07/1975
144.	James Fisher and Sons plc	FSJ	Oil, Gas & Consumable Fuels	30/12/1996
145.	Jardine Lloyd Thompson Group PLC	JLT	Insurance	n/a
146.	JD Sports Fashion PLC	JD	Specialty Retail	22/10/1996
147.	John Laing Infrastructure Fund Ltd	JLIF	Investment	24/11/2010
148.	John Wood Group PLC	WG	Energy Equipment & Services	05/06/2002
149.	JPMorgan American Investment Trust PLC	JAM		n/a
150.	JPmorgan Emerging Markets Investment Trust	JMG	Capital Markets	26/06/1991
151.	JPMorgan Indian Investment Trust PLC	JII		27/04/1994
152.	Jupiter Fund Management PLC	JUP	Capital Markets	16/06/2010
153.	Kaz Minerals PLC	KAZ	Metals & Mining	07/10/2005
154.	Keller Group PLC	KLR	Construction & Engineering	19/04/1994
155.	Kier Group PLC	KIE	Construction & Engineering	05/12/1996
156.	Kingfisher PLC	KGF	Specialty Retail	24/11/1982
157.	Ladbrokes Coral Group PLC	LCL	Hotels, Restaurants & Leisure	20/09/1967
158.	Lancashire Holdings Ltd	LRE	Insurance	16/03/2009
159.	Land Securities Group PLC	LAND	Equity Real Estate Investment Trusts (REITs)	06/09/2002
160.	Legal & General Group PLC	LGEN	Insurance	02/07/1979

161.	Lloyds Banking Group PLC	LLOY	Banks	08/10/1986
162.	London Stock Exchange Group PLC	LSE	Capital Markets	15/05/2006
163.	Londonmetric Property PLC	LMPL	Equity Real Estate Investment Trusts (REITs)	n/a
164.	Marks and Spencer Group PLC	MKS	Multiline Retail	19/03/2002
165.	Marshalls PLC	MSLH	Construction Materials	n/a
166.	Marston's PLC	MARS	Hotels, Restaurants & Leisure	n/a
167.	Meggitt PLC	MGGT	Aerospace & Defense	28/04/1947
168.	Mercantile Investment Trust PLC	MRCM	Capital Markets	n/a
169.	Micro Focus International PLC	MCRO	Software	n/a
170.	Millennium & Copthorne Hotels PLC	MLC	Hotels, Restaurants & Leisure	25/04/1996
171.	Mitchells & Butlers PLC	MAB	Hotels, Restaurants & Leisure	n/a
172.	Mitie Group PLC	MTO	Commercial Services & Supplies	n/a
173.	Mondi PLC	MNDI	Paper & Forest Products	n/a
174.	Moneysupermarket.Com Group PLC	MONY	Internet Software & Services	26/07/2007
175.	Monks Investment Trust PLC	MNKS	Capital Markets	n/a
176.	Morgan Advanced Materials PLC	MGAM M	Machinery	02/10/1946
177.	Murray International Trust PLC	MYI		21/06/1945
178.	National Express Group PLC	NEX	Road & Rail	26/04/1995
179.	National Grid PLC	NG	Multi-Utilities	31/01/2002
180.	Next PLC	NXT	Multiline Retail	12/03/1948
181.	NMC Health PLC	NMC	Health Care Providers & Services	n/a
182.	Northgate PLC	NTG	Road & Rail	n/a
183.	Northern Rock Building Society PLC	NRK	Bank	n/a
184.	Nostrum Oil & Gas PLC	NOGN	Oil, Gas & Consumable Fuels	03/04/2008

185.	Ocado Group PLC	OCDO	Internet & Direct Marketing Retail	21/07/2010
186.	Old Mutual PLC	OML	Insurance	12/07/1999
187.	Paddy Power Betfair PLC	PPB	Hotels, Restaurants & Leisure	30/11/2000
188.	Pagegroup PLC	PAGE	Professional Services	n/a
189.	Paragon Group of Companies Plc	PARA	Thrifts & Mortgage Finance	n/a
190.	PayPoint plc	PAYP	Commercial Services & Supplies	21/09/2004
191.	Pearson PLC	PSON	Media	13/08/1969
192.	Pennon Group PLC	PNN	Water Utilities	12/12/1989
193.	Perpetual Income and Growth Investment Trust	PLI	Capital Markets	16/11/2004
194.	Persimmon PLC	PSN	Household Durables	n/a
195.	Personal Assets Trust PLC	PNL	Capital Markets	n/a
196.	Petra Diamonds Ltd	PDL	Metals & Mining	22/04/1997
197.	Petrofac Ltd	PFC	Energy Equipment & Services	07/10/2005
198.	Phoenix Group Holdings	PHNX	Insurance	n/a
199.	Playtech PLC	PTEC	Software	n/a
200.	Polar Capital Technology Trust PLC	PCT		n/a
201.	Polymetal International PLC	POLYP	Metals & Mining	02/11/2011
202.	Provident Financial PLC	PFG	Consumer Finance	16/03/1962
203.	Prudential PLC	PRU	Insurance	29/12/1978
204.	PZ Cussons PLC	PZC	Household Products	26/11/1953
205.	Qinetiq Group PLC	QQ	Aerospace & Defense	10/02/2006
206.	Randgold Resources Ltd	RRS	Metals & Mining	01/07/1997
207.	Rank Group PLC	RNK	Hotels, Restaurants & Leisure	n/a
208.	Rathbone Brothers PLC	RAT	Capital Markets	n/a

209.	Reckitt Benckiser Group PLC	RB	Household Products	23/10/2007
210.	Redefine International PLC	RDI	Equity Real Estate Investment Trusts (REITs)	n/a
211.	Redrow PLC	RDW	Household Durables	28/04/1994
212.	Relx PLC	REL	Professional Services	21/04/1948
213.	Renishaw PLC	RSW	Electronic Equipment, Instruments & Components	n/a
214.	Rentokil Initial PLC	RTO	Commercial Services & Supplies	21/06/2005
215.	Restaurant Group PLC	RTN	Hotels, Restaurants & Leisure	n/a
216.	Rightmove PLC	RMV	Internet Software & Services	n/a
217.	Rio Tinto PLC	RIO	Metals & Mining	01/11/1973
218.	RIT Capital Partners PLC	RCP	Capital Markets	n/a
219.	Rolls-Royce Holdings PLC	RR	Aerospace & Defense	20/05/1987
220.	Rotork PLC	ROR	Machinery	23/07/1968
221.	Royal Bank of Scotland Group PLC	RBS	Banks	10/07/1968
222.	Royal Dutch Shell PLC	RDSb	Oil, Gas & Consumable Fuels	20/07/2005
223.	Royal Dutch Shell PLC	RDSa	Oil, Gas & Consumable Fuels	20/07/2005
224.	RPC Group PLC	RPC	Containers & Packaging	28/05/1993
225.	RSA Insurance Group PLC	RSA	Insurance	03/07/1989
226.	Safestore Holdings PLC	SAFE	Equity Real Estate Investment Trusts (REITs)	09/03/2007
227.	Sage Group PLC	SGE	Software	14/12/1989
228.	Savills PLC	SVS	Real Estate Management & Development	n/a
229.	Schroders PLC	SDR	Capital Markets	30/09/1959
230.	Scottish Investment Trust PLC	SCIN		n/a
231.	Scottish Mortgage Investment Trust PLC	SMT	Diversified Financial Services	n/a
232.	SEGRO PLC	SGRO	Equity Real Estate Investment Trusts (REITs)	01/12/1949

233.	Senior PLC	SNR	Aerospace & Defense	n/a
234.	Serco Group PLC	SRP	Commercial Services & Supplies	12/05/1988
235.	Severn Trent PLC	SVT	Water Utilities	12/12/1989
236.	Shaftesbury PLC	SHB	Equity Real Estate Investment Trusts (REITs)	n/a
237.	Shire PLC	SHP	Biotechnology	23/05/2008
238.	SIG PLC	SHI	Trading Companies & Distributors	18/05/1989
239.	Sky PLC	SKYB	Media	15/12/1994
240.	Smith & Nephew PLC	SN	Health Care Equipment & Supplies	13/08/1951
241.	Smiths Group PLC	SMIN	Industrial Conglomerates	20/12/1950
242.	Smurfit Kappa Group PLC	SKG	Containers & Packaging	14/03/2007
243.	Spectris PLC	SXS	Electronic Equipment, Instruments & Components	29/11/1988
244.	Spirax-Sarco Engineering PLC	SPX	Machinery	02/01/1986
245.	Sports Direct International PLC	SPD	Specialty Retail	02/03/2007
246.	SSE PLC	SSE	Electric Utilities	18/06/1991
247.	St. James's Place PLC	SJP	Insurance	n/a
248.	St. Modwen Properties PLC	SMP	Real Estate Management & Development	n/a
249.	Stagecoach Group PLC	SGC	Road & Rail	27/04/1993
250.	Standard Chartered PLC	STAN	Banks	02/02/1970
251.	Standard Life PLC	SL	Insurance	10/07/2006
252.	Stobart Group Ltd	STOB	Oil, Gas & Consumable Fuels	n/a
253.	SuperGroup PLC	SGP	Specialty Retail	24/03/2010
254.	SVG Capital PLC	SVI	Capital Markets	23/05/1996
255.	Synthomer PLC	SYNTS	Chemicals	n/a
256.	Talktalk Telecom Group PLC	TALK	Diversified Telecommunication Services	n/a

257.	Tate & Lyle PLC	TATE	Food Products	09/12/1938
258.	Taylor Wimpey PLC	TW	Household Durables	07/03/1947
259.	Ted Baker PLC	TED	Textiles, Apparel & Luxury Goods	n/a
260.	Telecom Plus PLC	TEP	Multi-Utilities	26/07/2000
261.	Temple Bar Investment Trust PLC	TMPL	Capital Markets	n/a
262.	Templeton Emerging Markets Investment Trust	TEM	Capital Markets	15/05/1996
263.	Tesco PLC	TSCO	Food & Staples Retailing	23/12/1947
264.	Thomas Cook Group plc	TCG	Hotels, Restaurants & Leisure	n/a
265.	TP ICAP PLC	TCAPI	Capital Markets	24/10/2000
266.	TR Property Investment Trust PLC	TRY		n/a
267.	Travis Perkins PLC	TPK	Trading Companies & Distributors	n/a
268.	Tui AG	TUIT	Hotels, Restaurants & Leisure	25/02/2008
269.	Tullow Oil PLC	TLW	Oil, Gas & Consumable Fuels	18/12/2000
270.	UBM PLC	UBM	Media	01/07/2008
271.	UDG Healthcare PLC	UDG	Health Care Providers & Services	05/03/1992
272.	UK Commercial Property Trust Ltd	UKCM	Real Estate Management & Development	n/a
273.	Ultra Electronics Holdings PLC	ULE	Aerospace & Defense	03/10/1996
274.	Unilever PLC	ULVR	Personal Products	11/08/1939
275.	Unite Group PLC	UTG	Equity Real Estate Investment Trusts (REITs)	n/a
276.	United Utilities Group PLC	UU	Water Utilities	28/07/2008
277.	Vectura Group PLC	VEC	Pharmaceuticals	02/07/2004
278.	Vedanta Resources PLC	VED	Metals & Mining	10/12/2003
279.	Victrex PLC	VCTX	Chemicals	13/12/1995
280.	Vodafone Group PLC	VOD	Wireless Telecommunication Services	26/10/1988

281.	Weir Group PLC	WEIR	Machinery	25/01/1946
282.	WH Smith PLC	SMWH	Specialty Retail	n/a
283.	Whitbread PLC	WTB	Hotels, Restaurants & Leisure	09/07/1948
284.	William Hill PLC	WMH	Hotels, Restaurants & Leisure	20/06/2002
285.	Witan Investment Trust PLC	WTAN	Diversified Financial Services	n/a
286.	WM Morrison Supermarkets PLC	MRW	Food & Staples Retailing	30/11/1972
287.	Wolseley PLC	WOS	Trading Companies & Distributors	26/11/2010
288.	Workspace Group PLC	WKP	Equity Real Estate Investment Trusts (REITs)	n/a
289.	Worldwide Healthcare Trust PLC	WWH		06/04/1995
290.	WS Atkins PLC	ATKW	Professional Services	18/07/1996

Appendix 2: Data collection

Source: Thomson Reuters and Bloomberg

Data	Abbrev.	Definitions	DSMnemonic/ Other databases
Book-to-Market value	B/M	The balance sheet value divided by the market value of the ordinary (common) equity	WC03501
Cash flow		Consist of three components: **Net Cash flow Financing:** the net cash receipts and disbursements resulting from reduction and/or increase in long or short term debt, proceeds from sale of stock, stock repurchased/redeemed/retired, dividends paid and other financing activities. **Net Cash flow Investing:** the net cash receipts and disbursements resulting from capital expenditures, decrease/increase from investments, disposal of fixed assets, increase in other assets and other investing activities. **Net Cash flow Operating Activities**: the net cash receipts and disbursements resulting from the operations of the company. It is the sum of Funds from Operations, Funds From/Used for Other Operating Activities and Extraordinary Items. The data is generally not available prior to 1989.	WC04890 WC04870 WC04860
Current Assets		Cash and other assets that are reasonably expected to be realized in cash, sold or consumed within one year or one operating cycle. Generally, it is the sum of cash and equivalents, receivables, inventories, prepaid expenses and other current assets. For non-US corporations, long term receivables are excluded from current assets even though included in net receivables.	WC02201
Current Liabilities		Represent debt or other obligations that the company expects to satisfy within one year.	WC03101

		It includes but is not restricted to: Accounts payable, Short term debt, Notes payable, Current portion of long term debt, All accrued expenses, Other current liabilities, Income taxes payable, Dividends payable, State franchise, taxes, Deferred credits, Negative inventories (non-US corporations)	
Depreciation and Amortization		The net decrease in value of assets, both tangible and intangible, over time.	Company profile in Bloomberg & Co. Financial Statements
Dividend yield	DY	A ratio in percentage of the total amount of dividends weighted by the total market value	WC05101
Earning before interest and taxes	EBIT	The earnings of a company before interest expense and income taxes. It is calculated by taking the pre-tax income and adding back interest expense on debt and subtracting interest capitalized.	WC18191, and in some cases: Company profile in Bloomberg database
Earnings per Price	E/P	The earnings rate per share divided by the price of the common equity	PE
Employees		The number of both full and part time employees of a company.	Company profile in Bloomberg database
Firm age		Firm age is the number of years the company has been in business. It is calculated using the firm's "base date" i.e. the date from which DataStream holds information about the stock issuing. Stocks are rebased in accordance to events of mergers, acquisitions and splitting.	BDATE
Funds from operations		The sum of net income and all non-cash charges or credits. It is the cash flow of the company. It includes but is not restricted to: Depreciation, Amortization of Intangibles, Deferred Taxes. It excludes: Extraordinary items, Changes in working capital.	WC04201
FTSE350 index		The index consists of the largest 350 companies by market capitalisation and their primary listing is on the London Stock Exchange.	FTSE350
Gross National	GNP	The sum of value added by all resident producers plus any product taxes (less subsidies) not included in the valuation	UKYBEV..

Product index		of output plus net receipts of primary income (compensation of employees and property income) from abroad. Data are in current local currency.	
Industry/ sector		Industry or sector in which a firm operates. For the UK market, the industry classification is provided by the FTSE ICB (Financial Times Stock Exchange Industry Classification Benchmark, used to be known as FTSE Global Classification System)	WC07040
Inventories		Represent tangible items or merchandise net of advances and obsolescence acquired for either (1) resale directly or (2) included in the production of finished goods manufactured for sale in the normal course of operation. In manufacturing companies this item is classified as follows (depending upon the stage of completion in the manufacturing process): A. Finished goods, consisting of products ready for sale. B. Work in process, consisting of products in various stages of production. C. Raw materials and supplies, consisting of items that will enter directly or indirectly into the production of finished goods. In non-manufacturing companies finished goods bought for resale is the major portion of the inventories.	Bloomberg database - Company profile and company Financial Statements
London Interbank Offered 1month-Rate	LIBOR	The average interbank rate at which a selection of banks on the London money market charge one another for loans with 1 month maturity, and is used in this thesis as a proxy for the Risk-free asset.	BOELI1M
Market value	MV	The share price multiplied by the total number of shares outstanding	WC08001
Market portfolio return	R_m	The average value-weighted rate of return on a portfolio consisting of all stocks in B/M and size portfolios plus negative B/M stocks.	Kenneth R. French’s website
Net Sales		Represent gross sales and other operating revenue less discounts, returns and allowances.	WC01001

Proceeds from Sale of property		The cash inflow from the sale of property that are used in the normal conduct of business to produce goods and services.	Company profile in Bloomberg & Co. Financial Statements
Price Index		A price index shows a theoretical growth in value of a share over a specified period, without an assumption that dividends are re-invested.	PI
Retained Earnings		The accumulated after tax earnings of the company which have not been distributed as dividends to shareholders or allocated to a reserve account.	WC03495
LIBOR 3-month	T-Bill	The 3-month LIBOR rate of return is a proxy for Short-term Treasury Bill.	BOELI3M
Total Assets		The sum of total current assets, long term receivables, investment in unconsolidated subsidiaries, other investments, net property plant and equipment and other assets.	WC02999
Total Liabilities		Represent all short- and long-term obligations expected to be satisfied by the company. It includes but is not restricted to: Current Liabilities, Long Term Debt, Provision for Risk and Charges (non-U.S. corporations), Deferred taxes, Deferred income, Other liabilities, Deferred tax liability in untaxed reserves (non-U.S. corporations), Unrealized gain/loss on marketable securities (insurance companies), Pension/Post retirement benefits, Securities purchased under resale agreements (banks) It excludes: Minority Interest, Preferred stock equity, Common stock equity, Non-equity reserve.	WC03351
Working capital		Represents the difference between current assets and current liabilities. It is a measure of liquidity and solvency.	WC03151

Appendix 3: Constructing Variables

Variable	Abbrev.	Construction/Formula
Campbell, Hilscher and Szilagy's (2008) model	CHS score	The conditional probability of failure, CHS score, is computed as follows. $$P_{t-1}(Y_{it}=1)=\frac{1}{(1+\ \mathrm{e}^{-\alpha-\beta x_{i,t-1}})}$$
	CASHMTA	Cash and short-term investments over the market value of total assets: $$CASHMTA_{i,t}=\frac{Cash\ and\ Short-term\ investments_{i,t}}{(Firm\ Market\ equity_{i,t}+Total\ Liabilities_{i,t})}$$
	EXRET	Gross excess return over FTSE350 return: $$EXRET=Log\left(1+R_{i,t}\right)-Log\left(1+R_{m,t}\right)$$
	MTBV	Market value over Book-value of Equity
	NIMTA	Net Income over Market value of Total Asset: $$NIMTA_{i,t}=\frac{Net\ Income_{i,t}}{(Firm\ Market\ equity_{i,t}+Total\ Liabilities_{i,t})}$$
	RSIZE	Logarithm of firm's market value over the total value of FTSE350
	SIGMA	Daily variation of stock returns calculated as Square root of a sum of squared firm stock returns over a period of three months. It is an annualised 3-month standard deviation around zero (rather than around the sample mean). It is assumed that there are 252 trading days in a year and N days in 3 months. $$SIGMA_{i,t-1,t-3}=(252*\frac{1}{N-1}\sum_{k\in\{t-1,t-2,t-3\}}r_{i,k}^{2})^{2}$$
	TLMTA	Total Liabilities over Market value of Total Asset: $$TLMTA_{i,t}=\frac{Total\ Liabilities_{i,t}}{(Firm\ Market\ equity_{i,t}+Total\ Liabilities_{i,t})}$$
Default risk	DEF	At the end of July of year *t*, stocks are split into 3 groups at the breakpoints of 30:40:30 based on their probability of bankruptcy, measured by the Ohlson's (1980) O-scores at the end of December year *t-1*. The portfolio returns are value weighted and rebalanced annually. The return differential between the top 30% O-score stocks and the bottom 30% O-score stocks means to capture the risk of default.

	DEF'	DEF' is calculated in the same way as DEF but based on the Altman's (1968) Z-score as the proxy for probability of bankruptcy instead of O-score.
	CHS	CHS variable is calculated in the same way as DEF and DEF' but based on ranking the Campbell et al.'s (2008) CHS-score as the proxy for probability of bankruptcy instead of O-score and Z-score.
Default spread	DES	As one of proxies for business cycles, in this thesis default spread is defined as the difference between the average yields on corporate bonds and on long-term Government bonds (UK Gilt with a 15+ year maturity).
Dividend yield	DIV	Dividend yield refers to the average value-weighted dividend yield of all stocks in the sample. It is also one of business cycle variables widely used in the asset pricing literature.
High-minus-Low	HML	The portfolio-based risk factor associated with B/M. At the end of July of year *t*, stocks are split into 3 portfolios using the breakpoints 30:40:30 based on their B/M in June. The monthly value-weighted returns are rebalanced annually. The return differential between the top 30% B/M stocks and the bottom 30% (i.e. HML) is used as a proxy for the B/M effect.
O-score		A measure of probability of bankruptcy proposed by Ohlson (1980). The formula is follows: $\boldsymbol{O-score} = -1.32 - 0.407\, log\, \frac{Total\ assets}{GNP\ price-level\ index} + 6.03\, \frac{Total\ liabilities}{Total\ assets} - 1.43\, \frac{Working\ capital}{Total\ assets} + 0.076\, \frac{Current\ liabilities}{Current\ assets} - 1.72\, (=1\ if\ total\ liabilities > total\ assets, 0\ otherwise) - 2.37\, \frac{Net\ income}{Total\ assets} - 1.83\, \frac{Funds\ from\ operations}{Total\ liabilities} + 0.285\, (=1\ if\ net\ loss\ for\ last\ two\ years, 0\ otherwise) - 0.521\, \frac{(Net\ income_t - Net\ income_{t-1})}{\lvert Net\ income_t - Net\ income_{t-1}\rvert}$
Risk-free rate	R_f	In theory, it is the return on asset that bears no risk. In practice, it is usually the safest asset available and guaranteed by the government, for example, the US Treasury Bill or the UK LIBOR 1-month.
Small-minus-Big	SMB	The mimic the risk factor in returns associated with size (i.e. market capitalization). At the end of July of year *t*, stocks are split into 2 groups by the median. The 1 month allows the factor to capture underlying risks and also avoid possible

		biases caused by asymmetric way of treating HML and SMB factors. The monthly portfolio returns are value weighted by the market value at the end of June, year *t*. The return differential between the small-cap stocks and the large-cap (i.e. SMB) means to capture the size effect.
Short-term Treasury Bill	T-Bill	As one of business cycle variable, Short-term Treasury Bill for the UK market is the 3-month LIBOR rate of return.
Stock return	R_i	The compound rate of return of stock *i* in month *t* is computed from Price index using the following formula: $$R_{i,t} = Ln\left(Price\ index_{i,t}\right) - Ln\ (\left(Price\ index_{i,t-1}\right)$$
Term spread	TERM	Term spread is the difference between average returns on long-term and short-term Government bonds (15+ year Gilt and 3-month rate, respectively).
Winner-minus-Loser	WML	The mimic the momentum factor of Jegadeesh and Titman (1993) in returns. 11-month past returns are used to classify the winners from the losers. The return differential between the top 30% stocks and the bottom 30% stocks means to capture the momentum effects. The monthly portfolio returns are calculated at July, year *t* with 1-month lag and value weighted by the market value at the end of June, year *t*.
Z-score		A measure of probability of bankruptcy proposed by Altman (1968). The indicator is given by the following formula. $$\boldsymbol{Z-score} = 0.012\text{X1} + 0.014\text{X2} + 0.033\text{X3} + 0.006\text{X4} + 0.999\text{X5}$$ Where, $$X_1 = \frac{Working\ capital}{Total\ assets}$$ $$X_2 = \frac{Retained\ earnings}{Total\ assets}$$ $$X_3 = \frac{Earnings\ before\ interest\ and\ taxes\ (EBIT)}{Total\ assets}$$ $$X_4 = \frac{Market\ value\ equity}{Book\ value\ of\ total\ debt}$$ $$X_5 = \frac{Sales}{Total\ assets}$$

Appendix 4: Alternative Asset Pricing Models

There are a large number of econometric models designed to explain the variation of asset returns. This section does not ambitiously seek to review all these asset pricing models arisen in the financial modelling history. It rather provides the readers with additional information about some models that could act as the alternatives to those used in this chapter should they are required. The models are listed in the chronological order.

(i) Merton (1973) Intertemporal Capital Asset Pricing Model (ICAPM)

Merton (1973) proposes the ICAPM as an alternative to the CAPM. It keeps the linear form of the CAPM but uses wealth and state variables that allow investors to hedge against potential shortfalls in consumption and changes in future investment opportunities. The theoretical model is based on consumer-investor behaviour which aims to maximise the expected value of the investors' lifetime consumption. Additionally, the ICAPM requires a set of assumptions to hold. For example, apart from usual assumptions of a perfect market (e.g. no transaction costs or taxes), it assumes that investor can trade continuously in time, and the vector set of stochastic state variables is a continuous Markov process.

Merton indicates that the equilibrium relationships among asset returns shown in the CAPM hold only under certain assumptions although this does not imply the ICAPM is more advanced in that sense. However, the ICAPM provides a station for further model enhancement. It allows for other effects than just the market risk to be included, such as changes in investment opportunity set.

(ii) Lettau and Ludvigson (2001) conditional Consumption CAPM

Lettau and Ludvigson (2001) link asset pricing models with economic conditions by looking at the correlation between consumption growth and stocks in different stages of the economy. They assume that risk and risk aversion are high in bad times and the opposite is true in good times. Following these, they conclude that as some stocks are more correlated with consumption growth "in bad times" and they are less correlated in good times, the (C)CAPM should take into account consumption growth. The model considers consumption growth ratio as a conditional variable in (C)CAPM and argues that this conditional version of (C)CAPM performs better than the unconditional model.

In addition, they also re-visit some augmented versions of CAPM, such as a human capital-augmented CAPM proposed by Campbell (1996) and Jagannathan and Wang (1996), and general conditional factor version of CAPM. They show that as previous studies did not test a conditional version of their models, the final conclusions might not valid.

(iii) Cooper's (2006) model

Cooper (2006) introduces a continuous time dynamic model based on real options. Fundamentally, the methodology is derived from the Fama and French (1993) model by using realised returns as the dependent variable and log(B/M) and log(MV), instead of HML and SMB, as proxies for B/M and size effects. In terms of methodology, their models are fundamentally similar. However, unlike the three-factor model, Cooper's (2006) method relies heavily on two assumptions: (a) Firm's investment is irreversible; (b) Firm faces quasi-fixed as well as proportional adjustment costs of investment. Thus, this more recent model does not necessarily outperform the conventional model.

(iv) Hahn and Lee (2006)

Hahn and Lee (2006) propose the usage of ΔDES and ΔTERM as an alternative set of variables to capture the value effect. ΔDES is the difference between default spread (DES) at year *t-1* and this at year *t*. ΔTERM is the difference between term spread (TERM) at year *t* and this of year *t-1*. They define DES as the yield spread between Baa corporate bond index (Bond Index) and 10-year Treasury constant maturity (10yTbill), and TERM as the spread between 10-year Treasury bill and one-year Treasury bill (1yTbill) rates.

To examine the relationship between SMB and ΔDES and HML and ΔTERM in a view to counteract Fama-French factors, Hahn and Lee (2006) document the following 2 regressions:

$$SMB_t = a_1 + b_1 R_{m,t} + c_1 \Delta DES_t + d_1 \Delta TERM_t + e_{1,t} \tag{A.1}$$

$$HML_t = a_2 + b_2 R_{m,t} + c_2 \Delta DES_t + d_2 \Delta TERM_t + e_{2,t} \tag{A.2}$$

They argue that ΔDES_t and $\Delta TERM_t$ are better proxies than Fama-French's factors, SMB and HML.

(v) Petkova (2006)

Petkova (2006) proposes using the Vector Autoregression (VAR) on an asset pricing model augmented from the CAPM with Fama-French's bond-market factors, default spread and term spread, and some other commonly used factors which are shor$t$-term Treasury bill variable (STBill), and Dividend yield (DIV). The regression model is as followed.

$$R_{i,t} - R_{f,t} = \alpha + \beta_m \left[R_{m,t} - R_{f,t}\right] + \beta_{DIV} DIV_t + \beta_{TERM} TERM_t + \beta_{DES} DES + \beta_{ST-Bill} ST - Bill_t + e_{i,t} \quad \text{(A.3)}$$

However, both Hahn and Lee (2006) and Petkova (2006) models might suffer from an econometric problem that could prevent them from drawing a conclusion on a better proxy for risk level in asset pricing models.

The way their controlling variables are built could potentially cause a correlation between the controlling variables. This could result a multicollinearity problem which does not invalidate the model as a whole but the high correlation between regressors, especially in OLS estimation, will call off the predictability power of each correlated individual predictor, and regarding which predictor are redundant with respect to others.

Two points rise to attention. The first is that high correlation between independent variables can damage the accuracy with which each of the variables' slopes is measured (Pastor and Stambaugh 2003). The second issue being that no conclusion on the significance of each regressor can be made. Petkova (2006) furthermore documents the need of a variable to be significant to be important. Unable to determine the significance implies this would mislead many interpretations, such as each factor's role to the regression.

Appendix 5: VBA programming code

A.5.1. Computing CHS in Visual Basic for Applications (VBA) programming language

Calculating CHS variable can be complex and time-consuming. Hence, in this section we propose the use of a set of programming codes written in VBA – a programming language in Excel – that can be used to compute values of the CHS variable. While there may be other programming languages that can perform the same tasks, the following VBA procedure provides a simple and quick way for researchers and practitioners to apply the theoretical CHS algorithm in their analysis. It should be viewed as a practical tool not the only mean to reach the results reported later in Chapter 4. See section A.5.2 of this Appendix for the detail VBA code written to calculate the CHS score in this thesis. The code is broken down into 3 sub-sections that correspond to Steps 2(a), 2(b) and 3 of the below procedure. Steps 1 and 4 are mandatory for any functions, and therefore, have already been incorporated in the other steps.

Step 1: Setting the scene

In VBA, the first step is letting VBA know where the data source and relevant variables are. This can be done using functions: *Workbooks (). Active* to open an active worksheet where input data are stored, *Sub* to introduce a new procedure and *If* to open a loop condition.

Step 2: Defining function

This step is divided into 2 parts: estimating vector parameters of the logit regressions and then computing the conditional probability of default.

a) Calculating **Logit** value

- A Logit regression (equation 2.13) estimates on a set of predictive variables, $x_{i, t-1}$, and reports vector parameters for the regressions. Predictive variables include: NIMTA (Net Income over Market value of Total Asset), TLMTA (Total Liabilities over Market value of Total Asset), EXRET (Logarithm of gross excess return over value weighted FTSE350 return), RSIZE (Logarithm of firm's market value over the total value of FTSE350), SIGMA (Standard deviation of firm daily stock returns over a period of three months), CASHMTA (Cash and short-term investments over the market value of total assets), and

MTBV (Firm's Market to book value). This simple linear regression can be run in any statistical packages.

- VBA functions: Based on the estimated vector parameters, the next step is calculating *Logit* value, whose formula is given in model (2.14). Since there are 79,246 firm-month observations, VBA will run 79,246 loops and produce *Logit* values.

b) Calculating the conditional probability of bankruptcy (i.e. **CHS score**)

CHS score can be computed using a similar VBA set of commands to Step 2(a), but using formula given in model (2.15) instead. The resulted values are recorded in VBA under the variable named *CHS*.

Step 3: Matching CHS score to firms each year

Once CHS scores are calculated, it is a time-consuming task to match each CHS score to the correct firm and month. These are usually in 2 different workbooks (in this thesis, they are named *CHS score* and *CHS.Each firm*). The VBA code for this is *Sub Match*.

Step 4: Completing the loops

A common coding error is leaving a loop unclosed. If that happens, a compile error will occur and the program cannot be run. For example, when an *If* condition is unclosed, VBA will show an error message that reads "*Block If without End If*".

To exit *Sub* and *If* commands, VBA uses *End Sub* and *End if*, respectively. A simple rule of completing the loops is that the number of *End* commands should be the same as the number of *Sub* and *If* statements.

A.5.2. VBA code

Step 1: Calculating *Logit* value

```
Workbooks("CHS score").Activate
Sub CHS() ' Computer Logit score
   Dim i, j As Integer
   For i = 1 To Range("Logit").Rows.Count
      For j = 1 To Range("Logit").Columns.Count
       If IsNumeric(Range("NIMTA").Cells(i, j).Value) = True And _
         IsNumeric(Range("TLMTA").Cells(i, j).Value) = True And _
         IsNumeric(Range("EXRET").Cells(i, j).Value) = True And _
         IsNumeric(Range("SIGMA").Cells(i, j).Value) = True And _
         IsNumeric(Range("RSIZE").Cells(i, j).Value) = True And _
         IsNumeric(Range("CASHMTA").Cells(j).Value) = True And _
         IsNumeric(Range("MTBV").Cells(i, j).Value) = True And _

Range("Logit").Cells(i, j).Value = -4.0127 - 2.6719 * Range("NIMTA").Cells(i, j).Value _
+ 0.3361 * Range("TLMTA").Cells(i, j).Value – 1.8506 * (Range("EXRET").Cells(i, j).Value) _
- 0.2017 * (Range("RSIZE").Cells(i, j + 2).Value + 1.5289 * Range("SIGMA").Cells(i, j).Value  _
- 2.0152 * Range("CASHMTA").Cells(i, j).Value     + 0.4170 * Range("MTBV").Cells(i, j + 2).Value

Else: Range("Logit").Cells(i, j).Value = "x"
      End If

      Next j
   Next i
End Sub
```

Step 2: Calculating the conditional probability of bankruptcy (*CHS score*)

```
   Dim i, j As Integer
   For i = 1 To Range("CHS").Rows.Count
      For j = 1 To Range("CHS").Columns.Count
       If IsNumeric(Range("Logit").Cells(i, j).Value) = True And _

Range("CHS").Cells(i, j).Value = 1/ (1+ e^ (- Logit)).Value

Else: Range("CHS").Cells(i, j).Value = "x"
      End If

      Next j
   Next i
End Sub
```

Step 3: Matching CHS score to firms each year

```
Function CountFirms()
   Dim m, i As Integer
   m = 0
   i = 1
   Do While IsEmpty(Cells(i, 1)) = False
       m = m + 1
       i = i + 1
   Loop
   CountFirmssheet = m - 1
End Function

Sub Match CHSvalue()
   Dim n, i, j, k, f, e, b, a As Integer
   Dim h, c, t As String
   Dim g As Date
   Dim d As Integer
   Dim ws As Worksheet
   Dim s As Boolean

Workbooks("CHS score").Activate
```

```
    Sheets("CHS").Select
    a = Range("Code").Rows.Count - 1
    b = Range("CHS").Columns.Count

Workbooks("CHS.Each firm").Activate
    For Each ws In Worksheets
        Workbooks("CHS.Each firm").Activate
        ws.Select
        f = 0
        n = CountFirmssheet

     For i = 1 To n
Workbooks("CHS.Each firm").Activate
            ws.Select
            h = Cells(i + 1, 3).Text

'If IsEmpty(h) = False Then

                "Workbooks("CHS.final").Activate
                "Sheets("CHS").Select
                "a = Range("Code").Rows.Count - 1
                For j = 1 To a 'or Range("Code").Columns.Count

                Workbooks("CHS.final").Activate
                Sheets("CHS").Select
                c = Cells(j + 4, 3).Text

If h = c Then
                    "Workbooks("CHS.final").Activate
                    "Sheets("CHS").Select
                    "b = Range("CHS values").Columns.Count

                     Workbooks("CHS.Each firm").Activate
                        ws.Select
                        g = Cells(1, 5).Value

                    For e = 1 To b
                      Workbooks("CHS score").Activate
                        Sheets("CHS").Select
                        'Range("CHS values").Select
                        d = Range("CHS values").Cells(1, e).Value 'k   'd = Date(t)

 If d = Year(g) - 1 Then
                      k = e
                      Workbooks("CHS score").Activate
                            Sheets("CHS").Select
                            'Range("CHS values").Select
                            f = Range("CHS values").Cells(j + 1, e).Value
 'If IsEmpty(f)= False Then

                       Workbooks("CHS.Each firm").Activate
                                ws. Select
                                Cells(i + 1, 4).Value = f
                                Exit For
                            'Else: Exit For
                       End If
                     Next e
                Exit For
                End If
            Next j
         'End If
        Next i

Next ws

End Sub
```

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