

Industry Concentration and Stock Returns:
Evidence from Publicly Listed Firms in the
U.K

Nawar Hashem

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DECLARATION

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

Signed:

Student_____ Date_____

Supervisor_____ Date_____

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ABSTRACT

In this dissertation, I examine the relationship between market structure and average stock returns in the London Stock Exchange during 1985 and 2010. Using Multifactor asset pricing theory, I test whether industry concentration is a new asset pricing factor in addition to conventional risk factors such as beta, size, book-to-market equity, momentum, and leverage. I find that industry concentration is negatively related to average stock returns in all Fama-MacBeth cross-sectional regressions, even after controlling for beta, size, book-to-market equity, momentum, and leverage. In addition, there is strong evidence of a growth effect. Firms or industry portfolios with smaller book-to-market equity ratios have significantly higher returns. In contrast, beta is never statistically significant. The above results are robust to firm- and industry-level regressions, and the formation of firms into 100 size-beta portfolios. The time-series results show some evidence that industry concentration premium contains separate information compared with other risk premiums or risk factors and helps explain the time-series variation in stock returns, even after accounting for the premiums of beta, size, book-to-market, momentum, and leverage. The empirical findings indicate that competitive industries earn, on average, higher risk-adjusted returns than concentrated industries. An explanation is that investors in more competitive industries require larger return premiums for greater distress risks associated with these industries.

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CHAPTER ONE

INTRODUCTION

One of the most important issues in investment is estimating stock returns. Although risk-return relationship proposes that risky investments should reward higher returns compared to risk free investments, it is with the development of rational assets pricing theories that economists have become capable of measuring risk-return relationship. In this regard, rational theories in asset pricing explain stock returns by determining the source of risk factors supported by theoretical assumptions. Examples of rational asset pricing theories include Capital Asset Pricing Model (CAPM) by Sharpe and Lintner (1964-5), Intertemporal Capital Asset Pricing Model (ICAPM) by Merton (1973a), and Arbitrage Pricing Theory (APT) by Ross (1976). In addition, Berk (1995) advances theoretical assumptions to justify the ability of market capitalisation in explaining expected stock returns.

However, there is a voluminous number of empirical studies indicates contradictory empirical results with rational asset pricing theories signifying either market inefficiency or possibility of essential errors in rational asset pricing models. For instance, Basu (1977) reports that firms with high earning-to- price' ratios (E/P) earn higher abnormal returns. In addition, Banz (1981) documents a size effect, noting that smaller size firms tend to earn higher returns compared to large size firms. In 1985, Rosenberg, Reid, and Lanstein observe the existence of value effect (Book-to-Market) in the US stock market acknowledging that firms with high book-to-market value earn higher abnormal returns. Fama and French (1992) assess the joint effects of previous factors in one model documenting the existence of both size and book-to-market effects. In fact, scholars refer to these empirical results as anomalies, since these results do not have theoretical

support. More specifically, anomalies refer to a significant difference between realized returns on assets and predicted returns by a focal asset pricing theory.

In the light of such findings regarding rational asset pricing models and stock market anomalies, there is scope for investigating new asset pricing factors. Therefore, in this dissertation, I examine the relationship between industry concentration and the cross-section of stock returns in the UK stock market between 1985 and 2010. Using creative destruction and barrier-to-entry hypotheses, I empirically test whether industry concentration is a new asset pricing factor in addition to conventional market beta, size, book-to-market, momentum, and leverage. Initially, if industry concentration captures the cross-section of stock returns, I should expect a better asset pricing model in explaining expected stock returns.

Although Hou and Robinson (2006) show that industry concentration is a priced risk factor in the US stock market, existing studies in asset pricing have not used industry concentration as a new pricing factor in the UK stock market. Therefore, I will collect data from the London Stock Exchange (LSE) through one main resource, namely; DataStream. Furthermore, I will build upon the reported findings of Hou and Robinson (2006) to evaluate the impact of industry concentration on stock returns in the UK. Empirically, I will employ industry concentration factor along with conventional stock market anomalies and risk factors to see whether and to what extent industry market competition explain stock returns beside other risk factors and stock market anomalies.

1.1 Motivation

A large and growing body of empirical asset pricing literature has accounted for different stock market anomalies and risk factors to explain the cross-section of stock returns (see for Basu, 1977; Banz, 1981; Rosenberg, Reid, and Lanstein, 1985; and Fama and French

1992-1993). These studies apply different asset pricing models. While some models ascertain that macro-economic factors have a major role in pricing securities (e.g., Arbitrage Pricing Theory APT by Ross 1976), others propose different factors related to the firms' fundamental characteristics (e.g., Fama and French Three-Factor Model).

Noticeably, previous researchers have mainly focused on how to price securities, and how to determine an appropriate model in asset pricing. Although previous researchers document different risk factors and stock market anomalies such as market beta, firm size, book-to-market ratio, earning-to-price ratio, leverage, and momentum; far too little attention has been paid to examine whether industry concentration is as a new risk factor in asset pricing literature.

In a recent study, Hou and Robinson (2006) demonstrates that industry concentration influence average stock returns. Because competitive industries extensively engage in innovation activities and face high distress risk, investors in highly competitive industries will require a positive return premium commensurate with the risk involved. Using data for all NYSE and AMEX firms in the US during 1963 and 2001, Hou and Robinson (2006) examines the relationship between average stock returns and industry concentration, and reports that firms in concentrated industries earn significantly lower return than those in competitive industries, even after controlling for size, book-to-market equity, momentum and other factors. However, Gallagher and Ignatieve (2010) shows that Australian firms in competitive industries earn, on average, lower risk-adjusted returns compared to those in concentrated industries. Therefore, whether and to what extent industry concentration affects average stock returns remains an open empirical question to be further addressed. In this thesis, I test whether industry concentration is a new risk factor in addition to conventional stock market anomalies and

risk factors using data from the UK stock market to find out an appropriate model which prices the securities. Mainly, if industry concentration has different risk characteristics compared to other risk factors and stock market anomalies, I should anticipate that the inclusion of industry concentration in an asset pricing model will enhance the explanatory power of this model in explaining the cross-section of stock returns.

The rationale for investigating the role of industry concentration on stock returns is motivated by theories in industrial organisations that propose the following theoretical assumptions: One of the most important sources of capital for firms is issuing new securities in primary market underwritten by investment bankers. The trading (pricing) of these securities occurs in the secondary market among private investors. Accordingly, since firms' issued securities are priced in financial markets, then the firms' product market structures and their characteristics should have an important role in pricing these securities. Therefore, a possible relationship is the link between market structures of product markets with stock returns. To date, the economic link between product market competition and average stock returns remains relatively unexamined.

The incremental contributions of this thesis are six-fold. First, given that the literature remains inconclusive about the role of market structure in asset pricing, it is necessary to test the link between industry concentration and stock returns using a variety of samples under different institutional settings. This thesis provides one of the first country-specific studies extending the evidence from the US to cover an extensive and more recent period in the UK (1985 to 2010). Second, extant studies on the behaviour of asset prices in the UK have not considered industry structure as a potential source of risk. This thesis is one of the first to link market competition with the average stock returns in the UK. Third, prior research on the cross-section of UK stock returns predominantly uses portfolio

returns formed on firm characteristics. This thesis examines whether market structure includes independent information in explaining the observed differences in average stock returns using both firm- and industry-level regressions. Thus, this thesis also contributes to the empirical asset pricing literature by providing new evidence on the linkage between industry concentration and stock returns. Fourth, prior research on industry concentration and stock returns in the US and Australia uses Herfindahl index as a measure of industry concentration. This thesis is one of the first to utilize Entropy index as a measure of industry concentration besides Herfindahl index to critically evaluate the role on industry concentration on the UK average stock returns. Fifth, prior research on industry concentration and stock returns in the US and Australia has not examined whether industry concentration premium predicts time-series of stock returns. This thesis is one of the first to examine if industry concentration premium explains time-series variation in stock returns in the UK stock market. Sixth, this thesis also tests whether the unexplained part of industry concentration premium by other risk factors and risk premiums explains time-series variation in stock returns, while prior research on market structure and stock returns in the US and Australia has focused on whether industry concentration premium includes independent information compared with other risk factors and risk premiums without considering the role of industry concentration premium in explaining time-series of stock returns.

1.2 Research Aims and Objectives

The aims and objectives of this dissertation are as follows. First, I intend to examine the relationship between industry concentration and the cross section of stock returns in the UK stock market between 1985 and 2010. In particular, I test whether industry concentration is a new risk factor in addition to conventional other risk factors and stock

market anomalies. Moreover, I examine whether and to what extent market competition affects the cross-section of stock returns. My second aim in this dissertation is to model the relationship between industry concentration and the cross-section of stock returns. This in turn will help determine a new asset pricing factor in finance literature. Furthermore, I intend to see whether industry concentration explains stock returns in addition to conventional factors such as market beta, firm size, book-to-market equity, momentum, and leverage. Determining whether industry concentration is a new risk factor in asset pricing will shed additional light on investment performance for both firms and industries. Third, I intend in this dissertation to evaluate investment performance in both firms and industries levels. That is, if industry concentration explains the cross-section of stock returns, I will have a clear answer as to what are industries that earn higher returns. For instance, do competitive industries earn higher returns compared to concentrated industries? If so, how empirically can this be proved? Fourth, besides linking industry concentration and stock returns, I intend to examine the implications that might be drawn on other anomalies and risk factors in the UK stock market. That is, if industry concentration succeeds in explaining the cross-section of stock returns, how other risk factors and stock market anomalies can be affected? Therefore, I test to see whether industry concentration is new risk factors in addition to conventional risk factors and stock market anomalies in the UK stock market applying different time-series and cross-sectional regressions. In order to link industry concentration with the cross-section of stock returns, I will make use of theories in industrial organizations, especially those theories based on ‘creative destruction’ and ‘barriers to entry’ hypotheses.

1.3 Research Questions

This research intends to shed additional light on the answers to the following questions. First, what determines the cross-section of stock returns in the UK stock market? Second, can industry concentration be a new risk factor in addition to conventional stock market anomalies and other risk factors? Third, will the results of industry concentration remain significant in explaining the cross-section of stock returns when beta, size, book-to-market, momentum, and leverage are accounted for? Fourth, will the results of industry concentration remain robust to firm-and industry-level regressions and the formation of firms into 100 size-beta portfolios? Fifth, does industry concentration premium contain separate information compared with the premiums of other risk factors in predicting time-series of stock returns? Sixth, can industry concentration premium explain time-series variation in stock returns? Seventh, if other risk factors and risk premiums partly or fully explain industry concentration premium, can the unexplained part of industry concentration premium still predict time-series variation in stock returns? Eighth, how does industry concentration interact with both firm size, and book-to-market to explain stock returns?

This research intends to empirically find out the sources of risk factors and economic forces that determine the cross-section of stock returns in the UK stock market. In fact, this research seeks to see whether industry concentration is a priced risk in the UK stock market in addition to conventional risk factors and stock market anomalies. This in turn will help evaluate investment performance in both firms and industries levels. That is, if industry concentration captures expected stock returns, this will give an answer as to what are the industries that earn higher returns. This research also examines whether industry concentration remains significant when other risk factors and stock market

anomalies are accounted for. In addition, the robustness of the results will be tested using time-series and cross-sectional regression applied on firm-and industry-level and formation of firms into 100 size-beta portfolios.

1.4 Research Hypotheses

There are various potential reasons why the structure of products markets may influence the cross-section of stock returns. For instance, firms generate cash flows through their product markets. In addition, firms' production decisions are based on the equilibrium of product markets. Therefore, firms' production decisions which are based on a specific market structure may affect the risk of firms' cash flows and consequently the firms' equilibrium rate of returns (Hou and Robinson, 2006).

Theories in industrial organisations specify two main channels where the structure of product markets may influence stock returns. Those channels are based on the following hypotheses: creative destruction hypothesis and barriers to entry hypothesis (e.g., Hou and Robinson, 2006).

The first hypothesis concerning creative destruction is related to innovation risk. In particular, Schumpeter's creative destruction hypothesis (1912) states that competitive industries are more likely to engage in innovation compared to concentrated industries. Therefore, if innovation is risky, and if this risk is priced in financial markets; then competitive industries should earn, on average, higher returns compared to concentrated industries. I illustrate the relationship between the structure of product markets and stock returns through the channel of innovation risk as below.

Competitive industries → more innovations → higher risks → higher returns

The second hypothesis is the barriers to entry which is related to distress risk. The hypothesis states that if barriers to entry in product markets affect firms, I should expect distress risk to fluctuate with market structure. That is, if barriers to entry in product markets expose some firms to aggregate demand shocks, while protecting other firms, then I would anticipate distress risk to fluctuate with market structure. Therefore, if industries are highly concentrated, then the barriers to enter into a market are high (less distress risk), leading the stock returns to be low. I can illustrate the relationship between the structure of product markets and stock returns through distress risk channel as below.

Concentrated industries → high barriers to entry → less distress risks → less returns

In summary, there are two main channels where the structure of product markets may have implications on stock returns. One channel is through innovation risk, while the second channel is through distress risk. Previous channels indicate that while highly concentrated industries are associated with high barriers to entry (less degree of distress risk); competitive industries are more likely to acquire innovations (high degree of innovation risk). Therefore, I propose the main research hypotheses as follows:

The Null Hypothesis (H0): There is no relationship between industry concentration and cross-section of stock returns.

The Alternative Hypothesis (H1): There is a negative relationship between industry concentration and the cross-section of stock returns after controlling for market beta, firm size, book-to-market, leverage, and momentum.

1.5 Empirical Results

The findings of thesis can be summarized as follows: First, industry concentration is negatively and significantly related to the expected stock returns in all Fama and

MacBeth cross-sectional regressions. Moreover, the negative relationship between industry concentration and expected stock returns remain significantly negative after beta, size, book-to-market, momentum, and leverage are accounted for, while beta is never significant. The results are robust to firm- and industry-level regressions and the formation of firms into 100 size-beta portfolios. The findings indicate that competitive industries earn, on average, higher returns compared to concentrated industries which is consistent with Schumpeter's concept of creative destruction. Second, book-to-market is negatively related to the cross-section of stock returns in all cross-sectional regressions. In addition, leverage is negatively related to cross-section of stock returns on firm level analysis, while momentum is positively related to the cross-section of stock returns on industry level analysis. Third, the time-series results show that industry concentration premium is not subsumed by other risk factors in all time-series regressions, and industry concentration premium can explain the time-series variation in stock returns. Moreover, if various risk factors subsume industry concentration premium, the unexplained part of industry concentration premium can still explain time-series of stock returns. In other words, industry concentration premium has independent information compared with other risk factors in predicting the time-series variation in stock returns. Fourth, the results indicate that small companies operating in highly competitive industries earn on average higher returns compared to small companies operating in highly concentrated industries. On the other hand, large companies earn on average higher stock returns when they operate in highly concentrated industries compared to large companies that operate in highly competitive industries. The results also demonstrate that when both industry concentration and book-to-market decrease; the average stock returns increase. The aforementioned empirical findings are robust and not sensitive to a change in industry concentration measures.

1.6 Structure of the Dissertation:

The overall structure of this dissertation takes the form of seven chapters, including this introductory chapter. Chapter Two discusses empirical asset pricing literature and explains the economic link between the structure of product markets and stock returns. Chapter Three explains multifactor asset pricing theory and the main statistical hypotheses. Chapter Three also entails a detailed description on the empirical methods. Chapter Four describes the data, the variables, and the sorting methods. Chapter Five reports the empirical results from the cross-sectional regression for the relationship between industry concentration and stock returns. Chapter Six presents the results from the time-series regressions. Finally, Chapter Seven concludes and reports the implication of this research, limitations, and areas for conducting further research.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

During the past 50 years, there has been an increasing amount of empirical asset pricing studies based on the US markets, documenting various stock market anomalies. For instance, Sharpe (1964) and Lintner (1965) report the impact of excess returns on market portfolios (Beta) on the cross-section of stock returns using the Capital Asset Pricing Model. Basu (1977) detects the effect of earning-to-price (E/P) ratio on average returns. Banz (1981) documents size effect. Rosenberg, Reid, and Lanstein (1985) observe the existence of value effect (Book-to-Market ratio) in the US stock returns. Fama and French (1992) examine the previous factors in one model. However, in 1993, Fama and French report their well-known three-factor model including size (SMB) (small minus big size portfolios), value (HML) (high minus low value portfolios), and excess returns on market portfolios. After Fama and French two models (1992, 1993), several attempts have been made to verify and validate their academic work. For instance, Black (1993), Kothari, Shanken, and Sloan (1995), and Shumway (1997) document that Fama and French' data suffer from data snooping and survivorship bias. Conversely, Barber and Lyon (1997) conclude that Fama and French three-factor model is valid and the results are conducted using biasfree data. With regard to momentum effect, Jegadeesh and Titman (1993), Lakonishok, Shleifer, and Vishny (1994) report the existence of momentum and value stock strategies in the US.

In terms of the UK market, the empirical asset pricing studies are not as voluminous as that in the US. Moreover, the UK asset pricing literature appears to be contradictory compared to the US studies. For instance, while value, size, and momentum effects appear in the US empirical studies (e.g., Fama and French 1992, Jegadeesh and Titman

1993); the UK empirical studies remain ambiguous to document the effects of different stock market anomalies. For instance, Miles and Timmermann (1996), Strong and Xu (1997), Malin and Veeraraghavan (2004), and others show that size effect does not exist. Other researchers including Charitou and Constantinidi (2003), and Leledakis, Davidson, and Smith (2004) find that size effect exists. In terms of momentum effect, Liu, Strong, and Xu (1999) indicate that momentum effect plays a vital role in the UK stock exchange. However, Hon and Tonks (2003) reveal that momentum effect is not a general feature of the UK stock market.

After the introduction of the previous empirical asset pricing studies in the US and UK markets; in the next subsections, I intend to review empirical asset pricing literature in the US market. Afterwards, I will review the UK related studies in asset pricing. Subsequently, I will discuss empirical literature based on markets in other countries. Finally, I will explain the economic link between the structure of product market and stock returns.

2.2 Empirical Asset Pricing Literature Based on the US Markets

A considerable number of studies in the field of finance have attempted to explain the cross-section of stock returns. Some studies link different factors with stock returns. In fact, the majority of these factors are related to firms' characteristics such as firm size, earning-to-price ratio, book-to-market ratio, leverage, momentum, etc. In order to have a clear idea on asset pricing literature based on the US market; this section intends to review and discuss aforementioned literature. This section also compares and contrasts various empirical studies.

Since the capital asset price model (CAPM) has come into existence, many studies have attempted to argue whether beta of the (CAPM) is dead or is still alive. Since beta could

not explain much of the cross-section of stock returns; early empirical works show different factors have significantly explained the cross-section of stock returns. For example, Basu (1977) links the cross-section of stock returns to earning-to-price (E/P) ratio. The author contends that when stocks are sorted according to earning-to-price ratio, stocks with high (E/P) ratio will have higher expected returns. The study has been carried out between 1956 and 1971 using firms that trade in the New York Stock Exchange (NYSE). Theoretically, it seems that the (E/P) ratio captures the cross section of stock returns. In particular, when earning on stocks increases relative to their prices, investors will demand higher (E/P) ratio, leading stock returns to increase.

Subsequently, Banz (1981) identifies firm size as an important factor in explaining the cross-section of stock returns. The author applies market capitalization as a proxy for firm size. Banz also concludes that when firms are sorted according to size portfolios, firms with small size portfolios tend to have, on average, higher returns compared to firms with high size portfolios. Although firms' size reflects public information in stock market, the author finds an inverse and significant relationship between firms' size and the cross-section of stock returns.

While Basu (1977) and Banz (1981) look at the (E/P) ratio and size effect respectively, other researchers such as Rosenberg, Reid and Lanstein (1985) examine book-to-market ratio as a predictor of the cross-section of stock returns. The authors show that stocks with high book values relative to their market values tend to have, on average, higher stock returns. Subsequently, Bhandari (1988) analyses the role of leverage on the cross-section of stock returns using data from the Centre for Research in Security Prices (CRSP) between 1970 and 1979. The author uses debt-to-equity ratio as a proxy for leverage. The author claims that when firm size and beta are controlled, firms with high

leverage tend to have, on average, higher returns. This is because when the debt increases in firms, the risk on equity will increase. Therefore, this demands to increase the required rate of returns.

In a following and consistent study on firm size effect, Chan and Chen (1988) use firm size reported by Banz (1981) to explain the cross-section of average returns in the NYSE between 1949 and 1983. The authors note that after controlling market beta, size can capture significant percentage of the cross-section of stock returns. The authors find that when beta affects stock returns, the relation between beta and average stock returns tend to be biased. This might be due to the error included on the estimated beta portfolios. The researchers suggest using portfolios formed on size, as it is highly correlated with risk. Therefore, the researchers can test whether or not the cross-section of average returns can be explained by one factor model by using beta or size portfolios.

In contrast to Bhandari (1988) and Chan and Chen (1988), Berk (1995) argues that the firm size should not be regarded as an asset pricing anomaly. While the anomaly implies that the observed facts from the test cannot be justified according to some theories, the author advances a theory to justify the link between firm size and stock returns. In fact, the proposed theoretical assumption for the link between firm size and stock returns comes from the theoretical negative relation between market value of stocks and firm's risks. That is, if firm is big, market value tends to be high. On the other hand, if firm is risky, the market value tends to be low. Accordingly, if the market values of the equity are small, the firms will encounter more risks. Provided that firm size and risk are not being positively correlated, therefore, the author suggests that when firm size and risk are not linked, the logarithm of the market value would be negatively associated with anticipated returns. In addition, in the case of miss-specified asset pricing model, if size

and predicted returns in firms are not positively related, the unpredicted part of the returns will be negatively related to the logarithm of the market value.

As a consequence of those previous studies implemented by Basu (1977) and Banz (1981), Rosenberg, Reid and Lanstein (1985), and Bhandari (1988), a dramatic revolution has occurred in finance literature based on a new direction of Fama and French (1992) empirical model in which they examine all previous factors in a cross-sectional analysis of stock returns. The authors collectively use earning-to-price ratio, book-to-market ratio, leverage, beta, and firm size as explanatory factors in describing the cross-section of stock returns. The findings confirm that during the period 1963 to 1990, the cross-section of stock returns appear to be significantly explained by firm size and book-to-market ratio. The authors show that the relation between market beta (excess return on the market portfolios) and stock returns is positive and linear concluding that the Capital Asset Pricing Model (CAPM) holds. The authors attributed this due to the high correlation between size and beta. To eliminate the high correlation between beta and size, beta has given permission to diverge in a way that is not associated with size by forming portfolios on size and betas. As a result, the link between stock returns and size becomes strong, while the relationship between beta and stock returns is vanished.

As a result of Fama and French findings, a considerable number of studies have been trying to verify the validity of Fama and French results. While some studies have tried to invert their findings claiming that their used data suffer from survivorship biases, other studies have tried to confirm Fama and French (1992) empirical findings. For instance, Davis (1994) studies the cross-section of stock returns in the pre COMUSTAT era, which is survivorship bias-free between 1940 and 1963. The author uses book-to-market ratio, earning yield, cash flow yield, and firm size to account for the cross-section of stock

returns. The small firms with low stock prices are not included in the sample of the study. The reported results reveal that individually book-to-market ratio and earnings yield can explain stock returns using single regression. If variables such as natural logarithm of book-to-market ratio, earnings yield, and cash flow yield are all included in the regressions; the process of marginally estimating the explanatory power of each variable on the cross-section of stock returns will become difficult, as the aforementioned variables will suffer from the correlation caused by the prices. On the other hand, small firm size tends not to have an explanatory power in explaining the cross-section of stock returns. This is due to the exclusion of small firms with low stock prices from the sample. According to the author, the reported results between 1940 and 1963 in the period of Pre-COMPUSTAT era are consistent with Fama and French (1992) results in which they use the COMPUSTAT database from (1963). This leads to the judgment that the reported relationship between book-to-market ratio, earnings yield and other variables with the cross-section of stock returns do not clearly appear to be as a result of survivorship bias. This could be seen as a support of Fama and French (1992) model.

On the other hand, other studies have been trying to prove that there is a survivorship bias in the COMPUSTAT data used in Fama and French (1992) model. For instance, Kothari, Shanken, and Sloan (1995) report this bias. The authors examine a sample of listed firms in the Centre for Research for the Security Prices (CRSP) that is on the COMPUSTAT; and on the other hand, the authors examine other firms on the (CRSP) that are not on the COMPUSTAT. The researchers conclude that there exists survivorship bias, as the annual returns for small firms' size in the sample of COMPUSTAT are, on average, significantly higher compared to those firms that are not on the COMPUSTAT. According to the authors, when scholars are using annual returns and betas are estimated on annual basis, the regression would give more significant

relation between beta and returns if the monthly returns betas are used in the estimation. Another example of the criticism regarding Fama and French (1992) findings is the one reported by Black (1993). The author argues that in order to get a precise estimate of expected returns, the data should be taken on a large time span, which seems to be a difficult process. The author reports the problem of data snooping as a major problem in estimating average stock returns.

In relation to studies that are related to survivorship bias in COMPUSTAT, Shumway (1997) examines and reports the bias of delisting in the CRSP files in the US markets including NASDAQ, AMEX, and NYSE between 1962 and 1992. The delisted returns are the returns that are calculated after the firms have been delisted due to different factors such as the bankruptcy, capital loss, etc. The author studies this bias reporting that most of the delisting returns are not conducted and missed for the delisted firms in the CRSP file. Therefore, when academics use the CRSP data, the delisted returns for the delisted firms are not calculated and therefore the sample would suffer from the delisting bias, leading to an impact on research findings. The author examines Fama and French (1992) findings by calculating and comparing the delisting returns that are used in CRSP, over the counter data, and the performance related delist (-1). The author sorts the portfolios according to size (10 portfolios), and then each of these portfolios is sorted according to their book-to-market value in an annual basis. The reported results show that delisting returns based on both over the counter data and performance related delists are extremely correlated with size portfolios that are formed according to the CRSP data. Conversely, no correlation has been reported between high minus low book-to-market (CRSP data) and the delisting returns (over the counter and performance related delists). In size formed portfolios, the delisted returns are found to weaken small size returns. However, large size stocks returns are not affected. With regard to book-to-market

portfolios, 1% and 1.7% cut in returns related to the high and low book-to-market respectively are influenced by the performance related delists.

In contrast to these criticisms and in light of examining the effects of firm size, and book-to-market ratio on the cross-section of stock returns for both financial and non-financial firms; Barber and Lyon (1997) show that both firm size and book-to-market ratio have significant effects in explaining the expected stock returns. The reported results do not reveal that COMPUSTAT survivorship bias has a significant impact on estimating size and book-to-market ratio in relation to security returns. This totally contradicts the findings of Kothari, Shanken, and Sloan (1995), Black (1993), and Shumway (1997), since their results show that survivorship bias in COMPUSTAT could not have a precise interpretation for the relationship between size and book-to-market with the cross-section of securities returns.

Another impressive study reported by Fama and French in (1993). Their recent study appears to overcome their entire previous model related problems. The authors advance a new model which addresses the criticism in their 1992 empirical model. To explain the cross-section of stock returns, the authors use book-to-market ratio, firms' size, and excess market returns. The authors find that book-to-market ratio and firms' size can detect the fluctuation in stock returns. However, when the market excess returns is used with previous factors, the constant term tends to be close to zero indicating that market excess returns and other risk factors associated with size and book-to-market appear to have an important role in explaining the variation of stock returns. The authors explain the implications of previous risk factors on stock returns by forming portfolios on the SMB (small size minus big size firms), HML (high minus low book-to-market ratio), and market weighted portfolios.

Inconsistent with Fama and French (1993) three-factor model findings in the US, Ferson and Harvey (1999) examine Fama and French (1993) three factors model. The authors try to improve the predictability power by using economic lagged factors on portfolios that are formed on common stocks in the US between 1963 and 1994. The lagged value of excess returns on three months treasury bills and one-month treasury bills are used in the cross-section of stock returns in addition to Fama and French three factors. Those lagged factors are significant enough to explain cross-section of stock returns. This led to the conclusion that there exists a part of stock returns that cannot be predicted and explained by the three factor model of Fama and French (1993), and this part is significantly explained by the lagged values of interest rates in the short-term. The authors conclude that by controlling the loading factors in Fama and French three factors model, the predictability of stock returns will be better. Nevertheless, there is still an unpredictable part of stock returns which is observed according to the reported errors in the used model.

In a related study to Fama and French (1993) three-factor model, Lewellen (1999) tests the predictability of stock returns using time-series technique in the US stock markets (NYSE, AMEX, and NAZDAQ) between 1964 and 1994. The author uses book-to-market value to see whether this indicator interprets the variation in expected returns. Lewellen finds that book-to-market value predicts expected stock returns, and the three-factor model can interpret the time-series variations in expected returns. However, in applying Fama and French (1993) three-factor model, the author finds that this model cannot interpret the cross-section of stock returns as the constant term was not zero.

Jegadeesh and Titman (1993) analyse the strategy of buying well-fulfilled stocks and selling poorly-fulfilled stocks between 1965 and 1989 in the US stock market. The

strategy achieves high significant returns during the specified period. The authors examine this strategy using portfolios formed on winners (well-performed stocks) and losers (poorly-performed stocks). The results indicate that the winners' portfolios witness positive returns and losers' portfolios witness negative returns. The authors justify that by the following potential reasons. First, this has been due to the overreaction that is caused by buying past winners' stocks and selling past losers' stocks, as this will help to temporarily shift the prices from their long-term rates leading the prices to over respond. Another potential justification is the market inefficiency. For instance, the market may under-respond to the short-term firms' reported information and over-respond to the information, which is related to their long-run expected views.

In an article, Lakonishok, Shleifer, and Vishny (1994) investigate the idea of why high value of book-to-market stocks earns higher returns according to value strategies and vice versa. The authors find out that during the period between 1968 and 1990 in the US, investors tend to buy value stocks (high book-to-market ratio) compared to growth stocks (low book-to-market ratio). This has been due to exaggerated prediction of expected growth rate for growth stocks compared to value stocks as the actual growth rate for the growth stocks has decreased significantly compared to what it was in the past. The authors believe that value stocks involve more risks than growth stocks do. However, this does not account for the higher returns for value stocks compared to growth stocks. The authors assert that investors' demand for low book-to-market ratio (growth stocks) lead the prices to increase and the expected rate of returns on these stocks to decrease.

Consistent with value strategy in the US acknowledged by Lakonishok, Shleifer, and Vishny (1994), Chen and Zhang (1998) investigate the relationship between value stocks and stock returns. The authors find that value stocks earn higher returns. The authors use

three variables including firms that cut 25 % or more from their dividends, leverage as a proxy of financial risk (book debt-to-market equity), and the standard deviation of the earning (fluctuation in the earnings). Previous variables detect the pricing information included in size and book-to-market effects on the cross section of stock returns. The authors formed and ranked portfolios on size and book-to-market respectively in different countries. The inference from the findings is clear; value stocks earn higher returns as those stocks are probably existed in firms that are in distress and financial risks, and in those firms that are expected to have a high level of uncertainty regarding to expected earnings in the future.

He and Ng (1994) examine the role of firm size, book-to-market ratio, and macroeconomic variables on the cross-section of stock returns using NASDAQ and NYSE stocks between 1958 and 1989. The authors assert that book-to-market ratio cannot explain the cross-section of stock returns when other macroeconomic variables are included. However, size effect seems to include macroeconomic risk factors (such as term structure of interest rate, and default factors). This is because when the authors include firm size in the regression, the explanatory power of macroeconomic risk factors is reduced significantly. The authors illustrate the relation between size, book-to-market, and distress risk represented by the dividend cut factor. The authors conclude that distress risk factor has significantly lost its explanatory power when it is included with either size and/or book-to-market. However, when book-to-market (or size) is included with distress risk, the former factor plays a greater role (weaker role) in explaining the cross-section of stock returns. Therefore, the model which includes macroeconomic factors does not capture both the size effect and the role of book-to-market in explaining the cross section of stock returns. While if the model is related to distress factor, book-to-market ratio will have an important power in explaining expected stock returns. Hence,

the authors indicate that both size and book-to-market detect different risk features that are crucial in asset pricing.

Fama and French (1995) study whether there are common factors affect the variability of stock returns as well as the earnings of the firms. The authors find that market and size factors help explain both stock returns and earnings. However, no evidence has existed regarding the ability of book-to-market factor in earnings to influence stock returns. In 1996, Fama and French find that the three factors risk- return relation can explain the variation in stock returns. Those factors are excess returns on market portfolio, SMB (small size minus big size firms), HML (high minus low book-to- market ratio). However, they claim that those factors cannot explain momentum in short-term stock returns. As suggested by Lakonishok, Shleifer, and Vishny (1994), Fama and French (1996) reveal that returns can be observed based upon three-factor model when portfolios are formed on earning-to-price ratio, cash flow-to- price ratio, and sales growth. On the other hand, Fama and French (1996) test their model to see whether the overreaction hypothesis tested and introduced by Jegadeesh and Titman (1993) holds. In this respect, Fama and French (1996) find that the three-factor model does not explain the short-term continuation.

Daniel and Titman (1997) find that firm size and book-to-market ratio are procurators of the distress risk and the latter pushes stock returns to move. However, the writers achieved the conclusion that the characteristics of firms represented by firm size and book-to-market ratio play a vital role in explaining expected returns regardless to risk factor loadings. For instance, the authors give an example about small size and high book-to-market stocks. Their returns are high regardless their risk loadings values. The authors claim that the idea of returns within industries may be co-varied. Therefore, the

loading risk factors may be partially determined by them. As a result, loading risk factors do not explain the expected stock returns. In addition, the authors find that beta of market portfolios does not help explain average stock returns although after controlling other variables represented by firm size and book to market ratio.

Cohen and Polk (1998) divide book-to-market effect into three parts including the intra industry book-to-market, deviation of industry book-to-market from long-term mean, and the mean of the industry in the long term. The writers find that intra industry book-to-market is the only significant factor that has an influence on stock returns.

Davis, Fama, and French (2000) examine the relationship between both book-to-market and size effects on the cross-section of stock returns. The authors examine this relationship to see whether it is risk-compensation relation or whether it is because of investor over-response. The study has been carried out between 1929 and 1997 using industrial firms from NYSE (Moody's Industrial Manuals) and industrial firms listed in the NYSE, AMEX, and NASDAQ in the COMPUSTAT. The authors conclude that book-to-market ratio does a better job compared to firm size in explaining the cross-section of stock returns. In addition, the constant terms of the three factors model tend to be negative and close to zero leading to the rejection of investor overreaction hypothesis in explaining the relation between the industry characteristics (size and book-to-market ratio) and the cross-section of stock returns. This contradicts with the findings proposed by Daniel and Titman (1997) since they provide evidence that this relation is explained by the overreaction model. Davis, Fama, and French argue that this might be due to the period of study covered by Daniel and Titman.

Hawawini and Keim (2000) discuss how beta of Capital Asset Pricing Model does not explain the cross-section of stock returns. The authors show that different variables

account for the cross-section of stock-returns. Although those variables are not being supported by theories, empirical evidence shows that those variables do have an explanatory power in explaining average stock returns. Such variables include firm size, book-to-market ratio, dividend yield, and others. The authors suggest that in order to account for cross-section of stock returns, one should have a multi-factor risk-returns model, as it is empirically proved that beta has done a poor job in explaining average returns.

In relation to size and book-to-market effects that have been examined by Hawawini and Keim (2000), Gutierrez (2001) examines the role of size and book-to-market effects in both the cross-section of stock returns and bond returns. The author investigates whether size or book-to-market is a proxy for distress risk. The author finds that Book-to-market and size effects can both predict the cross-section of bond and stock returns using the Lehman brothers' data between 1974 and 1994 for bond and Pre-COMPUSTAT for stocks. However, the author reveals that the role of book-to-market ratio in explaining the cross-section of stock returns is higher than the size' role. On the other hand, the role of size effect in explaining the cross-section of bond returns is higher than the book-to-market role. The author concludes that in case of distress risks existence in asset pricing, the distress risks are more likely to exist in bond pricing as it is based on default risk (distress). Therefore, the author finds that size effect has the highest chance to be associated with distress risk if compared to book-to-market in case of stock and bond pricing.

Dichev (1998) uses bankruptcy as a proxy for financial risk to assess whether bankruptcy is considered as a systematic risk, i.e. to see whether bankruptcy is considered as a pricing factor in security returns. The author finds that bankruptcy risk within firms is not

having higher returns. Therefore, one implication the author suggests is that other effects on the cross-section of stock returns including size and book-to-market are not as a consequence of the bankruptcy distress risk. The author reports that firms with high distress risk represented by bankruptcy have had, on average, low returns since 1980.

Inconsistent with Dichev (1998), Griffin and Lemmon (2002) investigate the relationship between both book-to-market, and distress risk (represented by O-score, which is a measure of bankruptcy) on stock returns. They find that firms with high distress risk encounter large difference in returns between high and low book-to-market ratios. This difference cannot be explained by the three factors model of Fama and French (1993) or even it cannot be explained by other variables related to economic fundamental analysis, which links some variables to distress risk such as leverage and profitability. The authors justify this by mispricing idea; they assume that firms with high distress risk will have some features that make the firms' securities mispriced by investors.

Bansal, Dittmar, and Lundblad (2002) examine the cross-section of equity returns by using the concept of dividend and consumption. The authors find that consumption based on dividend measurement can account for the cross-section of stock returns. The authors use 30 portfolios formed on size, book-to-market and momentum (10 portfolios for each factor). The cash flow is expressed by the covariance between dividend and consumption. The reported results confirm that low momentum (not well performing companies) and low book-to-market have low cash flow beta and hence low returns and vice versa. In brief, the fluctuation in consumption affects the dividend, which will influence the cross-section of stock returns. The higher the fluctuation, the higher the dividend movement will be, leading to a higher rate of returns.

Korteweg (2004) examines the role of financial leverage on the cross-section of stock returns in the US stock market between 1979 and 2001 using pure capital structure changes. The author uses debt-to-equity ratio as a proxy for leverage. The reported results do not support the claim that highly leveraged firms earn, on average, higher returns. This is because the empirical results revealed a negative relationship between stock returns and highly leveraged firms.

Another example for the inverse relationship between leverage and stock returns in the US is reported by Dimitrov and Jain (2006). The authors apply the hypothesis which states that financial leverage is influenced by economic performance. That is, the increase in the economic performance will lead to a decrease in the financial leverage and vice versa. Moreover, because of some information regarding stock prices is held in the market, one should expect that leverage should be negatively related to the contemporaneous stock returns. This inverse relationship has been supported by the empirical results reported by the authors where the correlation between both leverage and stock returns appeared to be negative. Furthermore, the results seem to be robust after accounting for growth and earning based measures.

In examining the role of idiosyncratic risk on the cross-section of stock returns in the US; Xu and Malkiel (2004) use portfolio residual volatilities to account for the idiosyncratic risk. The authors find that idiosyncratic risk does affect the cross-section of stock returns even after controlling other factors such as size, book-to-market ratio, and liquidity. This has clearly been shown in different countries, particularly in both the US and Japanese equity markets. The authors observe that the explanatory power of idiosyncratic risk is high compared to other factors in asset pricing model. Furthermore, the authors report that including idiosyncratic risk in the model would not affect the power of other factors.

In the United States, and in a more recent study, Hou and Robinson (2006) link the structure of the product markets with stock returns using a risk-based channel. The researchers relate market structure with stock returns using theories in industrial organisations. They use industry concentration as a proxy for market structure. The authors advance two ways through which the structure of product markets is linked to stock returns. One way is called creative destruction asserting that innovation is more likely to exist in the competitive firms compared to concentrated ones. Therefore, the authors hypothesize that if creative destruction can capture the relation between market structure and innovation which involves risks, then concentrated firms would have lower returns compared to competitive firms as the latter tend to involve less innovation which means less degree of risk. The other way the authors use to link the structure of product markets with stock returns is based on the point of structure-conduct-performance (S/C/P), which asserts that expected returns are affected by barriers to entry. The authors hypothesize that highly concentrated industries earn low returns. The authors give evidence that the industry concentration, which is a component of product market, is essential in determining stock returns. The researchers prove that industries with high distress and innovation risks would witness, on average, higher stock returns.

The research introduced by Hou and Robinson (2006) will form a starting point for this dissertation to deeply and widely investigate the economic link between market structures and stock returns based on both firms and industries levels in the UK stock exchange. I will investigate this relation empirically to find a model, which explicitly explains this link. I will also focus on innovation and distress risks based on previous theories in industrial organisations. In addition, I will make use of the early empirical works on finance literature introduced by Fama and French (1992) to economically derive the relation between industry concentration and average stock returns. In fact, for

the purpose of study, I will use different proxies for the industry concentration. This will be explained in details in the methodology section.

2.3 Empirical Asset Pricing Literature Based on the UK Markets

In contrast to the US, there are not many published articles that test asset pricing models using data from the UK. Instead, the majority of the UK empirical studies investigate the existence of stock market anomalies. In order to have a general outline of what have been examined and reported in the UK stock market, I review the UK empirical asset pricing studies comparing and contrasting various applied models and achieved results. In fact, accounting for different studies in empirical asset pricing will give a clear picture of what should be considered in pricing the securities in the UK stock market and worldwide, i.e. considering the role on industry concentration as a new risk factor seems to affect the cross-section of stock returns.

Although several empirical evidences in asset pricing show that various anomalies have existed in different stock markets, the UK empirical asset pricing literature document contradictory results. For instance, while the US literature supports the strong and clear existence of value effect, size effect, and momentum strategy (e.g., Fama and French 1992, Jegadeesh and Titman 1993, and others), the UK empirical evidence remains weak and doubtful to verify the existence of both size effect and momentum strategy. In fact, the documentations of size effect and momentum strategy are contradictory in the UK stock market. For example, Miles and Timmermann (1996), Strong and Xu (1997), and Malin and Veeraraghavan (2004) argue that size effect does not exist in the UK stock market. However, Charitou and Constantinidi (2003), Leledakis, Davidson, and Smith (2004) show the existence of size effect in the UK stock market.

Momentum related studies are also controversial in the UK stock market. For instance, Liu, Strong, and Xu (1999) show the existence of momentum effect. However, Hon and Tonks (2003) find that although momentum effect has existed, the existence of momentum effect is not a general feature in the UK stock market. The authors relate this to the disappearance of momentum effect in the period prior to 1977. Therefore, the existence of momentum effect, in the authors' point of view, is dependent on the entire period of investigation in the UK stock market.

Previous introduction can show the contradiction in the UK empirical asset pricing studies. Moreover, the UK empirical evidence indicates that different periods of investigation might have different results. Since the number of empirical investigations on the possibility of new anomaly existence is becoming extensive, a considerable body of evidence documentation has appeared to verify the effects of anomalies in different stock markets. Therefore, in this section, I review empirical asset pricing literature based on the UK market. I look at working papers and published journal articles in attempt to identify different numbers of stock market anomalies that have been documented and observed in various time-spans. Having mentioned the general characteristics of the UK empirical asset pricing studies, I can precede reviewing related empirical work in asset prices.

One of the earliest studies on the cross-section of stock returns in the UK is reported by Miles and Timmermann (1996) between 1975 and 1990. The authors evaluate the role of some firms' characteristics on the cross-section of stock returns using beta of the (CAPM), book-to-market ratio, market size, leverage, price-to-earnings ratio, and dividend yield. The authors also apply different statistical methods including Fama and French approach in formulating mimicking portfolios. In order to account for conditional

and simple correlation, Miles and Timmermann (1996) employ Fama and MacBeth cross-sectional regression. The main findings confirm that beta of the (CAPM) is negatively and insignificantly related to average stock returns, leading to the conclusion that the Capital Asset Pricing Model does not hold in the UK stock market. In addition, the authors reveal that firm size (market capitalisation) does not play an essential role in pricing the securities. That is, the size effect appears insignificant. However, book-to-market value shows a positive and significant relationship with the cross-section of stock returns. Other factors including: leverage, price-to-earnings ratio, and dividend yield do not show any significance in terms of explaining the cross-section of stock returns. The researchers conclude that some of the Fama and French three factors model are applicable in the UK stock market such as book-to-market ratio and firm size to a lesser extent. However, the authors question why beta does not do a better job in explaining the cross-section of stock returns in the UK compared to other factors.

Clare and Thomas (1995) test the hypothesis of stock returns overreaction. The overreaction hypothesis proposes that stocks that have poor performance in previous periods (e.g., 3 to 5 years) tend to perform well in subsequent periods (e.g., over the coming 3 to 5 years) compared to stocks that have performed well in previous periods. That is, past losers' portfolios outperform winners' portfolios in upcoming periods. The authors use monthly returns data from the UK stock market between 1955 and 1990. The researchers also apply a random sample including up to 1000 stocks in any random year. In testing the overreaction hypothesis, the authors find that poorly-performed stock portfolios outpace the previous well-performed portfolios over the coming two-year periods. However, these differences in portfolios returns seem to be more likely economically insignificant. The researchers relate these differences to firms' size. That is, past portfolios losers tend to belong to small firms' size causing these differences

between losers-winners portfolios. A final demarcation the authors show is that when annual returns are used to test the overreaction hypothesis, the latter will show weaker results. Therefore, the results with monthly data should be regarded with some caution.

In a related study, Strong and Xu (1997) examine the cross-section of stock returns using data from the UK between 1973 and 1992. The authors apply the following factors: beta of the (CAPM), book-to-market ratio, market value of equity (firm size), leverage, and earning-to-price ratio. The authors' essential findings indicate that beta seems to be positive and significant in single regression. However, the inclusion of other factors (e.g., market value or/and other variables) in the regressions destroys beta's explanatory power in explaining average returns. In addition, the authors find that market value does a better job compared to beta in explaining average returns during the period of study. On the other hand, the explanatory power of market value appears insignificant when other factors are included (book-to-market or leverage). Practically, during the study, the authors reveal that book-to-market ratio plays a vital role with leverage in explaining average returns. In performing single regressions, the authors find that book-to-market ratio is positively and significantly related to average returns. However, the market value of equity seems to be negatively and significantly related to average returns.

In 1999, Liu, Strong and Xu examine the role of momentum strategies in explaining the cross-section of stock returns in the UK stock market between 1977 and 1998. The authors examine whether historical returns help to forecast future excess returns (the profitability of momentum strategy). The results show the existence of momentum profits during the period of analysis. The results are also robust and significant. In analysing momentum profits, the authors control different factors that explain expected returns such as: firm size, stock prices, book-to-market ratio, cash earning-to-price ratio,

and expected returns (estimated by using Fama and French three-factor model). Although previous factors play a key role in the UK stock market, they failed to explain momentum profits. Therefore, the authors conclude that the momentum profits in the UK stock market have existed as an autonomous effect. Furthermore, the researchers indicate that momentum effect is not related to other factors' effects since momentum effect has different risk characteristics compared to other risk factors in the UK stock market. Moreover, the authors relate the momentum effect to the late reaction to the industry information or to particular information related the firm characteristic.

In relation to momentum effect in the UK stock market, Hon and Tonks (2003) examine the existence of momentum effect between 1955 and 1996. The authors' findings indicate that momentum effect does not exist between 1955 and 1977. However, the results support the existence of momentum effect in the period after 1977 in both short and medium time-span. The authors relate this due to positive and significant returns difference in winners and losers' portfolios. The authors find that momentum effect is due to sub-sample rather than the whole sample. The authors justify that because stock prices before 1977 have had less fluctuation compared to the period after 1977. Overall, the authors document that momentum effect in the UK stock exchange does exist in the whole period, leading to declaim that momentum effect is not a general characteristic in the UK stock exchange in the entire period of investigation.

Following Lakonishok, Shleifer, and Vishny (1994) in the US, Gregory, Harris, and Michou (2001) investigate why high value of book-to-market stocks earns higher returns based upon value strategies in the UK between 1975 and 1998. The authors examine the investment strategy of buying value stocks and selling glamour stocks. This strategy has benefited many investors of gaining considerable profits. The researchers sort the stock

according to their book-to-market value, earnings-to-price ratio, and cash flow-to-price ratio into deciles. The authors use one variable sort for value and glamour stocks. The mean returns on the deciles for weighted portfolios show that value stocks have had significant returns compared to glamour stocks. On the other hand, when stocks are classified according to past and expected growth (book-to-market, earning price, and cash flow price ratios), the results are consistent with one variable classification. That is, the returns on value stocks exceed the returns on glamour stocks. The authors apply Fama and French three-factor model (1993). The results confirm value strategy using one variable classification in explaining excess returns. However, the excess returns, using Fama and French (1993) model cannot be explained using two factors sort (past growth/ book-to-market value, and past growth/ earning-to-price ratio).

Muradoglu and Whittington (2001) examine whether leverage can predict stock returns in the UK stock market between 1990 and 1999. The authors use gearing ratio as a proxy for leverage and form deciles portfolios according to leverage. The results indicate that the firms in the lowest leverage deciles earned, on average, higher excess returns compared to firms in highest leverage deciles. The authors recommend that investors should direct their investment to low leverage ratios as an attractive investment. Moreover, the firms should make use of low leverage (low debts) as the investors may find that their long-run expected wealth will increase. The findings contradict the hypothesis of Modigliani-Miller assumption 2 which states that average stock returns should increase in the existence of financial leverage. However, in the US stock market, many empirical evidences show that this assumption does not hold. For instance, Korteweg (2004) documents a negative relationship between stock returns and highly leveraged firms. Also, in the US, Dimitrov and Jain (2006) report an inverse relationship between leverage and stock returns.

More recent evidence on role of leverage is reported by Sivaprasad and Muradoglu (2009). The Authors examine the relationship between leverage and average returns in addition to other anomalies and risk factors in the London Stock Exchange between 1980 and 2004. The results are contradictory. While positive and significant relationship between leverage and average stock returns is found in the Utilities sector; the relationship appears to be negative and significant in other sectors such as Consumer Goods, Consumer Services, and Industrial sectors. Moreover, While the positive relationship between leverage and average stock returns is consistent with Modigliani-Miller assumption 2, the negative relationship appears to be consistent with Muradoglu and Whittington (2001), Korteweg (2004), and Dimitrov and Jain (2006) in both the US and UK stock markets. Sivaprasad and Muradoglu (2009) find that the reported positive relationship between leverage and average stock returns might be due to the cheap debt that the firms have acquired, which led the firms to benefit from the cheap credit that is specified for gainful investments. Therefore, the firms in some sectors witnessed high stock returns even after accounting for the cost of the capital.

Fletcher (2001) examines the validity of different asset pricing models in explaining the cross-section of stock returns in the UK between 1982 and 1997. The author applied single factor model, arbitrage-pricing theory, Fama and French three-factor model (1993), and Carhart model. The author tests the mean-variance efficiency for the aforementioned models and examines whether there are either other risks' or non-risks' factors that detect non-priced risk in the excess returns (pricing errors). Fletcher (2001) concludes that the mean-variance efficiency is not accepted. Also, the test for risk factors to capture pricing errors is not accepted for all tested models. On the other hand, the possibility of non-risk factors to capture pricing errors is not normally rejected in

majority of the tested models. Therefore, the author concludes that caution should be taken when researchers apply different multifactor models.

In applying the three-factor model of Fama and French in the UK equity market, Quigley and Sinqurfield (2000) investigate the performance of Unit Trusts between 1978 and 1997. The authors test whether Fama and French three-factor model is applicable in measuring the cross-section of stock returns after accounting for following risk factors: beta, book-to-market ratio, and firm size (market capitalisation). The results show that Fama and French three-factor model did a better job compared to the (CAPM) in explaining average returns. However, the performance of Unit Trust equity managers was under the standard after accounting for previous risk factors. Furthermore, the authors find that small firms did not do a good job in terms of offering higher securities returns compared to big firm' size.

In a related study to the performance of Unit Trusts; Fletcher and Frobes (2002) test whether the performance of Unit Trusts will vary across different performance measurements in the UK between 1982 and 1996. Furthermore, the authors question the possibility of performance change relative to factor benchmark specification. The results show some bias in pricing the returns using different models such as single-factor model (based on the market index), Elton et al, arbitrage pricing theory (APT), Fama and French three-factor model (1993), and Carhart (1997). The authors point out that this bias in pricing the returns will appear when two performance measurements are either applied (Jensen, or /and Ferson-Schadt) on either individual stocks or portfolios. However, the Carhart model performs better compared to other models in explaining small stocks portfolios' returns. The results also indicate that the performance measurements for Unit Trusts differ across various models. For instance, while Unit Trusts appear to do a poor

job when the Fama and French model is used, the Carhart model shows that Unit Trusts did not do a better job compared to alternative passive strategies (portfolios or individual stocks).

Husain, Toms, and Diacon (2002) examine and compare the Capital Asset Pricing model (CAPM) with the Fama and French Three-Factor Model in the UK stock market between 1974 and 1998. The authors compare their results with what have been reported in the US stock markets. The results show that market beta of (CAPM) does not capture the cross-section of stock returns. Rather, the Fama and French Three-Factor model plays a key role in explaining the cross-section of stock returns in the UK stock market. Consistent with the US results, the use of Fama and French Three-Factor model reveals that stocks with high book-to-market value, high Earnings-to-Price ratio, high Cash Flow-to-Price ratio, and low net sales growth have positive slopes on HML portfolios (High Minus Low book-to-market ratio) and vice versa. Since the results in the UK and US are consistent; the authors reject the claim that data snooping problems have existed in the UK stock market. Therefore, the authors conclude that risk premium have existed and it has not been due to data snooping problem.

Dimson, Nagel, and Quigley (2003) examine whether the value premium has existed in the UK stock market between 1955 and 2001. The authors use various factors including book-to-market value, market capitalisation (firm size), and dividend yield. The results show that value premium has existed across small and large market capitalisation (firm size) in explaining the cross-section of stock returns. In addition, dividend yield does a good job in explaining average returns in the UK. The authors point out that in the UK stock market, the small firm size stock is not liquid compared to the small firm size stock

in the US stock markets. Consequently, the transaction cost (trading cost) is an important feature for investment performance in the UK stock market.

Charitou and Constantinidi (2003) examine the three-factor model of Fama and French in the UK stock market between 1991 and 2001. Moreover, the authors investigate whether the firm size and book-to-market value are related to both profitability and performance. The authors use earning-to-book equity ratio and cash flow-to-book equity ratio as proxies for profitability and performance respectively. The results from Fama and French Three-factor model indicate that market factors including size and book-to-market ratio explain the cross-section of stock returns. The explanatory power of book-to-market (HML) predominates the size effect (SMB) one. Moreover, the results show that (CAPM) underperforms Fama and French three-factor model. In addition, while there is a negative relationship between size and stock returns, the relationship between book-to-market and stock returns is positive but it is not apparent for small stocks. The authors conclude that book-to-market does a better job in comparison with firm size in predicting profitability and performance. Furthermore, the authors point out that while high book-to-market indicates continuous poor performance and profitability, low book-to-market indicates the opposite. The authors also find that firm size and book-to-market factors have a role in profitability and performance measurements. Therefore, firm size and book-to-market factors seem to be related to risk factors in stock returns.

Hung, Shackleton, and Xu (2003) examine the (CAPM) and Fama and French three-factor model in the UK stock market between (1979) and (1999). The results show that the (CAPM) model holds in the UK stock market. Furthermore, in testing Fama and French three-factor model, the authors find that although firm size and book-to-market factors are included in the model; beta of the (CAPM) is still significant in explaining the

cross-section of stock returns. The results are inconsistent with other UK studies, which show that beta has no role in explaining the cross-section of stock returns. However, the authors justify their findings by using the methods of Pettengill et al (1995). This method suggests splitting the market up and down in way that negative realised risk premium is assigned to down market, while a positive realised risk premium is assigned to high market. The authors suggest that any test for the (CAPM) which neglects this method will reject the (CAPM) interpretation of positive trade off between average returns and beta. In more interesting findings, the authors state that size factor in the Fama and French three-factor model does not move in a consistent way with the market movements (up and down). For instance, size effect seems to modify itself through high returns that the small stocks had in the down market. However, book-to-market factor seems to be moving symmetrically within the market upward and downward movements.

Recent study in the UK stock market examines whether the research and development expenses (R&D) can capture the variation in the cross-section of stock returns. Al-Horani, Pope, and Stark (2003) examine the role of (R&D) in predicting the cross-section of stock returns in the UK stock market between 1990 and 1999. The authors introduce the (R&D) effect in the UK stock market after the significant existence of (R&D) effect in the US stock market. The authors apply Fama and French three-factor model. The results reveal that accounting (or not) for market value of equity (firm size) and book-to-market ratio; the research and development (R&D) activity is significantly and positively related to the cross-section of stock returns in the UK. The authors conclude that the research and development activities are important in modelling the cross-section of stock returns.

Malin and Veeraraghavan (2004) examine the validity of Fama and French three-factor model in three different countries including France, Germany, and the UK. While the study covers the period between 1992 and 2001 in both France and Germany stock markets, it covers the period between 1991 and 2001 in the UK stock market. The results vary across the aforementioned countries. For instance, while the results in France and Germany show that small size effect and growth effect (low book-to-market) have existed, the results in the UK show the existence of big size effect and growth effect (low book-to-market). The results contradict the Fama and French three-factor model findings that indicate the existence of small size and value stock effects. The authors conclude that investors in both France and Germany should direct their investments towards small size and low book-to-market firms. Moreover, investors should invest in market portfolios since it shows significant excess returns. However, in the UK stock market, the researchers support investing in more big size and high book-to-market firms as well as in market portfolios since that latter shows significant positive risk premium.

Leledakis, Davidson, and Smith (2004) examine the role of firm size in predicting the cross-section of stock returns in the London Stock Exchange Market (LSE) during a 12-year period. The authors use market measure of firm size (market value of equity) and other non-market measures of firm size including book values of total assets and fixed assets, annual sales, and the number of employees. The authors find that market value of equity is significantly and negatively related to average returns. However, when other non-market measures of firm size are used; the firm size cannot capture average stock returns. The results indicate that accounting for non-market measures of firm size does not influence the relationship between market value of equity and average returns. Moreover, the authors find that beta of (CAPM) significantly explains average returns when non-market measures of firms' size are used. However, when market value of

equity is controlled, the beta becomes negative and insignificant. The authors conclude that none of the non-market measures of firms' size has explanatory power in explaining expected stock returns. Moreover, the authors support Berk (1995) interpretation which indicates that the inverse relationship between average returns and market value of equity (market measure of firm size) cannot be seen as result of whole firm size measures with average returns.

Yurtsever and Zahor (2007) estimate the capital asset pricing model (CAPM) in the UK stock market between 1986 and 2005. The authors test whether there is a linear relationship between stock returns and risk using both individuals' securities and portfolios. In addition, the authors examine whether high risks are related to high-expected returns and risk aversion. The results show that the relationship between individual stocks returns and risk is non-linear. However, portfolios returns and risk encounter a linear relationship. With regard to risk-return associations, the authors indicate that while high risk- high expected returns relation is clear in the case of individual stocks, the portfolios returns do not show high risk-high expected returns relation. The authors conclude that the capital asset pricing model (CAPM) does not hold and is not applicable in the UK stock market.

In a very recent study, Fletcher (2007) examines the ability of different asset pricing models to price the idiosyncratic risk in the UK stock market between 1997 and 2005. The author uses different models such as capital asset pricing model (CAPM), conditional (CAPM), consumption-based (CAPM), Fama and French three-factor model, Carhart (1997), and arbitrage pricing theory (APT). The author finds that while linear models do a good job in pricing the systematic risk, the consumption-based models do a good job in pricing the idiosyncratic risk. In addition, in using quarterly returns data,

some consumption-based models play a good role in pricing the systematic risk. Nevertheless, consumption-based models do a poor job in pricing the idiosyncratic risk. The author states that there is a trade off in pricing both risk components using consumption-based models. In using monthly returns; the author points out that the arbitrage pricing theory (APT) is the best linear factor model to explain both systematic and idiosyncratic risks. The author indicates that there is no trade off between both parts of risks when arbitrage pricing theory (APT) is used. Overall, the author finds that many models have some difficulties in pricing the idiosyncratic risk.

In examining the role of new anomaly on the cross-section of stock returns, Lu and Hwang (2007) test the role of liquidity in the UK stock market between 1987 and 2004. The authors use different factors such as firm size, book-to-market ratio, beta, and the liquidity measure (using different proxies). The authors find that size effect is indistinguishable from zero, leading to declaim that size effect do not exist in the UK. The authors indicate that small stocks underperformed big stocks, since the average returns on the big stocks exceed the average returns of small stocks. The results also show that book-to-market ratio is positively and significantly related to average stock returns. With regard to liquidity factor, the results indicate that illiquid stocks seem to be small reporting that illiquid stocks have negative returns, while liquid stock have positive returns. The difference between illiquid and liquid returns is more than 22% using Amihud (2002) measure of liquidity. The size effect as well as the beta of (CAPM) fails to explain the cross-section of stock returns in the UK between 1991 and 2004.

In a recent study, Michou, Mouselli, and Stark (2007) survey various empirical studies in asset pricing, comparing and contrasting different methods in the UK between 1980 and 2003. The authors find nine unique methods in the UK literature to construct (SMB) and

(HML) portfolios based on the works of following authors: Al-Horani et al (2003), Dimson et al (2003), Fletcher (2001), Fletcher and Forbes (2002), Gregory et al (2001), Hussain et al (2002), Liu et al (1999), and Miles and Timmerman (1996). Michou, Mouselli, and Stark (2007) construct SMB and HML portfolios applying all aforementioned methods. The main conclusion points out that caution must be taken when researchers estimate (SMB) and (HML) portfolios. The results indicate that the estimated factors (SMB and HML) show significant differences in their characteristics when applying different methods. Furthermore, the conducted results reveal that the three-factor model of Fama and French (1993) cannot detect perfectly risk premium, since the constant term is significantly different from zero. Therefore, the authors recommend taking more caution in estimating the abnormal returns in the UK stock market.

Overall, although empirical asset pricing literature based on UK market is not voluminous compared to that in the US, one can see significant difference in terms of the applied methods and conducted results. In addition, the existence of anomalies effect in the UK stock market varies across studies that apply different methods and use different time spans. Moreover, the nature of the anomaly is crucial. A clear demarcation is that different methods applied by different academics in the UK stock market led (according to Michou, Mouselli, and Stark, 2007) to different results in constructing size and value factors in the three-factor model of Fama and French. Therefore, I would argue in favour of using different methods when I test the relationship between industry concentration and cross-section of stock returns.

A controversy characteristic of the UK stock market is that anomalies' effects fluctuate across different periods within various studies. For instance, Miles and Timmermann

(1996), Strong and Xu (1997), Malin and Veeraraghavan (2004) and others report that size effect does not exist. On the other hand, Charitou and Constantinidi (2003), Leledakis, Davidson, and Smith (2004) point out that size effect does exist. Moreover, Liu, Strong, and Xu (1999) show the existence of momentum effect. However, Hon and Tonks (2003) show that the existence and persistence of momentum effect is dependent on the entire period of investigation. In addition, several UK studies show that book-to-market effect exists in the UK stock market. For instance, Gregory, Harris, and Michou (2001) reveal the appearance of value strategies (e.g., high book-to-market value stocks earn higher returns in the UK stock market).

With regard to leverage effect in the UK stock market, Muradoglu and Whittington (2001) report an inverse relationship between leverage and average returns. Although Sivaprasad and Muradoglu (2009) find a positive and significant relationship between leverage and average returns in Utilities sector, all other sectors show an inverse and significant relationship between leverage and stock returns which is consistent with Muradoglu and Whittington (2001). In terms of applying the Capital Asset Pricing Model (CAPM) and Fama and French three-factor model (FF 1993) in the UK stock market, Husain, Toms and Diacon (2002), and Charitou and Constantinidi (2003) show that beta of the (CAPM) cannot capture the cross-section of stock returns. Conversely, the three-factor model of Fama and French holds and explains the cross-section of stock returns in the UK. However, Hung, Shackleton, and Xu (2003) show that the (CAPM) holds in the UK. Michou, Mouselli, and Stark (2007) also show that Fama and French three-factor model could not perfectly capture the cross-section of stock returns using different types of empirical studies.

Accounting for different risk factors in the UK stock market will provide precise results in capturing the cross-section of stock returns. Therefore, I test whether industry concentration is a new risk factor in addition to other risk factors and stock market anomalies. I argue that if industry concentration captures the cross-section of stock returns; firms in concentrated industries should earn, on average, lower returns compared to firms in competitive industries. My motives are based on some theories in industrial organisations; namely, creative destruction and barrier to entry hypotheses. Although industry concentration captures the cross-section of stock returns in the US stock market, I test the role of industry concentration in UK stock market using various methods, since the literature in both the US and UK shows difference in terms of anomalies effects and applied methods.

Having reviewed empirical asset pricing literature based on the US, and UK markets, the next subsection reviews asset pricing literature based on other countries empirical studies.

2.4 Empirical Literature Based on markets in other countries

Previous sections describe empirical asset pricing literature based on both the US and UK markets. In this section, I review empirical asset pricing literature based on market in other countries; namely, the Japanese and Australian stock markets. Accounting for various empirical studies in different stock markets will formulate a general picture of stock market anomalies characteristics and identify the possibility of testing industry concentrations as a new risk factor in the UK stock market.

In the Japanese stock market, Chan, Hamao, and Lakonishok (1991) test the relationship between different risk factors and the cross-section stock returns between 1971 and 1988. The authors use both manufacturing and nonmanufacturing firms to examine the roles of

earnings yield, firm size, book-to-market ratio, and cash yield on average stock returns. The results indicate that book-to-market ratio plays a key role in explaining stock returns. In addition, the relationship between cash flow yield and stock returns is positive and significant. The results also show that size effect has existed but seems to be insignificant in explaining stock returns because of model specification. The results reveal a negative and significant relationship between earning yield and stock returns. The authors relate their findings due to either inefficient market or due to asset pricing model specification.

Recently, researchers have shown an increased interest in investigating the role of different risk factors on the cross-section of stock returns in the Australian stock market. However, one question needs to be asked is whether or not similar results in the US stock market hold in the Australian stock market. In fact, it is interesting to notice that in many studies related to Australian stock market, the results are consistent with that in the US. However, in some cases the results appear to be contradictory. For instance, Faff (2001) examines Fama and French three-factor model in the Australian stock market. The authors use daily data exclude risk-free rate from the regressions. The Author finds that the relationship for both beta and book-to-market ratio with the cross-section of stock returns seems to vary in terms of statistical significance. However, when the author controls the risk-free interest rate; both beta and book-to-market ratio have a positive and significant relation with stock returns. The results also indicate that risk premium on size formed portfolios (SMB) is negative and significant which contradicts the results of Fama and French three-factor model in the US stock market.

Chan and Faff (2002) test the role of liquidity on asset pricing in the Australian stock market between 1989 and 1999. The authors use the Fama and French (1992) approach and apply stocks turnover as a proxy for liquidity. The results show that liquidity is

negatively and significantly related to the cross-section of stock returns. In addition, the authors find that although there is a seasonality effect in January and July, the liquidity effect is still negative and significant. Moreover, the authors account for momentum, value and growth effects in the cross-sectional regression. The results also indicate that liquidity effect expressed shares turnover is still negative and significant. The authors conclude that shares turnover is considered as a procurator of liquidity rather than a proxy for value/growth effect.

In relation to liquidity effect, Clayton, Dempsey, and Veeraraghavan (2006) study the cross-section of stock returns in the Australian stock market between 1980 and 2003. The authors find that although beta affects stock returns, controlling firm size will destroy beta's explanatory power. Moreover, the authors indicate that while size effect exists, liquidity effect does not appear on the Australian stock market. The authors conclude that unsystematic risk dominates the liquidity effect to explain stock returns. In other words, small firms seem to have higher returns. Within those small firms, it appears that the small firms with higher unsystematic (idiosyncratic) risk have had higher returns. The results contradict the findings of Chan and Faff (2002) who find that liquidity is negatively and significantly related to the cross-section of stock returns in the Australian Stock Market.

In a more recent study in the Australian stock market; O'Brien, Brailsford, and Gaunt (2008) test whether the Fama and French three-factor model and (CAPM) can explain the cross-section of stock returns between 1982 and 2006. The authors use a new dataset covers 98% of the Australian equity firms over 25 years. Inconsistent with Faff (2001) results, O'Brien, Brailsford, and Gaunt (2008) find that the three-factor model of Fama and French holds in the Australian stock market. The authors find a positive premium on

size formed portfolios (SMB), value formed portfolios (HML), and on the excess returns on the market portfolios. In addition, the authors show that the (CAPM) explains average stock returns. However, the authors indicate that the performance of the Fama and French three-factor model is better compared to the (CAPM) although the constant term in Fama and French three-factor model is insignificant. The authors conclude that investors in the Australian stock market should rely on firm size and book-to-market factors in their trading strategy.

In a recent study, Gallagher and Ignatiev (2010) shows that Australian firms in competitive industries earn, on average, lower risk-adjusted returns compared to those in concentrated industries. The authors test whether the industry concentration premium is subsumed by other risk premiums and find some evidence that industry concentration premium partly includes independent information which already spanned by other risk factors.

Having looked at empirical asset pricing literature based on the US, UK, and other countries, I establish the risk-based channels through which industry concentration may have an influence on the cross-section of stock returns. Therefore, in the next section, I explain some theories in industrial organisations and derive the link between industry concentration and average stock returns. Also, in the next section, I identify the sources of risk forces where the structures of product markets may influence average stock returns.

2.5 Industry Structure and Stock Returns

In this section, I establish the risk-based channels through which industry concentration may have an influence on the cross-section of stock returns. In deriving the risk-based link between industry concentration and average stock returns, I use some theories in

industrial organisations and identify the sources of risk forces where the structures of product markets may affect average stock returns.

There are various potential reasons why the structure of products markets may influence the cross-section of stock returns. For instance, firms generate cash flows through their product markets. In addition, firms' production decisions are based on the equilibrium of product markets. Therefore, firms' production decisions which are based on a specific market structure may affect the risk of firms' cash flows and consequently the firms' equilibrium rate of returns (Hou and Robinson, 2006).

Theories in industrial organisations specify two main channels where the structure of product markets may influence stock returns. Those channels are based on the following hypotheses (Hou and Robinson, 2006):

- 1- Creative destruction (innovation risk)
- 2- The concept of structure-conduct-performance (S/C/P) (distress risk)

Both hypotheses link industry concentration with stock returns. Industry concentration denotes to the properties and the characteristics of an industry. In fact, industry concentration refers to whether or not productions in an industry are controlled by a limited number of firms in the same industry.

In this context, I explain in next sections previous hypotheses indicating how industry concentration may affect the cross-section of stock returns. Also, I derive the link between the structure of product markets (represented by industry concentration) and average stock returns.

2.5.1 Creative Destruction Concept

Schumpeter concept of creative destruction proposes two main assumptions that illustrate the relationship between competition and innovation. The first proposition assumes that competitive firms or firms in highly competitive industries attempt to maintain profitability by engaging in innovation. Therefore, competition induces firms to innovate. The second proposition posits that concentrated firms or firms in highly concentrated industries are likely to engage in innovation, as highly concentrated industries are better able to fund innovation and capture the benefit of innovation compared with highly competitive industries. Therefore, market competition may also induce firms to escape from innovation.

The consequence of the aforementioned assumptions on stock returns depends on which proposition holds. If the Schumpeterian' first proposition holds, then highly competitive firms engage in innovation and face greater innovation risk, as there is a possibility for innovation failure and innovations are not predictable. Therefore, if innovation risks are priced in the financial markets, then highly competitive industries earn higher stock returns than highly concentrated industries. On the other hand, if the Schumpeterian' second proposition holds, then highly concentrated industries engage in innovation and face higher innovation risks than highly competitive industries. Consequently, highly concentrated industries earn higher stock returns than highly competitive industries.

Schumpeter's creative destruction concept (1912) refers to the existence of innovation within firms. The concept is based upon destroying old methods of production and simultaneously creating new ones, which enables firms to compete. The process of destroying old methods and creating new ones should be balanced according to both market size and its movement. In other words, creative destruction involves the creation

in technology and total radical changes in production methods. Creative destruction also implies the innovation within firms in the industries (Carr, 2001:4).

The economic prediction of creative destruction concept (innovation within the firms) refers to the structural characteristics of the firms within industries. For instance, when firms engage in innovation; they will have the opportunity to transform from competing with rivals to a monopolistic position which controls the market. In fact, innovation within firms (e.g., new technology, patent... etc) is one of the determinants of market's power, which involves the degree of competition and monopolistic position of the firms in industries.

In a brief review of related research to innovations and industry market structure (i.e., competitive and concentrated industries), several studies examine the relationship between innovation and competition in the market. For instance, Gilbert (2007: 22) points out that *“Economic theory supports the proposition that competition is more likely to provide greater incentives for product and process innovations”*. This shows that when industry is competitive, innovation tends to increase within the firms in those competitive industries. Consistently, Bundell, Griffith, and VanReenen (1999) find that firms in less competitive industries (or higher concentrated industries) tend to have less degree of innovation. This supports the notion that innovation is positively linked to the degree of competition.

Nickell (1996) uses 670 companies in the UK to examine the relationship between market competition and innovation. The author applies the number of competitors as a proxy for competition. The results indicate that the increase in the number of competitors in the market leads to an increase in the levels of innovative production and hence to an increase in the efficiency growth. Consistent with Nickell (1996), Crespi and

Patel (2008) study the relationship between innovation and competition across different sectors, investigating the role of competition in increasing the firms' innovative performance. The authors find that there is a significant positive relationship between product market competition and innovation. The authors also reveal that previous variables are mutually positively correlated.

To sum up, previous description about the relation between innovation and industry market structure demonstrates that the structure of product markets “competition versus concentration” is related to innovation in the firms within industries. Therefore, since competition and innovation are positively related, (i.e., the innovation increases if the industry is competitive), it is possible to conclude that innovation tends to exist in competitive industries and less exists in concentrated industries. Consequently, I hypothesize the following:

Innovations are risky since there is a possibility of innovation failure within firms as well as innovation is not foreseeable. Therefore, innovations involve risks, and tend to exist in competitive industries compared to concentrated industries. Consequently, if innovation risk is priced in financial markets, one should expect competitive industries to earn, on average, higher returns compared to concentrated industries. This hypothesis is so-called Creative Destruction (Hou and Robinson, 2006).

I illustrate the relationship between the structure of product markets and stock returns through the channel of innovation risk as below.

Competitive industries → more innovations → higher risks → higher returns

2.5.2 Structure-Conduct-Performance (S/C/P) Concept

The other channel to link the structure of product markets with stock returns is through the concept of structure-conduct-performance. According to Church and Ware (2000: 425), the concept assumes that there is a casual relationship: (i) industry structure or characteristics, (ii) conduct of the firms (the ability to price over the marginal cost), (iii) and the performance (market power) of the firms. This casual relation flows from the structure, passing to the conduct, and it ends in performance. That is, the structure affects the conduct and conduct affects the performance. Hence, the structure affects the performance. For instance, if the industry is concentrated (*structure*), firms will behave in a monopolistic way; say, for instance, firms can increase the prices over the marginal costs or increase the amount of output (*conduct*). This, in turn, will lead to a high market power (*performance*).

Looking at the model of structure-conduct-performance, it is possible to notice that each part of this model has its own factors. For instance, the structure factors include the following factors: competition, concentration, barrier-to-entry, demand, and cost. With regard to conduct factors, some of factors are related to pricing strategy, spending on advertising, and differentiated products. Performance factors include profitability as an indicator of market power.

After looking at the characteristics of the Structure, Conduct, and Performance (S/C/P), I show how (S/C/P) paradigm links industry concentration with average stock returns as follows: Hou and Robinson (2006) use the paradigm of (S/C/P) to link industry concentration with stock returns. I, therefore, follow aforementioned authors to generate the Barriers to entry hypothesis as follows.

If barriers to entry in product markets affect firms, I should expect distress risk to fluctuate with market structure. That is, if barriers to entry in product markets expose some firms to aggregate demand shocks, while protecting other firms, then I would anticipate distress risk to fluctuate with market structure. For instance, in concentrated industries where the barrier to entry is high; the increase in demand shocks will lead the firms in concentrated industries either to increase their prices or production to meet this increasing demand without having the risk of new firms' entry (high barrier to entry restrictions in concentrated industries). The subsequent implications of this reaction will appear as an increase in the firms' long-term expected profitability. Accordingly, firms will use this high rate of profitability in the case of economic down-turn. That is, these firms in concentrated industries will have the ability not to exist from the market in the case of economic down-turn. As a result, if the priced risks induced by the increase in demand shocks are related to concept of exit from the industries, the concentrated industries will have low degree of distress risks. In other words, the less distress the risks concentrated firms encounter, the less the average returns the concentrated firms expect. This hypothesis can be illustrated:

Concentrated industries → high barriers to entry → high profitability → ability not to exit from the industry (in the case of economic downturn) → less distress risks → less rate of returns.

To sum up, previous sections establish the link between industry concentration and average stock returns. Following Hou and Robinson (2006), I use two hypotheses to establish the economic link between industry concentration and stock returns. The first hypothesis is the creative destruction, while the second one is the barrier to entry. The former hypothesis uses innovation risk, while the latter hypothesis uses distress risk. If

industry concentration captures the cross-section of stock returns, it is possible to observe that average stock returns decrease when the degree of concentration increases. That is, if industries are concentrated, one should expect lower average returns compared to competitive industries (less concentrated). Accordingly, industry concentration should be negatively related to the cross-section of stock returns.

In order to test previous hypotheses, I tackle this issue empirically. Therefore, Chapter Three explains multifactor asset pricing theory and the main statistical hypotheses. Chapter Three also entails a detailed description on the empirical methods to explain the cross-sectional and time-series variations in stock returns using industry concentration as a new risk factor.

CHAPTER THREE

EMPIRICAL METHODOLOGY

3.1 Theoretical framework

In this dissertation, I will link industry concentration with the cross-section of stock returns using multifactor asset pricing models based on arbitrage pricing theory. The multifactor asset pricing model based on arbitrage pricing theory has been chosen because:

1. Multifactor asset pricing models help to link industry characteristics including firm specific factors with the cross-section of stock returns, which in this research will help to examine the relationship between industry concentration and the cross-section of stock returns.
2. Multifactor asset pricing models based on arbitrage pricing theory will provide the opportunity to use multiple risk factors that are identified through statistical approaches (e.g., factor analysis and principal components) and/or theoretical approaches (e.g., macroeconomic variables, financial market variables, and firms' characteristics variables) (Campbell et al, 1997). Multifactor asset pricing models based on arbitrage theory facilitates the examination of the relationship between security markets and economic forces, as well as providing the ability to test firm specific characteristics and macro-economic factors with stock returns.
3. A main advantage of the multifactor asset pricing model is that it does not specify the nature or the number of pricing factors in the model.
4. In testing the multifactor asset pricing model, one can test for the following versions: Factors that are portfolios of traded assets with the existence of risk free

asset; factors are portfolios of traded assets without risk free asset; factors are not portfolios of traded assets (macroeconomic variables); and factors are portfolios of traded assets and the factor portfolios span the mean-variance frontier of risky assets (Campbell et al, 1997:222).

Based upon previous reasons, which has indicated that the use of multifactor asset pricing theory is essential in illustrating the relationship between the structure of product markets and the cross-section of stock returns; this research is based on the multifactor asset pricing theory. In applying multifactor asset pricing models, I use fundamental factors including financial ratios, accounting ratios, and macroeconomic factors, which in turn help to account for different characteristics to model the relationship between industry concentration and the cross-section of stock returns. The following section will explain the multifactor asset pricing theory.

3.1.1 Multifactor Asset Pricing Theory

In multifactor asset pricing theory, many factors are considered to have an impact on stock returns. In particular, the multifactor asset pricing theory does not specify the number of variables in the model (Groenewold and Fraser, 1997). In multifactor asset pricing models, different factors may have different influences on stock returns. For instance, while some factors might have significant impact, other variables can have an insignificant impact. Accordingly, empirical studies are important to determine the various factors that influence stock returns, and consequently offer a clear indication of both the number and the nature of variables that should be included in the model.

Although the multifactor asset pricing model does not determine both the nature and the number of factors, this can be seen as an advantage. This will provide the researcher with the freedom to choose factors that explain stock returns in the sample and to outline the

impact of specific factors on stock returns, excluding other variables. For instance, if a researcher wants to examine a specific factor or factors on stock returns, he or she could use the multifactor asset-pricing model (e.g., Fama and French, 1993 use firm size, book-to-market ratio, and excess returns on the market portfolios to see whether these factors can explain average stock returns).

The use of the multifactor asset pricing models provides opportunity of explaining individual stock returns as well as portfolios' returns. This facilitates the examination of the link between industry concentration and the cross-section of stock returns in different levels; considering firm and industry portfolio levels. Furthermore, the use of multifactor asset pricing models assists in the employment of different factors such as macro-economic (e.g., inflation rate, interest rate, and gross domestic product), fundamental firm characteristics (e.g., firm size, earning-to-price ratio), and statistical factors (e.g., momentum which refers to historical characteristics of firms' returns.).

The following equation represents the multifactor asset pricing models based upon arbitrage theory (Bailey, 2005:215, and Azeez and Yonezawa, 2006:573):

$$R_{it} = b_{i0} + b_{i1}F_{1t} + b_{i2}F_{2t} + b_{i3}F_{3t} + \dots + b_{ik}F_{kt} + \varepsilon_t, i = 1, 2, \dots, n$$

Where:

R_i : is the rate of return for the stock i

F_{kt} : represents the factor value in the time t

b_{ik} : represents the slope coefficient of the factors that measure the variation of those factors relative to the variation in the stock returns.

ε_{it} : represents the error term (unsystematic risk)

The multifactor model based on arbitrage theory proposes the following (Bailey 2005:191):

1. The number of factors (k) should be smaller than the number of the assets (n).
2. The expected value of unobserved random error is zero, indicating that the unsystematic risk is, on average, zero: $E[\varepsilon_{it}] = 0$
3. There is no correlation in the unsystematic (idiosyncratic) risk among different assets: $E[\varepsilon_{it}\varepsilon_{jt}] = 0$
4. The random error and the factors are uncorrelated: $E[\varepsilon_{it}F_{kt}] = 0$
5. The factors are uncorrelated among each other: $E[F_{kt}F_{mt}] = 0$
6. The rate of return on an asset (i) is linearly related to the factors $F_1, F_2, F_3, \dots, F_n$ (systematic risk) and to unsystematic risk (random error ε_{it})

The arbitrage pricing theory asserts that there is a relationship between the expected returns on an asset (i) and the loading factors (beta coefficients) as follows (Azeez and Yonezawa, 2006:573)

$$E(R_{it}) = \lambda_0 + \lambda_1 b_{i1} + \lambda_2 b_{i2} + \dots + \lambda_k b_{ik}$$

Where:

λ_0 : is the return on the risk-free interest rate.

λ_k : is the market premium for the factor k.

In applying the multifactor asset-pricing models based upon macroeconomic factors or/and fundamental firms' factors, I use the following general derived multifactor model (Amenc and Sourd, 2003:152-153):

$$E(R_i) - RF = \sum_{k=1}^k b_{ik} \alpha_k + \varepsilon_i$$

Where:

$E(R_i)$: represents the expected rate of returns on an asset (i).

RF : represents the returns on the riskless asset.

b_{ik} : represents the value of the factor K that is specific to the firms i.

α_k : represents the coefficient associated with factor K which is related to the market premium for the factor K.

ε_i : is the specific return on an asset i.

3.2 Empirical Model and Hypotheses

I follow Hou and Robinson (2006) to test the following model using Fama and MacBeth cross-sectional regression (1973):

$$\bar{R}_i = \gamma_0 + \gamma_1 \hat{\beta}_i + \gamma_2 H(Sales) + \gamma_3 \ln(Size) + \gamma_4 \ln(B/M) + \gamma_5 Lev. + \gamma_6 Momentum + \nu_i$$

Where:

\bar{R}_i : is the time-series of monthly stock returns in logarithmic form.

β_i : is the measure of risk estimated using market model.

γ_i (i=1, 2, 3...6) is the premium associated with the both risk factors and anomalies effects.

$H(Sales)$: is the Herfindahl index used as a proxy for industry concentration.

$Ln(Size)$: is the annual market value of equity as a proxy for firm size.

$Ln(B/M)$: is the book-to-market equity ratio.

$Lev.$: is the leverage effect (represented by debt to equity).

$Momentum$: is the momentum which is 12 months past returns.

ϵ_i : is the error term from the time-series cross-sectional regression.

The study covers the UK stock market between 1985 and 2010. I test for each variable, and then I control other variables concurrently. Moreover, I carry out the test using the time series averages of each cross-section regression of previous coefficients. The standard t-test will be accomplished as follows:

For more than one factor where $j=6$ (the factors including: the measure of risk, industry concentration, the logarithm of annual market value of equity, the logarithm of book-to-market, leverage, and momentum), I test the following Null Hypotheses for each of these factors:

$$H_0: \bar{\gamma}_j = 0$$

The alternative hypotheses will be:

$$H1: \gamma_j \neq 0$$

It is possible to calculate the t-test as follows:
$$t(y_j) = \frac{\bar{y}_j}{\hat{\sigma}(\bar{y}_j)}$$

Previous test helps illustrate the relationship between industry concentration $H(Sales)$ and the cross-section of stock returns in the existence of other risk factors and stock market anomalies. In addition, previous test helps to see whether the aforementioned relation is significant either it is positive or negative.

Using Multifactor asset pricing theory, I test whether industry concentration is a new asset pricing factor in addition to conventional market beta, size, book-to-market, leverage and momentum based on firm level, industry level, and the formation of firms into 100 size-beta portfolios.

In the next sub-sections, I describe empirical methods including cross-sectional and time-series methods in explaining the variation in stock returns.

3.3 Industry Concentration and the Cross-Sectional Variation in Stock Returns

3.3.1 The Concentration Spread and Industry Average Characteristics

In June each year, I sort the measurement of industry concentration into Quintile portfolios and report summary statistics across concentration quintiles. The main reason for forming Quintiles is to see whether there is a concentration spread between competitive industries and concentrated industries. Moreover, the industry concentration quintile portfolios will give the opportunity to examine the industry characteristics and

financial ratios between the most competitive industries and most concentrated industries. Therefore, I calculate the average monthly returns, average industry characteristics and average financial ratios, explaining the difference between competitive and concentrated industries.

This procedure will give a clear and precise idea to see whether I should control for industry concentration when analysing the cross-section of stock returns on both firm and industry levels.

3.3.2 Fama and MacBeth Cross-sectional Regression

I apply Fama and MacBeth (FM) (1973) cross-sectional regression to test the relationship between industry concentration and average stock returns. Fama and MacBeth (1972) use a simple and robust approach in conducting the standard error for variables. In fact, the (FM) cross-sectional regression uses the time series estimates for the variables in the consequence of the cross-section regressions. Empirically, Fama and MacBeth (FM) (1973) cross-section regression accounts for different risk factors that are expected to have an impact on stock returns. However, one major disadvantage of using (FM) regression is the problem of caveat. For instance, in applying (FM) regression, the test will form factor-mimicking portfolios for independent variables. As a result, when any variable related to firms' characteristics is used in the (FM) regression as an anomaly or as a pricing factor, (even in the case that this factor is not correlated with the risk), the (FM)' test may give an indication through mimicking portfolios returns that the variable is a function of a risk factor (Constantinides et al, 2003: 778). This caveat problem is first discovered by Ferson, Sarkissian and Simin (1999) (cited in Constantinides et al, 2003: 778).

An advantage of using Fama and MacBeth cross-section regression is that the FM cross-section regression can be applied on different levels. For instance, Fama and MacBeth cross-section regression uses individual stocks in firm level, while in industry portfolios level; FM' test requires the use of the mean values of risk factors for the companies that belong to the same industry. Applying FM cross-section regression on Fama and French 100 size-beta portfolios requires the formation of portfolios according to firm size, and beta. As indicated by Cuthbertson and Nitzche (2004), forming portfolios will enable reducing the errors in variables when estimating betas. In addition, this will allow for a large dispersal in average returns throughout the formed portfolios. The most effective method in forming portfolios is to estimate the portfolios according to quintiles (Cuthbertson and Nitzche, 2004). Therefore, I build upon Fama and French (1992) using 100 size-beta portfolios to test whether the industry concentration is a new risk factor in addition to conventional market beta, size, book-to-market, momentum, and leverage. The empirical results' Chapter includes explanation on sorting methods to conduct Fama and French (1992) 100 size-beta portfolios.

Accounting for previous different levels (firm, industry, and 100 size-beta portfolios) in testing the relationship between industry concentration and the cross-section of stock returns will provide the chance to see whether similar results will hold under different empirical analysis. Moreover, using different levels of analysis will give the chance to see whether the results are robust.

The Fama and MacBeth cross-sectional regression will run using 6 factors (as indicated in the main research empirical model). These factors are: the beta (measure of risk), the Herfindahl index (measurement of industry concentration), the natural logarithm of both size and book-to-market equity, leverage, and the momentum factor. The regression will

run for each variable and then adding other variables concurrently. The procedure to estimate Fama and MacBeth regression involves two steps (for more details about the test procedure, see Cuthbertson and Nitzche, 2004: 203).

The first step:

1- Estimate the beta of each stock concurrently using the (CAPM) formula:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}$$

(R_{it} : represents the security excess returns; R_{mt} : represents the excess market returns).

Previous estimation will be accomplished using the time series of monthly returns for a period of 5 years (60 months).

2- In month 61, portfolios are formed according to firm size. Afterwards, I divide firm size portfolios according to the estimated betas from previous time series regression. Then, for one year ahead (from month 61 until month 72), I calculate the monthly returns on the sorted portfolios. Hence, until this stage I have monthly returns on portfolios sorted according to size and beta. I repeat the previous procedure for each year.

3- Then I will use time series regression to estimate the betas for each sorted portfolios for each year. To do that, I run a time-series regression on each return of the sorted portfolios from the previous procedure on the market returns.

4- Each stock in size-beta sorted portfolios will be appointed to stock portfolio beta in each year.

The second step:

I use previous estimated betas portfolios in the cross-section regression for the total period ($t=1, 2, 3 \dots T$). This will give the time series coefficients for $\lambda_0, \lambda_1, \lambda_2$ and those coefficients can be analysed in the following equation.

$$\bar{R}_i = \lambda_0 + \lambda_1 \hat{\beta}_i + \lambda_2 Z_i + \nu_i \quad \text{Where:}$$

Z_i is any firm factors conducted in the cross-section regression.

The coefficients of previous equation are the time series estimates of sorted portfolios returns according to different characteristics. Therefore, it is possible to carry out t-tests to examine whether those coefficients are different from zero by using the time series averages. That is, to see whether the specified factors (beta, the Herfindahl index, the natural logarithm of both size and book to market equity, leverage, and the momentum) help to explain the cross-section of stock returns.

The detailed steps to estimate Fama and MacBeth (1973) are as follows (Cochrane, 2005:245):

- 1- The first step involves estimating betas $\hat{\beta}_i$ ($i=1, 2 \dots n$) through the use of time-series regression (past 3-5 years monthly share returns).
- 2- In the second step, Fama and MacBeth (1973) runs a cross-sectional regression for each single time period (on monthly basis) as follows

$$R_i^t = \lambda_t \hat{\beta}_i + \varepsilon_{it}, \quad i = 1, 2, \dots, N, \text{ for each period } t \quad \text{Where}$$

ε_{it} is the cross-sectional regression residuals (pricing errors), $\hat{\beta}_i$ are the regressors including industry concentration, estimated beta from the first step, size, book-to-market, leverage, and momentum, and λ are the regression coefficients.

3- In the final step, Fama and MacBeth (1973) calculate λ and i as the average of the cross-sectional regression estimates as follows:

$$\hat{\lambda} = \frac{1}{T} \sum_{t=1}^T \hat{\lambda}_t, \quad \hat{\varepsilon}_i = \frac{1}{T} \sum_{t=1}^T \hat{\varepsilon}_{it}, \quad i = 1, 2, \dots, N \text{ (for every asset)}$$

The second step in Fama and MacBeth above uses estimated betas from the first step which induces an error-in-variable problem as betas are estimated and measured with error. This measurement error will bias the estimator of λ_t towards zero and both the intercept and mean of the residuals will be biased upward. To overcome this problem, Fama and Macbeth (1973) suggest using portfolios to estimate betas rather than individual stocks so that the individual assets noise from the first step regressions decreases, leading a small measurement error of estimated betas β . Therefore, the use of Fama and French (1992) methodology to construct 100 size-beta portfolios and estimate the post-ranking portfolios betas will account for the measurement error bias caused by individual stocks betas in Fama and MacBeth cross-sectional regression.

One way to test the above model is to see if $\varepsilon_i = 0$ (where ε_i is the time-series average of the residual for asset i , ε_{it}) by calculating the test statistic as

$$\hat{\varepsilon}_i / STD(\hat{\varepsilon}_i)$$

However, Fama and MacBeth (1973) propose that the standard deviation should be obtained by studying the time-variation in ε_{it} . Therefore, Fama and MacBeth suggest using the variance of ε_{it} (instead of ε_i) calculated as the average squared variation around its mean as follows:

$$\sigma^2(\hat{\varepsilon}_{it}) = \frac{1}{T} \sum_{i=1}^T (\hat{\varepsilon}_{it} - \hat{\varepsilon}_i)^2$$

Because ε_i is the average of ε_{it} , the variance of ε_i equals to the variance ε_{it} divided by the sample size (T) given that ε_{it} is independent and identically distributed (iid). Therefore, the variance of ε_i is as follows:

$$\sigma^2(\hat{\varepsilon}_i) = \frac{1}{T} \sigma^2(\varepsilon_{it}) = \frac{1}{T^2} \sum_{i=1}^T (\hat{\varepsilon}_{it} - \hat{\varepsilon}_i)^2,$$

Similarly, the variance of λ is calculated as follows:

$$\sigma^2(\hat{\lambda}) = \frac{1}{T^2} \sum_{t=1}^T (\hat{\lambda}_t - \hat{\lambda})^2,$$

The rationale for Fama and MacBeth (1973) to compute the sampling error is that the sampling errors will show how a statistic varies from one sample to next sample if observations are repeated. Because the estimation of sampling errors is not applicable if only one sample is used, Fama and MacBeth (1973) divide the sample according the time-periods and compute sampling error through the variation in the cross-sectional coefficient estimate $\hat{\lambda}_t$ over time to conduct $\hat{\lambda}_t$ variation across samples. The Fama and MacBeth (1973) apply the sampling errors to the slopes and pricing errors estimate and assume that error term is not serially correlated, as stock returns are close to independent.

In sum, the Fama and MacBeth procedure (1) runs a cross-sectional regression for each single time period (2) calculates the average of the cross-sectional $\hat{\lambda}_t$ to obtain an estimate of $\hat{\lambda}$ and utilise the time-series standard deviation of $\hat{\lambda}_t$ to estimate the standard error of $\hat{\lambda}$.

3.4 Industry Concentration and the Time-Series Variation in Stock Returns

3.4.1. Time-Series Variation of the Industry Concentration Premium and Risk Factors

The objective of this section is to examine the concentration premium that has been generated from previous Fama and MacBeth cross-sectional regression when individual stocks are regressed on industry concentration, controlling other variables (beta, size, book-to-market ratio, leverage, and momentum). Therefore, I use risk factors that explain the time-series variation in stock returns to see whether these risk factors explain the variation in the industry concentration premium. The reason for that is to see whether the concentration premium is still significant when considering other risk factors that explain the time-series variation in asset pricing. In addition, examining the variation of industry concentration premium by using risk factors clarifies whether industry concentration has separate information compared to other risk factors in predicting time-series variation in stock returns. Therefore, I follow Hou and Robinson (2006:1946) in using the following models:

$$\lambda_t^H = \alpha + \sum_{i=1}^I \beta_i F_{it} + \varepsilon_t$$

Where α : is the concentration premium from the regression (it is so-called alpha); λ_t^H : $H(\text{sales})$ risk premium is the monthly time series of industry concentration risk premium conducted on the firm level from Fama and MacBeth cross-section regression, in which the cross-section of individual stock returns are regressed on industry concentration, controlling for other factors; F_{it} : is Fama and French (1993) factor-mimicking portfolios (on monthly basis t), including market excess return ($R_m - R_f$), size (SMB), book-to-market (HML), as well as momentum. Empirical results' Chapter

includes a detailed explanation on the sorting methods to construct (SMB) and (HML) according to Fama and French (1993).

I also examine whether risk premiums associated with risk factors explain industry concentration risk premium. Therefore, I use risk premiums associated with risk factors from Fama and MacBeth firm level cross-section regression, in which the cross-section of individual stock returns are regressed on industry concentration, controlling for other risk factors. These premiums of risk factors include: size, book-to-market, momentum, beta, and leverage. Therefore, I estimate the following model:

$$\lambda_t^H = \alpha + \sum_{i=1}^I \beta_i \lambda_{it} + \varepsilon_t$$

Where α : is the concentration premium from the regression (it is so-called alpha); λ_t^H : $H(\text{sales})$ risk premium is the monthly time series of industry concentration risk premium conducted on the firm level from Fama and MacBeth cross-section regression, in which the cross-section of individual stock returns are regressed on industry concentration, controlling for other factors; λ_{it} represents risk premiums of size, book-to-market, momentum, beta, and leverage from Fama and MacBeth firm level cross-section regression, in which the cross-section of individual stock returns are regressed on industry concentration, controlling for other risk factors.

I report t-statistics accompanied with adjusted R^2 and P-value. I carry out previous tests for each variable, adding other factors simultaneously. This will help to illustrate if the concentration premium (alpha) is still significant when accounting for other variables. In addition, this will provide an indication of the robustness of the relationship between

industry concentration and the cross-section of stock returns after accounting for risk factors and risk premiums that explain the time-series variation in stock returns.

If previous risk factors and risk premiums, that explain the time-series variation in stock returns, fail to explain or partly explain the industry concentration premium (α alpha), I test whether the industry concentration premium and other risk factors explain the time-series variation in stock returns in the next subsection.

3.4.2 Can Industry Concentration Explain the Time-Series Variation in Stock Returns?

Based upon previous section, the aim of this section is to examine the relationship between the time-series variation in stock returns and industry concentration premium. In this respect, I use the generated concentration premium from previous Fama and MacBeth cross-sectional regression when individual stocks are regressed on industry concentration, controlling other variables (beta, size, book-to-market ratio, leverage, and momentum). Consequently, I regress stock returns on the time-series of concentration premium. This will help to assess the ability of industry concentration premium in explaining the time-series variation in stock returns.

In order to test the relationship between industry concentration premium and time-series variation in stock returns, I adopt the following model:

$$R_{it} = \alpha + \beta_i \lambda_t^H + \varepsilon$$

Where R_{it} represents the time-series of the stock returns; α : is the intercept from the regression; β_i : is the beta coefficient that indicates how much in the variation in the industry premium concentration captures the time-series variation in stock returns; λ_t^H :

is the time series of industry concentration risk premium conducted on the firm level from Fama and MacBeth cross-section regression, in which the cross-section of individual stock are regressed on industry concentration, controlling for other factors.

3.4.3 Is Concentration Premium Subsumed by other Risk Factors?

In order to examine whether the role of industry concentration premium in explaining the time-series variation in stock returns is not subsumed by other asset-pricing factors, I use other risk factors and risk premiums that explain stock returns with the industry concentration premium. This method gives the opportunity to investigate whether other risk factors and risk premiums have similar information compared to industry concentration premium in explaining stock returns. This method also allows investigating whether the information those other risk factors and risk premiums have is similar to the industry concentration premium' information in explaining stock returns.

In order to account for previous method, I regress stock returns on the time-series of industry concentration premium and other risk factors including Fama and French mimicking portfolios factors. Therefore, I adopt the following model:

$$R_{it} = \alpha + \delta_i \lambda_t^H + \sum_{i=1}^I \beta_i F_{it}$$

Where R_{it} represents the time-series of the stock returns; α : is the intercept from the regression; λ_t^H is the time series of industry concentration risk premium conducted on the firm level from Fama and MacBeth cross-section regression, in which the cross-section of individual stock are regressed on industry concentration, controlling for other factors; ***Fit***: is Fama and French (1993) factor-mimicking portfolios (on monthly basis t), including market excess return ($R_m - R_f$), size (SMB), book-to-market (HML), as well

as momentum. Empirical results' Chapter includes a detailed explanation on the sorting methods to construct (SMB) and (HML) according to Fama and French (1993).

I also use risk premiums associated with other risk factors from Fama and MacBeth firm level cross-section regression, in which the cross-section of individual stock returns are regressed on industry concentration, controlling for other risk factors. These premiums of risk factors include: size, book-to-market, momentum, beta, and leverage. Therefore, I estimate the following model:

$$R_{it} = \alpha + \delta_i \lambda_t^H + \sum_{i=1}^I \beta_i \lambda_{it}$$

Where R_{it} represents the time-series of the stock returns; α : is the intercept from the regression; λ_t^H is the time series of industry concentration risk premium conducted on the firm level from Fama and MacBeth cross-section regression, in which the cross-section of individual stock are regressed on industry concentration, controlling for other factors; λ_{it} represents risk premiums of size, book-to-market, momentum, beta, and leverage from Fama and MacBeth firm level cross-section regression, in which the cross-section of individual stock returns are regressed on industry concentration, controlling for other risk factors.

3.4.4 Can Concentration Premium Residuals Predict Time-series of Stock Returns:

The aim of this section is to examine whether the unexplained part of industry concentration premium by other risk factors or risk premiums explains the time-series variation in stock returns. In other words, this section intends to address the following question: if other risk factors or risk premiums explain or partly explain industry concentration premium, will the unexplained part of concentration premium predicts

time-series variation in stock returns? The reason for this procedure is to see whether industry concentration premium includes independent information compared to other risk factors and risk premiums in explaining time-series of stock returns. Therefore, I use the residuals from the two equations in Section 3.4.1, in which I regress the monthly time-series of industry concentration risk premium on (a) various risk factors and (b) various risk premiums. These residuals represent the unexplained part of industry concentration premium by either various risk factors or various risk premiums depending on which equation in Section 3.4.1 is used. Afterwards, I regress the time-series of monthly stock returns on the residuals of industry concentration risk premium and (a) various risk factors (b) various risk premiums.

Following the above steps, I estimate the following models:

$$R_{it} = \alpha + \delta_i \varepsilon_t^H + \sum_{i=1}^I \beta_i F_{it}$$

Where R_{it} represents the time-series of the stock returns; α : is the intercept from the regression; ε_t^H is the residuals from the *first* equation in Section 3.4.1, and these residuals represent the time series of industry concentration risk premium that are not explained by risk factors or risk premiums; ***Fit***: is Fama and French (1993) factor-mimicking portfolios (on monthly basis t), including market excess return ($R_m - R_f$), size (SMB), book-to-market (HML), as well as momentum. Empirical results' Chapter includes a detailed explanation on the sorting methods to construct (SMB) and (HML) according to Fama and French (1993).

$$R_{it} = \alpha + \delta_i \varepsilon_t^H + \sum_{i=1}^I \beta_i \lambda_{it}$$

Where R_{it} represents the time-series of the stock returns; α : is the intercept from the regression; ε_t^H is the residuals from the *second* equation in Section 3.4.1, and these residuals represent the time series of industry concentration risk premium that are not explained by risk factors or risk premiums; λ_{it} represents risk premiums of size, book-to-market, momentum, beta, and leverage from Fama and MacBeth firm level cross-section regression, in which the cross-section of individual stock returns are regressed on industry concentration, controlling for other risk factors.

Previous sections account for the theory, the model, and the empirical methods. Chapter Four describes the data, the variables, and the sorting methods. In particular, Chapter Four reports the measures of industry concentration and explains both stock market anomalies, and risk factors. Finally, Chapter Four includes explanations on sorting methods to construct Fama and French (1992, 1993) 100 size-beta and mimicking portfolios respectively.

CHAPTER FOUR

EMPIRICAL ANALYSIS AND RESULTS

4.1 Data Description

The sample used in this study is an unbalanced panel consisting of 1300 companies publicly listed in the London Stock Exchange (LSE) during 1985 and 2010. I obtain data on monthly share returns and various accounting ratios from Thomson Reuters Datastream. Datastream classifies each company into an industry based on the firm's primary business activity published by the FTSE Actuaries. There are a total of six levels of industrial classifications. Throughout this study, I use the most detailed level 6 classification consisting of 82 industries.

Consistent with prior studies, I exclude de-listed companies, financial companies (banks, investment trusts, insurance companies, and properties companies), companies that have more than one classification of ordinary shares, and companies with negative book-to-market-ratio. To ensure that stock prices for listed companies reflect prior accounting information, I extract data on market value of equity, book-to-market ratio, leverage, total assets, and net sales at the end of the fiscal year $t-1$. I then match stock returns data from July of year t to June of year $t+1$ with accounting information for fiscal year ending in $t-1$, as in Fama and French (1992) and Hou and Robinson (2006). In addition, to allow estimation of market beta and calculation of post-ranking beta, I require a company to have monthly return data during the previous 3-5 years.

For every sample company in each year, I collect information on the following firm-specific characteristics and accounting variables: (1) *Size* is the annual market value of equities calculated as the end-of-year share price multiplied by the number of outstanding ordinary shares; (2) *B/M* is book-to-market equity ratio calculated as the balance sheet value of the common equity divided by the market value of common equity; (3) *LEV* is

the ratio of total debt and common equity; (4) *Assets* is the book value of total assets; (5) *Sales* is net sales revenue defined as total sales minus returns and other deductions; (6) *R&D* is research and development expense; (7) *R&D/A* is the ratio of *R&D* and total assets; (8) *Post.Beta* is the post-ranking beta.

To calculate the post-ranking beta, I obtain monthly firm- or industry-level returns or returns from 100 size-beta portfolios constructed based on the methodology of Fama and French (1992) during year t and $t+1$. I then regress the monthly stock/industry/portfolio returns on market returns over the 12-month period. Finally, I assign the post-ranking beta to each stock/industry/portfolio on a yearly basis so that it has the same beta within the 12-month period.

Table 4.1 below shows the industry characteristics variables as well as other risk factors applied in this study. In addition, Table 4.2 reports industries name used in this study.

Table 4. 1 Variables Definition

<i>Variable</i>	<i>Description</i>	<i>Definition</i>
<i>Size</i>	Firm Size	The annual market value of equities calculated as the end-of-year share price multiplied by the number of outstanding ordinary shares
<i>B/M</i>	Book-to-market Ratio	Calculated as the balance sheet value of the common equity divided by the market value of common equity
<i>Lev.</i>	Leverage	The ratio of total debt and common equity
<i>Assets</i>	Total Assets	The book value of total assets
<i>Sales</i>	Net Sales Revenue	Total sales minus returns and other deductions
<i>R&D</i>	Research and Development	Research and development expense
<i>R&D/A</i>	Research and Development to Total Assets	The ratio of <i>R&D</i> and total assets
<i>Beta</i>	Measure of Risk (pre-ranking beta)	Estimated using previous 5 years returns by market model
<i>Post.Beta</i>	Post ranking beta	Estimated as in Fama and French (1992)
<i>Momentum</i>	Momentum	Past 12 month stock returns can proxy for the momentum
<i>SMB</i>	Small minus big firm size	As defined by Fama and French (1993) portfolios will be formed on market size (small minus big)
<i>HML</i>	High minus low book-to-market equity ratio	As defined by Fama and French (1993) portfolios will be formed on book-to-market equity (large minus low)

Table 4.2 Industries Name

Aerospace	Exploration & Prod.	Paper
Airlines	Farming & Fishing	Personal Products
Alt. Electricity	Fixed Line Telecom.	Pharmaceuticals
Alternative Fuels	Food Products	Plat.& Precious Metal
Apparel Retailers	Food Retail, Wholesale	Publishing
Auto Parts	Footwear	Recreational Products
Biotechnology	Forestry	Recreational Services
Brewers	Furnishings	Renewable Energy Eq.
Broadcast & Entertain	Gas Distribution	Restaurants & Bars
Broadline Retailers	General Mining	Semiconductors
Building Mat.& Fix.	Gold Mining	Soft Drinks
Bus.Train & Employment	Healthcare Providers	Software
Business Support Svs.	Heavy Construction	Spec. Consumer Service
Clothing & Accessory	Home Construction	Specialty Chemicals
Coal	Home Improvement Ret.	Specialty Retailers
Comm. Vehicles, Trucks	Hotels	Telecom. Equipment
Computer Hardware	Industrial Machinery	Tobacco
Computer Services	Industrial Suppliers	Toys
Con. Electricity	Integrated Oil & Gas	Transport Services
Consumer Electronics	Internet	Travel & Tourism
Containers & Package	Iron & Steel	Waste, Disposal Svs.
Defence	Marine Transportation	Water
Delivery Services	Media Agencies	
Diamonds & Gemstones	Medical Equipment	
Distillers & Vintners	Medical Supplies	
Divers. Industrials	Mobile Telecom.	
Drug Retailers	Multiutilities	
Dur. Household Prod.	Nondur. Household Prod	
Electrical Equipment	Nonferrous Metals	
Electronic Equipment	Oil Equip. & Services	

4.2 Variables and Sorting Methods

4.2.1 The Measurement of Industry Concentration

In order to conduct industry concentration, I follow Hou and Robison (2006) in using the Herfindahl index to measure industry concentration and link it to the cross-section of stock returns. In fact, Church and Ware (2000:462) illustrate two methods to calculate industry concentration.

The first method uses **Herfindahl** index. Church and Ware (2000:429) illustrate how to calculate industry concentration by using Herfindahl-Hirschman index as follows:

$$H(Sales)_j = \sum_{i=1}^N S_{ij}^2 \quad 0 \leq H(Sales) \leq 1$$

Where: S_{ij} represents the market share of firm i in industry j for a given year, and N is the number of firms in industry j . For robustness, I compute H_j based on net sales, book value of total assets, and book value of equity, respectively. Thus I have three types of Herfindahl index denoted as $H(Sales)$, $H(Assets)$ and $H(Equity)$. If the value of index is high, the market shares will be distributed to small number of firms, indicating that the industry is concentrated. On the other hand, if the index has a small value, the market shares will be distributed to a large number of firms, indicating that the industry is more competitive. I also follow Hou and Robinson (2006) in conducting Herfindahl index. Therefore, I calculate Herfindahl index annually for each industry and then I average Herfindahl index for the past three years to reduce potential errors in measuring industry concentration.

The following steps illustrate how I calculate the Herfindahl Index based on net sales. First, I compute the total net sales for each industry in each year defined as the sum of net sales for all firms within an industry in each year. Second, I calculate the market

share for each firm in each industry on an annual basis. Therefore, I divide the annual net sales data for each firm (numerator) on the total net sales for the industry that the firm belongs to in each year (denominator). Third, I compute the squares of market shares for all firms within each industry in each year. Finally, the Herfindahl index is the sum of the squares of market shares for all firms that belong to each industry in each year. For instance, in 2006, there are 5 listed companies in Airlines industry including Air Partner, British Airways, Dart Group, Easy Jet, and Skywest Airline. The net sales for Air Partner, British Airways, Dart Group, Easy Jet, and Skywest Airline are as follows: £140368, £8515000, £319600, £1619700, and £98949; respectively. The total net sales for the Airline industry in 2006 are £10693617 (sum of net sales for the previous firms in Airline industry in 2006). The market shares for each firm is the net sales for each firm (numerator) divided to total industry net sales (denominator). The Herfindahl index for Airline industry in 2006 will be 0.6581375 which indicates a high market concentration. I follow the same aforementioned steps to calculate Herfindahl index based on total assets and common equity; respectively.

The second method in calculating industry concentration is the concentration ratio, i.e. the largest firms that hold the majority of market shares.

Consistent with prior studies, I use of Herfindahl index as a measurement for industry concentration. In fact, the use of Herfindahl index as a measure of concentration entails some advantages and disadvantages. For instance, one of the main disadvantages is that the interpretation of Herfindahl index is not classified as clear as concentration ratio, as the Herfindahl index just offers classification to whether the industry can lie in high, medium, or low concentration. Moreover, in order to calculate the Herfindahl index, information on market shares for all firms within the industries should be accessible

compared with concentration ratio, which requires information on market shares for the largest four companies in the industries. Therefore, the use of Herfindahl index requires sufficient amount of information on all listed firms within their industries.

With regards to the advantages of using **Herfindahl** index as a measure of industry concentration, the Herfindahl index is considered as the most common measure reported in the literature to precisely measure concentration. In addition, Herfindahl index gives a precise estimate compared to concentration ratio, since the Herfindahl index uses all firms included in an industry to measure the concentration, while the concentration ratio method just reports the sum of the market shares owned by the largest firms.

For robustness tests, I also apply Entropy index as a measure of industry concentration besides Herfindahl Index to see whether the empirical results based on Herfindahl index are sensitive when other measures of industry concentration are applied. Therefore, the use of Entropy index will provide the opportunity of comparing and contrasting different empirical results based on different measures of industry concentration.

To measure industry market concentration using Entropy index, I follow Barthwal (2004) in using the following Entropy index formula:

$$E(Sales)_j = \sum_{i=1}^N S_{ij} \ln\left(\frac{1}{S_{ij}}\right) \quad 0 \leq E(Sales) \leq \ln(N)$$

Similar to the Herfindahl Hirschman Index, S_{ij} represents the market share of firm i in industry j for a given year, and N is the number of firms in industry j . I calculate the Entropy index for each year in a given industry. In contrast to Herfindahl Hirschman Index, the interpretation of Entropy index is as follows: if the market is controlled by large number of firms (competitive or non-concentrated market), the value of the

Entropy index will be the natural logarithm of number of firms within the industry. However, when the market is extremely concentrated (i.e. case of monopoly when one firm controls the market), the Entropy index has the value of Zero ($N=1$). Therefore, the relationship between Entropy index and industry concentration is negative. That is, when the values of Entropy index increase, the market concentration decreases vice versa; which is in apposite to Herfindahl Hirschman index.

4.2.2 Size, Book to Market Equity, Leverage, Momentum, and Beta

In this section, I report and explain the variables that are employed in this research. The use of multifactor asset pricing model will give the opportunity to link different firms' characteristics with stock returns. However, the theory of multifactor asset-pricing model does not specify the number and the nature of the variables that should be included in the model. Therefore, in order to choose the factors, I look at empirical asset pricing literature. This will give the chance to highlight factors that are used in empirical asset pricing literature and consequently apply those factors in this research. In the following subsections, I explain the variables employed in this research and report the researchers who adopt those factors in empirical asset pricing literature.

Firms Size

In this research, I use firms' size, as the firm size will have an impact on the cross-section of stock returns. Banz (1981) reports the effect of firm size represented by market capitalisation on the cross-section of stock returns. The author uses the securities' prices times share outstanding as a proxy for market capitalisation, reporting that firm size effect (market capitalization) as an important factor in explaining the cross-section of stock returns. The author finds that when firms are sorted according to size portfolios, small firms' size tend to have, on average, higher returns compared to big firms' size.

Book-to-Market Equity

Rosenberg, Reid, and Lanstein (1985) examine book-to-market ratio as an indicator of the cross-section of stock returns. The authors indicate that stocks with high book values relative to their market values tend to have, on average, higher stock returns. Therefore, in this research, I use book-to-market ratio as a factor that affects the cross-section of stock returns. The book-to-market ratio can be defined as book value of the equity reported in the company annual report divided to market value of the company shares.

Leverage

Some studies use leverage as an important factor predicts the cross-section of stock returns. The leverage is defined as the money borrowed to fund investment in the company. In this research, I adopt debt-to-equity ratio as a proxy for leverage. One probable impact of the leverage (represented by debt-to-equity) on the cross-section of stock returns is that when companies borrow to finance the investment, the debt increases, leading the risk on equity to increase. Consequently, the required rate of returns on investments will increase, since there will be a risk for bankruptcy within the firms. Bhandari (1988) initially uses leverage, analysing its role on the cross-section of stock returns. The author finds that when firms' size and beta are accounted for, firms with high leverage (represented by debt-to-equity ratio) tend to have, on average, higher expected returns.

Momentum

In this research, I use momentum factor. Momentum is traced through empirical tests. The main idea of momentum is that securities that are historically having a good performance (high returns) tend to continue having this good performance in the future. That is, there is a tendency for well-performed stocks in the past to continue having a positive trace (high returns), while poorly performed stocks in past will have the same

tendency in the future. Jegadeesh and Titman (1993) analyse the strategy of buying well-performed stocks and selling poorly-performed stocks in the past between 1965 and 1989. According to the authors, this strategy achieved high significant returns during the specified period. The authors examine this strategy using portfolios formed on the winners (well-performed stocks) and losers (poorly-performed stocks). The results indicate that the winners' portfolios witness positive returns and losers' portfolios witness negative returns. In order to use the momentum factor, I follow Hou and Robinson (2006) in using past 12 months stock returns as a proxy for momentum to see whether the well-performed stocks will have high returns in the future according to momentum policy.

Beta: Excess Returns on Market Portfolios

Initial studies in asset-pricing literature document the beta of the capital asset pricing model (CAPM) as an important factor captures the cross-section of stock returns. The beta can be defined as the excess returns on market portfolios (after accounting for the risk free interest rate). That is, beta captures the sensitivity of stock returns in relation to the total movements of financial markets. Mathematically, beta is defined as the covariance between stock returns and market portfolios divided on the variance of market portfolios. Sharpe (1964) and Lintner (1965) report beta of the (CAPM) as a predictor of the cross-section of stock returns. The use of beta of (CAPM) has undergone through extensive criticism, since empirical studies show that beta of market portfolio could not explain much of the cross section of stock returns. That is, stock prices have some information that is neglected by market beta. A considerable number of studies debate whether the beta of the CAPM is still alive or dead. In this research, I use beta of the (CAPM) in the model to see whether beta can predict the cross-section of stock returns in the UK stock market in addition to other risk factors and stock market anomalies.

4.2.3 Fama and French Sorting Methods: FF (1992) 100 Size-Beta Portfolios

In assessing the role of industry concentration in explaining the cross-section of stock returns, I follow Fama and French (1992) in forming 100 size-beta portfolios. Fama and French (1992) form 100 size-beta portfolios to assess the joint function of beta (market risk), size, and other stock market anomalies in explaining the cross-section of stock returns. Therefore, the use of Fama and French (1992) method will provide the opportunity for testing the role of industry concentration in explaining the cross-section of stock returns in the UK stock market.

According to Fama and French (1992), the standard procedure to form 100 size-beta portfolios is as follows: in June each year, stocks are sorted according to firms' size (market capitalisation). Then stocks are divided into deciles (10 portfolios) according to the firms' size. Afterwards, within each size portfolio, stock are divided according to the estimated (5) years pre-ranking beta into deciles. Consequently, 100 size-beta portfolios are formed according to the size and pre-ranking betas. After that, the monthly returns on 100 size-beta equally weighted portfolios are calculated for the next year (excluding the current year). To measure the beta of 100 size-beta portfolios, the mean returns of 100 size-beta equally weighted portfolios are regressed on both the current and previous (lagged value) month market returns.

Having formed 100 size-beta portfolios, and calculated the returns, the size and the beta; I use the Fama and MacBeth cross-section regression (1973) to estimate the joint effect of size, beta, and industry concentration on 100 size-beta portfolios returns.

4.2.4 Fama and French Sorting Methods: FF (1993) Mimicking Portfolios

In assessing the role of industry concentration in explaining the time-series variation in stock returns, I use Fama and French (1993) sorting method to construct mimicking portfolios. Fama and French (1993) employ a method in forming portfolios on firms' size and Book-to-market ratio. This method is so-called independent sort. Providing that the sort takes place at the end of June each year (say for instance year t), and the portfolios are formed on size and book-to-market equity to account for the risk factors represented by **SMB** and **HML**. The procedure to form Fama and French (1993) mimicking portfolios are summarized as follows: Using firms' size, I appoint stocks to two main categories according to their market value. These categories are Small market value (**S**) and Big market value (**B**). Afterwards, I appoint stocks using book-to-market ratio to three main categories. These categories are: Low (**L**) (30% of the lowest book-to-market equity value), Medium (**M**) (40% of book-to-market value that will on middle), and High (**H**) (30% of the highest book-to-market value). I exclude Firms with negative book-to-market ratio as suggested by Fama and French (1993-1995).

The intersection between previous portfolios on (size) and (book-to-market value) will generate six portfolios as follows: (**S/L, S/M, S/H, B/L, B/M, and B/H**). Subsequently, I calculate portfolios returns for the next 12 months from June in year (t) until next June in year ($t+1$). Consequently, I conduct **SMB** and **HML** risk factors as follows: **SMB** refers to the small size monthly portfolios returns (**S/L, S/M, and S/H**) minus big size monthly portfolios returns (**B/L, B/M, and B/H**). **HML** refers to high book-to-market monthly portfolios returns (**S/H, and B/H**) minus low book-to-market monthly portfolios returns (**S/L, and B/L**). Clearly, one could easily calculate the **SMB** and **HML** as the following:

$$\text{SMB} = (S/L, S/M, S/H) / 3 - (B/L, B/M, B/H) / 3$$

$$\text{HML} = (S/H, B/H) / 2 - (S/L, B/L) / 2$$

Previous sections explain the measures of industry concentration, risk factors, and stock market anomalies. Moreover, previous sections discuss sorting methods to construct Fama and French (1992, 1993) 100 size-beta and mimicking portfolios respectively. Chapter Five reports the results from Fama and Macbeth cross-sectional regressions on the relationship between industry concentration and industry average characteristics; and the relationship between industry concentration and the UK cross-section of stock returns.

CHAPTER FIVE

EMPIRICAL RESULTS FROM CROSS-SECTION REGRESSION

5.1 Industry Concentration and Industry Characteristic

5.1.1 Descriptive Statistics

Table 5.1 presents summary statistics for industry concentration measurements in 82 industries. As shown in the table, the mean value of H (*Sales*) is (0.3988) and is slightly higher compared to the mean values of other concentration measurements: (0.3852) for H (*Assets*) and (0.3709) for H (*Equity*). While H (*sales*) ranges between (0) (indicating competition drives the industry) and (1) (indicating high level of concentration among firms), H (*assets*) and H (*Equity*) range between (0.045907) and (1), (0.043607) and (1) respectively. In addition, 75% of H (*Sales*) observations range between (0) and (0.5302), while 75% of both H (*Assets*) and H (*Equity*) range between (0.045907) and (0.5259), (0.043607) and (0.504) respectively. However, the Spearman-Pearson correlation matrix represented by the last three columns in Table 5.1 indicates that H (*Assets*) and H (*Equity*) are highly correlated with correlation of (0.9604). Moreover, while H (*Sales*) is highly correlated with H (*Assets*) with correlation of (0.9197), correlation for H (*Sales*) with H (*equity*) decreases to (0.8837).

Table 5. 1 Descriptive Statistics

	Summary of Industry Concentration Measures									Spearman-Pearson Correlation		
	Mean	Median	SD	Max	Min	10%	25%	75%	90%	H(Sales)	H(Assets)	H(Equity)
H(Sales)	.3988639	.3344858	.260666	1	0	.11454	.1955	.5302	.84378	1	0.9195	0.8837
H(Assets)	.3852407	.3143526	.264169	1	.045907	.0989	.1788	.5259	.84678	0.9197	1	0.9604
H(Equity)	.3709617	.2986895	.265331	1	.043607	.09177	.171	.504	.8372	0.8837	0.9604	1

Table 5.1 presents descriptive statistics of industry concentration measurements. I calculate Herfindahl Index as the sum square of market shares for the firms in a given industry in each single year. I use net sales H (*Sales*), total assets H (*Assets*), and book equity H (*Equity*) to construct Herfindahl Index. The last three columns in Panel (A) show the Spearman- Pearson correlation matrix among different concentration measures.

5.1.2 Industry Average Characteristics and Concentration Quintiles

Table 5.2 displays Concentration Quintiles based on Herfindahl index H (*Sales*) using net sales in each year. Quintile (1) is equivalent to the 20% of the industries with the lowest concentration ratio, while quintile (5) corresponds to the 20% of the industries with the highest concentration ratio. Afterwards, according to each quintile from (1 to 5), I report firms and industry levels returns as well as industry average characteristics. Firm level returns and industry average characteristics are calculated at firm level and consequently averaged within each of the concentration Quintile portfolios, while industry level returns are calculated at industry level and then averaged within each of the concentration Quintile portfolios. This will help to give an indication about the characteristics of the sorted portfolios based on concentration Quintiles.

Table 5. 2 Industry Average Characteristics and H (Sales) Concentration Quintiles

Industry Mean Characteristics across H (Sales) Sorted Quintile Portfolios												
<i>Rank</i>	<i>H (Sales)</i>	<i>Fir. Ret</i>	<i>Ind. Ret</i>	<i>Size</i>	<i>Assets</i>	<i>Sales</i>	<i>R&D</i>	<i>R&D/Sales</i>	<i>R&D/A</i>	<i>Lev.</i>	<i>B/M</i>	<i>Post.Beta</i>
<i>Low</i>	0.1185	0.0003998	0.0003135	220.8116	241598.60	296767.50	3644.741	42.4923	0.0324	3.237	0.941	0.7934
<i>Q2</i>	0.2276	0.0014769	0.0014524	481.8460	573222.60	490065.70	6863.404	26.3740	0.0707	3.026	0.733	0.8444
<i>Q3</i>	0.3352	-0.0012	-0.001122	579.9622	839980.30	746634.60	9892.196	202.0061	0.0747	3.024	0.764	0.8306
<i>Q4</i>	0.5032	-0.0027	-0.002648	2157.979	2322140.0	2496584.0	92509.74	382.2384	0.0787	3.392	0.841	0.7704
<i>High</i>	0.8094	-0.001833	-0.001822	1768.650	2353596.00	1398816.0	46782.130	285.0641	0.0573	3.2701	0.7575	0.8539

Table 5.2 above reports industry average characteristics across H (Sales) sorted quintile portfolios. Quintile (1) is equivalent to the 20% of the industries with the lowest concentration, while quintile (5) corresponds to the 20% of the industries with the highest concentration.

As shown in Table 5.2, the mean returns on firm level are decreasing across concentration Quintiles. For instance, while the mean returns on firm level for both (Quintile 1) and (Quintile 2) are positive (.03998% and .14769% respectively), the mean returns for Quintiles 3, 4, and 5 are negative (-.1212%, -.2666% and -.1833% respectively). Therefore, the mean returns on firm level vary significantly to decrease across concentration quintiles. Thus, companies in low concentration Quintiles earn, on average, higher returns compared to companies in higher concentration Quintiles, which lead to an initial conclusion that industry concentration seems to be negatively related to average stock returns during 1985 and 2010. Accordingly, when the industry is concentrated, the average stock returns decrease. Generally, the concentration effect seems to be active in the London Stock Exchange (LSE) during the period of the study.

Similarly, the industry level returns decrease across concentration Quintiles. For instance, the mean returns at industry level slightly increase from Quintile 1 to Quintile 2 from .03135% to .14524% respectively. However, subsequent Quintiles show that the mean returns at industry level decrease to reach -.1122%, -.2648%, and -.1822% for Quintiles 3, 4, and 5 respectively. Accordingly, competitive industries earn, on average, higher returns compared to highly concentrated industries. Overall, both firm and industry levels returns are associated with the degree of competition and concentration. In other words, I conclude that not only the mean returns for individual stocks decrease across concentration Quintiles, but also industry average return do.

The average firm size, total assets, and net sales are higher for the most concentrated industries compared to highly competitive industries. For instance, the average size for both Quintile 4 and 5 are 2157.979 and 1768.65 respectively and are higher compared to Quintiles 1, 2, and 3 that show average size of 220.8116, 481.846, and 579.9622

respectively. Moreover, the average total assets increase significantly to reach 2322140, and 2353596 at Quintile 4, and 5 respectively, whereas the average total assets at Quintile 1, 2 are 241598.6 and 573222.6 respectively. Similarly, average net sales witness significant increase across concentration Quintiles to reach 1398816 at Quintile 5. Overall, I observe that the firms in concentrated industries seem to be large in size (*Size*) with high values of total assets (*Assets*) and net revenues (*Sales*).

The average Research and Development expenditures (*R&D*) increase across concentration Quintiles from £ 3.64 Million in Quintile 1 to reach £ 92.5 Million in Quintile 4 and then decrease to reach £ 46.78 Million in Quintile 5 (the most concentrated industries). Following the same direction, R&D to sales (*R&D/S*) and R&D to total assets (*R&D/A*) increase throughout concentration Quintiles 1 to 5. Leverage for highly concentrated industries (Quintiles 4 and 5) are higher compared with more competitive industries (Quintiles 1 and 2). For instance, the average leverage ratio for competitive industries in Quintile 1 is 3.2374, while the average leverage ratio increases to reach 3.39 and 3.27 in both concentration Quintiles 4 and 5 respectively. The average value of book-to-market ratio (B/M) decreases from 0.9414 in Quintile 1 to 0.7575 in Quintile 5, indicating that the average book-to-market ratio is lower for more concentrated industries compared to highly competitive industries. That is, in the case of highly concentrated industries, the market values of equity are higher compared to their book values. Consequently, highly concentrated industries have lower book-to-market ratios, provided that companies in similar Quintiles have similar book values of equity. Since less risky investments are more likely to have higher market values of equity, companies in highly concentrated industries are less risky compared to companies in highly competitive industries. Finally, the average betas increase across concentration

Quintiles. For instance, the average betas increase from 0.7933 in Quintile 1 to reach 0.8306 in Quintile 3, and 0.8539 in Quintile 5.

In order to examine whether previous summary statistics is sensitive to a change in industry concentration measurement, Table 5.3 displays Concentration Quintiles based on Entropy index $E(Sales)$ using net sales in each year. Quintile (1) is equivalent to the 20% of the industries with the highest concentration ratio, while quintile (5) corresponds to the 20% of the industries with the lowest concentration ratio. As shown in Table 5.3, the results mimic those presented in Table 5.2. In particular, the mean returns on both firm and industry level increase significantly from quintile 1 (highly concentrated industries) to quintile 5 (highly competitive industries) to reach 0.02% for both firm and industry levels returns. The results reinforce previous findings in Table 5.2, which show that concentrated industries earn on average lower stock returns than competitive industry and verify that concentration effect is active on both firm and industry levels in the London Stock Exchange (LSE).

The average firm size, total assets, and net sales are higher for the most concentrated industries (Quintile 1) compared to highly competitive industries (Quintile 5). For instance, the average size for both Quintile 1 and 2 are 2702.5120 and 1295.006 respectively and are higher compared to Quintiles 4 and 5 that show average size of 333.0364 and 208.0264 respectively. Moreover, the average total assets decrease significantly to reach 384115.90, and 210962.60 at Quintiles 4, and 5 respectively, whereas the average total assets at Quintile 1, 2 are 3215562 and 1630092 respectively. Similarly, average net sales witness significant decrease across concentration Quintiles to reach 250547.2 at Quintile 5. Overall, I observe that the firms in concentrated industries

seem to be large in size (*Size*) with high values of total assets (*Assets*) and net revenues (*Sales*), which support previous results in Table 5.2.

Table 5. 3 Industry Average Characteristics and E (Sales) Concentration Quintiles

Industry Mean Characteristics across E (Sales) Sorted Quintile Portfolios												
<i>Rank</i>	<i>E (Sales)</i>	<i>Fir. Ret</i>	<i>Ind. Ret</i>	<i>Size</i>	<i>Assets</i>	<i>Sales</i>	<i>R&D</i>	<i>R&D/Sales</i>	<i>R&D/A</i>	<i>Lev.</i>	<i>B/M</i>	<i>Post.Beta</i>
<i>Low</i>	0.4009	-0.0015	-0.0015	2702.5120	3215562.00	2461947.00	83746.2600	504.3134	0.0752	3.2670	0.7485	0.8112
<i>Q2</i>	1.0479	-0.0024	-0.0024	1295.0060	1630092.00	1534157.00	41346.9700	56.5391	0.0499	3.3619	0.8362	0.8018
<i>Q3</i>	1.4463	-0.0017	-0.0017	531.5577	719247.90	617338.70	9578.3390	192.9319	0.0748	3.0937	0.7765	0.8706
<i>Q4</i>	1.8554	0.0016	0.0016	333.0364	384115.90	435011.10	5328.9340	70.5481	0.0634	3.0776	0.7616	0.8167
<i>High</i>	2.7221	0.0002	0.0002	208.0264	210962.60	250547.20	4516.6790	36.1680	0.0453	3.1650	0.9342	0.7921

Table 5.3 above reports industry average characteristics across E (Sales) sorted quintile portfolios. Quintile (1) is equivalent to the 20% of the industries with the highest concentration, while quintile (5) corresponds to the 20% of the industries with the lowest concentration.

The average Research and Development expenditures (*R&D*) decrease across concentration Quintiles from £83.746 Million in Quintile 1 (the most concentrated industries) to reach £4.516 Million in Quintile 5 (the most competitive industries). Following the same direction, R&D to sales (*R&D/S*) and R&D to total assets (*R&D/A*) decrease throughout concentration Quintiles 1 to 5. Leverage seems to be flat across concentration Quintiles. For instance, the average leverage ratio for highly competitive industries in Quintile 5 is 3.165, while the average leverage ratio for the highly concentrated industries in Quintile 1 is 3.276. The average value of book-to-market ratio (*B/M*) increases from 0.7485 in Quintile 1 to 0.9342 in Quintile 5, indicating that the average book-to-market ratio is lower for more concentrated industries compared with highly competitive industries, which support Table 5.2 findings. Finally, the average betas decrease across concentration Quintiles. For instance, the average betas decrease from 0.8112 in Quintile 1 to reach 0.7921 in Quintile 5. Overall, the results in Table 5.3 mimic those presented in Table 5.2 and confirm that my results are not sensitive to a change in industry concentration measurement, indicating the robustness of the empirical findings

5.1.3 Cross-section Regression of H (Sales) on Industry Average Characteristics

To account for the correlation between the cross-section of industry concentration and average industry characteristics, I apply Fama and MacBeth cross-sectional regression (1973). I then follow Hou and Robinson (2006) in estimating the following model:

$$H(Sales)_{jt} = \alpha_t + \sum_{n=1}^N \lambda_{nt} X_{jt} + \varepsilon_{jt} \text{ (Hou and Robinson, 2006:1936)}$$

Where *H (Sales)* is the Herfindahl Index used as a proxy for industry concentration, *X_{jt}* is the industry average characteristics, including different industry characteristics ratios

as reported in Table 5.2. I estimate Fama and MacBeth cross-section regression (single and multiple) on annual basis during the period of study and report T-statistics accompanied with the time-series averages of the yearly cross-sectional coefficients for the simple and multiple regressions. Fama and MacBeth (1973) cross-sectional test is robust in conducting the cross-correlation of the residuals and helps to account for the simple and conditional correlations between industry concentration and average industry characteristics.

Panel (A) of Table 5.4 shows the results from Fama and MacBeth (1973) Cross-section Regressions of industry concentration measurement $H(Sales)$ on each of industry characteristics (Simple Regressions). Panel (B) of Table 5.4 shows the results of Fama and MacBeth Cross-section Regression of industry concentration measurement on multiple industry characteristics in which multiple industry characteristics are included as independent variables concurrently. The time series test statistics are reported in *italics* under the time-series averages of the yearly cross-sectional coefficients for the simple and multiple regressions.

Table 5. 4 Fama and MacBeth Regressions of H (Sales) on Industry Average Characteristics

Panel A: Simple Regressions						
Ln(Size)	Ln(Assets)	Ln(Sales)	R&D/A	Lev.	Ln(B/M)	PostBeta
0.0145283	0.0119131	0.0029929	-0.035216	0.007924	-0.015695	0.0029629
<i>28.55*</i>	<i>19.09*</i>	<i>5.31*</i>	<i>-0.8</i>	<i>11.72*</i>	<i>-17.95*</i>	<i>3.07*</i>
Panel B: Multiple Regressions						
Ln(Size)	Ln(Assets)	Ln(Sales)	R&D/A	Lev.	Ln(B/M)	PostBeta
			-0.085547	0.0148575	-0.039878	-0.002025
			<i>-2.37*</i>	<i>11.97*</i>	<i>-15.18*</i>	<i>-0.58</i>
0.027685			0.0451302	0.0066083	-0.026640	-0.0333
<i>39.31*</i>			<i>0.99</i>	<i>5.73*</i>	<i>-10.03*</i>	<i>-6.83*</i>
	0.0266077		0.0930626	0.002171	-0.044353	-0.0308
	<i>36.36*</i>		<i>2.01**</i>	<i>1.8***</i>	<i>-16.39*</i>	<i>-6.30*</i>
		0.0202161	0.0617377	0.0051784	-0.043678	-0.027493
		<i>24.69*</i>	<i>1.34</i>	<i>4.25*</i>	<i>-15.62*</i>	<i>-5.64*</i>
0.0110126	0.0789912	-0.065683	-0.043195	-0.001049	-0.042168	-0.035869
<i>2.92*</i>	<i>8.39*</i>	<i>-9.66*</i>	<i>-0.8</i>	<i>-0.43</i>	<i>-10.64*</i>	<i>-7.60*</i>

Table 5.4 reports Fama and MacBeth cross-section regression of H (Sales) on industry average characteristics. The variables are defined in Table 4.1. Panel A reports the results from univariate regression of H (Sales) on each industry characteristic. Panel B reports the results from the multiple regressions of industry H (Sales) on multiple industry characteristics in which multiple industry characteristics are included as independent variables concurrently. The time series test statistics are reported in *italics* under the time-series averages of the yearly cross-sectional coefficients for the simple and multiple regressions. *, **, and *** denote statistically significant at the 1%, 5% and 10% level, respectively.

Combining descriptive statistics in Table 5.2 with Fama and MacBeth cross-section regressions in Table 5.4, I observe that the natural logarithms of firm size, total assets, and net sales are significantly and positively related to industry concentration measurement $H(Sales)$ at the 1% level in simple regression. Moreover, the positive effects of firm size, total assets, and net sales remain positively significant after accounting for industry characteristics including research and development to total assets ($R\&D/A$), Leverage ($Lev.$), natural logarithm of book-to-market ratio $Ln(B/M)$, and post ranking beta ($PostBeta$). However, when all variables are accounted for in the last row of Table 5.4, the natural logarithm of net sales becomes significantly negative at the 1% level with a test statistics of (-9.66). The effect of ($R\&D/A$) on industry concentration is statistically insignificant in simple and multiple regressions (last row of Table 5.4). However, depending on the control variables, the effect of ($R\&D/A$) is negative and significant at the 1% level after accounting Leverage ($Lev.$), $Ln(B/M)$, and post ranking beta ($PostBeta$). On the other hand, when the natural logarithm of total assets is accounted for in addition to the aforementioned control variables, ($R\&D/A$) seems to be positively and significantly related to $H(Sales)$. While positive effect of ($R\&D/A$) on $H(Sales)$ indicates that highly concentrated industries involve in risky innovations, the impact of ($R\&D/A$) on $H(Sales)$ is not clear when different control variables are accounted for.

Regarding the effect of leverage on industry concentration, it is positive and statistically significant in both single and multiple regressions. Accounting for different variables, the leverage effect remains significantly positive except in the case of all control variables are accounted for, in which the leverage effect becomes statistically insignificant (last row of Table 5.4). The positive effect of leverage on industry concentration $H(Sales)$ indicates that highly concentrated industries use debts to fund investments.

With respect to natural logarithm of book-to-market ratio $Ln (B/M)$, I find that the effect of $Ln (B/M)$ on industry concentration $H (Sales)$ is significantly negative in both simple and multiple regressions at the 1% level in all reported cross-sectional regressions. This finding favors the assumption that highly concentrated industries are less risky compared with more competitive industries. Finally, the effect of beta on industry concentration appears to be positive in simple regression. However, when other control variables are accounted for, the beta effect on industry concentration is negatively significant, indicating that highly concentrated are less risky in comparison with more competitive industries.

This change of PostBeta effect on industry concentration from positive in a single regression to a negative in multiple regressions is potentially due to either measurement error in beta or omitted variable bias. The measurement error occurs because beta is measured with noise. Therefore, the error in estimating beta will be absorbed by the error term in the regression. If the measurement error is correlated with true beta values, it is likely to have changing sign in beta coefficient, as the correlation between measurement error and true beta values will violate the assumption of no correlation between the error term and explanatory variables in the regression. To reduce the probability of measurement error in estimating beta, I use the methodology of Fama and French (1992) to construct 100 size-beta portfolios and estimate post-ranking beta (PostBeta). The methodology of Fama and French (1992) helps reduce the Error-In-Variable (EIV) problem in estimating beta by constructing a precise measure of beta on portfolios level and reducing the potential correlation between pre-ranking and firm size.

Another possible reason for changing sign in PostBeta is the omitted variable bias in the single regression model (Roberts and Whited, 2011). In fact, the determinant of industry

concentration is Panel A of Table 5.4 is not limited to the PostBeta, but also includes some other factors that are not included in the single regression such as firm size, net sales, total assets, RD/A among others. If the previous omitted variables are correlated with the PostBeta, the estimated PostBeta coefficient will be biased which may lead to a change in PostBeta effect on industry concentration. Therefore, when I include various characteristics, the coefficient estimate for PostBeta becomes statistically negative.

Finally, the PostBeta effect on industry concentration reflects whether the highly concentrated or competitive industries are risky. Schumpeter advances two competing hypotheses that illustrate the relationship between industry concentration and innovation (i.e. innovation risk channel), and show the potential PostBeta effect on industry concentration. If highly competitive (concentrated) industries are risky, it is likely to have positive (negative) relationship between PostBeta and industry concentration $H(sales)$. However, if there is nonlinear relationship between industry concentration and innovation, changes in PostBeta effect on industry concentration are not uncommon.

Table 5.5 re-examines the relationship between the cross-section of industry concentration and average industry characteristics using Entropy index rather than Herfindahl index. Panel (A) of Table 5.5 shows the results from Fama and MacBeth (1973) Cross-section Regressions of industry concentration measurement $E(Sales)$ on each of industry characteristics (Simple Regressions). Panel (B) of Table 5.5 shows the results of Fama and MacBeth Cross-section Regression of industry concentration measurement on multiple industry characteristics in which multiple industry characteristics are included as independent variables concurrently. The time series test statistics are reported in *italic* under the time-series averages of the yearly cross-sectional coefficients for the simple and multiple regressions.

Table 5. 5 Fama and MacBeth Regressions of E (Sales) on Industry Average Characteristics

Panel A: Simple Regressions						
Ln(Size)	Ln(Assets)	Ln(Sales)	R&D/A	Lev.	Ln(B/M)	PostBeta
-0.04733	-0.0390845	-0.012955	0.0195051	-0.014896	0.036403	-0.01566
<i>-46.42*</i>	<i>-30.99*</i>	<i>-9.96*</i>	<i>4.73*</i>	<i>-9.04*</i>	<i>18.72*</i>	<i>-5.95*</i>
Panel B: Multiple Regressions						
Ln(Size)	Ln(Assets)	Ln(Sales)	R&D/A	Lev.	Ln(B/M)	PostBeta
			-0.527962	-0.038583	0.096759	0.0026323
			<i>-6.25*</i>	<i>-14.05*</i>	<i>14.12*</i>	<i>0.32</i>
-0.09676			-1.082926	-0.012536	0.042135	0.1012051
<i>-61.84*</i>			<i>-9.55*</i>	<i>-4.76*</i>	<i>6.26*</i>	<i>8.38*</i>
	-0.0931067		-1.242089	0.0028597	0.103036	0.092648
	<i>-59.29*</i>		<i>-10.68*</i>	<i>1.07</i>	<i>15.2*</i>	<i>7.82*</i>
		-0.071827	-1.134297	-0.006291	0.103433	0.0810121
		<i>-38.71*</i>	<i>-9.79*</i>	<i>-2.27**</i>	<i>14.57*</i>	<i>6.82*</i>
-0.05352	-0.2177874	0.183361	-0.821628	0.005538	0.079465	0.1075889
<i>-5.08*</i>	<i>-9.31*</i>	<i>11.51*</i>	<i>-6.358*</i>	<i>0.83</i>	<i>7.65*</i>	<i>9.17*</i>

Table 5.5 reports Fama and MacBeth cross-section regression of E (Sales) on industry average characteristics. The variables are defined in Table 4.1. Panel A reports the results from univariate regression of E(Sales) on each industry characteristic. Panel B reports the results from the multiple regressions of industry E (Sales) on multiple industry characteristics in which multiple industry characteristics are included as independent variables concurrently. The time series test statistics are reported in *italics* under the time-series averages of the yearly cross-sectional coefficients for the simple and multiple regressions. *, **, and *** denote statistically significant at the 1%, 5% and 10% level, respectively

Combining descriptive statistics in Table 5.3 with Fama and MacBeth cross-section regressions in Table 5.5, I observe that the natural logarithms of firm size, total assets, and net sales are significantly and negatively related to industry concentration measurement $E(Sales)$ at the 1% level in simple regression. Moreover, the negative effects of firm size, total assets, and net sales remain negatively significant after accounting for industry characteristics including research and development to total assets ($R\&D/A$), Leverage ($Lev.$), natural logarithm of book-to-market ratio $Ln(B/M)$, and post ranking beta ($PostBeta$). However, when all variables are accounted for in the last row of Table 5.5, the natural logarithm of net sales becomes significantly positive at the 1% level with a test statistics of (11.51).

The effect of ($R\&D/A$) on $E(Sales)$ appears to be positive in simple regression and negative when other control variables are accounted for at the 1% level. While positive effect of ($R\&D/A$) on $E(Sales)$ in single regression indicates that highly competitive industries involve in risky innovations, the negative effect of ($R\&D/A$) on $E(Sales)$ in multiple regressions indicates that highly concentrated industries involve in risky innovation.

Leverage effect on industry concentration $E(Sales)$ varies depending on control variables. For instance, leverage effect is negative and statistically significant in both single and multiple regressions except in the case of all control variables are accounted for, in which the leverage effect becomes statistically insignificant (last row in panel B of Table 5.5). The negative effect of leverage on industry concentration $E(Sales)$ indicates that highly concentrated industries use debts to fund investments.

With respect to natural logarithm of book-to-market ratio $Ln(B/M)$, the effect of $Ln(B/M)$ on industry concentration $E(Sales)$ is significantly positive at the 1%

level in all reported cross-sectional regressions. This finding favors the assumption that highly competitive industries are riskier compared with highly concentrated industries. Finally, the effect of beta on industry concentration $E(Sales)$ appears to be negative and significant in simple regression and statistically positive when other control variables are accounted for, indicating that highly competitive industries are riskier in comparison with highly concentrated industries. Overall, the results in Table 5.5 are in line with those in Table 5.4, indicating that the results are not sensitive to the use of different industry concentration measurements and thus the results are robust.

5.2 Industry Concentration and the Cross-section of Stock Returns

5.2.1 Empirical Results Based on Firm Level Regressions

To test the relationship between industry concentration and the cross-section of stock returns without using Quintiles limits, I perform Fama and MacBeth (FM) (1973) cross-sectional regression on firm level controlling for firm-specific characteristics and other risk factors. Therefore, I regress monthly stock returns for individual stocks (Ret) on the following factors: the industry concentration measurement $H(Sales)$, the natural logarithm of annual market value of equity for individual firms $Ln(size)$, the natural logarithm of book-to-market ratio $Ln(B/M)$, momentum, beta of individual stocks ($Beta$), and leverage ($Lev.$). In Fama and MacBeth (1972) cross-section regression, the cross-section regression is estimated in each single period by averaging the value of the slope coefficient estimates from the previous step in order to get the final coefficients estimates. The Fama and MacBeth cross-section regressions (1973) are implemented on individual stocks over a period of 25 years from 1985 to 2010 in the London Stock Exchange (LSE) using 1300 companies in 82 industries. Because the nature of unbalanced panel data, the number of monthly time-series estimates for each

cross-section parameter γ_i is 298. The firm level Fama and MacBeth (1973) cross-section regression is specified as follows:

$$\bar{R}_i = \gamma_0 + \gamma_1 H(Sales) + \gamma_2 \ln(Size) + \gamma_3 \ln(B/M) + \gamma_4 Momentum + \gamma_5 Beta + \gamma_6 Leverage + v_i$$

The average test statistics and the average time-series coefficients are reported in the regression results. Table 5.6 shows the empirical results from Fama and MacBeth cross-sectional regression (1973) based on firm level. The numbers in *italics* are the time-series of the test statistics, while all other numbers represent the time-series average of the cross-sectional coefficients.

Table 5. 6 Fama-Macbeth Cross-Sectional Regressions of Firm-Level Returns on Industry Concentration H (Sales) and other Risk Factors

Firm-Level Regressions					
H(Sales)	Ln(Size)	Ln(B/M)	Momentum	Beta	Leverage
-0.00374					
<i>-2.03**</i>					
	0.000627				
	<i>1.34</i>				
		-0.00643			
		<i>-7.22*</i>			
			0.004608		
			<i>1.32</i>		
				-0.00245	
				<i>-0.84</i>	
					-0.00081
					<i>-2.43**</i>
	0.000448	-0.00689	0.0043183	-0.00403	-0.00149
	<i>1</i>	<i>-7.69*</i>	<i>1.25</i>	<i>-1.28</i>	<i>-4.89*</i>
-0.00503	-0.00012	-0.00683	0.003609		
<i>-2.76*</i>	<i>-0.26</i>	<i>-7.09*</i>	<i>1.05</i>		
-0.00369	0.000513	-0.00692	0.003955	-0.00411	-0.0015
<i>-2.06**</i>	<i>1.14</i>	<i>-7.78*</i>	<i>1.14</i>	<i>-1.32</i>	<i>-4.96*</i>

Table 5.6 presents Fama and MacBeth cross-section regression of firm level returns on H (Sales) and firm level characteristics. Particularly, individual companies' returns are regressed on the industry H (Sales) which the company belongs to, and individual companies characteristics including Ln(Size), Ln(B/M), past 12 months returns (Momentum), beta, and leverage. The numbers in *italics* are the time-series of the test statistics, while all other numbers represent the time-series average of the cross-sectional coefficients. *, **, and *** denote statistically significant at the 1%, 5% and 10% level, respectively.

The first six rows in Table 5.6 show the results of single regressions between the cross-section of stock returns and different firm-specific characteristics (simple correlation), while the last three rows present the results of multiple regressions after controlling for different variables (conditional correlation). The first row of Table 5.6 shows that industry concentration $H(Sales)$ is negatively and significantly related to the cross-section of stock returns. The time-series average of the cross-sectional coefficients of industry concentration is significant at the 5% level with a test statistics of (-2.03). The results imply that companies operating in highly concentrated industries earn, on average, lower risk-adjusted returns compared to companies operating to highly competitive industries, which is consistent with the prediction of the null hypothesis. The results are also consistent with the reported summary statistics in Table 5.2, in which I show that the mean value of stock returns decrease significantly from the lowest concentration Quintiles to the highest concentration Quintiles. The coefficient estimate from Fama and MacBeth cross-sectional regression of returns on Herfindahl index represents the returns to a zero-cost portfolio constructed by going long a considerably highly concentrated industry (A Herfindahl index of 1) and short a considerably highly competitive industry (A Herfindahl index of 0). For instance, when I regress stock returns on industry concentration alone, the time-series average of the monthly cross-sectional coefficient of $H(Sales)$ is (-0.00374). Because $H(Sales)$ ranges between (0) to (1), the interpretation of Fama and MacBeth coefficient of Herfindahl index on stock returns indicates that a shift from highly concentrated industries to highly competitive industries generates a 37.4 basis point spread per month in average stock returns.

The next seven rows (rows 2 to 8) in Table 5.6 show that individual stock returns are negatively and significantly related to natural logarithm of book-to-market ratio $Ln(B/M)$, and leverage ($Lev.$) with high test statistics in all reported single and

multiple regressions. The results are consistent with Muradoglu and Whittington (2001), and Sivaprasad and Muradoglu (2009), who find negative and significant relationship between leverage and stock returns. The results are also in line with Malin and Veeraraghavan (2004), who show the existence of big size effect and growth effect (low book-to-market). I also observe that the cross-section of individual stock returns is insignificantly related to the natural logarithm of firm size $Ln(Size)$, *Momentum* (past 12 months returns), and beta (*Beta*) in all reported single and multiple regressions. The insignificant relationships between the cross-section of stock returns and natural logarithm of firm size, momentum, and beta are consistent with existing asset pricing studies in the UK stock market (e.g., Miles and Timmermann 1996, and Strong and Xu 1997, Al-Horani, Pope, and Stark 2003 and Hon and Tonks 2003). The results imply that neither size nor beta can explain the cross-section of stock returns in the London Stock Exchange Market (LSE) during 1985 and 2010. The inability of beta to explain the cross-section of stock returns reflects that the beta is not priced in the cross-section of stock returns. In addition, there is some information in the stock prices that cannot be detected by market beta. This further indicates that market beta does not capture the risk fully and differences in beta do not provide precise explanation about the differences in expected stock returns. Overall, the inability of market beta to explain stock returns raises concerns whether beta is dead or still alive. Although the use of beta in the cross-sectional regression does not provide interesting findings, it remains essential in any asset pricing test to include beta as one of main explanatory variables.

The last two rows of Table 5.6 re-examine the relationship between industry concentration $H(Sales)$ and average stock returns for individual stocks after controlling for different characteristics. The results indicate that industry concentration is significantly and negatively related to the cross-section of stock returns at the 1% level

with a test statistics of (-2.76) after controlling for the natural logarithm of firm size, book-to-market ratio, and momentum. Moreover, the magnitude of industry concentration increases in absolute value by (0.0013). In fact, controlling for the natural logarithm of firm size, book-to-market ratio, and momentum will increase the spread in average stock returns to a 50.3 basis point per month when moving from highly concentrated to highly competitive industries. Further, when all control variables are included (last row of Table 5.6), the coefficients of industry concentration is still negative and significant at the 5% level, indicating that highly concentrated industries earn, on average, lower risk-adjusted returns compared with competitive industries. In addition, the spread in average stock returns remains marginally similar compared with single regression, which shows that a shift from highly concentrated industries to highly competitive industries generates a 37 basis point spread per month in average stock returns. The results are consistent with Hou and Robinson (2006) study in the US stock market, in which they document a negative and significant relationship between industry concentration and the cross-section of stock returns.

Overall, combining the results from Table 5.6 with the results from Table 5.4, in which I regress the industry concentration measurement $H(Sales)$ on industry average characteristics, I find that concentrated industries are dominated by large companies with high market values of equity (and hence low book-to-market ratios). These concentrated industries generate lower returns, as they engage in less risky activities compared with competitive industries that are dominated by small companies and engage in more risky activities.

Table 5.7 re-investigates the relationship between firm level returns and industry concentration using Entropy index. As shown in Table 5.7, the time-series average of

the cross-sectional coefficients of industry concentration $E(Sales)$ on firm level returns in a simple regression is positive and significant at the 5% level with a test statistics of (1.77), implying that companies operating in highly competitive industries earn, on average, higher risk-adjusted returns compared to companies operating in highly concentrated industries, which is consistent with previous finding in Table 5.6. The results are also consistent with the reported summary statistics in Table 5.3, in which I show that the mean value of stock returns increase significantly from the highest concentration Quintiles to the lowest concentration Quintiles.

Table 5.7 Fama-Macbeth Cross-Sectional Regressions of Firm-Level Returns on Industry Concentration E (Sales) and other Risk Factors

Firm-Level Regressions					
E (Sales)	Ln(Size)	Ln(B/M)	Momentum	Beta	Leverage
0.001061					
<i>1.77**</i>					
	0.0006267				
	<i>1.34</i>				
		-0.006433			
		<i>-7.23*</i>			
			0.0040071		
			<i>1.36</i>		
				-0.00245	
				<i>-0.84</i>	
					-0.000811
					<i>-2.43**</i>
	0.0004655	-0.006582	0.002997	-0.0039	-0.001393
	<i>1.02</i>	<i>-7.33*</i>	<i>0.98</i>	<i>-1.25</i>	<i>-4.69*</i>
0.001227	-0.000138	-0.006648	0.0032265		
<i>2.1**</i>	<i>-0.27</i>	<i>-6.85*</i>	<i>1.08</i>		
0.000972	0.0005206	-0.006592	0.0030324	-0.0039	-0.001413
<i>1.72***</i>	<i>1.13</i>	<i>-7.36*</i>	<i>0.99</i>	<i>-1.26</i>	<i>-4.81*</i>

Table 5.7 presents Fama and MacBeth cross-section regression of firm level returns on E(Sales) and firm level characteristics. Particularly, individual companies' returns are regressed on the industry E (Sales) which the company belongs to, and individual companies characteristics including Ln(Size), Ln(B/M), past 12 months returns (Momentum), beta, and leverage. The numbers in *italics* are the time-series of the test statistics, while all other numbers represent the time-series average of the cross-sectional coefficients. *, **, and *** denote statistically significant at the 1%, 5% and 10% level, respectively.

The last two rows in Table 5.7 re-examine the relationship between industry concentration $E(Sales)$ and average stock returns for individual stocks after controlling for different characteristics. The results indicate that $E(Sales)$ is significantly and positively related to the cross-section of stock returns at the 5% level with a test statistics of (2.1), and the magnitude of industry concentration increases by (0.000166) to reach (0.001227) after controlling for the natural logarithm of firm size, book-to-market ratio, and momentum. Further, when all control variables are included (last row of Table 5.7), the coefficients of $E(Sales)$ is still positive and significant at the 10% level, indicating that highly competitive industries earn, on average, higher risk-adjusted returns compared with concentrated industries. The coefficients of Entropy Index from Fama and MacBeth cross-sectional regression indicate that moving from highly concentrated industries (An Entropy index of 0) to highly competitive industries (An Entropy index of $\ln(n)$) generates a 10.61 basis point spread in average monthly stock returns if I do not control for other factors. Further, the spread in average stock returns increases to 12.27 basis point per month when I control for size, book-to-market and momentum, and decrease to a 9.72 basis point per month when I control for other risk factors and stock market anomalies.

The results in Table 5.7 also indicate that the cross-section of stock returns is insignificantly related to firm size, momentum and beta. In addition, the relationship between stock returns and book-to-market ratio and leverage appears to be statistically significant and negative at the 1% level when other control variables are accounted for. Overall, the findings in Table 5.7 replicate those shown in Table 5.6, implying that my results are robust whether or not different industry concentration measures are applied.

5.2.2 Empirical Results Based on Industry Portfolio Level Regressions

To shed additional light on the relationship between industry concentration and stock returns, I apply Fama and MacBeth (1973) cross-section regression on industry portfolio level. The use of industry portfolio level will to assess whether the relationship between industry concentration and the cross-section of stock returns is still strong and robust compared with firm level analysis. Therefore, in this section, I regress industry average returns (*Ind.Ret*) on industry concentration *H (Sales)*; natural logarithm of industry size *Ind.(Size)*; natural logarithm of industry book-to-market ratio *Ind.(B/M)*; industry momentum *Ind.Momentum* (past 12 months returns on industry portfolio); industry beta *Ind.Beta*; and industry leverage *Ind.leverage*.

Table 5.8 reports the results from Fama and MacBeth cross-sectional regression (1973) on industry level returns. The numbers in *italics* are the time-series of the test statistics, while all other numbers represent the time-series average of the cross-sectional coefficients.

Table 5. 8 Fama-Macbeth Cross-Sectional Regressions of Industry-Level Returns on Industry Concentration H (Sales) and Industry Risk Factors

Industry-Level Regressions					
H(Sales)	Ind.(Size)	Ind. (B/M)	Ind. Momentum	Ind. Beta	Ind. Leverage
-0.00373					
<i>-2.02**</i>					
	0.0010303				
	<i>2.18**</i>				
		-0.004764			
		<i>-3.28*</i>			
			0.0266252		
			<i>3.07*</i>		
				-0.00444	
				<i>-1.26</i>	
					0.0003969
					<i>0.47</i>
	0.0007333	-0.0044	0.0181485	-0.00400	-0.0006646
	<i>1.49</i>	<i>-3.12*</i>	<i>2.34**</i>	<i>-1.15</i>	<i>0.97</i>
-0.00511	0.0007273	-0.0046	0.0218922		
<i>-2.81*</i>	<i>1.31</i>	<i>-2.81*</i>	<i>2.55**</i>		
-0.00441	0.0009296	-0.0045	0.0159469	-0.00436	-0.0005929
<i>-2.50**</i>	<i>1.85***</i>	<i>-3.27*</i>	<i>2.05**</i>	<i>-1.26</i>	<i>-0.98</i>

Table 5.8 presents Fama and MacBeth cross-section regression of industry level returns on H (Sales) and industry average characteristics. Particularly, industry average returns are regressed on the industry H (Sales) measure, and industry average values of Ln(size), Ln(B/M), past 12 months returns industry portfolios (Momentum), beta, and leverage. The numbers in *italics* are the time-series of the test statistics, while all other numbers represent the time-series average of the cross-sectional coefficients. *, **, and *** denote statistically significant at the 1%, 5% and 10% level, respectively.

The first six rows in Table 5.8 show the results of single regressions between the cross-section of stock returns and different characteristics (simple correlation), while the last three rows show the results of multiple regressions after accounting for different variables (conditional correlation). Consistent with firm level results, the first column in Table 5.8 demonstrates that highly concentrated industries earn, on average, lower returns compared with highly competitive industries. The time-series average of the cross-sectional coefficients for Herfindahl index $H(Sales)$ is always negative and statistically significant in all regressions. For instance, when industry average returns are regressed on $H(Sales)$ alone, the time-series average of the cross-sectional coefficients of $H(Sales)$ is (-0.00373) and statistically significant at the 1 % level. The results indicate that a move from highly concentrated industries to highly competitive industries generates a 37.3 basis point spread per month in industry average returns. Further, when I control for natural logarithm of industry size $Ind.(Size)$, natural logarithm of industry book-to-market $Ind.(B/M)$, and industry momentum $Ind.Momentum$ (past 12 months returns on industry portfolio), the coefficient of industry concentration $H(Sales)$ is still negative and significant at the 5 % level, signifying that the spread in industry average returns is 51.1 basis point per month when moving from highly concentrated to highly competitive industries.. Finally, when I control for all variables including industry beta $Ind.Beta$, and industry leverage $Ind.leverage$, the industry concentration $H(Sales)$ is still negative and significant at the 5% level and shows that a shift from highly concentrated industries to highly competitive industries generate 44.1 basis point spread per month in industry average returns.

The first seven rows in Table 5.8 show that the industry average returns is negatively related to industry book-to-market, positively related to industry momentum and insignificantly related to both industry beta and industry leverage. Depending on the

control variable, the industry size is insignificantly related to industry average returns when I control for industry book-to-market, industry momentum, industry beta, and industry leverage. However, when I account for industry concentration $H(Sales)$ in addition to the aforementioned variables, the industry size is positively and significantly related to the cross-section of industry returns at the 10% level. The results are consistent with Malin and Veeraraghavan (2004) study which shows the existence of big size effect and growth effect (low book-to-market). With regards to momentum effect and beta, the results are also in line with the studies of Liu, Strong, and Xu (1999), and Yurtsever and Zahor (2007) respectively.

Consistent with firm level analysis, I conclude that not only individual companies' returns fluctuate with industry concentration, but also industries average returns do. Particularly, competitive industries earn, on average, higher returns compared to concentrated industries. The results remain stable and robust under different empirical tests in simple and conditional cross sectional regression(s).

Table 5.9 applies Entropy index to measure industry concentration, and tests the relationship between industry concentration and industry level returns. As shown in Table 5.9, the industry concentration $E(Sales)$ is statistically positive at 10% level with a test statistics of (1.77), indicating that highly competitive industries earn higher risk-adjusted returns compared to highly concentrated industries. This positive relationship between $E(Sales)$ and industry average returns remains significantly positive even after accounting for different industry characteristics such as industry size, industry book-to-market ratio, industry momentum, industry beta, and industry leverage (last two rows in Table 5.9).

The results indicate that when I regress industry average returns on Entropy index alone, the coefficient of Entropy index on industry average returns is 0.001061, signifying that a shift from highly concentrated to a highly competitive industry generates a spread of 10.61 basis point per month in industry average returns. The spread in industry average returns increases to 13.46 basis point per month when I account for different industry characteristics including industry beta, industry size, industry book-to-market, industry momentum, and industry leverage.

The results from Table 5.9 also indicate that the cross-section of industry average returns is insignificantly related industry momentum, industry beta, and industry leverage in all multiple regressions. While the industry average returns is negatively related to industry book-to-market ratio in all reported regressions, the relationship between industry average returns and industry average size varies depending on control variables. Overall, the results in Table 5.9 are consistent with those findings reported in Table 5.8, in which I use Herfindahl index as a proxy for industry concentration. Therefore, my results are robust and not sensitive to a change in the proxy of industry concentration.

Table 5. 9 Fama-Macbeth Cross-Sectional Regressions of Industry-Level Returns on Industry Concentration E (Sales) and Industry Risk Factors

Industry-Level Regressions					
E (Sales)	Ind.(Size)	Ind. (B/M)	Ind. Momentum	Ind. Beta	Ind. Leverage
0.001061					
<i>1.77***</i>					
	0.0010303				
	<i>2.18**</i>				
		-0.004766			
		<i>-3.28*</i>			
			0.017327		
			<i>2.07**</i>		
				-0.00444	
				<i>-1.26</i>	
					0.000397
					<i>0.47</i>
	0.0007708	-0.003878	0.0103187	-0.00399	-0.0006453
	<i>1.56</i>	<i>-2.73*</i>	<i>1.23</i>	<i>-1.13</i>	<i>-1.06</i>
0.001346	0.0007766	-0.003939	0.0131366		
<i>2.23**</i>	<i>1.36</i>	<i>-2.39**</i>	<i>1.54</i>		
0.001346	0.0009558	-0.003862	0.0101377	-0.00398	-0.0007147
<i>1.78***</i>	<i>1.84***</i>	<i>-2.71*</i>	<i>1.2</i>	<i>-1.13</i>	<i>-1.19</i>

Table 5.9 presents Fama and MacBeth cross-section regression of industry level returns on E (Sales) and industry average characteristics. Particularly, industry average returns are regressed on the industry E (Sales) measure, and industry average values of Ln(size), Ln(B/M), past 12 months returns industry portfolios (Momentum), beta, and leverage. The numbers in *italics* are the time-series of the test statistics, while all other numbers represent the time-series average of the cross-sectional coefficients. *, **, and *** denote statistically significant at the 1%, 5% and 10% level, respectively.

5.2.3 Empirical Results Based on 100 Size-Beta Portfolios Level Regressions

In order to re-evaluate the role of industry concentration with other characteristics on stock returns, I perform Fama and MacBeth (1973) cross-section regression using Fama and French (1992) method. Fama and French (FF) (1992) form 100 size-beta portfolios to assess the joint role of size, beta, and other risk factors on the cross-section of stock returns. Therefore, I use Fama and French (1992) method to assess whether the existence of industry concentration effect is robust in the UK stock market compared with firm and industry levels analysis.

To perform 100 size-beta portfolios according to Fama and French (1992), I first sort the companies in each year according to size (the natural logarithm of annual market value of equity for individual companies). Then, I form size deciles according to firms' size. Therefore, up to this stage, I have 10 size portfolios. Afterwards, I sort the companies in each year according to their beta values. Consequently, I form deciles according to beta. Therefore, I will have 10 portfolios formed according to beta. The intersection between 10 size portfolios and 10 beta portfolios will give 100 size-beta portfolios. Subsequently, I calculate the post-ranking mean returns for each of the 100 size-beta portfolios in each year. In order to estimate the post ranking betas, I regress post ranking mean returns for each of the 100 size-beta portfolios in each year on the market returns. I then assign the post-ranking beta to each stock on a yearly basis so that it has the same beta within the 12-month period. Afterwards, I use the estimated post ranking betas *Post. Beta* in Fama and MacBeth cross-section regression (1973) with other firms' characteristics including: the industry concentration measurement $H(Sales)$, the natural logarithm of annual market value of equity for individual firms $Ln(size)$, the natural logarithm of book-to-market ratio $Ln(B/M)$, momentum, and leverage (*Lev.*).

Table 5. 10 Fama-Macbeth Cross-Sectional Regressions of Firm-Level Returns on H (Sales) Using Fama and French (1992) Method

Firm-Level Regressions FF (1992) post ranking beta					
H(Sales)	Ln(Size)	Ln(B/M)	Momentum	Beta	Leverage
-0.00374					
-2.03**					
	0.000627				
	<i>1.34</i>				
		-0.00643			
		-7.22*			
			0.0046084		
			<i>1.32</i>		
				-0.00343	
				-1.19	
					-0.00081
					-2.43**
	0.00044	-0.00682	0.0052269	-0.004111	-0.00129
	<i>1.02</i>	-7.62*	<i>1.51</i>	-1.44	-4.35*
-0.00503	-0.00012	-0.00683	0.0036097		
-2.76*	-0.26	-7.09*	<i>1.05</i>		
-0.00416	0.000516	-0.0068	0.004817	-0.0042	-0.00129
-2.37**	<i>1.18</i>	-7.70*	<i>1.39</i>	-1.47	-4.39*

Table 5.10 presents Fama and MacBeth cross-section regression of firm level returns on H (Sales) and firm level characteristics. Particularly, individual companies returns are regressed on the industry H (Sales) which the company belongs to, and individual companies characteristics including Ln(Size), Ln(B/M), past 12 months returns (Momentum), post ranking beta, and leverage. The numbers in *italics* are the time-series of the test statistics, while all other numbers represent the time-series average of the cross-sectional coefficients. *, **, and *** denote statistically significant at the 1%, 5% and 10% level, respectively.

Table 5.10 reports the results from Fama and MacBeth cross-sectional regression (1973) on firm level returns using post-ranking beta as in Fama and French (1992). The time series test statistics are reported in *italics* under the time-series averages of the monthly cross-sectional coefficients for the simple and multiple regressions.

Consistent with both firm and industry level results; the first row in Table 5.10 shows that industry concentration H (*Sales*) helps explain the cross-section of stock returns during the period of study. The time-series from the monthly cross-sectional regression of returns on industry concentration is (-.003745) with a test statistics of (-2.03). This authentic negative relationship remains strong regardless whether or not other explanatory variables are accounted for in all regressions. In fact, the inclusion of other factors such as firms Ln (*size*), book-to-market Ln (B/M), and momentum in the model does not ruin the ability of industry concentration in explaining the cross-section of stock returns. Rather, the relationship appears to be strong. For instance, when I account for all variables including leverage and post ranking beta, the coefficients of industry concentration is still negative and significant at the 5% level with a test statistics of (-2.37), indicating that highly concentrated industries earn, on average, lower risk-adjusted returns compared with competitive industries. The interpretation of Fama and MacBeth coefficient of Herfindahl index on stock returns is that a shift from highly concentrated industries to highly competitive industries generates a 37.4 basis point spread in average monthly stock returns when I regress stock returns on Herfindahl index alone. The spread in average stock returns increases to 50.3 basis point per month when moving from highly concentrated to highly competitive industries after controlling for firm size, book-to-market ratio, and momentum. Finally, when I control for all risk factors and stock market anomalies, a shift from highly concentrated industries to highly competitive industries generates a 41.6 basis point spread in average monthly stock returns.

Rows 2 to 8 in Table 5.10 show that individual stock returns are negatively and significantly related to book-to-market $Ln(B/M)$, and leverage ($Lev.$) with high test statistics in all reported single and multiple regressions. In addition, the cross-section of individual stock returns is insignificantly related to firm size $Ln(Size)$, *Momentum* (past 12 months returns), and post ranking beta *Post.Beta* in all reported single and multiple regressions. The insignificant relationships between the cross-section of stock returns and both natural logarithm of firm size $Ln(Size)$ and post ranking beta *Post.Beta* are consistent with existing asset pricing literature in the UK stock market (e.g., Miles and Timmermann 1996, and Strong and Xu 1997, Al-Horani, Pope, and Stark 2003 and others). Therefore, the results imply that neither size nor post ranking beta is statistically significant in explaining the cross-section of stock returns in the London Stock Exchange Market (LSE) between 1985 and 2010.

Overall, I find that $H(Sales)$ is negatively related to the expected stock returns in all Fama and MacBeth cross-sectional regressions. In addition, the negative relationship between industry concentration and expected stock returns remain significantly negative after $Ln(size)$, $Ln(B/M)$, momentum, leverage ($Lev.$), and beta (or post ranking beta) are included, while beta (post ranking beta) and $Ln(size)$ are never significant. The results are robust to firm- and industry-level regressions and the formation of firms into 100 size-beta portfolios. The findings indicate that competitive industries earn, on average, higher returns compared to concentrated industries which is consistent with Schumpeter's concept of creative destruction.

Using Entropy index as a proxy for industry concentration, Table 5.11 re-tests the relationship between industry concentration and firm level returns with other firm-specific characteristics and post-ranking beta as in Fama and French (1992). As shown in

Table 5.11, the results mimic those presented in Tables 5.10 and 5.7. In particular, the industry concentration measured by Entropy index is always positive and statistically significant in all simple and multiple regressions. The time-series from the monthly cross-sectional regression of returns on $E(Sales)$ is (0.001061) with a test statistics of (1.77) in single regression. In addition, when firm size, book-to-market ratio, momentum, leverage and post ranking beta are accounted for, the relationship between $E(Sales)$ and the cross-section of stock returns remains significantly positive at the 10 % level with a test statistics of (1.75), indicating that highly competitive industries earn, on average, higher risk-adjusted returns compared to highly concentrated industries. The results also confirm that the cross-section of firm level returns is insignificantly related to firm size, momentum, and post ranking beta, and negatively related to book-to-market, and leverage ratios.

Overall, the results in Table 5.11 are consistent with the reported findings in Table 5.10, signifying that the results are robust to different industry concentration measures.

Previous sections report the results from Fama-MacBeth cross-sectional regressions. Chapter Six reports the results from the time-series regressions on the relationship between industry concentration premium and both risk premiums and risk factors. Moreover, Chapter Six presents the results on the relationship between industry concentration and time-series variation in the UK stock returns, and tests how industry concentration interacts with both firm size, and book-to-market equity to explain average stock returns in the UK stock market.

Table 5. 11 Fama-Macbeth Cross-Sectional Regressions of Firm-Level Returns on E (Sales) Using Fama and French (1992) Method

Firm-Level Regressions Using Fama and French 1992 post ranking beta					
E (Sales)	Ln(Size)	Ln(B/M)	Momentum	Post.Beta	Leverage
0.001061					
<i>1.77**</i>					
	0.0006267				
	<i>1.34</i>				
		-0.006433			
		<i>-7.23*</i>			
			0.0040071		
			<i>1.36</i>		
				-0.003433	
				<i>-1.19</i>	
					-0.000811
					<i>-2.43**</i>
	0.0004739	-0.006464	0.001689	-0.004025	-0.00123
	<i>1.07</i>	<i>-7.2*</i>	<i>0.55</i>	<i>-1.41</i>	<i>-4.27*</i>
0.001227	-0.000138	-0.006648	0.0032265		
<i>2.1**</i>	<i>-0.27</i>	<i>-6.85*</i>	<i>1.08</i>		
0.000981	0.0005352	-0.006471	0.0016386	-0.00407	-0.001248
<i>1.75***</i>	<i>1.19</i>	<i>-7.23*</i>	<i>0.53</i>	<i>-1.43</i>	<i>-4.39*</i>

Table 5.11 presents Fama and MacBeth cross-section regression of firm level returns on E (Sales) and firm level characteristics. Particularly, individual companies returns are regressed on the industry E (Sales) which the company belongs to, and individual companies characteristics including Ln(Size), Ln(B/M), past 12 months returns (Momentum), post ranking beta, and leverage. The numbers in *italics* are the time-series of the test statistics, while all other numbers represent the time-series average of the cross-sectional coefficients. *, **, and *** denote statistically significant at the 1%, 5% and 10% level, respectively.

CHAPTER SIX

EMPIRICAL RESULTS FROM TIME-SERIES REGRESSION:

6.1 Time-Series Variation in Industry Concentration Premium and Risk Factors:

In this section, I examine whether the time-series changes in industry concentration premium is associated with the premiums of various risk factors such size, book-to-market, momentum, beta, and leverage. Therefore, I follow Hou and Robinson (2006:1946) in estimating the following model:

$$\lambda_t^H = \alpha + \sum_{i=1}^I \beta_i Fit + \varepsilon_t$$

Where α : is the concentration premium from the regression (it is so-called alpha); λ_t^H : $H(\text{sales})$ premium is the monthly time series of industry concentration risk premium conducted on the firm level from Fama and MacBeth cross-section regression, in which the cross-section of individual stock returns are regressed on industry concentration, controlling for other factors (the last row in Table 5.6); Fit ; is Fama and French (1993) factor-mimicking portfolios (on monthly basis t), including market excess return ($R_m - R_f$), size (SMB), book-to-market (HML), as well as momentum. I also use risk premiums of size, book-to-market, momentum, beta, and leverage from Fama and MacBeth firm level cross-section regression, in which the cross-section of individual stock returns are regressed on industry concentration, controlling for other factors (the last row in Table 5.6).

Table 6.1 Time-Series Variation in Industry Concentration Premium of H (Sales) and the Premiums of other Risk Factors

Panel A :Time-Series Variation of the Industry Concentration Premium and other Risk Factors' Premiums						
<i>Alpha (Intercept)</i>	<i>Ln(Size)-Prem.</i>	<i>Ln(B/M)-Prem.</i>	<i>Momentum-Prem.</i>	<i>Beta-Prem.</i>	<i>Leverage-Prem.</i>	<i>Adjusted R²</i>
-0.0052328	-0.809718	-0.1863236	-0.0579149	0.0070841	-0.6116692	8.42%
<i>-2.69*</i>	<i>-3.29*</i>	<i>-1.43</i>	<i>-2.00**</i>	<i>0.22</i>	<i>-1.72***</i>	
Panel B :Time-Series Variation of the Industry Concentration Premium and other Risk Factors' Premiums						
<i>Alpha (Intercept)</i>	<i>Ln(Size)-Prem.</i>	<i>Ln(B/M)-Prem.</i>	<i>Momentum-Prem.</i>	<i>R_m- R_f</i>	<i>Leverage-Prem.</i>	<i>Adjusted R²</i>
-0.0038343	-0.8195001	-0.1789686	-0.0579236	0.022907	-0.665049	8.52%
<i>-1.43</i>	<i>-3.34*</i>	<i>-1.37</i>	<i>-1.99**</i>	<i>0.78</i>	<i>-1.82***</i>	
Panel C :Time-Series Variation of the Industry Concentration Premium and returns on Factor Mimicking Portfolios						
<i>Alpha (Intercept)</i>	<i>SMB</i>	<i>HML</i>	<i>Momentum</i>	<i>R_m- R_f</i>	<i>Adjusted R²</i>	
-0.0036345	0.1650333	-0.0666401	-0.0247839	0.0294067	4.41%	
<i>-1.12</i>	<i>2.60*</i>	<i>-1.22</i>	<i>-1.77***</i>	<i>0.87</i>		

Table 6.1 shows the results from the time-series regressions of industry concentration risk premium of H (sales) on various risk premiums and risk factors. Panel A and B present the time-series results of the monthly H (Sales) premium on the premiums of Ln(Size), Ln(B/M), Momentum, and leverage. All risk premiums are obtained from monthly Fama and MacBeth cross-sectional regression, in which the cross-section of individual stock returns are regressed on industry concentration H(Sales), controlling for other factors (last row in Table 5.6). Panel C reports the time-series results of industry concentration risk premium of H(sales) on various risk factors including: SMB (Small market capitalization minus big), HML (High book-to-market minus low), Momentum, and market excess returns. Numbers in *italics* are *t*-statistics. *, **, and *** denote statistically significant at the 1%, 5% and 10% level, respectively.

Panel A of Table 6.1 presents the results from regressing the monthly time-series of industry concentration premium of $H(Sales)$ on the risk premiums of size, book-to-market, momentum, beta, and leverage. As Panel A of Table 6.1 indicates, the regression intercept is negative and statistically significant at the 1% level after controlling for all risk premiums. In addition, the industry concentration risk premium of $H(Sales)$ increases (in absolute value) from 0.369% (the last row in Table 5.6) to 0.5233% and the regression Adjusted R^2 is 8.42%, indicating that various risk premiums explain 8.42% of the industry concentration premium. Interestingly, the time-series results in Panel A show that constant term (alpha) is negative and statistically significant at the 1% level, implying that the risk premiums of size, book-to-market, momentum, beta, and leverage cannot explain the industry concentration premium. Therefore, industry concentration premium of $H(Sales)$ has separate information compared with other risk premiums in predicting the time-series variation in stock returns. The results reinforce the findings in previous cross-sectional regressions, in which I demonstrate that industry concentration is negative and statistically significant in all reported cross-sectional regressions and includes independent information about the cross-section of average stock returns (see Tables 5.6, 5.8, 5.10). The results in Panel A of Table 6.1 are also in line with Hou and Robinson (2006) study in the US market, which confirms similar findings.

Panel B of Table 6.1 re-tests the relationship between industry concentration premium of $H(Sales)$ and the premiums of other risk factors using market excess return instead of beta premium. The results indicate that $H(Sales)$ risk premium increases slightly (in absolute value) from 0.369% (the last row in Table 5.6) to 0.3834% and the regression Adjusted R^2 increases marginally to reach 8.52%, indicating that the risk premiums of size, book-to-market, momentum, market excess returns, and leverage explain 8.52% of the industry concentration premium. However, the regression intercept (alpha) is

statistically insignificant and negative, signifying that industry concentration premium is subsumed by various risk premiums. Therefore, industry concentration premium can partly include separate information compared with other risk premiums.

Panel C of Table 6.1 show the results from regressing the monthly time series of industry concentration risk premium on Fama and French (1993) risk factors including market excess return ($R_m - R_f$), size (SMB), and book-to-market (HML), as well as momentum. Consistent with Panel B of Table 6.1, the regression intercept is statistically insignificant and negative, signifying that industry concentration premium can partly include information which is already subsumed by various risk factors. Notably, the regression adjusted R^2 decreases significantly to reach 4.41% compared to the adjusted R^2 in both Panels A and B of Table 6.1 and the H (*Sales*) risk premium decreases slightly (in absolute value) from 0.369% (last row of Table 5.6) to 0.363%.

The results in both Panels B and C of Table 6.1 are in line with Gallagher and Ignatiev (2010) study in the Australian market, which shows that industry concentration' premium can partly include information that is already spanned by other risk factors. Overall, the findings in Panels A, B and C of Table 6.1 imply that H (*Sales*) risk premium can include independent information compared with the premiums of various risk factors. Moreover, when Fama and French (1993) risk factors and momentum are accounted for, the H (*Sales*) risk premium can partly include information that is already spanned by other risk factors.

Table 6.2 re-examines whether the time-series changes in industry concentration premium of Entropy index E (*Sales*) is associated with the risk premiums of size, book-to-market, momentum, beta, and leverage. Panel A of Table 6.2 shows the results from regressing the monthly time-series of industry concentration premium of E (*Sales*) on

the risk premiums of size, book-to-market, momentum, beta, and leverage. The results in Panel A of Table 6.2 indicates that the regression intercept is positive and statistically significant at the 1% level and the industry concentration risk premium of $E(Sales)$ increases significantly from 0.09715% (the last row of Table 5.7) to 0.20052%. The regression Adjusted R^2 is 12.99% indicating that various risk premiums explain 12.99% of $E(Sales)$ risk premium. The time-series results in Panel A show that the intercept (alpha) is statistically significant at the 1 % level, indicating that industry concentration premium has separate information compared with other risk premiums in predicting stock returns. The results reinforce the findings in previous cross-sectional regressions, in which I demonstrate that industry concentration $E(Sales)$ is positive and statistically significant in all reported cross-sectional regressions and includes independent information about the cross-section of average stock returns (see Tables 5.7, 5.9, 5.11).

Panel B of Table 6.2 re-tests the relationship between industry concentration premium and other risk premiums using market excess return instead of beta premium. The results indicate that $E(Sales)$ risk premium increases from 0.09715% (the last row of Table 5.7) to 0.148%. In addition, the regression intercept is positive and statistically significant at the 10% level, signifying that $E(Sales)$ risk premium includes independent information compared with other risk premiums in predicting stock returns. The regression Adjusted R^2 increases marginally to reach 13.04%, indicating that the risk premiums explain 13.04% of $E(Sales)$ risk premium.

Panel C of Table 6.2 shows the results from regressing the monthly time series of $E(Sales)$ risk premium on Fama and French (1993) risk factors including market excess return ($R_m - R_f$), size (SMB), and book-to-market (HML), as well as momentum. As shown in Panel C of Table 6.2, the regression intercept is insignificant and positive,

signifying that $E(Sales)$ risk premium can partly include information which is already subsumed by other risk factors. Notably, the regression adjusted R^2 decreases significantly to reach 5.59% compared to the Adjusted R^2 in both Panels A and B of Table 6.2. Moreover, the $E(Sales)$ risk premium decreases from 0.09715% (last row of Table 5.7) to 0.04262%.

Overall, the findings in Panels A, B and C of Table 6.2 imply that $E(Sales)$ risk premium can include independent information compared with the premiums of various risk factors. Moreover, when Fama and French (1993) risk factors and momentum are accounted for, the $E(Sales)$ risk premium can partly include information that is already spanned by other risk factors. The results are also consistent with those reported in Table 6.1. Therefore, the results are robust and not sensitive to a change in industry concentration measures.

Next section empirically investigates whether the industry concentration risk premium and other risk premiums can explain the time-series variation in stock returns. In particular, next section tests whether industry concentration premium is subsumed by either the premiums of risk factors or by existing risk factors.

Table 6.2 Time-Series Variation in Industry Concentration Premium of E (Sales) and the Premiums of other Risk Factors

Panel A :Time-Series Variation of the Industry Concentration Premium and other Risk Factors' Premiums						
<i>Alpha (Intercept)</i>	<i>Ln(Size)-Prem.</i>	<i>Ln(B/M)-Prem.</i>	<i>Momentum-Prem.</i>	<i>Beta-Prem.</i>	<i>Leverage-Prem.</i>	<i>Adjusted R²</i>
0.0020052	0.2591008	0.1211438	-0.0025063	-0.003808	0.2670217	12.99%
<i>3.38*</i>	<i>3.49*</i>	<i>3.05*</i>	<i>-0.25</i>	<i>-0.38</i>	<i>2.37**</i>	
Panel B :Time-Series Variation of the Industry Concentration Premium and other Risk Factors' Premiums						
<i>Alpha (Intercept)</i>	<i>Ln(Size)-Prem.</i>	<i>Ln(B/M)-Prem</i>	<i>Momentum-Prem.</i>	<i>R_m- R_f</i>	<i>Leverage-Prem.</i>	<i>Adjusted R²</i>
0.0014881	0.261645	0.1168402	-0.003268	-0.0089013	0.2892889	13.04%
<i>1.81***</i>	<i>3.55*</i>	<i>2.93*</i>	<i>-0.32</i>	<i>-0.98</i>	<i>2.51*8</i>	
Panel C :Time-Series Variation of the Industry Concentration Premium and returns on Factor Mimicking Portfolios						
<i>Alpha (Intercept)</i>	<i>SMB</i>	<i>HML</i>	<i>Momentum</i>	<i>R_m- R_f</i>	<i>Adjusted R²</i>	
0.0004262	-0.0516294	0.0377174	0.0011995	-0.0183102	5.59%	
<i>0.44</i>	<i>-2.57**</i>	<i>2.15**</i>	<i>0.32</i>	<i>-1.72***</i>		

Table 6.2 shows the results from the time-series regressions of industry concentration risk premium of E (sales) on various risk premiums and risk factors. Panel A and B present the time-series results of the monthly E (Sales) premium on the premiums of Ln(Size), Ln(B/M), Momentum, and leverage. All risk premiums are obtained from monthly Fama and MacBeth cross-sectional regression, in which the cross-section of individual stock returns are regressed on industry concentration E(Sales), controlling for other factors (last row in Table 5.7). Panel C reports the time-series results of industry concentration risk premium of E (sales) on various risk factors: SMB (Small market capitalization minus big), HML (High book-to-market minus low), Momentum, and market excess returns. Numbers in *italics* are *t*-statistics. *, **, and *** denote statistically significant at the 1%, 5% and 10% level, respectively.

6.2 Can Industry Concentration Explain the Time-Series Variation in Stock Returns?

In this section, I examine whether industry concentration premium explains the time-series variation in stock returns after accounting for various risk premiums. Moreover, I test whether the industry concentration premium is subsumed by either the premiums of risk factors or by existing risk factors in explaining time-series variation in stock returns. Therefore, I regress time-series of stock returns on the time-series of industry concentration premium and the premiums of other risk factors (Table 6.3). Afterwards, I regress time-series of stock returns on the time-series of industry concentration premium and other risk factors including Fama and French mimicking portfolios factors and momentum factor (Table 6.5). Therefore, I adopt the following model:

$$R_{it} = \alpha + \delta \lambda_t^H + \sum_{i=1}^I \beta_i F_{it} + \varepsilon$$

Where: R_{it} represents the time-series of the stock return; α : is the intercept from the regression; λ_t^H : is the time series of industry concentration risk premium conducted on the firm level from Fama and MacBeth cross-section regression, in which the cross-section of individual stock are regressed on industry concentration, controlling for other risk factors; F_{it} : is Fama and French (1993) factor-mimicking portfolios (on monthly basis t), including market excess return ($R_m - R_f$), size (SMB), and book-to-market effect (HML), as well as Momentum. I also use risk premiums of size, book-to-market, momentum, beta, and leverage from Fama and MacBeth cross-section regression on firm level, in which the cross-section of individual stock returns are regressed on industry concentration, controlling for other factors (the last row in Table 5.6).

6.2.1 Industry Concentration Premium, Risk Premiums, and Time-series of Stock Returns

Panel A of Table 6.3 shows the results from regressing the time-series stock returns on industry concentration premium of $H(Sales)$ and the risk premiums of size, book-to-market, momentum, beta, and leverage. The first row in Panel A of Table 6.3 indicates that in a single regression, $H(Sales)$ risk premium explains the time-series variation of stock returns with a test statistics of (-6.08) at the 1% level. Rows (2 to 7) test whether $H(Sales)$ risk premium explains the time-series variation in stock returns after accounting for various risk premiums. Particularly, when size premium is accounted for (Row 2), $H(Sales)$ risk premium is negative and statistically significant with a test statistic of (-23.72) at the 1% level. Moreover, when various risk premiums such as size, book-to-market, momentum, market excess returns, and leverage are accounted for, $H(Sales)$ risk premium remains negative and statistically significant at the 1% level with a test statistics of (-24.57) (Row 7). The adjusted R^2 in the last two rows of Panel A increase significantly to reach 9.88% and 9.15% respectively, indicating that the inclusion of various risk premiums increases the explanatory power in explaining the time-series variation in stock returns. In particular, the inclusion of beta premium (market excess returns) increases significantly the adjusted R^2 , highlighting the importance of beta premium as essential factor in capturing the time-series variation in stock returns.

The results in panel A also indicate that although the industry concentration risk premium of $H(sales)$ is negative and statistically significant at the 1% level in the single regression, both the adjusted R^2 and the magnitude of $H(sales)$ risk premium are significantly small (0.02%) and (-0.0789); respectively. If I account for size premium, the adjusted R^2 increases to reach (3.12%) and the $H(sales)$ remains negatively significant at the 1% level and increases in absolute value to reach (0.3139). The magnitude of

$H(\text{sales})$ risk premium marginally increases in absolute value to reach (0.32) with a high test statistics of (-24.57) and the adjusted R^2 becomes significantly higher (9.15%) after accounting for the premiums of size, book-to-market, leverage, and momentum; and market excess return. The magnitude of $H(\text{sales})$ risk premium indicates that a 1 percentage point increase in $H(\text{sales})$ risk premium leads to a 0.32 percentage point decrease in average monthly stock returns.

Overall, Panel A of Table 6.3 presents empirical evidence about the ability of $H(\text{Sales})$ risk premium in explaining the time-series of stock returns after controlling for various risk premiums. Consistent with Hou and Robinson (2006), the ability of $H(\text{Sales})$ risk premium in explaining time-series of stock returns is not subsumed by other risk premiums, signifying that $H(\text{Sales})$ risk premium has separate information in explaining time-series variation in stock returns.

In Panel B of Table 6.3, I empirically investigate whether the unexplained part $H(\text{Sales})$ risk premium by various risk premiums can still explain the time-series variation in stock returns. Therefore, I use the residuals from Panels A and B of Table 6.1, in which I regress the monthly time-series of $H(\text{Sales})$ risk premium on various risk premiums such as size, book-to-market, momentum, beta (market excess returns), and leverage. Afterwards, I regress the time-series of stock returns on the residuals of $H(\text{Sales})$ risk premium and on the risk premiums of size, book-to-market, momentum, beta, and leverage.

The first row in Panel B of Table 6.3 indicates that the residuals of $H(\text{Sales})$ risk premium are negative and statistically significant at the 1% level after accounting for all risk premiums. Moreover, the risk premiums of size, book-to-market, momentum, beta, and leverage are statistically significant; indicating that risk premiums can explain the

time-series variation in stock returns. The adjusted R^2 shows that various risk premiums including the residuals of $H(Sales)$ risk premium explain 9.91% of the time-series variation in stock returns. The results also imply that whether or not the premiums of risk factors can subsume industry concentration premium, $H(Sales)$ risk premium can explain the time-series variation in stock returns. Hence, the results favor the assumption that $H(Sales)$ risk premium has separate information compared with other risk premiums in explaining the time-series variation in stock returns.

In the second row of Panel B in Table 6.3, I re-examine whether the unexplained part of $H(Sales)$ risk premium by various risk premiums still predicts the time-series variation in stock returns using market excess returns ($R_m - R_f$) instead of beta premium. Therefore, I use the residuals from Panel B of Table 6.1, in which I regress the monthly time-series of $H(Sales)$ risk premium on the risk premiums of size, book-to-market, momentum, market excess returns, and leverage. The results are consistent with previous findings in Row 1 of Panel B in Table 6.3. In particular, the residuals of $H(Sales)$ risk premium are negative and statistically significant at the 1% level, implying that $H(Sales)$ risk premium has separate information compared with various risk premiums in explaining the time-series variation in stock returns. Overall, the findings show that whether or not the premiums of risk factors subsume $H(Sales)$ risk premium, $H(Sales)$ risk premium can explain the time-series variation in stock returns.

Table 6. 3 Time Series of Stock Returns, H (Sales) Risk Premium, and the Premiums of Other Risk Factors

Panel A: Time-Series Variation of Stock Returns, Industry Concentration Premium, and other Risk Factors' Premiums							
<i>Alpha (Intercept)</i>	<i>H (Sales)-premium</i>	<i>Ln(Size)- Premium</i>	<i>Ln(B/M)- Premium</i>	<i>Momentum-Premium</i>	<i>1-Beta-Premium $R_m - R_f$</i>	<i>Leverage-Premium</i>	<i>Adjusted R^2</i>
-0.0018702 <i>-4.58*</i>	-0.0789612 <i>-6.08*</i>						0.02%
0.0007127 <i>1.77***</i>	-0.3139017 <i>-23.72*</i>	-3.64406 <i>-69.21*</i>					3.12%
0.0049202 <i>10.32*</i>	-0.2837204 <i>-21.26*</i>	-3.96859 <i>-70.67*</i>	0.475352 <i>16.51*</i>				3.30%
0.0057706 <i>12.02*</i>	-0.2997703 <i>-22.4*</i>	-3.899011 <i>-69.22*</i>	0.5073268 <i>17.58*</i>	-0.1033672 <i>-14.4*</i>			3.43%
0.0058845 <i>12.23*</i>	-0.2937217 <i>-21.78*</i>	-3.851101 <i>-66.53*</i>	0.4585044 <i>14.36*</i>	-0.1042307 <i>-14.52*</i>		0.3273285 <i>3.58*</i>	3.44%
0.0066764 <i>14.36*</i>	-0.2569682 <i>-19.71*</i>	-2.841175 <i>-50.05*</i>	0.2809004 <i>9.09*</i>	0.0415999 <i>-5.97</i>	0.6971658 <i>103.44*</i>	0.2218514 <i>2.51**</i>	9.88%
0.0395803 <i>67.75*</i>	-0.321691 <i>-24.57*</i>	-3.656676 <i>-65.04*</i>	0.4839827 <i>15.62*</i>	-0.0823675 <i>-11.74*</i>	0.6531946 <i>96.56*</i>	-0.744403 <i>-8.32*</i>	9.15%
Panel B: Time-Series Variation of Stock Returns, Residuals of Industry Concentration Premium, and other Risk Factors' Premiums							
<i>Alpha (Intercept)</i>	<i>H(Sales)-Prem. Residuals</i>	<i>Ln(Size)- Premium</i>	<i>Ln(B/M)- Premium</i>	<i>Momentum-Premium</i>	<i>1-Beta-Premium $R_m - R_f$</i>	<i>Leverage- Premium</i>	<i>Adjusted R^2</i>
0.008021 <i>17.48*</i>	-0.2569682 <i>-19.71*</i>	-2.633103 <i>-47.38*</i>	0.3287796 <i>10.66*</i>	-0.0267177 <i>-3.85 *</i>	0.6953455 <i>103.12*</i>	0.3790309 <i>4.32*</i>	9.91%
0.040813 <i>70.30*</i>	-0.321691 <i>-24.57*</i>	-3.39305 <i>-61.63*</i>	0.5415553 <i>17.51*</i>	-0.063734 <i>-9.11*</i>	0.6458257 <i>95.47 *</i>	-0.5304627 <i>-5.98*</i>	9.16%

Panel A reports the results from time-series regression of stock returns on H (Sales) risk premium and risk premiums of Ln(Size), Ln(B/M), Momentum, and leverage. All risk premiums are obtained from monthly Fama and MacBeth cross-sectional regression, in which the cross-section of individual stock returns are regressed on industry concentration H (Sales), controlling for other factors (last row in Table 5.6). Panel B reports the results from regressing stock returns on the residuals from panels A and B in Table 6.1, and various risk premiums to assess whether the residuals of industry concentration explain time-series variation in stock returns after accounting for various risk premiums. Numbers in *italics* are *t*-statistics. *, **, and *** denote statistically significant at the 1%, 5% and 10% level, respectively.

Using Entropy index, Table 6.4 re-examines whether the premium of $E(Sales)$ explains the time-series of stock returns after controlling for various risk premiums. As shown Panel A of Table 6.4, $E(Sales)$ risk premium explains the time-series variation in stock returns with a test statistics of (4.37) at the 1% level after controlling for beta premium. When size premium is accounted for (Row 2 of Panel A), $E(Sales)$ risk premium is positive and statistically significant with a test statistic of (23.3) at the 1% level. When various risk premiums such as size, book-to-market, momentum, market excess returns, and leverage are accounted for, $E(Sales)$ risk premium is positive and statistically significant at the 1% level with a test statistics of (23.18) (Row 7 of Panel A). The adjusted R^2 in the last two rows of Panel A increase significantly to reach 9.71% and 9.16% respectively, indicating that the inclusion of various risk premiums increases the explanatory power in explaining the time-series variation in stock returns. In particular, the magnitude of $E(sales)$ risk premium marginally increases in absolute value to reach (0.78) with a high test statistics of (17.02) and the adjusted R^2 becomes significantly higher (9.71%) after accounting for the premiums of beta, size, book-to-market, leverage, and momentum. The magnitude of $E(sales)$ risk premium indicates that a 1 percentage point increase in $E(sales)$ risk premium leads to a 0.78 percentage point increase in average monthly stock returns.

Overall, Panel A of Table 6.4 presents empirical evidence about the ability of $E(Sales)$ risk premium in explaining the time-series of stock returns in the presence of various risk premiums. Consistent with Hou and Robinson (2006), the ability of $E(Sales)$ risk premium in explaining time-series of stock returns is not subsumed by the premiums of other risk factors, signifying that $E(Sales)$ risk premium has separate information in explaining time-series of stock returns.

In Panel B of Table 6.3, I empirically investigate whether the unexplained part $E(Sales)$ risk premium by various risk premiums explain the time-series variation in stock returns. Therefore, I use the residuals from Panel A of Table 6.2, in which I regress the monthly time-series of $E(Sales)$ risk premium on various risk premiums such as size, book-to-market, momentum, beta, and leverage. Afterwards, I regress the time-series of stock returns on the residuals of $E(Sales)$ risk premium and on the risk premiums of size, book-to-market, momentum, beta, and leverage.

The first row of Panel B of Table 6.4 indicates that the residuals of $E(Sales)$ risk premium are positive and statistically significant at the 1% level after accounting for various risk premiums. Moreover, the risk premiums of size, book-to-market, momentum, beta, and leverage are statistically significant, demonstrating their ability to explain the time-series variation in stock returns. The adjusted R^2 shows that the risk premiums including the residuals of $E(Sales)$ risk premium explain 9.71% of the time-series variation in stock returns. The results imply that whether or not the premiums of risk factors can subsume $E(Sales)$ risk premium, $E(Sales)$ risk premium can explain the time-series variation in stock returns. The results also favor the assumption that $E(Sales)$ risk premium has separate information compared with other risk premiums in explaining the time-series of stock returns.

In the second row of Panel B of Table 6.4, I re-examine whether the unexplained part of $E(Sales)$ risk premium by various risk premiums predict the time-series variation in stock returns using market excess returns ($R_m - R_f$) instead of beta premium. Therefore, I use the residuals from Panel B of Table 6.2, in which I regress the monthly time-series of $E(Sales)$ risk premium on other risk premiums such as size, book-to-market, momentum, market excess returns, and leverage. The results are consistent with previous

findings in Row 1 of Panel B in Table 6.4. In particular, the residuals of $E(Sales)$ risk premium are positive and statistically significant at the 1% level with a test statistics of (23.18) after accounting for various risk premiums. The findings imply that $E(Sales)$ risk premium has separate information compared with various risk premiums in explaining the time-series variation in stock returns. Overall, the findings show that whether or not the various risk premiums subsume $E(Sales)$ or $H(Sales)$ risk premium, $E(Sales)$ and $H(Sales)$ risk premiums can explain the time-series variation in stock returns. Therefore, the results are robust and do not vary when different concentration measurements are used.

Table 6. 4 Time Series of Stock Returns, E (Sales) Risk Premium, and the Premiums of Other Risk Factors

Panel A: Time-Series Variation of Stock Returns, Industry Concentration Premium, and other Risk Factors' Premiums							
<i>Alpha (Intercept)</i>	<i>E (Sales)-premium</i>	<i>Ln(Size)-Premium</i>	<i>Ln(B/M)-Premium</i>	<i>Momentum- Premium</i>	<i>1-Beta-Premium R_m- R_f</i>	<i>Leverage-Premium</i>	<i>Adjusted R²</i>
0.035143 <i>64.78*</i>	0.1871398 <i>4.37*</i>				0.6772657 <i>99.64*</i>		6.25%
0.0011146 <i>2.77*</i>	1.047402 <i>23.03*</i>	-3.787266 <i>-72.89*</i>					3.43%
0.0048582 <i>10.11*</i>	0.8895523 <i>19.02*</i>	-4.061877 <i>-73.36*</i>	0.428898 <i>14.28*</i>				3.56%
0.0048326 <i>10.05*</i>	0.8904217 <i>19.03*</i>	-4.058076 <i>-73.19*</i>	0.4295282 <i>14.3*</i>	0.0103446 <i>1.28</i>			3.56%
0.0049774 <i>10.32*</i>	0.8630302 <i>18.2*</i>	-4.006675 <i>-69.94*</i>	0.3831243 <i>11.7*</i>	0.0102585 <i>1.27</i>		0.3309994 <i>3.56*</i>	3.56%
0.0057003 <i>12.21*</i>	0.7810979 <i>17.02*</i>	-2.936603 <i>-52.03*</i>	0.2455594 <i>7.75*</i>	0.0147926 <i>1.9***</i>	0.6839799 <i>100.97*</i>	-0.0308401 <i>-0.34</i>	9.71%
0.0379207 <i>65.09*</i>	1.069422 <i>23.18*</i>	-3.70257 <i>-66.43*</i>	0.3836207 <i>12.06*</i>	0.0356319 <i>4.52*</i>	0.6484734 <i>95.53*</i>	-0.8114567 <i>-8.92*</i>	9.16%
Panel B: Time-Series Variation of Stock Returns, Residuals of Industry Concentration Premium, and other Risk Factors' Premiums							
<i>Alpha (Intercept)</i>	<i>E (Sales)-Prem. Residuals</i>	<i>Ln(Size)-Premium</i>	<i>Ln(B/M)-Premium</i>	<i>Momentum- Premium</i>	<i>1-Beta-Premium R_m- R_f</i>	<i>Leverage-Premium</i>	<i>Adjusted R²</i>
0.0072666 <i>15.97*</i>	0.7812074 <i>17.03*</i>	-2.734171 <i>-49.75*</i>	0.3401555 <i>10.84*</i>	0.0128255 <i>1.64***</i>	0.6810104 <i>100.45*</i>	0.1779884 <i>2**</i>	9.71%
0.0395118 <i>68.6*</i>	1.069442 <i>23.18*</i>	-3.422731 <i>-63.02*</i>	0.5085522 <i>16.16*</i>	0.0321316 <i>4.08*</i>	0.638956 <i>94.22*</i>	-0.5019488 <i>-5.59*</i>	9.16%

Panel A reports the results from time-series regression of stock returns on E (Sales) risk premium and risk premiums of Ln(Size), Ln(B/M), Momentum, and leverage. All risk premiums are obtained from monthly Fama and MacBeth cross-sectional regression, in which the cross-section of individual stock returns are regressed on industry concentration E(Sales), controlling for other factors (last row in Table 5.7). Panel B reports the results from regressing stock returns on the residuals from panels A and B in Table 6.2, and various risk premiums to assess whether the residuals of industry concentration explain time-series variation in stock returns after accounting for various risk premiums. Numbers in *italics* are *t*-statistics. *, **, and *** denote statistically significant at the 1%, 5% and 10% level, respectively.

6.2.2 Industry Concentration Premium, Risk Factors, and Time-series of Stock Returns

In Table 6.5, I re-investigate whether $H(Sales)$ risk premium explains the time-series of stock returns after accounting for various risk factors. Therefore, I regress the time-series of stock returns on $H(Sales)$ risk premium and Fama- French (1993) risk factors including market excess return ($R_m - R_f$), size (SMB), and book-to-market effect (HML), as well as momentum.

As shown in Panel A of Table 6.5, the $H(Sales)$ risk premium is negative and statistically significant at the 1% level with a test statistics of (-8.06) after controlling for market excess returns. Moreover, when Fama and French (1993) risk factors are accounted for, the $H(Sales)$ risk premium remains significantly negative at the 1% level with a test statistics of (-12.03) and adjusted R^2 of 6.91%. The $H(Sales)$ risk premium also remains significantly negative at the 1% level after controlling for Fama and French (1993) risk factors and momentum. In addition, the adjusted R^2 in the last row of Panel A indicates that $H(Sales)$ risk premium and various risk factors explain 7.04% of the time-series variation in stock returns. Overall, the $H(Sales)$ risk premium in all reported time-series regressions can explain the time-series variation in stock returns after controlling for various risk factors. The results imply that $H(Sales)$ risk premium has independent information compared with various risk factors in explaining the time-series of stock returns, which is consistent with Hou and Robinson (2006) findings in the US market.

The time-series results in Panel A indicate that the coefficient estimate for industry concentration risk premium $H(sales)$ remains significantly negative whether or not I account for market excess return, size portfolios (SMB), book-to-market portfolios

(HML), and momentum. In addition, the results suggest that a 1 percentage point increase in H (*sales*) risk premium leads to a 0.10 percentage point monthly decrease in stock returns after controlling for market excess returns. The monthly stock returns also decrease by 0.14 percentage point when there is 1 percentage point increase in H (*sales*) risk premiums after accounting for momentum in addition to Fama and French (1993) 3-factor model.

In Panel B of Table 6.5, I reassess whether the unexplained part of H (*Sales*) risk premium by various risk factors predicts the time-series variation in stock returns. Therefore, I use the residuals from Panel C in Table 6.1, in which I regress the monthly time-series of H (*Sales*) risk premium on various risk factors including Fama and French (1993) risk factors such as market excess return ($R_m - R_f$), size (SMB), and book-to-market effect (HML), as well as Momentum. Afterwards, I regress the time-series of stock returns on the residuals of H (*Sales*) risk premium and on various risk factors such as market excess return ($R_m - R_f$), size (SMB), book-to-market effect (HML), and momentum.

As shown in Panel B of Table 6.5, the residuals of H (*Sales*) risk premium are negative and statistically significant at the 1% level after accounting for various risk factors with a test statistics of (-10.67). Moreover, the risk premia on other risk factors such market excess return ($R_m - R_f$), size (SMB), book-to-market effect (HML), and momentum are positive and statistically significant at the 1% level. The findings imply that H (*Sales*) risk premium has separate information in explaining the time-series variation in stock returns compared with various risk factors. Overall, the H (*Sales*) risk premium can explain the time-series variation in stock returns and has independent information compared with other risk factors.

Table 6. 5 Time series Variation in Stock Returns, H (Sales) Risk Premium, and Risk Factors

Panel A: Time series Variation in Stock Returns, Concentration Premium, and Factor Mimicking Portfolios						
<i>Alpha (Intercept)</i>	<i>H (Sales)-prem.</i>	<i>R_m-R_f</i>	<i>SMB</i>	<i>HML</i>	<i>Momentum</i>	<i>Adjusted R2</i>
0.0349392 <i>64.36*</i>	-0.1014379 <i>-8.06*</i>	0.6771949 <i>99.69*</i>				6.28%
0.0443539 <i>71.25*</i>	-0.1553495 <i>-12.03*</i>	0.766291 <i>100.72*</i>	0.4207653 <i>30.17*</i>	0.2561282 <i>21.32*</i>		6.91%
0.0448642 <i>69.45*</i>	-0.142317 <i>-10.67*</i>	0.7608095 <i>96.79*</i>	0.3825336 <i>26.42*</i>	0.2269739 <i>18.37*</i>	0.0078047 <i>2.95*</i>	7.04%
Panel B: Time-Series Variation in Stock Returns, Residuals of Industry Concentration Premium, and Factor Mimicking Portfolios						
<i>Alpha (Intercept)</i>	<i>H (Sales)-Prem. Residuals</i>	<i>R_m-R_f</i>	<i>SMB</i>	<i>HML</i>	<i>Momentum</i>	<i>Adjusted R2</i>
0.0453484 <i>70.23*</i>	-0.142317 <i>-10.67*</i>	0.7566245 <i>96.68*</i>	0.3590465 <i>25.22*</i>	0.236458 <i>19.17*</i>	0.0113318 <i>4.25*</i>	7.04%

Panel A reports the results from time-series regressions of stock returns on H (Sales) risk premium and various risk factors including: market excess returns, SMB (Small market capitalization minus big), HML (High book-to-market minus low), and Momentum. H (Sales) risk premiums is obtained from monthly Fama and MacBeth cross-sectional regression, in which the cross-section of individual stock returns are regressed on industry concentration H (Sales), controlling for other factors (last row in Table 5.6). Panel B reports the results from regressing stock returns on the residuals of H (Sales) from panel C in Table 6.1, and other risk factors to assess whether the residuals of industry concentration explain time-series variation in stock returns after accounting for other risk factors. Numbers in *italics* are *t*-statistics. *, **, and *** denote statistically significant at the 1%, 5% and 10% level, respectively.

In Table 6.6, I re-investigate whether $E(Sales)$ risk premium explains the time-series of stock returns after accounting for various risk factors. Therefore, I regress the time-series of stock returns on industry concentration premium of $E(Sales)$ and Fama and French (1993) risk factors including market excess return ($R_m - R_f$), size (SMB), and book-to-market effect (HML), as well as momentum. As shown in Panel A of Table 6.6, the $E(Sales)$ risk premium is positive and statistically significant at the 1% level with a test statistics of (4.38) after controlling for market excess returns. Moreover, when Fama and French (1993) risk factors are accounted for, the $E(Sales)$ risk premium remains significantly positive at the 1% level with a test statistics of (8.37) and adjusted R^2 of 6.86%. The $E(Sales)$ risk premium also remains significantly positive at the 1% level after controlling for Fama and French (1993) risk factors and momentum. In addition, the adjusted R^2 in the last row of Panel A indicates that $E(Sales)$ risk premium and various risk factors explain 6.98% of the time-series variation in stock returns. Overall, the $E(Sales)$ risk premium in all reported time-series regressions can explain the time-series variation in stock returns after controlling for various risk factors. The results imply that $E(Sales)$ risk premium has independent information compared with various risk factors in explaining the time-series of stock returns, which is consistent with Hou and Robinson (2006) findings in the US market.

The time-series results in Panel A indicate that the coefficient estimate for industry concentration risk premium $E(sales)$ remains significantly positive whether or not I account for market excess return, small minus big firm size portfolios (SMB), high minus low book-to-market ratio portfolios (HML), and momentum. In addition, the results suggest that a 1 percentage point increase in $E(sales)$ risk premium leads to a 0.18 percentage point monthly increase in stock returns after controlling for market excess returns. The monthly stock returns also increase by 0.31 percentage point when there is 1

percentage point increase in E (*sales*) risk premium after accounting for momentum in addition to the Fama and French (1993) 3-factor model.

In Panel B of Table 6.6, I reassess whether the unexplained part of E (*Sales*) risk premium by various risk factors predicts the time-series variation in stock returns. Therefore, I use the residuals from Panel C in Table 6.2, in which I regress the monthly time-series of E (*Sales*) risk premium on various risk factors such as market excess return ($R_m - R_f$), size (SMB), and book-to-market effect (HML), and Momentum. Afterwards, I regress the time-series of stock returns on the residuals of E (*Sales*) risk premium and various risk factors such as market excess return ($R_m - R_f$), size (SMB), book-to-market effect (HML), and momentum.

As shown in Panel B of Table 6.6, the residuals of E (*Sales*) risk premium are positive and statistically significant at the 1% level after accounting for various risk factors with a test statistics of (6.95). Moreover, the risk premia on other risk factors such market excess return ($R_m - R_f$), size (SMB), book-to-market (HML), and momentum are positive and statistically significant at the 1% level and the 10% level for momentum. The findings imply that E (*Sales*) risk premium has separate information in explaining the time-series variation in stock returns compared with various risk factors. Overall, the E (*Sales*) risk premium can explain the time-series variation in stock returns and has independent information compared with other risk factors.

The findings in Table 6.6 are in line with those reported in Table 6.5. Therefore, the use of Entropy index as a measure of industry concentration will not bias the empirical result. Therefore, the results are robust and not sensitive to a change in industry concentration proxies.

Table 6. 6 Time series Variation in Stock Returns, E (Sales) Risk Premium, and Risk Factors

Panel A: Time series Variation in Stock Returns, Concentration Premium, and Factor Mimicking Portfolios						
<i>Alpha (Intercept)</i>	<i>E (Sales)-prem.</i>	<i>Rm- Rf</i>	<i>SMB</i>	<i>HML</i>	<i>Momentum</i>	<i>Adjusted R2</i>
0.035143 <i>64.78*</i>	0.187281 <i>4.38*</i>	0.67727 <i>99.64*</i>				6.25%
0.044429 <i>71.34*</i>	0.376933 <i>8.37*</i>	0.766037 <i>100.01*</i>	0.415748 <i>29.57*</i>	0.251141 <i>20.76*</i>		6.86%
0.044776 <i>69.82*</i>	0.317556 <i>6.95*</i>	0.75154 <i>95.75*</i>	0.373317 <i>25.8*</i>	0.233728 <i>18.91*</i>	0.004469 <i>1.71***</i>	6.98%
Panel B: Time-Series Variation in Stock Returns, Residuals of Industry Concentration Premium, and Factor Mimicking Portfolios						
<i>Alpha (Intercept)</i>	<i>E (Sales)-Prem. Residuals</i>	<i>Rm- Rf</i>	<i>SMB</i>	<i>HML</i>	<i>Momentum</i>	<i>Adjusted R2</i>
0.044911 <i>70.1*</i>	0.317556 <i>6.95*</i>	0.745725 <i>96.05*</i>	0.356921 <i>25.24*</i>	0.245705 <i>20.06*</i>	0.00485 <i>1.85***</i>	6.98%

Panel A reports the results from time-series regressions of stock returns on E (Sales) risk premium and various risk factors including: market excess returns, SMB (Small market capitalization minus big), HML (High book-to-market minus low), and Momentum. E (Sales) risk premiums is obtained from monthly Fama and MacBeth cross-sectional regression, in which the cross-section of individual stock returns are regressed on industry concentration H (Sales), controlling for other factors (last row in Table 5.7). Panel B reports the results from regressing stock returns on the residuals of E (Sales) from panel C in Table 6.2, and other risk factors to assess whether the residuals of industry concentration explain time-series variation in stock returns after accounting for other risk factors. Numbers in *italics* are *t*-statistics. *, **, and *** denote statistically significant at the 1%, 5% and 10% level, respectively.

6.3 Value, Growth and Industry Concentration

Based on the empirical findings in Tables 6.3 and 6.4, which show that the industry concentration risk premium increases in magnitude when controlling for size premium and decreases when controlling for both size and book-to-market risk premiums, this section intends to empirically analyse the interaction between size and industry concentration, as well as the interaction between book-to-market and industry concentration.

6.3.1 Size Premium and Industry Concentration

To examine the interaction between size premium and industry concentration, Panel A of Table 6.7 reports Fama and MacBeth cross-section regression of firm level returns on H (Sales), Ln(Size), Ln(B/M), Momentum, Beta, Leverage, and the interaction term between size and concentration H (Sales) x Ln(Size). The results in Panel A of Table 6.7 show that the coefficients on firm level characteristics remain similar in significance and magnitude compared with those reported in Table 5.6. The coefficient on the interaction term H (Sales) x Ln(Size) is positive and statistically significant, indicating that with increasing industry concentration, the average stock returns increases for large size companies. Contrary, for the small size companies, the increase in industry concentration indicates lower expected returns.

Panel B of Table 6.7 reports the value weighted average of stock returns across both size and concentration quintiles. The method used to construct average stock returns across both concentration and size quintiles is as follows: in each year, stocks are grouped independently into quintiles according to their H (Sales) values (concentration quintiles) and firm size (size quintiles). Afterwards, within each of the concentration-size quintiles, I calculate the average value weighted of monthly stock returns.

As shown in Panel B of Table 6.7, the monthly average returns for individual companies increase with increasing firm size across all concentration quintiles of H (Sales). For instance, the monthly average returns for small companies is (-0.086%), while large companies earn (0.381%) monthly average returns across all industry concentration quintiles. The results also indicate differences on average stock returns depending on market structure. For instance, when firm size increases, the increase in industry concentration leads to an increase in average stock returns. While the increase in concentration indicates higher average returns for the large companies (0.073% for Q1 rises to 0.632% for Q5), it leads to a decrease in monthly average returns for the small companies (0.178% for Q1 drops to -0.238% for Q5). The spread in returns associated with firm size is on average (0.467%) and is the largest among the most concentrated industries. Overall, the results suggest that firms with similar size diverge with respect to their market structure. Particularly, small companies operating in highly competitive industries earn on average higher returns compared to small companies operating in highly concentrated industries. On the other hand, large companies earn on average higher stock returns when they operate in highly concentrated industries compared to large companies that operate in highly competitive industries.

Table 6. 7 Interaction Between Industry Concentration H (Sales) and Firm Size

<i>Panel A: Fama-MacBeth Cross-Sectional Regression</i>						
<i>H(Sales)</i>	<i>Ln(Size)</i>	<i>Ln(B/M)</i>	<i>Momentum</i>	<i>Beta</i>	<i>Leverage</i>	<i>H(Sales) X Ln(Size)</i>
-0.01017	-0.00021	-0.00700	0.00375	-0.0040	-0.00154	0.00150
<i>-2.68*</i>	<i>-0.36</i>	<i>-7.88*</i>	<i>1.07</i>	<i>-1.31</i>	<i>-5.07*</i>	<i>2.28**</i>
<i>Panel B: Value-Weighted Average Returns of H(Sales) and Size Sorted Portfolios</i>						
H (Sales) Quintiles	Size Quintiles					
	<i>Q1 (Low)</i>	<i>Q2</i>	<i>Q3</i>	<i>Q4</i>	<i>Q5 (High)</i>	<i>All</i>
<i>Q1 (Low)</i>	0.00178	-0.00139	0.00125	0.00107	0.00073	0.00072
	<i>0.91</i>	<i>-0.73</i>	<i>0.77</i>	<i>0.68</i>	<i>0.39</i>	<i>0.90</i>
<i>Q2</i>	0.00413	-0.00420	-0.00199	0.00457	0.00422	0.00149
	<i>1.71***</i>	<i>-1.98**</i>	<i>-0.92</i>	<i>2.98*</i>	<i>2.47**</i>	<i>1.66***</i>
<i>Q3</i>	-0.00222	-0.00057	-0.00463	-0.0022	0.00360	-0.00133
	<i>-0.88</i>	<i>-0.28</i>	<i>-2.31**</i>	<i>-1.11</i>	<i>2.27**</i>	<i>-1.45</i>
<i>Q4</i>	-0.00693	-0.00614	-0.00314	-0.0018	0.00278	-0.00266
	<i>-2.62*</i>	<i>-2.98*</i>	<i>-1.67***</i>	<i>-0.97</i>	<i>2.17**</i>	<i>-3.09*</i>
<i>Q5 (High)</i>	-0.00238	-0.00621	-0.00400	-0.0064	0.00632	-0.00187
	<i>-0.99</i>	<i>-2.84*</i>	<i>-1.93***</i>	<i>-2.69*</i>	<i>4.96*</i>	<i>-2.06*</i>
<i>All</i>	-0.00086	-0.00362	-0.00245	-0.0005	0.00381	-0.00073
	<i>-0.81</i>	<i>-3.93*</i>	<i>-2.83*</i>	<i>-0.63</i>	<i>5.68*</i>	<i>-0.92</i>

Panel A shows the results from monthly Fama and MacBeth cross-sectional regressions of individual stock returns on H (Sales), Ln(Size), Ln(B/M), Momentum, Beta, Leverage, and the interaction term between H (Sales) and Ln(Size). Panels B reports the value weighted average of stock returns across both size and concentration quintiles with their *t*-statistics. In each year, stocks are grouped independently into quintiles according to their H (Sales) values (concentration quintiles) and firm size (size quintiles). Afterwards, within each of the concentration-size quintiles, I calculate the average value weighted of monthly stock returns. The row (column) entitled “All” reports average returns of firm size quintiles (concentration quintiles) across concentration quintiles (firm size’ quintiles). Numbers in *italics* are *t*-statistics. *, **, and *** denote statistically significant at the 1%, 5% and 10% level, respectively.

In order to see whether the results are sensitive to a change in industry concentration measurement, Table 6.8 repeats previous analysis using Entropy index as a measurement of concentration. As shown in Panel A of Table 6.8, the results confirm the findings in Table 6.7. Mainly, the coefficient on the interaction term between size and concentration $E(\text{Sales}) \times \ln(\text{Size})$ is negative and statistically significant, indicating that with increasing competition and increasing size, average stock returns decreases. Contrary, for the small size companies, the increase in industry competition indicates higher expected returns.

Panel B of Table 6.8 also confirms corresponding results in Panel B of Table 6.7. For instance, the increase in industry competition leads to an increase in average stock returns. While the increase in competition indicates lower average returns for the large companies (0.632% for Q1 drops to 0.33% for Q5), it leads to an increase in monthly average returns for the small companies (-0.277% for Q1 rises to .005% for Q5). The spread in returns associated with firm size is on average (0.492%) and is the largest among the most concentrated industries (0.91% for Q1). Overall, the results suggest that firms with similar size diverge with respect to their market structure. Particularly, small companies operating in highly competitive industries earn on average higher returns compared to small companies operating in highly concentrated industries. On the other hand, large companies earn on average higher stock returns when they operate in highly concentrated industries compared to large companies that operate in highly competitive industries. The results also confirm that the use of other industry concentration measures will not lead to a change in the empirical findings, proving that the empirical findings are robust and not sensitive to a change in concentration measures.

Table 6. 8 Interaction Between Industry Concentration E (Sales) and Firm Size

<i>Panel A: Fama-MacBeth Cross-Sectional Regression</i>						
<i>E(Sales)</i>	<i>Ln(Size)</i>	<i>Ln(B/M)</i>	<i>Momentum</i>	<i>Beta</i>	<i>Leverage</i>	<i>E(Sales) X Ln(Size)</i>
0.00308	0.00111	-0.00664	0.00324	-0.00385	-0.00144	-0.00050
<i>2.36**</i>	<i>2.24**</i>	<i>-7.44*</i>	<i>1.05</i>	<i>-1.24</i>	<i>-4.88*</i>	<i>-1.97**</i>
<i>Panel B: Value-Weighted Average Returns of E(Sales) and Size Sorted Portfolios</i>						
<i>E (Sales) Quintiles</i>	<i>Size Quintiles</i>					
	<i>Q1 (Low)</i>	<i>Q2</i>	<i>Q3</i>	<i>Q4</i>	<i>Q5 (High)</i>	<i>All</i>
<i>Q1 (Low)</i>	-0.00277 <i>-1.14</i>	-0.00536 <i>-2.32**</i>	-0.00296 <i>-1.43</i>	-0.00429 <i>-1.85***</i>	0.00632 <i>5.42*</i>	-0.00102 <i>-1.14</i>
<i>Q2</i>	-0.00497 <i>-1.87***</i>	-0.00691 <i>-3.45*</i>	-0.00402 <i>-2.17**</i>	-0.00348 <i>-1.72***</i>	0.00270 <i>2.04**</i>	-0.00313 <i>-3.55*</i>
<i>Q3</i>	-0.00227 <i>-0.88</i>	-0.00409 <i>-1.90***</i>	-0.00482 <i>-2.30**</i>	-0.00416 <i>-2.08**</i>	0.00281 <i>1.60</i>	-0.00262 <i>-2.75*</i>
<i>Q4</i>	0.00442 <i>1.90***</i>	0.00143 <i>0.69</i>	-0.00086 <i>-0.44</i>	0.00554 <i>3.80*</i>	0.00290 <i>1.88***</i>	0.00283 <i>3.39*</i>
<i>Q5 (High)</i>	0.00005 <i>0.02</i>	-0.00323 <i>-1.81***</i>	0.00068 <i>0.40</i>	0.00125 <i>0.00</i>	0.00333 <i>1.72***</i>	0.00011 <i>0.14</i>
<i>All</i>	-0.00110 <i>-1.02</i>	-0.00364 <i>-3.96*</i>	-0.00236 <i>-2.72*</i>	-0.00056 <i>-0.67</i>	0.00382 <i>5.75*</i>	-0.00077 <i>-0.72</i>

Panel A shows the results from monthly Fama and MacBeth cross-sectional regressions of individual stock returns on E (Sales), Ln(Size), Ln(B/M), Momentum, Beta, Leverage, and the interaction term between E (Sales) and Ln(Size). Panels B reports the value weighted average of stock returns across both size and concentration quintiles with their *t*-statistics. In each year, stocks are grouped independently into quintiles according to their E (Sales) values (concentration quintiles) and firm size (size quintiles). Afterwards, within each of the concentration-size quintiles, I calculate the average value weighted of monthly stock returns. The row (column) entitled “All” reports average returns of firm size quintiles (concentration quintiles) across concentration quintiles (firm size’ quintiles). Numbers in *italics* are *t*-statistics. *, **, and *** denote statistically significant at the 1%, 5% and 10% level, respectively.

6.3.2 B/M Premium and Industry Concentration

To analyse the interaction between Book-to-market and industry concentration, I apply Fama and MacBeth cross-sectional regression and use independent sort method to calculate average value weighted of monthly stock returns across concentration-book-to-market value quintiles, as in previous section.

Panel A of Table 6.9 reports Fama and MacBeth cross-section regression of firm level returns on $H(\text{Sales})$, $\text{Ln}(\text{Size})$, $\text{Ln}(\text{B/M})$, Momentum, Beta, Leverage, and the interaction term between book-to-market and concentration $H(\text{Sales}) \times \text{Ln}(\text{B/M})$. The results in Panel A of Table 6.9 show that the coefficients on firm level characteristics remain similar in significance and magnitude compared with those reported in Table 5.6. The only exemption is that the industry concentration coefficient $H(\text{Sales})$ drops in magnitude from (0.00369) in absolute value in Table 5.6 to (0.00208) in absolute value in Panel A of Table 6.8, and becomes statistically insignificant. Since the coefficient of industry concentration $H(\text{Sales})$ is negative and statistically insignificant, and the coefficient of book-to-market $\text{Ln}(\text{B/M})$ is negative and statistically significant, a positive coefficient on the interaction term $H(\text{Sales}) \times \text{Ln}(\text{B/M})$ indicates that with decreasing concentration and decreasing book-to-market, the average stock returns increases.

Panel B of Table 6.9 report the value weighted average of monthly stock returns for the companies grouped into concentration and book-to-market quintile portfolios. Across all concentration quintiles, I observe that the average stock returns decreases from (0.796%) for small book-to-market companies to (-1.472%) for high book-to-market companies. Similarly, average stock returns within each concentration quintiles decrease with increasing book-to-market. However, the average stock returns for highly competitive industries are higher compared with those associated with highly concentrated industries.

For instance, the average stock returns across all book-to-market quintiles for the highly competitive industries (Q1) is (0.072%), and drops to (-0.187%) for the highly concentrated industries (Q5).

Table 6.9 Interaction Between Industry Concentration H (Sales) and Book-to-market

<i>Panel A: Fama-MacBeth Cross-Sectional Regression</i>						
<i>H(Sales)</i>	<i>Ln(Size)</i>	<i>Ln(B/M)</i>	<i>Momentum</i>	<i>Beta</i>	<i>Leverage</i>	<i>H(Sales) X Ln(B/M)</i>
-0.00208	0.00048	-0.00794	0.00395	-0.0040	-0.00149	0.00203
<i>-0.93</i>	<i>1.06</i>	<i>-6.54*</i>	<i>1.13</i>	<i>-1.30</i>	<i>-4.93*</i>	<i>1.10</i>
<i>Panel B: Value-Weighted Average Returns of H(Sales) and B/M Sorted Portfolios</i>						
<i>H (Sales) Quintiles</i>	<i>B/M Quintiles</i>					
	<i>Q1 (Low)</i>	<i>Q2</i>	<i>Q3</i>	<i>Q4</i>	<i>Q5 (High)</i>	<i>All</i>
<i>Q1 (Low)</i>	0.00773 <i>3.97*</i>	0.00677 <i>3.97*</i>	0.00471 <i>2.94*</i>	-0.0033 <i>-1.77***</i>	-0.01077 <i>-5.80*</i>	0.00072 <i>0.90</i>
<i>Q2</i>	0.01092 <i>5.65*</i>	0.01131 <i>6.51*</i>	0.00285 <i>1.49</i>	-0.0015 <i>-0.80</i>	-0.01879 <i>-7.44*</i>	0.00149 <i>1.66***</i>
<i>Q3</i>	0.00555 <i>2.08**</i>	0.00608 <i>3.32*</i>	0.00122 <i>0.67</i>	-0.0051 <i>-2.79*</i>	-0.01279 <i>-5.93*</i>	-0.00133 <i>-1.45</i>
<i>Q4</i>	0.00574 <i>2.51**</i>	<i>0.00245</i> <i>1.35</i>	-0.00021 <i>-0.13</i>	-0.0033 <i>-1.96***</i>	-0.01672 <i>-7.91*</i>	-0.00266 <i>-3.09*</i>
<i>Q5 (High)</i>	0.00893 <i>4.74*</i>	0.00171 <i>0.86</i>	-0.00277 <i>-1.36</i>	-0.0059 <i>-2.86*</i>	-0.01550 <i>-7.25*</i>	-0.00187 <i>-2.06**</i>
<i>All</i>	0.00796 <i>8.37*</i>	0.00571 <i>7.04*</i>	0.00126 <i>1.56</i>	-0.0038 <i>-4.52*</i>	-0.01472 <i>-15.35*</i>	-0.00073 <i>-0.92</i>

Panel A shows the results from monthly Fama and MacBeth cross-sectional regressions of individual stock returns on H (Sales), Ln(Size), Ln(B/M), Momentum, Beta, Leverage, and the interaction term between H(Sales) and Ln(B/M). Panels B reports the value weighted average of stock returns across both book-to-market and concentration quintiles with their *t*-statistics. In each year, stocks are grouped independently into quintiles according to their H (Sales) values (concentration quintiles) and book-to-market (Book-to-market quintiles). Afterwards, within each of the concentration-book-to-market quintiles, I calculate the average value weighted of monthly stock returns. The row (column) entitles “All” reports average returns of book-t--market quintiles (concentration quintiles) across concentration quintiles (Book-to-market’ quintiles). Numbers in *italics* are *t*-statistics. *, **, and *** denote statistically significant at the 1%, 5% and 10% level, respectively.

In order to see whether the results are sensitive to a change in industry concentration measurement, Table 6.10 repeats previous analysis using Entropy index as a measurement of industry concentration. As shown in Panel A of Table 6.10, the results confirm the findings in Table 6.7. Mainly, the coefficient on the interaction term between book-to-market and concentration $E(\text{Sales}) \times \text{Ln}(\text{B/M})$ is negative and statistically significant, indicating that with increasing competition and increasing book-to-market, average stock returns decreases.

Panel B of Table 6.10 reports the value weighted average of monthly stock returns for the companies grouped into concentration and book-to-market quintile portfolios. Across all concentration quintiles, I observe that the average stock returns decreases from (0.763%) for small book-to-market companies to (-1.452%) for high book-to-market companies. Similarly, average stock returns within each concentration quintiles decrease with increasing book-to-market. However, the average stock returns for highly competitive industries are higher compared with those associated with highly concentrated industries. For instance, the average stock returns across all book-to-market quintiles for the highly competitive industries (Q5) is (0.011%), and drops to (-0.10%) for the highly concentrated industries (Q1).

Table 6. 10 Interaction Between Industry Concentration E (Sales) and Book-to-market

<i>Panel A: Fama-MacBeth Cross-Sectional Regression</i>						
<i>E(Sales)</i>	<i>Ln(Size)</i>	<i>Ln(B/M)</i>	<i>Momentum</i>	<i>Beta</i>	<i>Leverage</i>	<i>E(Sales) X Ln(B/M)</i>
0.00004	0.00048	-0.00509	0.00255	-0.00382	-0.00140	-0.00117
<i>0.05</i>	<i>1.05</i>	<i>-4.22*</i>	<i>0.83</i>	<i>-1.22</i>	<i>-4.75*</i>	<i>-1.82***</i>
<i>Panel B: Value-Weighted Average Returns of E(Sales) and B/M Sorted Portfolios</i>						
<i>E (Sales) Quintiles</i>	<i>B/M Quintiles</i>					
	<i>Q1 (Low)</i>	<i>Q2</i>	<i>Q3</i>	<i>Q4</i>	<i>Q5 (High)</i>	<i>All</i>
<i>Q1 (Low)</i>	0.00837 <i>4.44*</i>	0.00334 <i>1.81***</i>	-0.00170 <i>-0.87</i>	-0.00750 <i>-3.51*</i>	-0.01258 <i>-5.83*</i>	-0.00102 <i>-1.14</i>
<i>Q2</i>	0.00540 <i>2.31**</i>	0.00114 <i>0.61</i>	-0.00060 <i>-0.36</i>	-0.00359 <i>-2.02**</i>	-0.01670 <i>-7.78*</i>	-0.00313 <i>-3.55*</i>
<i>Q3</i>	0.00423 <i>1.62</i>	0.00770 <i>4.07*</i>	0.00056 <i>0.29</i>	-0.00658 <i>-3.51*</i>	-0.01690 <i>-7.29*</i>	-0.00262 <i>-2.75*</i>
<i>Q4</i>	0.01283 <i>6.76*</i>	0.01069 <i>6.10*</i>	0.00519 <i>2.87*</i>	0.00166 <i>0.97</i>	-0.01526 <i>-7.17*</i>	0.00283 <i>3.39*</i>
<i>Q5 (High)</i>	0.00702 <i>3.55*</i>	0.00586 <i>3.51*</i>	0.00325 <i>1.97**</i>	-0.00521 <i>-2.57**</i>	-0.01087 <i>-5.54*</i>	0.00011 <i>0.14</i>
<i>All</i>	0.00763 <i>7.98*</i>	0.00571 <i>7.06*</i>	0.00143 <i>1.78***</i>	-0.00406 <i>-4.80*</i>	-0.01452 <i>-15.09*</i>	-0.00077 <i>-0.72</i>

Panel A shows the results from monthly Fama and MacBeth cross-sectional regressions of individual stock returns on E (Sales), Ln(Size), Ln(B/M), Momentum, Beta, Leverage, and the interaction term between E (Sales) and Ln(B/M). Panels B reports the value weighted average of stock returns across both Book-to-market and concentration quintiles with their t-statistics. In each year, stocks are grouped independently into quintiles according to their E (Sales) values (concentration quintiles) and book-to-market (Book-to-market quintiles). Afterwards, within each of the concentration-book-to-market quintiles, I calculate the average value weighted of monthly stock returns. The row (column) entitled “All” reports average returns of book-t--market quintiles (concentration quintiles) across concentration’ quintiles (Book-to-market’ quintiles). Numbers in *italics* are *t*-statistics. *, **, and *** denote statistically significant at the 1%, 5% and 10% level, respectively.

CHAPTER SEVEN

CONCLUSION

7.1 Summary of Results

This study empirically investigates the relationship between industry concentration and stock returns using 1300 publicly listed companies (PLCs) in the UK during 1985 and 2010. Specifically, this research intends to shed additional light on the answers to the following questions. First, what determines the cross-section of stock returns in the UK stock market? Second, can industry concentration be a new risk factor in addition to conventional stock market anomalies and other risk factors? Third, will the results of industry concentration remain significant in explaining the cross-section of stock returns when beta, size, book-to-market, momentum, and leverage are accounted for? Fourth, will the results of industry concentration remain robust to firm-and industry-level regressions and the formation of firms into 100 size-beta portfolios? Fifth, does industry concentration premium contain separate information compared with other risk premiums and risk factors in predicting time-series of stock returns? Sixth, can industry concentration premium explain time-series variation in stock returns? Seventh, if various risk factors and risk premiums partly or fully explain industry concentration premium, can the unexplained part of industry concentration premium still predict time-series variation in stock returns? Eighth, how does industry concentration interact with both firm size, and book-to-market to explain stock returns?

Rational asset pricing theories determine the sources of risk factors supported by theoretical assumptions. For instance, Sharpe and Lintner (1964-5), Merton (1973), and Ross (1976) prove that Capital Asset Pricing Model (CAPM), Intertemporal Capital Asset Pricing Model (ICAPM), and Arbitrage Pricing Theory (APT) respectively are the main theoretical models that explain expected stock returns. Empirical studies further

enrich the literature on asset pricing by identifying various risk factors that explain stock returns. In particular, empirical asset pricing studies indicate contradictory empirical results with rational asset pricing theories, demonstrating that firm-specific characteristics can proxy for various risk factors that explain stock returns (e.g. Basu 1977, Banz 1981, Rosenberg, Reid, and Lanstein 1985, and Fama and French 1992-3). Recent asset pricing studies in the US by Hou and Robinson (2006) and in Australia by Gallagher and Ignatiev (2010) demonstrate that industry concentration can explain stock returns through the channel of distress risk. Little research has examined whether industry concentration can be a new asset pricing factor in the UK stock market that is consistent with the predictions of rational asset pricing theories or the empirical studies in asset pricing literature.

This thesis helps to fill the gap in the literature by empirically investigating the relationship between industry concentration and stock returns in the UK stock market for the following interesting reasons. First, existing asset pricing literature in the UK pays no attention in examining whether industry concentration explains stock returns. Second, many empirical studies in the UK asset pricing literature document inconclusive empirical results compared with the US literature and entail contrary empirical findings. Moreover, given the differences in the UK-US empirical asset pricing literature, the UK is a large open economy and shares many similar characteristics in terms of market structure and trading with the US. Therefore, it will be of interest to test the relationship between industry concentration and average stock returns in the UK stock market in a manner that is consistent with the US. Hence, this thesis tests the robustness of the relationship between industry concentration and stock returns established in the US by using data from the UK market.

The findings of this thesis can be summarized as follows: First, industry concentration is negatively and significantly related to the expected stock returns in all Fama and MacBeth cross-sectional regressions. Moreover, the negative relationship between industry concentration and expected stock returns remain significantly negative after beta, size, book-to-market, momentum, and leverage are accounted for, while beta is never significant. The results are robust to firm- and industry-level regressions and the formation of firms into 100 size-beta portfolios. The findings indicate that competitive industries earn, on average, higher returns compared to concentrated industries which is consistent with Schumpeter's concept of creative destruction. Second, book-to-market is negatively related to the cross-section of stock returns in all cross-sectional regressions. In addition, leverage is negatively related to cross-section of stock returns on firm level analysis, while momentum is positively related to the cross-section of stock returns on industry level analysis. Third, the time-series results show that industry concentration premium is not subsumed by other risk factors in all time-series regressions, and industry concentration premium can explain the time-series variation in stock returns. Moreover, if various risk factors subsume industry concentration premium, the unexplained part of industry concentration premium can still explain time-series of stock returns. In other words, industry concentration premium has independent information compared with other risk factors in predicting the time-series variation in stock returns. Fourth, the results indicate that small companies operating in highly competitive industries earn on average higher returns compared to small companies operating in highly concentrated industries. On the other hand, large companies earn on average higher stock returns when they operate in highly concentrated industries compared to large companies that operate in highly competitive industries. The results also demonstrate that when both industry concentration and book-to-market decrease; the average stock returns increases. The

aforementioned empirical findings are robust and not sensitive to a change in industry concentration measures.

The results of this thesis are similar to those of the prevailing researches. In particular, in the US market, Hou and Robinson (2006) demonstrate that industry concentration has negative and significant relationship with the cross-section stock returns and prove that industry concentration premium has separate information compared with other risk factors that predict the time-series variation in stock returns. Moreover, the insignificant relationships between the cross-section of stock returns and natural logarithm of firm size, momentum, and beta are consistent with existing asset pricing studies in the UK stock market (e.g., Miles and Timmermann 1996, and Strong and Xu 1997, Al-Horani, Pope, and Stark 2003 and Hon and Tonks 2003). In addition, the relationship between leverage and stock returns are in line with Muradoglu and Whittington (2001), and Sivaprasad and Muradoglu (2009), which find negative and significant relationship between leverage and stock returns. Finally, the negative (positive) relationship between book-to-market (size) and stock returns are consistent with Malin and Veeraraghavan (2004), which shows the existence of big size effect and growth effect (low book-to-market).

This thesis makes six main contributions to the literature on asset pricing. First, previous studies in asset pricing ignore industry concentration as a new asset pricing factor in the UK stock market. Therefore, this thesis presents first out-of-sample support apart from the US and Australian markets applied to the UK market. Second, existing asset pricing studies in the UK pay too little attention on using Firm and industry levels analysis to examine the cross-section of stock returns. Consequently, this thesis empirically investigates whether industry concentration includes independent information in

explaining the cross-section of stock returns using both firm and industry levels analysis. Thus, this thesis also contributes to the debate on the economic determinant of stock returns by providing new empirical evidence on market structure ability in explaining stock returns. Third, previous asset pricing studies on the relationship between industry concentration and stock returns in the US and Australia apply Herfindahl index as a measure of industry concentration, while this research utilizes Entropy index besides Herfindahl index to measure industry concentration. Fourth, Fourth, prior research on the cross-section of UK stock returns predominantly uses portfolio returns formed on firm characteristics. This paper examines whether market structure includes independent information in explaining the observed differences in average stock returns using both firm- and industry-level regressions. Fifth, prior research on industry concentration and stock returns in the US and Australia has not examined whether industry concentration premium predicts time-series of stock returns. This thesis is one of the first to examine if industry concentration premium explains time-series variation in stock returns in the UK stock market. Sixth, this thesis also tests whether the unexplained part of industry concentration premium by other risk factors and risk premiums explains time-series variation in stock returns, while prior research on market structure and stock returns in the US and Australia has focused on whether industry concentration premium includes independent information compared with other risk factors and risk premiums without considering the role of industry concentration premium in explaining time-series of stock returns.

7.2 Empirical Implications

The empirical results in this thesis reveal many interesting empirical implications. For instance, the industry concentration H (Sales) is negatively and significantly related to the cross-section of both firm and industry average returns, implying that companies operating in concentrated industries earn, on average, lower risk-adjusted returns compared to those operating in competitive industries. The results mimic my findings in Section 5.2, in which I show that the mean value of stock returns decreases from the least concentration quintile to the highest concentration quintile. An explanation is that firms in concentrated industries face less competition and less distress risks compared with those in competitive industries. The results are consistent with Hou and Robinson (2006), which documents a significantly negative relationship between industry concentration and average stock returns in the US stock market, but are in contrast to Gallagher and Ignatiev (2010), which finds that industry concentration is positively related to the cross-section of stock returns in the Australian stock market.

In addition, the empirical findings indicate that the average stock and industry returns are negatively related to book-to-market equity. A risk-based explanation is that growth stocks (low book-to-market stocks) are riskier compared with value stocks (high book-to-market stocks), as investors may have bought growth stocks for their high earnings potentials, but the risk might be due to the investors' overestimation of growth stocks' earnings and performance. On the other hand, the prices of value stocks (high book-to-market stocks) are lower than their original prices, leading to very small chances that value stocks' prices will further decrease. Thus, value stocks are less risky compared to growth stocks. The empirical results regarding book-to-market equity in this thesis are consistent with Malin and Veeraraghavan (2004), which documents a significant growth

effect in the UK stock market, but are in contrast to Hou and Robinson (2006), which finds a strong value effect for the US stocks.

The results show that firm size, momentum and post-ranking beta are unrelated to the cross-section of firm-level returns. The results are consistent with many existing studies of the UK stock market (see for instance, Miles and Timmermann, 1996; Strong and Xu, 1997; Al-Horani, Pope and Stark, 2003; among others). In contrast, Hou and Robinson (2006) documents negative firm size effect and positive momentum effect in the US stock markets. Gallagher and Ignatiev (2010) shows that average stock returns are positively related to size and market beta, while unrelated to momentum in Australia.

The results indicate that highly levered firms earn, on average, significantly lower returns than low leverage firms. An explanation is that low levered firms encounter more risk during financial distress compared with highly levered firms and use less debt, while highly levered firms' operating assets further price during distress periods. Therefore, the risk premium on low levered firms compared to highly levered firms is due to the highly distress risks that low levered firms face. The results are consistent with Sivaprasad and Muradoglu (2009) and Gallagher and Ignatiev (2010), which report significantly negative relationship between leverage and stock returns in the UK and Australia, respectively, but are in contrast to Hou and Robinson (2006), which finds positive leverage effect for the US stock markets.

In contrast to firm-level results, the average coefficient estimates for $\ln(\text{Size})$ on industry level regressions become significantly positive in simple regression and multiple regressions with all characteristic variables, indicating that large industries have higher average returns than small industries. A possible explanation is that there is smaller number of investors, who hold large stocks than small stocks due to investors' under-diversification. Thus, to attract the small number of investors to further allocate their

wealth in large stocks, large stocks offer higher rate of returns compared to small stocks. The results are in line with the findings of Malin and Veeraraghavan (2004) and Gallagher and Ignatiev (2010) in the UK and Australian stocks markets, respectively, but are in contrast to those documented in Hou and Robinson (2006) on the US stock markets.

The results also demonstrate that Momentum at industry level regressions are significantly and positively related to the cross-section of industry average returns, suggesting that industries with larger returns in the previous year continue to experience higher returns in the current year. One explanation for momentum profit is that companies that perform better in previous year may have committed to risky investment in upcoming periods, leading to high risk exposure due to the fluctuation in investment goods prices in the future. The results are consistent with the findings of Liu, Strong, and Xu (1999) and Hon and Tonks (2003) regarding the UK stock markets, and Hou and Robinson (2006) with respect to the US stock markets.

Finally, the industry beta cannot explain the cross-section of industry average returns, indicating that market risks are not priced for the cross-section of industry returns.

7.3 Limitations of Study

The limitations of this thesis are fourfold. First, although this thesis analyses the relationship between industry concentration and stock returns using publicly listed companies (PLCs) in the UK stock market, few empirical studies in asset pricing argue that the sample should include delisted companies from the stock market to control for survivorship bias. Hence, one of the main limitations of this study is the exclusion of delisted companies from sample. However, I argue that the intension of this thesis is to analyse the determinant of stock returns among the listed companies that are able to

survive in the stock market. Moreover, prior asset pricing studies use listed firms to analyse the determinant of stock returns (i.e. Al-Horani, Pope, and Stark 2003, Hou and Robinson 2006, Gallagher and Ignatiev 2010, and others).

Second, another main limitation of this study is that measures of industry concentration tend to be imprecise when survivorship bias and sample selection bias are present. In fact, the use of publicly listed companies from DataStream to compute Herfindahl Index based on net sales data enables to construct a long time-series measures of industrial concentration for a wide range of industries. However, the use of publicly listed companies from DataStream also induces a potential survivorship bias due to the exclusion of private firms and delisted firms from the sample. Therefore, measures of industrial concentration based on publicly listed companies from DataStream can potentially lead to an imprecise estimate of the actual degree of industrial concentration. The aforementioned biases may occur and influence the measures of industry concentration due to the following potential reasons:

1. When an industry includes private firms that account for a large percentage of industry total net sales, a measure of industrial concentration which includes publicly listed firms and excludes private firms will be problematic and lead to an incorrect measure of industry concentration (Ali, Klasa, and Yeung, 2009).
2. When an industry faces higher competition by other firms that are not listed, a measure of industry concentration based on listed companies and does not account for delisted companies will lead to biasness in measuring the degree of concentration for an industry.

Third, another limitation of this study is the sample selection bias induced by the requirement to include companies that have at least past 3-5 years monthly share returns

data in the sample to allow the estimation of pre and post-ranking beta. In this case, a measure of industry concentration which excludes companies that do not satisfy the previous criteria can be also imprecise for the following reason. A listed firm in highly concentrated industries has higher profitability and therefore remains always in the sample. However, if a listed firm exists in a highly competitive industry in which the degree of entry and exist is high, a listed firm in a highly competitive industry which is required to have at least past 3-5 years monthly share returns data will encounter positive shocks and therefore earn higher returns. As a result, the measure of industry concentration will be biased towards listed firms in highly competitive industries.

The above bias occurs when the sample includes listed firms in each year regardless whether the firms are delisted in subsequent periods. However, the rule for a firm to be included in my sample is that a firm should be listed for the whole period of the analysis. For instance, if a company is listed in 1985, the company is included in the sample and remains in the sample until 2010. Although this criteria help reduce the bias in measuring industry concentration, it also induces survivorship bias due the exclusion of delisted firms if the number of delisted firms is higher than new listed firms over time. However, if the number of new listed firms is higher than delisted firms over time, the measure of industry concentration will include most of the listed firms during the period of the analysis and exclude delisted firms that account for extremely small percentage of industry total sales.

Fourth, a final limitation of this study is the proxy for the independent variable, namely industry concentration. The literature on industrial organisation suggests the use of Herfindahl Hirschman Index as a proxy for industry concentration in favour of other industry concentration measures. However, the use of Herfindahl index also entails some

disadvantages. For instance, the interpretation of Herfindahl index is not classified as clear as concentration ratio and other industry concentration measures, as the Herfindahl index just offers classification to whether the industry can lie in high, medium, or low concentration. Moreover, in order to calculate the Herfindahl index, information on market shares for all firms within the industries should be accessible compared with concentration ratio, which requires information on market shares for the largest four companies in the industries. Therefore, the use of Herfindahl index requires sufficient amount of information on all listed firms within their industries. To test the robustness and overcome previous limitation, I apply Entropy index as a measure of industry concentration besides Herfindahl index. However, extensive evidence on the relationship between industry concentration and average stock returns should utilize other industry concentration measures such as concentration ratio and Lerner index.

7.4 Areas for Further Research

While this thesis contributes to the literature on the determinants of stock returns in the context of UK stock market, further areas for research should include the following. First, further research should consider the use of different proxies for industry concentration beyond conventional Herfindahl index and Entropy index to re-assess the robustness of the relationship between industry concentration and stock returns. Second, further research should evaluate whether macro-economic variables can subsume the industry concentration premium in predicting the time-series of stock returns. Third, further research should look at the different channels, in which industry concentration may influence stock returns in addition to innovation and distress risk channels. Fourth, further research should investigate whether and to what extent local and national product markets affect stock returns.

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