FIRM'S DISTRESS RISK AND PROFITABILITY IN THE CROSS-SECTIONAL STOCK RETURNS

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ABSTRACT

This thesis investigates the cross-sectional stock returns in connection with two corporate characteristics: distress risk and profitability. These are two fundamental factors that determine expected stock returns.

The research seeks to explain stock return premiums which are driven by these factors. The first chapter, *Limit of Arbitrage and the Distress Puzzle,* investigates what lies behind the long-term, persistent distress risk premiums. This chapter finds the distress risk premium is clustered in firms with high bid-ask spread, dollar volume, idiosyncratic volatility and short-selling constraints such as low institutional ownership and low short interest ratio. Upon dissecting the distress risk indicator as measured by failure probability based on Campbell et al. (2008, 2011), it appears that high distress risk firms with extremely small market capitalisation primarily contribute to this equity premium. After the double-sorting method is applied to firms based on these factors and distress risk, the average value-weighted distress premium increases from 0.62% per month for market-wide level to 1.35%-2.17% per month for the top 20% limit-of-arbitrage effect firms. Furthermore, the interaction of distress risk with stock's bid-ask spread, illiquidity ratio, short-selling constraints and idiosyncratic volatility further distinguishes the predicting power of distress risk, in which the difference of predicting power of firm's failure probability can be as large as five standard errors from zero.

The second chapter, *Profitability, Insider Ownership and Cross-sectional Stock*

Returns, examines how profitability anomalies are related to firm's insider ownership regarding determining cross-sectional stock returns in the U.S. market. Gompers et al (2003) find low agency cost firms tend to outperform others and attribute the effect to improved profitability and value-creating decision from corporate governance channel. Portfolio-level analyses confirm that firms with lower agency costs, as proxied by various forms of insider ownership, are positively associated with stock returns. Besides firm's insider ownership is positively related to the profitability premium in the U.S. stock market for the period 1980-2015. However, in cross-sectional analyses the interactive relationship between firm's profitability and institutional ownership is sensitive to additional risk factors and sample volume.

The third chapter, *Profitability Premium, Firm's Distress Risk and Stock Returns* documents a robust relationship between the two pricing factors, linking the two empirical findings together. This chapter finds a significant interaction effect of firm's profitability, as well as distress risk, in co-determining stock returns cross-sectionally. In line with the findings of Altman (1968), as well as Fama and French (2006), that firm's past information of profitability predicts future distress event and vice versa. This chapter finds that the profitability premium is partially clustered with firms having high distress risk, and the predicting power of firm's profitability ratio is different over three standard errors from zero between low and high distress risk firms. Theses findings shed light on exploring the two fundamental pricing factors under a unified framework of asset pricing.

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LIST OF ABBREVIATIONS

Abbreviation	Explanation
BA	Bid-Ask Spread
$BEME$	Book-to-Market Equity Ratio
$CAPM$	Capital Asset Pricing Model
CEO	CEO Ownership
$CRSP$	Center for Research in Security Prices
DD	Distance-to-Default
DLI	Vassalou and Xing (2004) 's Default Likelihood Indicator
DV	Dollar Volume
E/P	Earning-to-Price Ratio
EMH	Efficient Market Hypothesis
$FF-3$	Fama-French Three-factor Model
$FFC-4$	Fama-French-Carhart Four-factor Model
FP	Failure Probability
$GPTA$	Gross Profitability to Total Assets
$ILLIQ$	Amihud (2002)'s Illiquidity Ratio
$INSIDER$	Top Five Manager's Ownership
IO	Institutional Ownership
$IO-HHI$	The Herfindahl Index of The Top Five Institutions' Ownership
$IVOL$	Idiosyncratic Volatility Relating to $FF-3$
ME	Market Value of Equity
$MOM12$	Twelve-month Momentum Effect
$OPTA$	Operating Profitability to Total Assets
$O-score$	Ohlson's O-score

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1 INTRODUCTION

1.1 Motivations

The research on asset pricing aims to explain how asset prices are determined, under which the Efficient Market Hypothesis (EMH) theory plays a central role. As described by Fama (1970), an efficient market is a market where the information set is fully reflected in the current asset price, depending on the trichotomy of information. The EMH theory proposed three levels of market efficiency and each level contains a set of information that could influence asset prices: historical prices or returns; fundamental information that is publicly-known; private information. Under such a state, stocks always trade at their fair value on the market. It inferes that it is impossible to outperform the overall market performance through exploiting trading strategies based on past price (meaning “weak form” efficient market), or on public information (meaning “semi-strong form” efficient market), or even on private information (meaning “strong-form” efficient market). The only way an investor can obtain higher returns is by purchasing riskier investments. EMH provides a consensus framework for understanding asset prices and explaining why returns of assets are not predictable. However, empirical research such as Basu (1977) and Banz (1981) challenges the predictability of asset return by showing asset prices are predictable with various fundamental firm characteristics, and investors can, therefore, make profits without taking extra risk. In a recent survey, Harvey et al. (2016) find academia has identified 316 pricing factors from papers that have been published in leading journals since 1967, revealing how empirical findings are challenging the EMH.

To explain cross-sectional stock returns and why asset returns are predictable conditioning on specific fundamental information, two schools of explanations have been proposed, based on the belief as to whether bearing systematic risk leads to the expected return, or returns are mispriced due to complex investor behaviour patterns. Research based on rational expectation, for example, Fama and French (1993, 2015), Kapadia (2011) and Novy-Marx (2013) have boosted the research findings in terms of proposing new asset pricing models, identifying risk factors, and seeking economic reasons to fulfil the gap of empirical findings and theories. Research based on behavioural finance, like Daniel et al. (1998) Baker and Wurgler (2006) and Stambaugh et al. (2012), have made several interpretations in explaining anomalies on investor's overreaction, learning process and other investor psychology. The debate on which theory describes asset pricing more efficient is still ongoing, due to some long-lasting, seemingly unexplainable anomalies like the distress puzzle (Campbell et al. 2008), and profitability premium (Novy-Marx, 2013) which have been identified in the recent literature.

In the last few decades, scholars of asset pricing have observed a persistent abnormal return from portfolios where small size and high book-to-market equity firms (in the literature, those are named as size and value premiums) are grouped. These patterns of return, together with other factors that generate excess returns by not bearing extra systematic risk, are known as anomalies. The risk of financial distress was introduced by Chan and Chen (1991) to explain market anomalies related to the failure of Capital Asset Pricing Model (CAPM). Along with Fama and French (1993), they attribute size and book-to-market anomalies to the effect of distress risk which is not captured by CAPM. They argue that distress risk is liable on a firm's size and value premium as small firms and high book-to-market equity firms are likely to be financially distressed, and hence, those firms under exposure of distress risk are expected to be more rewarded. After controlling the variation of firm's distress risk, asset pricing models can explain a sizable proportion of CAPM-related anomalies. However, distress risk has become a new type of anomaly that requires investigation: Dichev (1998) finds high distress risk firms earn substantially lower returns than low distress risk firms. Also, firm's distress risk can capture cross-sectional stock return variation beyond firm's size and book-to-market ratio. Dichev's (1998) work raised two questions related to firm's distress risk: (1) whether firm's size and book-to-market ratio are proxying distress risk, and (2) why is high distress risk not rewarded with a higher stock return than low distress risk stock.

Campbell et al. (2008, 2011), Fama and French (1996, 2008), Dichev (1998), George and Hwang (2010), Griffin and Lemmon (2002), Kapadia (2011), Opler and Titman (1994), in common with Vassalou and Xing (2004), investigate the distress puzzle. Using various proxy variables for firm's distress risk, these scholars have verified the predicting power of distress risk through different asset pricing models in the cross-sectional level. However, whether the distress puzzle is from the perspective of the rational school is still ongoing. Furthermore, Campbell et al.

(2008) point out that distress risk may not be a rational asset pricing effect. They find that the pricing power of distress risk and returns from distress risk-driven portfolios are tied into a different form of behaviour finance theory. Therefore, Campbell et al. concluded that distress puzzle is a new type of anomaly.

The distress puzzle derives three main topics. The first is interpreting why distress risk negatively influences stock returns. While Fama and French (1992) successfully interpret the U.S. stock market based on their prestigious model in cross-sectional regression, they also find that two leverage measurements proxying for firm's relative-distress have different signs on coefficients in determining stock's expected return. In section III.B.2 of Fama and French (1992), the ratio of a firm's total assets over the market value of its equity is positively related to portfolio returns, whereas the relationship is negative when leverage is measured in terms of total assets over the book value of equity. The negative sign of the relative distress risk to equity return is crucial, as it violates the core of asset pricing theory wherein a higher expected return is the result of bearing greater risk. The second topic is to understand the predicting power of financial distress in terms of equity price cross-sectional. Fama and French (1992) claim that the firm's book-to-market ratio proxies firm's distress risk, but their finding is challenged by Dichev (1998) who finds distress risk measures have additional pricing power explaining variations among stocks' average returns, even when firm's book-to-market ratio and firm's size are considered. Furthermore, Campbell et al. (2008) find a significant return premium generated from low-minus-high distress risk stocks and the premium cannot be explained by common risk factors. If distress risk is a systematic risk, why is it not captured by market risk factors as predicted by CAPM or other common risk factors such as size and book-to-market ratio? If distress risk is not a systematic risk, is there a resolution to explain the premium from distress risk? The third topic is an extension of the two topics testing whether firm's distress risk as one of the firm's characteristics can explain other anomalies. Conrad et al. (2014), Fama and French (1998), Franzen et al. (2007), Griffin and Lemmon (2002), Stambaugh et al. (2012), Tykvová and Borell (2012), and Tang et al. (2013) produce research designs to explain anomalies by using numerous distress risk measures. However, the existing literature remains unclear as to the reasons why investors do not gain positive rewards by bearing high distress risk.

Recent works have identified a new anomaly related to firm's profitability ratio within the research of Novy-Marx (2013) and Ball et al. (2015). Their findings reveal the predicting power of profitability ratios in the cross-sectional stock returns, which are firm's gross profitability over total assets and operating profitability over total assets respectively. By showing the variation of firm's profitability independent of the market risk, firm's size, and book-to-market equity in determining stock returns, Novy-Marx (2013) and Ball et al. (2015) also investigate how profitability is related to stock return anomalies. Firms with high profitability have earned high expected stock returns with robust statistical significance in the post-1960 period, depicting the independence to firm's fundamental risks (Fama and French, 2006). Thus, Fama and French (2015) admit the pricing power of profitability ratios alongside firm investment intensity as two additional common risk factors.

The profitability premium is resulting from bearing a high expectation of future earning, in which high future dividends implies a higher discount rate or expected returns controlling for potential influences from firm's size and book-to-market ratio, as argued by Novy-Marx (2013) and Ball et al. (2015). To prove this Novy-Marx (2013) shows that firm's gross profitability as a measure of economic profitability is better than other measures such as net income to total assets. Further, Ball et al. (2015) show the estimation of firm's profitability ratio also captures the pricing power from the ratio of market equity to book assets value, which is another factor that has predicting power in the stock returns. However, the question of whether other theories could explain the profitability premium is still open, as it is identified recently and, therefore, has been investigated by researchers to a limited extent.

Existing literature has identified several potential explanations in addition to the rational expectation theory that has been proposed by Novy-Marx (2013) as well as Ball et al. (2015). One explanation that has strong economic links to firm's profitability is the theory of agency cost, where, for example, research on corporate governance, Gompers and Metrick (2001) and Gompers et al. (2003) find consistent evidence that low agency cost firms continuously outperform high agency cost firms, in terms of firm's profitability and long-term stock returns. Therefore, it is arguable that the profitability premium, driven by firm's profitability, is associated with firm's agency cost, where good corporate governance status drives firm's high profitability. Furthermore, the relation of the profitability to firm's distress risk has not been examined as well. In the existing literature of accounting, multiple researchers including Altman (1968), Ohlson (1980) and Campbell et al. (2008) have discovered and repeatedly verified that there is a stable relationship between firms' profitability and distress risk. Therefore, a detailed analysis linking these two fundamental risk factors is desirable in terms of asset pricing research.

Investigating the distress puzzle and profitability anomalies has significant meaning for financial practice and, possibly more importantly, for theory building. Investors can make profits by adopting trading strategies based on similar anomalies. Fama and French (1998) show that by using anomaly-driven trading strategies in the U.S. equity market, investors earned 7.68% annualised returns from 1975 to 1995, almost three times the market average return in the same period. In terms of the distress puzzle, Campbell et al. (2008) find that the annualised return is 9.80%, or 23.85% for risk-adjusted returns, with both figures significantly outperforming most well-documented anomalies. Additionally, in terms of the profitability premium, Ball et al. (2015) find the corresponding annualised return is approximately 4% or 9% adjusted for risks, and that both figures are robust in 1963-2013 U.S. stock market with high t-statistics values. According to the definition of the semi-strong efficient market from the EMH, return from fundamental information-driving trading strategy cannot exceed market return unless additional risk is taken. However, some anomalies, in particular, the distress premium and profitability premium, have realised significant excess returns whilst carrying fewer risks. Understanding how these two anomalies are related to a firm's fundamental risk would be helpful in terms of testing whether investors can beat the market when composing new portfolio investment strategies.

From the perspective of financial theory, the distress puzzle and profitability premium question the EMH and the completeness of asset pricing models. If the market is efficient, why do low distress risk firms outperform high distress risk companies, and why do high profitability firms outperform low profitability firms for decades? If the asset pricing model is correct, then why have asset pricing models like CAPM and Fama-French 3-factor models have failed to explain the puzzle of distress risk and profitability? One of the features of the distress puzzle and profitability anomaly is their risk-adjusted return is even higher than raw return, indicating that these two anomalies have negative factor loadings to identified risk factors. Therefore, the explanation for the distress puzzle and profitability anomaly may present new evidence of EMH and develop new asset pricing models, where true risk factors more precisely determine asset prices.

1.2 Research Questions

Deriving from controversial empirical findings and reviewing the existing literature, this research aims to answer research questions around the distress puzzle and the profitability anomaly.

- Does limit of arbitrage account for the distress puzzle?

Campbell et al. (2008, 2011) and Conrad et al. (2014) document that high distress risk firms tend to have extremely small firm size, low institutional ownership and high return volatility. Those are typical evidence that arbitrage limit exists among those stocks, and the returns of these stocks are not exploitable, because the cost incurred as a result of holding, trading, and short-selling restricts trading activities related to high distress risk stocks. Explaining anomaly by arbitrage limit theory has achieved fruitful results, where several well-documented anomalies like value premium (see Ali et al. 2003), idiosyncratic volatility puzzle (see Han and Lesmond, 2011; Stambaugh et al. 2016) and cash holding anomaly (see Li and Luo, 2016). Do investors trade high distress risk stocks frictionlessly, or does costly trading limit the exploitability of the distress premium? Is there any interaction between firm's distress risk and common arbitrage limit factors and can the relationship between the two variables help explain the pricing power of distress risk? Those research gaps are filled in this thesis.

- Does corporate governance explain profitability premiums?

Gompers et al. (2003) note that corporate governance drives firm profitability and causes excess returns that the CAPM and Fama-French three-factor model cannot explain. They also find supporting evidence that the abnormal returns are associated with high agency cost firms, which are mostly having lower stock returns than low agency cost firms. Lilienfeld-Toal and Ruenzi (2014) document that CEO ownership, a proxy for internal governance surveillance, is also associated with stock returns. This is in line with the argument of Gompers et al. (2003) that high CEO ownership has a positive incentive effect based on the fact that they are insiders who have access to the firm’s decision-making processes. This offers a potential explanation of why agency cost theory helps to explain profitability premiums, as documented by Novy-Marx (2013) and Ball et al. (2015), by testing whether agency costs also account for the variation in stock returns between low and high profitability firms. This research seeks to find suitable agency cost proxies and test if they are associated with the profitability anomaly.

- What is the relationship between profitability premium and firm’s distress risk?

The existing literature in the accounting area, such as Altman (1968), Ohlson (1980), and Shumway (2001), has revealed a consistent relationship between firm’s profitability and firm’s likelihood of bankruptcy. This work tests whether the distress risk is better at distinguishing the variation of stock returns from low and high profitability firms, seeking evidence of whether firm’s distress risk attributes to the profitability premium documented by Novy-Marx (2013) as well as Ball et al. (2015).

Furthermore, the question of whether the pricing power of a firms’ profitability is distinctive with high/low distress risk firms is also investigated. An examination of the interaction effect of firm’s profitability and distress risk provides additional pricing power in terms of cross-sectional stock returns when added to commonly recognised pricing factors. This is accompanied by a robust examination that recognises whether these results are affected by the selection bias of distress risk/profitability proxies.

1.3 Findings and Contributions

In Chapter 4, the limit of arbitrage effect underlying the distress risk puzzle is laid out. In brief, distress risk creates a persistent risk-adjusted return anomaly that is negatively related to expected returns and subjects to a strong arbitrage limit effect in 1981-2014 U.S. market. Novel empirical findings are presented, arguing that the distress risk premium documented by Campbell et al. (2008) are heavily affected by its transaction costs and holding costs implied, which is measured by bid-ask spread, dollar volume, illiquidity ratio and idiosyncratic volatility. By demonstrating the strong interaction effect of distress risk with several proxies of the arbitrage limit effect at both portfolio and individual stock level, one of the most prominent anomalies pointed out by Harvey et al. (2016) can potentially be resolved.

Chapter 4 is constructed as follows. First and foremost, to verify the consistency of the research methodology with earlier research, the major conclusion of Campbell et al. (2008) that on average, stock return negatively associated with distress risk is replicated. With annually updated parameters to avoid look-ahead bias that most relevant research has not covered, the distress risk premium in the 1981-2003 U.S. equity market is replicated, and using the extended sample of 1981-2014 US equity market data, the negative distress risk-return pattern continues to persist and is unaffected by different sampling criteria. Second, returns from the distress risk-sorted portfolios are positively related with firm's bid-ask spread, illiquidity measure, idiosyncratic volatility and negatively related with firm's dollar volume. Third, in the independent double sort portfolio analyses, the value-weighted distress premium is positively associated with average arbitrage limit and is no longer significant in firms with low arbitrage limits. The Fama-MacBeth regression analyses confirm the significant divergence of distress risk's pricing power in low and high arbitrage limit firms.

Chapter 5 attempts to explain the profitability anomaly in terms of a firm's characteristic of insider ownership. Supported by the theory of agency cost, an examination of whether agency cost measured as firm's corporate governance is related to the profitability premium that Novy-Marx (2013) and Ball et al. (2015) have proposed. The results from portfolio level analyses show that a list of insider ownership variables, including CEO ownership, top managers' ownership, institutional ownership and institutional ownership concentration is higher at portfolios constructed with high profitability. However, using firm-level analysis with Fama-MacBeth regressions, the hypothesised interaction effect of firm's profitability and insider ownership appears to be mostly related to certain well-documented risk factors such as firm size, book-to-market ratio, and momentum.

Controlling those factors helps to explain the difference of return from high and low profitability firms, but this finding requires further investigation.

Chapter 5 is constructed as follows. First, to suit the data availability of several insider ownership variables, the dataset is trimmed to the 1980-2015 period, where the major conclusion that high profitability firms outperform low profitability firms with significant value-weighted premium is still observed. Second, in the portfolio analyses, the gross profitability premium and operating profitability premium are all lower in the high agency cost firms but higher in the low agency cost firms. Third, results from Fama-MacBeth regressions show that the interaction of firm's profitability and insider ownerships are driven by other firm's fundamental factors, as the interaction effect is less significant when those factors enter into regressions as control variables. One of the reasons for this phenomenon is the sample size of insider ownership, which covers only a small fraction of the stocks traded on the market.

Chapter 6 examines the relationship between distress risk and firm profitability in the context of determining cross-sectional stock returns and explaining the profitability premium. The interaction between a company's profitability and its distress risk adds additional predictive power in terms of understanding stock returns, and this effect is robust across various distress risk measures, including failure probability, O-score, Distance-to-Default and profitability measures. The interaction effect partially come from existing firm characteristics as documented by Fama and French (1993). However, when the variables of the above-mentioned characteristics are controlled for, the interaction effect between profitability and distress risk remains significant at the 1%-5% level. In addition, profitability premiums are clustered in high distress risk firms, which account for 20% to 45% of total excess returns driven by firm's profitability in the Fama-MacBeth regression analysis.

Chapter 6 is constructed as follows. First, in the 1980-2015 period, two distress risk measures, Ohlson's O-score and Bharath and Shumway (2008)'s Distance-to-Default are measured with constituent methodology as target paper. Together with Campbell et al. (2008) failure probability, the average distress risk has a variation across low and high gross profitability/operating profitability sorted stocks. Second, the change of distress risk contributes to the profitability premium by showing that the premium is positively associated with average distress risk in the portfolio analyses. However, this relation is not significant where distress risk is proxied by Distance-to-Default. Third, Fama-MacBeth regressions present the comparable results as portfolio analysis, showing that the predicting power of firm's gross profitability and operating profitability is significantly different in low and high distress risk firms.

Therefore, the findings of the current research illuminate asset pricing studies by re-thinking the roles of several fundamental pricing factors. The pricing power of firm distress risk and firm profitability are investigated and related to other characteristics of firms to show how they interact. These results help rational asset pricing credibility by refining the multi-factor models in terms of the relationship between distress risk and firm profitability. From the perspective of behaviour asset pricing, the current research supports the view that arbitrage limit theory can explain a significant fraction of the distress risk premium. Moreover, market participants can exploit profitable passive trading strategies by constructing portfolios with higher risk-adjusted returns that offer compelling profits with a factor mimicking portfolio.

1.4 Thesis Structure

Chapter 2 summarises the relevant literature, reviews the concept of EMH and the core theories of asset pricing research with its relation to anomalies including distress puzzle and profitability anomaly. Particular attention is paid to related work that aims to explain anomalies from the perspectives of the rational school and the behaviourist school, and the paradigm of analysing market anomalies is discussed. Research on the impact of distress risk and firm profitability on stock's expected returns is also reviewed. Specifically, the numerous contradictory findings of distress risk and expected returns are listed. Furthermore, the link between firm profitability and distress risk is explored, and the relationship of the two pricing factors within the literature delineated.

Chapter 3 introduces research methodology. The procedure and analytical steps for investigating anomalies are explained in detail, and their advantages and disadvantages are noted in order to clarify any inconsistent results. In addition, the methodology of estimating and simulation of Campbell et al. (2008) failure probability is introduced.

Chapters 4 to 6 provide the empirical findings based on portfolio analysis and cross-sectional regression. Before presenting the empirical findings, the relevant literature is referenced, and appropriate hypotheses presented. This is followed by an introduction to the data and analysis techniques used. Where necessary, target research is replicated to verify that the initial results are in line with prior research. In addition to the standard research paradigm, which includes portfolio sorts and cross-sectional regressions, robustness tests are conducted as necessary.

A summary of the finding that highlights the limitations of the current project and suggests potential future research perspectives is given in Chapter 7.

2 LITERATURE REVIEW

2.1 Efficient Market Hypothesis and Anomalies

2.1.1 The concept of market efficiency and anomaly

The concept of Efficient Market Hypothesis (EMH) has been proposed to describe the condition of capital market equilibrium and to explain why some assets offer higher returns than others. The EMH is widely interpreted as follows: Efficiency is defined by whether the market can adjust the price of an asset-in-the-market fully and instantly, and an efficient market means that the price for an asset in the market is fully reflective of all existing information (Nobel Prize Committee, 2013). EMH has become widely accepted, and many economic and financial theories rely on this assumption about markets and asset prices. Fama (1970), identifies three dimensions of market efficiency that helps to understand the level of information efficiency embed in EMH: a weak-form efficient market means that historical prices contain all available information for pricing future returns; a semi-strong form efficient market occurs where the speed of price adjustments to information-generating events is timely, and a strong-form efficient market occurs where all private and public information is fully expressed in historical prices. There are several other interpretations of EMH like Jensen (1978). However, the core notion of EMH is consistent with Fama (1970). The concept of EMH has been extended and revised by Fama (1991) to fit the recent findings on asset pricing. The definition of the weak-form efficient market has revised to a test of “return predictability”, where time-series and cross-sectional analyses are used to forecast asset returns using historical information; in the semi-strong form, efficient market tests are revised as "event studies"; and in the strong-form, efficient market tests are revised as "private information impacts". Of the three EMH tests, the return predictability, formerly the weak-form market efficiency, is the most discussed subject of research, and it is here that return anomalies are discovered that represent a challenge to the concept of the efficient market.

Anomaly refers to evidence from empirical analysis when researchers try to explain stock returns using asset pricing models; per Fama (1991) "many of the front-line empirical anomalies in finance (like the size effect) come out of tests directed at asset-pricing models" (p.1589). Fama and French (1996) describe an anomaly as a type of public information that an investor can employ in order to generate excess returns persistently. Despite the variety of asset pricing theories with their different beliefs in market efficiency, there is one fundamental concept that rules them all, the risk-return trade-off relationship. The risk-return trade-off is an approachable expression of mean-variance optimisation as used by Markowitz (1952), and it is accepted by Sharpe (1964), Lintner (1965), and Black (1972) as the theoretical foundation of the Capital Asset Pricing Model (CAPM). In non-mathematical terms, risk-return trade-off describes the profits people will make by bearing an equivalent amount of uncertainty. The concept that the benefits arise from the expectation of risk is the key essence of all tests verifying market efficiency; an anomaly is a violation of this rule, where asset returns do not fully reflect the risk. Fama and French (1998) admit that anomalies challenge the EMH. However, they argue that any empirical test of anomalies should consider the methodology issues given the fact that most anomalies disappear when research is carried out over a long enough time span. Besides, existing theory from rational asset pricing has solved many apparent anomalies. However, other researchers such as Gruber and Ross (1978) argue that certain anomalies arise from investor behaviour. The behaviour and emotions of investors, subject to the influence of market information, become complicated and sensitive, and they may not make rational decisions. Mispricing thus widely exists in the market.

Why is return anomaly a challenge of market efficiency? A central argument of the two surveys on EMH is the joint-hypothesis test, which is, according to Fama (1970) composed of two parts: proof of market efficiency in weak-form (otherwise known as return predictability) and a test of the suitability of asset pricing model in the cross-sectional analysis. Fama (1970) argues that market efficiency can only be tested where pricing factors are captured by an asset pricing model. Postulating a specific model of asset prices allows further study testing the hypothesis whether the deviation of asset returns from the model prediction is random or systematic. That is, whether the forecast errors embedded in the model are predictable. This joint hypothesis is further discussed by Jarrow and Larsson (2012), who provide mathematical proof of the joint-hypothesis test. They argue that one of the criteria for evaluating asset pricing model is to test whether a new asset pricing model can explain existing anomalies. This is consistent with the argument of Fama (1991), in which he points out that in order to conduct testing as to whether a market is efficient, a "good" asset pricing model is needed. An asset pricing model can only measure the speed and accuracy of price adjustments that occur through new information. Cross-sectional regression can examine how well public information can explain the realised return by measuring the R-square value, and testing if the variation of specific variables can systematically affect returns of assets in the market. Thus, if the market is efficient, then the expected return should be positively associated with measurable risks, which can be captured by an asset pricing model where the factor loading of risks is the coefficient of the pricing model variables. The existence of anomalies is, therefore, suggesting that either the market is inefficient, or the asset pricing model is imprecise.

2.1.2 Explanations of anomalies

Among studies explaining anomalies, there are two different schools of thought, both of which claim a resolution for how anomalies exist. The rational school continues to argue that the risk-return relationship in the modern portfolio theory is valid, and the market is efficient. They insist that the return anomaly be aroused by taking risks that are not well known or not measured precisely, and insist that a better proxy of market risk-*beta*, provides a resolution. To the point of finding market risk proxies, Ross (1976) argues that arbitrage pricing theory extends CAPM with more systematic factors that have linear relationships with the expected return, creating a multi-factor asset pricing model. A Significant contributions made in this area are Fama and French (1992, 1993), whose three-factor model (FF-3 Model) adds two premiums of two zero-cost portfolio sorted by book-to-market ratio and market value of equity as an addition to the market beta, which is the sole systematic risk factor considered in the CAPM, and successfully explains stock returns and many CAPM-related anomalies. Carhart (1997) contributes to the model by adding the momentum factor, another return anomaly that is past stock returns, composing the "four-factor model" that is seen in much of the literature (FFC-4 Model hereafter). Those models, alongside CAPM, are the ones that have been predominantly used in both practice and research in recent decades. Recently, Hou et al. (2015), as well as Fama and French (2015), contributed to the FF-3 Model by adding a firm's investments and profitability as new factors pricing asset prices. Allowing the addition of factors that are subtracted from a strongly identified return anomaly into the asset pricing model contributes to the revolutionary power of multi-factor models. Meanwhile, this leaves suspicions of data snooping to the sceptical. As Fama (1990) comments, the multi-factor model theory makes it feasible to reach the mean-variance efficiency; however, the importance and economic implications of systematic factors remain vague. Nevertheless, such factor models have successfully explained sizeable anomalies, thus upholding the EMH. As anomalies which are explainable by multi-factor models, particularly the FF-3 model, are no longer viewed as anomalies in contemporary literature.

Other rational explanations of anomalies include intertemporal CAPM, an asset pricing model based on CAPM but allowing change of investor's investment set. Developing from the economic theory of CAPM, the aim of these approaches is to estimate market risk betas more effectively by considering how consumption affects portfolio choices. Fama (1990) summarises the main contributions of ICAPM-inspired models by allowing a joint test of the random walk return and linear risk-expected return relationship. In addition, some literature presents factor models that include market risk factors, and one variable based on economic theory that infers a relationship with impact asset prices, like firm's investments to assets ratio (Hou et al. 2015), Distance-to-Default ratio (Vassalou and Xing, 2004), bankruptcy risk (Kapadia, 2011), and liquidity ratio (Acharya and Pedersen, 2005). Unlike multi-factor asset pricing models that are frequently questioned by data snooping, those factor models are developed based on the theoretical relation of stock return with a macroeconomic phenomenon that systematically impacts all assets, giving the necessary economic theory to support the rationality of factor models. However, as the explanatory power of intertemporal CAPM-based factor models is often less than multifactor models in terms of determining equity returns. Thus, their usefulness in practice is less recognised by investors.

The behaviour finance school claims that anomalies are mispricing phenomena caused by the sophisticated behaviours of investors, or by trading frictions that violate EMH. McLean and Pontiff (2016) find evidence that the market is learning to identify and utilise anomalies by showing the average excess returns from 97 anomaly-based trading strategies that significantly reduced after they were first published. Conrad et al. (2014) find that investors have a preference for stocks that have positively skewed past returns, which can be used to explain distress risk anomalies. Baker and Wurgler (2006) identify a macroeconomic factor - sentiment index can explain sizeable long-short excess returns from anomalies, especially those caused by returns of short-side portfolios. These findings are categorised as "Behavioural Finance" as they violate some key assumptions made by rational investors, as well as rejecting the axiom of a frictionless market.

Arbitrage limit is one of the most fruitful theories explaining anomalies in the behavioural finance school. Shleifer and Vishny (1997) argue that the EMH assumes that most investors, along with the economists, see available arbitrage opportunities and take them. However, certain types of trading are costly. In extreme situations, arbitrageurs trying to eliminate glamour/value mispricing might lose sufficient money and force them to liquidate their positions. In light of this, Ali et al. (2003) develop the concept of arbitrage risk. They find that the book-to-market anomaly is associated with high arbitrage limit conditions such as high bid-ask spreads, low institutional ownership, lower analyst coverage, and particularly, high idiosyncratic volatility. Later work also notes that arbitrage limit theory can explain some of the most predominant anomalies that are otherwise unsolvable using rational asset pricing models. Stambaugh et al. (2015) find that the idiosyncratic volatility puzzle, along with an additional 11 anomalies, is explainable using limit of arbitrage theory with multifactor models like FF-3 model. Similarly, Li and Luo (2016) find that the cash-holding anomaly is mostly driven by proxies of the arbitrage limit, and they provide a behaviour prospect resolution by showing the return spread of high and low is sensitive to investor sentiment.

Other behavioural finance theories related to anomalies include learning theory, which emphasises the importance of the time gap between investors' awareness of an anomaly and their ability to exploit the anomaly's arbitrary opportunities. The theory is supported by Bebchuk et al. (2013), who find evidence that the abnormal returns related to firm's corporate governance, do not exist in out-of-sample data and are negatively associated with media coverage and investor analyst coverage.

Furthermore, McLean and Pontiff (2016) observe that most anomalies lose their significance after they are first published in leading academic journals and that arbitrage costs increase within the post-publishing period for anomaly returns. These finding shed a light on examining anomalous returns in the out-of-sample analysis.

Investor's over/under reaction to the variation of return constitutes another type of behaviour explanation. Fama and French (1998) argue that firms with poor historical earnings and negative cumulative returns tend to be undervalued by the rational prospect investors. Da and Gao (2010) find that the first month after forming portfolios accounts for most of the cumulative returns in a year, and further provide evidence that investors' overreactions to distress risk account for the distress puzzle. Controlling for the return from the previous month diluted the pricing power of distress risk measured by Distance-to-Default, with no significant monthly return for high default risk portfolios from the second month after portfolio formation.

Debates between these two schools constitute the main disputes around EMH research. Finding supportive evidence to relevant explanations contributes to most relevant literature, according to the survey of Schwert (2003). The ground remains primarily occupied by the rational school, with behaviour finance school theories acting as a supplement. The behaviourist school has an advantage in terms of explaining anomalies as mispricing arising from investors' behaviour, but insufficient research is conducted to propose a theory or asset pricing models like

CAPM or FF-3 model, leaving scholars only able to explain something that people are already aware of. The rational school thus outperforms the behaviourist school in terms of consensus theory and empirical paradigms to test anomaly phenomenon and market efficiency, with theoretical and research paradigms backed up by well-documented economic theory. This allows for better understanding of results and interpretations that are relatively well unified. New anomalies are observed every year, but attempts for finding a resolution to the occurrence of the anomalies still continue.

Several gaps exist in the research as a result of the complexity of the distress puzzle. Although attempts have been made to identify whether financial distress is a new type of anomaly, it remains unclear whether the pricing power of distress risk is a measuring error or driven by an unknown risk factor. While attempting to address the anomalies, one might be interested if distress risk can explain some strong anomalies like the profitability effect. Those are the questions that this research endeavours to address.

2.2 Distress Risk and Equity Returns

2.2.1 The mixed evidence of the distress risk-return relationship

The "relative distress" that HML represents in the Fama-French model leaves several theoretical and empirical questions to be answered. Fama and French (1992, 1993, 1996) have continuously claimed that relative distress risk is a way to understand the power of anomalies in their three-factor model. Yet empirical studies find divergent signs for market value of leverage and book value of leverage which undermines their use as a pricing factor in cross-sectional stock returns. Specifically, leverage measured by the market value of a firm is positively linked with stock returns, but leverage measured by book value is negatively related to returns.

The difference between the two leverage measurements has not been given sufficient attention in earlier work. Fama and French (1992) argue that, even if two measurements capture different information, they should be included in the market-to-book ratio, as the ratio is calculated as the difference of two leverage proxies. Following this logic, Fama and French (1993), Opler and Titman (1994), and Griffin and Lemmnon (2002) focus on explaining the difference between the two leverage variables' coefficient, but their responses to the emergent negative sign are similar to those of Fama and French (1993), as HML captured different information than book leverage. Griffin and Lemmon attribute the divergence of coefficients to the noisy measurement of the two leverage factors. They argue that the two financial ratios are also influenced by corporate financial decisions designed to optimise the firm's capital structure. Their works, combining with Chan and Chen (1991) attribute to the research by identifying satisfied proxy of distress risk.

The anomalous negative sign has prompted additional investigations since Dichev's work (1998) which finds that the negative relationship remains significant even when the proxy for distress risk is replaced by a Z-score. This finding is in line with other research (Griffin & Lemmon, 2002; Franzen et al. 2007) that adopts different proxies for financial distress risk to explain stock returns but find distress risk is negatively priced in the stock return. These findings suggest that measuring errors of distress risk may not be the reason for the negative distress risk-returns relationship. Garlappi et al. (2008) revisit the form of the distress risk-return relationship, and they find that negative sign is sensitive to the power of the shareholders facing the distress risk. Campbell et al. (2008) find firm's failure probability is associated with an abnormal excess return that cannot be explained by CAPM, FF-3 or FFC-4 model. They also note that the distress premium is concentrated in portfolios that focus on going short on firms with high distress risk. These findings challenge Fama and French's (1993) story, as distress risk should follow the basic concept that a high expected return results from investments bearing a high level of risk.

In contrast to the above studies, some research notes a positive slope of distress risk variables using complex modelling. Vassalou and Xing (2004) use default likelihood derived from Merton's Option pricing model to represent distress risk, and they find that a company's default risk is positively related to its stock returns. The positive sign not only exists in terms of the market-based distress factor but also within accounting-based measurements. Chava and Purnanandam (2010) find distress risk rewards positive expected equity returns from analysts' forecasting. The problem of the negative sign, they argue, exists because realised returns contain "noise" and are therefore not a good proxy of expected returns.

The negative relation between distress risk and equity returns is the primary research object, instead of the positive relation (Vassalou and Xing, 2004) for three reasons. First, the negative relation is what most literature has found and investigated, like Chan and Chen (1991), Dichev (1998), Griffin and Lemmon (2002), Campbell et al. (2008), Campbell et al. (2011), Avramov et al. (2013). Throughout literature, the significant negative return premium is robust in both portfolio-level and firm-level analysis and passes numerous robustness checks. Besides, the negative relation is not only supported with the above empirical findings but also documented by various theoretical models, especially the model in Gomes and Schmid (2010) that illustrates the relation of distress risk and anomalies e.g. momentum and value effect under the proposition of negative distress risk-return relationship. As for the positive relation, there has been no literature stating the mechanism except for the intuition that additional risk should bearing with high expected returns. Thus, the research primarily studies the negative distress risk-return relation in order to utilise existing literatures.

The second issue is the compatibility of research methodology in estimating distress risk. In a very insightful discussion, Friewald et al. (2014) argues that the fraction of random drift implied in Merton's (1974) model can drive the deviation of physical probability (according to historical information from the market, which most accounting-based distress risk measures are relying on) and risk-neutral probability (purely relying on the model assumption that the trigger of default is depending on the implied asset value and volatility) are affected. This paper highlights the compatibility issue of measuring distress risk, warning that the implied information in the measured distress risk may not be consistent between the two methods. In light of this, this research pays additional consideration in interpreting empirical results of the distress premium. Given that the failure probability of Campbell et al. (2008) is the main research object, this research scrutinizes the negative relation and only sets robustness tests for the distance-to-default measure, the distress risk measure with positive relation to stock returns.

A number of researches, including Chava and Purnanandum (2008), Da and Gao (2010), and Hackbarth et al. (2015), have proposed to explain the positive return, and made successes, which constitutes the third reason of downgrading the importance of the positive distress risk-return relation. For instance, Chava and Purnandum (2008) use analyst's forecasting return as "expected return". Specifically, neither Da and Gao (2010) nor Hackbarth et al. (2015) find the distress premium is significant when the database was extended in 2004. Their findings have presented that the distress risk and return relation were directly proportional in the pre-1980 period, whereas this research mainly focuses on post-1980 period. These successful explanations are relying on various crucial restrictions that may not be in line with Campbell et al. (2008). Therefore, the research pays concentrations primarily to the negative relation between firm's distress risk and equity return.

2.2.2 Interpreting the negative sign

There are three main types of resolution to the question of the existence of the distress anomaly. The first viewpoint is that the asset pricing model is not complete enough for describing return from real assets in the market. A new risk factor should be added to the model to explain the negative distress risk-return relationship. This assumes that the market is still efficient (Chan and Chen, 1991; Vassalou and Xing, 2004; Kapadia, 2011). The second opinion notes that efficient market theory does not reflect real market behaviour. Investors with different appetites for risk make different choices, and idiosyncratic firm characteristics can draw investors' attention to certain distressed firms more than others (Griffin and Lemmon, 2002; Garlappi et al. 2008; Campbell et al. 2008; Avramov et al. 2009; Avramov et al. 2013). The third viewpoint argues that errors in research design are the cause of the distress puzzle. Controlling research biases would, therefore, lead to the distress puzzle being resolved (Chava and Purnanandam, 2010; Tang et al. 2013).

The rational explanation asserts the effectiveness of existing equilibrium asset pricing models. Naturally, anomalies are then defined as missing risk exposures that correlate to either firm characteristics or systematic risk (Tang et al. 2013). As asset pricing theory is mathematically derived from CAPM, and the single-factor model asserts returns are calculated as bearing both systematic risk and the firm's characteristic risk, it is reasonable to assume under this paradigm that financial distress is a missing part of systematic risk or is correlated with a firm's characteristics such as size and leverage. This is also the conclusion of Chan and Chen (1991). Vassalou and Xing (2004) and Kapadia (2011) find that distress risk is associated with macroeconomic conditions and firm characteristics. Their asset pricing models, by constructing a distress risk factor using the same methodology as FF-3 model (Fama and French, 2003), explain anomalies and excess returns from CAPM, supporting the concepts put forward by the rational school.

Another angle based on corporate finance theory also explains distress risk based on the rational school. They argue that a firm's capital structure and its dynamic change results in complex effects on stock returns. George and Hwang (2010) find a threshold effect whereby a distress anomaly is connected with the firm's debt structure: the distress anomaly only appears when firms have particularly poor credit ratings. Gomes and Schmid (2010) find that high leverage firms with high total assets are able to place them at lower risk of depreciation when firms go into bankruptcy, while low leverage firms have more growth opportunities in the future. Hence, a premium is charged for low leverage firms resulting in a negative risk-return relationship when firm's leverage measures distress risk. This point of view is supported by some interesting findings in their cross-sectional regression analyse. But the main drawback, according to Gomes and Schmid (2010), is that their theoretical explanation is "more complex than static textbook examples suggest" (p.467), and their proposed explanation has not presented a good reason why common risk factor models are not capturing the predicting power of distress risk. Given the amount of research based on this viewpoint, the rational explanation provides the main body of empirical testing and dominates most of the debate in this area, but why some most-used asset pricing models cannot explain the pricing power of firm's distress risk is open for further research

Behaviour finance interpretations can be found in the work of researchers such as Schwert (2003), Campbell et al. (2008), and Tang et al. (2013) who also put forward some comments on their efforts to interpret the distress puzzle through the behavioural finance theory. Schwert (2003) argues that most anomalies are due to temporary investor behaviour, and notes that their impact on asset pricing declines over time. Campbell et al. (2008) start from an assumption based on the experience of institutional investors who favour distress stocks: they argue that institutional holders with high levels of risk-aversion drive down the prices of distress risk stocks, as active investors could participate in firms' operational running and reduce high-risk investments and sell poison assets, releasing positive signals to market participants. However, these are merely assertions and lack empirical examination or proof. Updated research by Campbell et al. (2011) argues that short-selling constraints may be contributing to the mispricing phenomena seen in short-side portfolio returns. A more common explanation is that investor sentiment leads to mispricing during the announcement of performance. Stambaugh et al. (2012) find that anomalies, especially those excess returns generated from the short-side portfolio, are due to investors' sentiment. Such sentiment damages the accuracy of pricing in the market, and, hence, unexpected events such as financial distress create considerable opportunities for obtaining excess returns.

Other explanations focus on the bias implied in the research methodology. Zmijewski (1984) questions the empirical tests around anomalies as frequently overlooking the requirement for data completeness. In the case of measuring distress risk, there are also several other biases identified within the existing literature. Shumway (1997), for example, notes a delisting bias. The selection of healthy firms and the rejection of distressed firms manually increases the returns from a portfolio. Chava and Purnanandam (2010) investigate several different biases when estimating cross-section of equity returns, and claim that ex-post returns cannot precisely reflect a breaking event such as a bankruptcy. They test this claim by calculating the expected return based on financial data and stock analysis and find that the ex-ante return is positively correlated to distress risk, results that are consistent with the equilibrium asset pricing model. A similar criticism of ex-ante bias is also put forward and tested by Tang et al. (2013), who put all known anomalies into their empirical model to test whether the true expected return emerges. On the contrary, their findings show that nearly all anomalies disappeared from the ex-ante adjustment return.

2.2.3 What drives the distress puzzle?

The distress puzzle is intriguing as it is not only controversial in terms of whether distress risk can be positively priced or negatively priced in the expected stock returns but is also difficult to explain why distress risk has pricing power to the expected stock returns. Contrary to Fama and French (1992, 1993, 1996) who claim the pricing power of distress risk is why firm's size and book-to-market equity has pricing power to asset returns, Griffin and Lemmon (2002) find that distress risk has pricing power even after controlling for size and value premium. The significant distress premium, interpreted from the significant intercept of CAPM and FF-3 model, provides straightforward evidence that distress risk is another return anomaly, and Griffin and Lemmon (2002), therefore, argue that the role of distress risk is divergent from the judgement of Fama and French (1992). Vassalou and Xing (2004) provide a similar but more robust result as Griffin and Lemmon (2002). They find that the distress risk indicator, inspired by Moody's bankruptcy risk model, has the power to predict expected returns, and using the probability of default as a distress risk indicator, they find default risk is positively priced stock returns. Novy-Marx (2013) also suggests that profitability factors explain stock returns driven by distress risk. In these results, a high-minus-low distress risk firm portfolio earns 0.40% monthly risk-adjusted return, a notable reduction compared with the return of 0.76% per month seen without risk adjusting. The finding of Novy-Marx (2013) presents a rational school explanation to the pricing power of distress risk. His conclusion is coming from portfolio-level analysis with no cross-sectional analysis to support his findings.

However, the story of financial distress as a result of rational theory is challenged by evidence relating to behavioural finance theory. Anomalies are easily discovered by data mining (Harvey et al. 2016). For example. Schwert (2003) investigates several of the most prestigious market anomalies and finds that most of them are not stable over a longer time span. One example is the decline of the size effect in the U.S. market. van Dijk (2011) reviews the debate around the size effect from the last 30 years and confirms that size effect has lost its power recently, compared to its former impact. Previous studies indicate the possibility that a distress anomaly is far removed from a documented anomaly such as momentum, return-reversal, or value effects. A direct research linking the behaviourist perspective to the distress puzzle is done by Campbell et al. (2008), who firstly define the distress risk as a new anomaly. Their research finds that the significance of distress premium cannot be diluted by either CAPM or the Fama-French three-factor model. They also find that the premium is more pronounced in low institutional ownership firms, which implies that the constraint for trading such stocks creates difficulties. Despite the debate as to whether the distress variable should have a positive or negative sign, most literature confirms the existence of the pricing power of distress risk.

Another view explaining the distress puzzle is that they are “created” by research design misspecification. This means that anomalies arise due to the quality of dataset in early years, inaccurate measuring of specific variables or database backfilling. Shumway (1997) finds that the record of stock return after it is delisted from the current exchange is omitted in the CRSP database, one of the most used asset pricing research databases, and he further notes that controlling the delisting return causes the size effect in NASDAQ stocks to vanish (Shumway, 1999). Tang et al. (2013) assert that most anomalies disappear when the expected return is defined as the average expected value from stock analysis, rather than the historical return, which is provided by CRSP and is predominately used in asset pricing research. These findings suggest potential biases in research design which could explain many anomalies and may work to explain distress risk, because identifying firm’s financial distress and measuring the return is relying heavily on the CRSP database and delisting return. Harvey et al. (2016) have completed a study on setting a new threshold of asset pricing determinants, and suggest that scholars endeavouring to identify pricing factors should make the results pass stricter hurdles such as a t-ratio significantly over 3.0. Within most research methods, testing how durable distress risk is when implementing different pricing factors is a key issue to preserving distress anomalies for investigation.

What explains the pricing power of distress risk? Can any of the existing theories based on methodology bias, behaviour finance, or the rational explanation given from the risk-return perspective solve this puzzle? Some behaviourist work provides potential answers, including investor's overreactions, where the power of institutional investors constitutes the main explanatory variable for the distress puzzle. Several rational explanations have been proposed, but few of them have supporting empirical results, and only a very few papers support the view that research bias is the origin of the distress puzzle. This is because of studies such as the most recent paper presented by Da and Gao (2010) prove that they cannot eliminate the pricing power of distress risk even after controlling for all known research biases. The lack of a coherent theory between the possible explanations and the huge shortage of empirical testing leaves a tempting blank to fill.

2.3 Predicting Financial Distress

2.3.1 Definition of financial distress

Financial distress at its most simple refers to any situation wherein a firm fails to meet its debt obligations. However, depending on the research design of a given piece of research, the definition of financial distress can vary. Most existing research has relied heavily on U.S. market data, and thus the definition of financial distress used within this work was also influenced by the U.S. legal system and accounting standards. Altman (1968, 1993), Dichev (1998), Hillegeist et al. (2004), Ohlson (1980), and Zmijewski (1984) defined financial distress simply as a firm's bankruptcy. Bankruptcy is a typical example of financial distress, as it is the ultimate legal destination of a distressed firm. However, this definition overlooks the fact that bankruptcy is not the only phenomenon of financial distress, and that even bankruptcy itself has two categories - under the U.S. bankruptcy code, *Liquidation and Reorganization*.

A clarification of the importance of identifying financial distress risk can be found in Gertner and Scharfstein (1991), who raise awareness of the Bankruptcy Reform Act of 1978 (The 1978 Act) that diversified bankruptcy into two types. Chapter 7 covers liquidation and Chapter 11 covers reorganisation. They further prove that investors under different types of financial distress exhibit distinctive preferences and behaviours as their expected returns change by the firm's bankruptcy procedures. In addition to bankruptcy, other scholars such as Campbell et al. (2008, 2011) and Vassalou and Xing (2004) propose a broader definition of financial distress by including bankruptcy and default, performance-related delisting events, and become a commonly used definition of financial failure in the literature. It is notable that scholars who create their definitions of financial distress tend to emphasise that their definition is coherent when examined in light of the core concept of bankruptcy. Each new definition of financial distress aims to capture the fundamental of financial distress and provides or information. Figure 2 depicts the way in which both bankruptcy and financial failure are affected by macroeconomic conditions and shows their co-movement. The peak time for bankruptcy is also the peak time for firm delisting, default, and other distress events. Distress risk prediction models also provide good results in terms of predicting bankruptcy and failure.

The expansion of the definition of financial distress still provides robust results that can coexist with other findings when using only bankruptcy data. Campbell et al. (2008) conjectured that a broader definition of financial distress creates an enlarged sample size that allows scope for new econometric methods and credit default models to be used. Such attempts provide robust results that conclude solely using bankruptcy data, and are used in subsequent research.

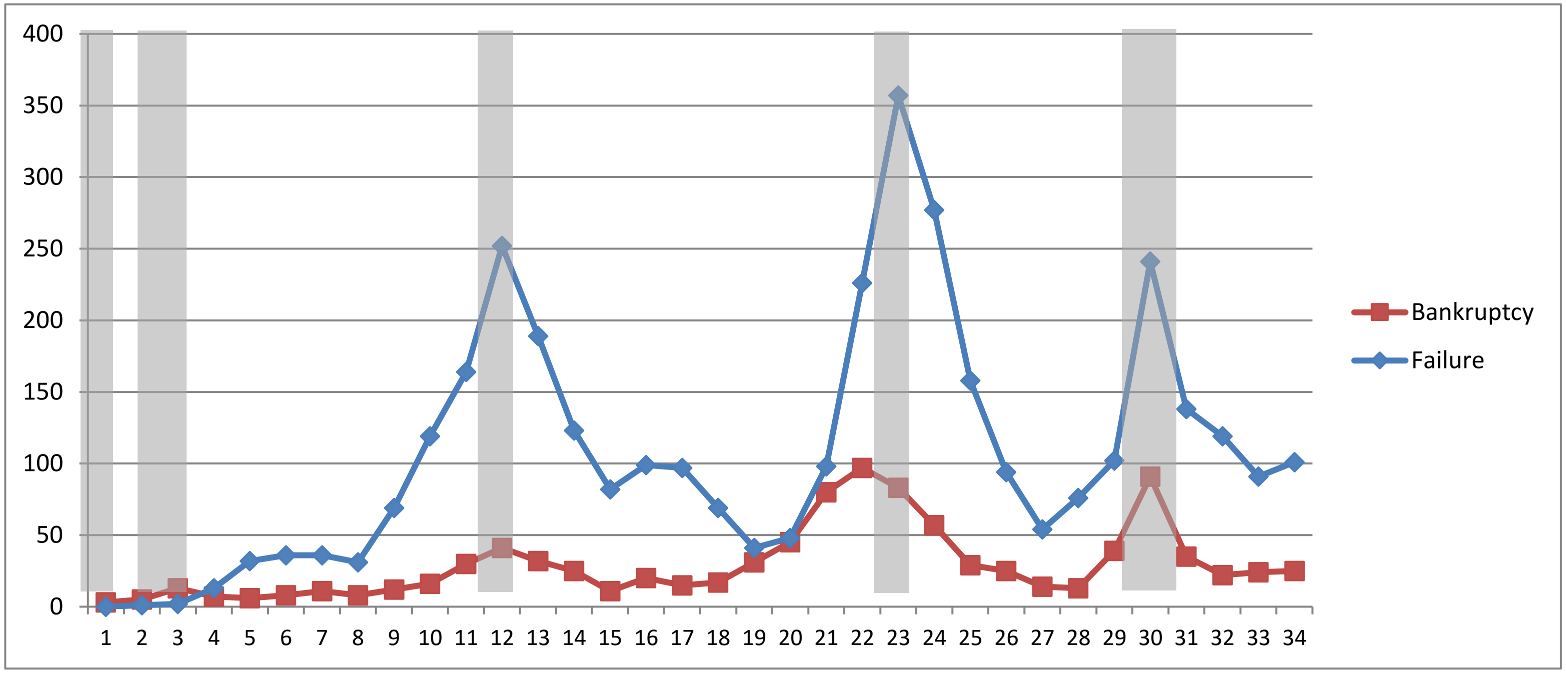

Figure 1 Bankrupt and failed firms in the United States of America (1980-2014)

This figure plots the rate of U.S. bankruptcy firms over total firms in the market and the rate of failure firms over total firms. A bankruptcy firm is defined as having filed a Chapter 7 or Chapter 11 form with the court, and a failure firm is defined as a) filing a bankruptcy form; b) being rated as a "D" by rating agencies, or c) suffering from performance-related delisting from the current exchange. Bankruptcy and failure firms are obtained from Moody's Default Research Database, UCLA-LoPucki bankruptcy database, Compustat, and SDC Platinum corporate bankruptcy database. U.S. recession (grey area) data is obtained from NBER.

2.3.2 Predicting a firm's failure

Whether pricing the distress risk or predicting a financial distress event, a proxy for financial distress risk is required. The substantial research of Altman (1968), predicting financial distress using accounting data from firm's financial reports and market data related to firm's stock, has become a fruitful area of research. As a result, according to Hillegeist et al. (2004) and Charitou et al. (2013), more than ten types of distress risk measures have already been identified. To clarify these current measurements, Hillegeist et al. (2004) introduced a categorification that identifies the two main types of measurements used in their research. Measurements relying on information from a firm's financial statements are named accounting-based methods. Meanwhile, distress risks that are estimated from market information, e.g. price, returns, and volatility, are called market-based measurements.

Almost all accounting-based measurements are the result of calculations based on one or more financial statement variables. Altman (1968) proposes the first index that can be used to measure a firm's possibility of distress. The Altman Z-score is the sum of six accounting variables. Each variable has a fixed coefficient that can be calculated by discriminant analysis, a statistical technique that extracts information from the known sample to estimate the data for an unknown sample with similar characteristics. It requires a complete data set that includes all bankrupted firms and firms' other financial statements including firm's net income, cash flows, return on asset and liquidity ratio, even though it can also be performed solely on a book-to-market ratio. Ohlson (1980) has developed another distress indicator, Ohlson's O-Score. The O-Score is also the result of calculations based on several financial statements with several consensus variables that have been adopted in other research. Those methods, though they display different statistical calculation procedures, are inspired by the same basic premise: that a firm's leverage, profitability, size and past earnings and level of solvency directly affects its default risk and the cost of default to investors. Shumway (2001) further presents a mathematic solution integrating the discriminate analysis and logit regression under a broader category of "hazard model", which presents a mathematic resolution of all accounting-based measures in the framework of hazard model analysis as physical probability of financial distress.

Market-based indicators are derived from Merton's option pricing formula. This is the finite sum of an integration formula, and it relies on asset price and price volatility to calculate a firm's value. By calculating the difference between a company's current value and its value when it is in financial distress, the likelihood of default can be derived from the transformed Merton formula, in which Vassalou and Xing (2004) and Hillegeist et al. (2004) present empirical calibration of the so called "default likelihood indicator". The default likelihood indicator is calculated relying on interative process of estimating firm's asset value volatility from the option pricing model. To relieve the complexity of the calculation, some reduced-forms have been invented for distress forecasting models, such as that invented by Campbell et al. (2008) as well as Bharath and Shumway (2008). Charitou et al. (2013) report that one main feature of the reduced-form predicting model is that it relies on less market information to make an estimation. The estimation of DLI requires assumption of asset's volatility and market value. Both are not directly observable from market data, and the estimation of the two parameters are often referring to a risk-neutral assumption in the distribution of probability.

In short, the benchmark in this field is a mainly accounting-based measurement. Option pricing methods are based on a different theory, but they represent a similar outcome, although some scholars, including Bharath and Shumway (2008), Campbell et al. (2011), Chava and Jarrow (2004), and Vassalou and Xing (2004), argue that their model outperforms other measurements. Empirical tests implementing those methods do not generally produce distinct results whether using purely accounting-based measurements or by mixing measurements. Blöchlinger (2012) and Charitou et al. (2013) compare several distress risk measurements using both accounting and market-based methods, and by using updated parameters. Their findings suggest that either accounting-based models or market-based models can predict an event of financial distress. Blöchlinger (2012) notes that more than 90% of firms that were identified as having the highest financial distress risk did indeed go into financial distress in the following year. Empirical research therefore usually chooses more than one measurement from Table 1 to pass a robustness test. Such studies have shown that expanding the definition of financial distress does not impair the accuracy of the predicting model.

Table 1 List of main financial distress risk measurements

This table lists seven distress risk measures that are commonly cited in the literature. The categorisation follows Hillegeist et al. (2004).

Accounting-based measurement		Market-based measurement	
Name	Main Papers	Name	Main Papers
Z-score	Dichev (1998) Agarwal and Taffler (2008)	Distance-to-Default	Campbell et al. (2008) Chava and Purnanandum (2010) Charitou et al. (2013)
O-score	Griffin and Lemmon (2002) George and Hwang (2010) Hillegeist et al. (2004) Avramov et al. (2013)	Default likelihood Indicator (DLI)	Vassalou and Xing (2004) Da and Gao (2010)
Book-to-Market Ratio	Chan and Chen (1991) Fama and French (1996) Gomes and Schmid (2010)	Other Merton Option Model	Hillegeist et al. (2004) Bharath and Shumway (2008) Charitou et al. (2013)
Hazard Model (FP)	Zmijewski (1984) Shumway (2001) Chava and Jarrow (2004) Campbell et al. (2008)		

2.4 Corporate Governance and Equity Returns

Corporate governance is the mechanism protecting firm's owners by "getting a return on their investment" (Shleifer and Vishny, 1997, p.737). Jensen (1986) uses plain language in his influential paper describing the conflict of interests between shareholders and managers, and he enumerates how managers could erode shareholder's interests via persuading large firm size, increasing bonuses and funding risky projects. Highlighting those costs will damage the firm's performance eventually. Shleifer and Vishny (1997) further summarise those as agency problems under scenarios of a) inadequate residual control rights; b) the discretion of managers; c) failure of incentive contracts. Corporate governance mechanisms like enforcing legal protections, introducing large shareholders, takeovers, and large creditors can reduce agency costs. Those early scholars have built the framework of studying corporate governance, but as Shleifer and Vishny (1997) point out, governance mechanism is designed with costs, and the benefit of governance, as well as cost-benefit analysis, has not been fully investigated.

This point is empirically studied by Gompers et al. (2003) using 1990-1999 U.S. market data, and they present striking empirical evidence that the variation of firm's governance index predicts firm's future performance and is negatively related to stock returns. The governance index is defined as a discrete number from 1 to 19. A higher governance index implies that shareholder rights are restricted to a greater extent, and stocks with an index lower than 5 are defined as "democracy" firms, while stocks with an index higher than 14 are defined as "dictator" firms. The difference between dictator and democratic stocks has a gap at 9% annualised return performance, which is not explained by FFC-4 model. Gompers et al. (2003) attribute this return anomaly to the implied agency costs that investors are underestimated to high governance index firms. This assertion is supported by their empirical findings that low governance firms tend to have more acquisition and capital expenditures than high governance index companies. This finding combines with Gompers and Metrick (2001) who find institutional ownership is positively priced in the expected returns, linking corporate governance positively to firm's performance. This conclusion is further supported by Bebchuk et al. (2008) as well as Harford et al. (2008) who also find firm's corporate governance status positively drives firm's performance measured by Tobin's Q.

Cremers and Nair (2005) expand Gompers et al. (2003) findings with internal shareholder's ownership. They find the difference of stock market performance between low and high corporate governance firms are better characterised by blockholder ownership, where the governance premiums are clustered in high insider ownership firms. An explanation for such findings is raised as follows: the well-governance firms potentially accrue long-term premiums from firm's profitability. Thus, investors are expecting higher returns from such firms. Cremers and Nair (2005) find supportive evidence that industry-adjusted profitability, measured as return on assets, return on equity and net profit margin, are all positively related to firm's governance mechanism. Lilienfeld-Toal and Ruenzi (2014), from the different perspective, again confirm the positive relation of firm's governance and performance by showing firm's CEO ownership is also positively related to firm's profitability, and the variation of ownership explains cross-sectional stock returns. They argue that CEO's effort is not fully priced and link the corporate governance premium to the prestigious Fama and French (1996) human resource explanation of market anomalies. It is noteworthy that the above studies of corporate governance and stock returns are under the broader categorisation investigating the relation between corporate governance and firm's performance, in which stock market performance is viewed as a measure of firm's performance. Those research findings, where Giroud and Mueller (2011) also summarised, suggest a stable relation of firm's profitability and corporate governance.

Possible explanations for the governance premium, are proposed by Gompers et al. (2003), and are extensively discussed by Giround and Mueller (2011) as well as Bebchuk et al. (2013). The Gompers et al. explanation where agency costs are liable to the weak firm performance pervasively existed in low governance firms are supported by Cremers and Nair (2005) as well as Harford et al. (2008) and Bebchuk et al. (2008). However, in an anatomy of governance index, Grioud and Mueller (2011) find the abnormal stock return related to the "democracy"- "dictator" portfolio is sensitive to the definition of portfolio breakpoints and does not exist in the post-1999 period. They argue the variation of competition across industries enforces different governance mechanism, wherein non-competitive industries, firms' performance are more positively benefited from good governance systems. The commonality of those findings insists that the return anomaly is as consequence of high expected firm performance, particularly a positive expectation of firm's profitability.

On the other side, Bebchuk et al. (2013) argue the disappearing of abnormal return associated with corporate governance is because investors are learning and adopting corresponding trading strategies to exploit such investing opportunities. They find the disappearing of positive governance-return relationship, observed by Grioud and Mueller (2011) is significantly related to the increasing research papers, more media attention and analyst's forecasting. They also present empirical evidence that the positive governance-expected firm performance maintains stability in the 1990-2008 period, suggesting the disappearing of return anomaly does not affect the well-documented governance-return relationship. However, this explanation does not apply to other governance related anomalies: Lilienfeld-Toal and Ruenzi (2014) find the monthly return anomaly from long-short CEO ownership firms does not weaken in the post-1999 period. Their findings also reject other behaviour finance-related explanations such as surprise and limits of arbitrage theory.

In addition, some researchers such as Abdioglu et al. (2013) argue that the legislation of Sarbanes-Oxley Act (2002) composes an exogenous shock to corporate governance, making institutional investors more willing to hold stocks as the requirement of Sarbanes-Oxley Act generally increases the transparency of firm's information and reduces the agency cost. To prove this point, they present evidence that firm's investments, as well as R&D expenditure, attracts more active/passive institutions, and thus increases the institutional ownership after the legislation. Their findings suggest a plausible robustness check on whether agency cost is the firm characteristics explaining the variation of firm's profitability by considering an exogenous shock to the market.

In summary, the existing literature presents one of the foremost findings relating to firm's corporate governance: good corporate governance induces higher expected firm's performance, which could also be a potential explanation for another return anomaly that is driven by firm's profitability found by Novy-Marx (2013) as well as Ball et al. (2015). If the abnormal return is truly driven by firm's profitability, controlling for other firm's characteristics that are related to systematic risk, then the relation of firm's profitability and corporate governance may explain the profitability premium. The detailed research design is disclosed in Chapter 5.

2.5 Firm Profitability and Cross-sectional Stock Returns

2.5.1 The Back-to-the-stage factor

In asset pricing studies, firm's profitability is another type of fundamental information that public can gain to achieve excess returns that seemingly violate the EMH. Inspired by the dividend-discount model, the stock return is determined by the discount of its expected cumulative dividends in each period and, thus, the dividend payment is one of the predictors understanding asset prices, stated by Beaver (1968). Early research like Basu (1977) also tests market efficiency related to firm's profitability by examining if post-announcement stock return changes are due to market inefficient, which is categorised as event study in Fama (1991) research. As for the return predictability tests, Haugen and Baker (1996) find that a firm's earning-to-price (E/P) ratio, commonly used in accounting research to represent a firm's profitability, earned positive returns over the S&P 500 index return of about 0.27% per month in the 1979.1 to 1986.6 period, and 0.26% per month in the subsequent 1986.7 to 1993.12 period.

High profitability firms tend to be those that are large or who have a low book-to-market ratio; thus, the researchers argue that a profitability anomaly is unlikely due to the high distress risk, one of the potential explanations to the entire universe of anomalies proposed by Fama and French (1993). However, Fama and French (1996) argue that the pricing power of E/P is driven by a firm's size and book-to-market ratio, with no statistically significant α_{FF3} among E/P sorted decile portfolios. The insignificant FF-3 alpha suggests that profitability has no ongoing pricing power on expected stock returns. Malkiel (2003) further confirms this finding by showing the pricing power of E/P is no longer significant to post-1985 U.S. stocks, and presents several plausible explanations based on rational school of thoughts.

Fama and French (2006) bring the profitability factor back to centre stage in terms of asset pricing research. They argue that a firm's profitability is predictable and, to show this, provide a predictive model where the O-score, a bankruptcy risk factor proposed by Ohlson (1980), is included with statistics significant predicting power. In addition, they also present empirical evidence that a firm's profitability, measured as positive earnings divided by book value of equity, has additional pricing power above and beyond the common risk factors in Fama and French (1996). In light of this, Novy-Marx (2013) dissects the relationship between a firm's profitability and cross-sectional stock returns and finds that most earning-related anomalies are explainable with the FF-3 model and a zero-cost factor portfolio formed by firm's gross profitability. Ball et al. (2015) further find that, depending on the deflator of profitability ratio, operating profitability gives higher pricing power than gross profitability and earning to book equity ratio. These two profitability ratios were both significant in the 1963 to 2010 period, an extended time offering a return pattern that is relatively unaffected by extreme events where stock returns are at an anomalous high.

2.5.2 Related theories explaining the pricing power of profitability

The expected cash flow theory suggests that most anomalies exist due to correlation with a firm's expected earnings, and firm's profitability is, as argued by Novy-Marx (2013), a "clean" proxy of such. Using a revised dividend discount model, Fama and French (2006) link firm's expected earnings to book-to-market ratio and expected stock return. They argue that expected earnings are positively related to stock dividends, and this revises their earlier assertation that distress risk is the reason of causing value and size anomaly. The Fama-French 5-factor model has some success with this, according to Fama and French (2015), offering better predictive power than $FF - 3$ or CAPM in terms of cross-sectional stock returns in U.S. domestic and international markets. These research findings incorporate the pricing power of firm's profitability and recognise it as a pricing factor rather than an anomaly.

Research on corporate governance has presented robust findings documenting that good corporate governance is related to firms' profitability and subsequent stock returns. Core et al. (1999) argue that the higher agency problem drives low firm performance, and this is due to failures on the part of the CEO and top managers in creating value-maximising decisions. Gompers et al. (2003) find anti-takeover intensity to be negatively priced in subsequent cross-sectional stock returns, while Giroud and Mueller (2011) further expand the findings of Gompers et al. (2003) by showing that pricing power is industry-related and can, therefore, be better identified by industry-adjusted profitability. This suggests that investors are sophisticated at exploiting corporate governance premium to support equity investing.

The logic that distress risk is liable to anomalies such as firm's profitability has several rational expressions. Fama and French (1996) propose a plausible theory that investors charge a surplus to hold stocks with high exposure to financial distress. The missing value of human capital, captured by measures of financial distress, therefore represents market anomalies. The correct way to measure human capital is, however, still an unsolved question. Recent studies expand the scale of such research by utilising financial distress to express other emerging anomalies. Agarwal and Taffler (2008) find that in the UK stock market, momentum anomaly represents for distress risk. George and Hwang (2010) and Avramov et al. (2013) use multiple proxies of distress likelihood to examine the predicting power of distress risk among several common anomalies and find a threshold effect driven by distress risk. Most anomalies do not repeatedly emerge in the portfolio of high distress risk businesses. To explain the size effect, Kapadia (2011) has created a “tracking” portfolio on underlying aggregate distress risk that can explain average realised gains as well as the Fama-French three-factor model. The highlight of this research is that under the new asset pricing model, the excess return is insignificant, and this suggests that the new model outranks existing accomplishments by being able to explain returns from a rational school perspective.

As proposed by Novy-Marx (2013) and Ball et al. (2015), there is no prior literature examining whether firm’s profitability is explainable by firm characteristics, which leads to a research gap. This is partly because these effects have only been recently identified. Future research could be based on existing accounting literature by considering the other determinants of firm’s profitability, then testing whether firms’ characteristics explain their profitability premiums in terms of cross-sectional stock returns.

3 RESEARCH METHODOLOGY

3.1 Portfolio Analysis

3.1.1 Properties of stock portfolio

A portfolio is a collection of investments, and in this research, a stock portfolio is defined as being composed of stocks that are available for trading at a given time. Portfolio analysis allows for techniques that exploiting trading strategies based on fundamental information gained from grouping stocks with similar characteristics, as highlighted by Fama and French (1992). Grouping stocks into portfolios based on a single variable is also known as a one-way portfolio sort. One-way sort analysis is commonly used to identify anomalies by constructing a long-short portfolio holding one side of the whole spectrum of variable-sorted portfolios, and short-selling the portfolio at the other side of the spectrum. Researchers that have used this technique include Banz (1981), for size effect, Campbell et al. (2008), for distress risk puzzle, and Novy-Marx (2013) and Ball et al. (2015), for the profitability anomaly. Two-way portfolio sorting is similar except that it refers to the methodology of evaluating two candidate variables that affect stock returns. Depending on the interaction of the two variables, the process can be analysed independently or dependently. This method is widely used to explain the pricing power of an anomaly by identifying whether the return of anomaly is more pronounced when another factor is present.

3.1.2 Evaluating portfolio performance

- Equal-weighted portfolio return

Portfolio returns are measured as the average rate of return in excess of the risk-free rate from all stocks in the portfolio within a specific holding period. Depending on whether stocks are allocated with the same weight, or weighted by firm size representing the marginal change in investor wealth, portfolio returns can be measured as either equal-weighted or value-weighted. If a portfolio contains N stocks, the return on stock i is denoted as r_i, and the equal-weighted portfolio excess return $r_{ew}^{p}$is the sum of the weighted stock return:

$$r_{ew}^{p} = \frac{\sum_{i}^{N} r_i - r_f}{N} \quad (3.1)$$

- Value-weighted portfolio return

The value-weighted portfolio return is the sum of all stock return weighted by each stock's size relative to the portfolio size, instead of the proportion of a total number of stocks in an equal-weighted portfolio. Denoting the size of stock i as V_i, the value-weighted portfolio excess return is then determined by the sum of the weighted stocks measured as:

$$w_i = V_i / \sum Vi \quad (3.2)$$

$$r_{vw}^{p} = \sum_{i}^{N} w_i r_i - r_f \quad (3.3)$$

Each measure has advantages and disadvantages. The equal-weighted return is a straightforward and direct indicator of portfolio performance, but Fama and French (1998) argue that equal-weighted portfolio returns could be biased since portfolio performances are mostly driven by small stocks, which represent 60% of total U.S. stocks but less than 3% of total market value. Value-weighted portfolio returns are less influenced by this, as the variation in firm size is noted in the weightings, but this, in turn, means that the value-weighted portfolio returns are likely to be driven by giant stocks.

- Risk-adjusted portfolio return

Another measure of portfolio performance is to use risk-adjusted returns rather than raw return. The most commonly used risk-adjusted returns are the CAPM alpha, Fama-French 3-factor alpha (FF-3 Alpha), and Fama-French-Carhart alpha (FFC-4 alpha), developed by Lintner (1965), Fama and French (1993), Carhart (1997) respectively. Risk-adjusted returns are measured as the average of time-series regressions to portfolio returns by premiums from bearing risk factor/factors that are/are specified in the model. The alpha, which can be used as an indicator of excess returns related to multifactor risks, is then calculated as the intercept of the linear regression. Inspired by the success of the FF-3 model as reviewed in the earlier section, a bunch of multi-factor models have been developed, and, hence, investors can choose which model is preferable. This research uses the CAPM alpha and FF-3 alpha together to test whether anomalies are explained by rational asset pricing models, and FFC-4 alpha is being used if literature finds momentum accounts for a certain anomaly:

$$r_p - r_f = \alpha_{CAPM} + \beta_{Market}(R_m - r_f) + \epsilon \quad (3.4)$$

$$r_p - r_f = \alpha_{FF-3} + \beta_{Market}(R_m - r_f) + \beta_{SMB} SMB + \beta_{HML} HML + \epsilon \quad (3.5)$$

$$r_p - r_f = \alpha_{FFC-4} + \beta_{Market}(R_m - r_f) + \beta_{SMB} SMB + \beta_{HML} HML + \beta_{UMD} UMD + \epsilon \quad (3.6)$$

The risk-adjusted alphas (α_{CAPM}, α_{FF-3}, α_{FFC-4}) are estimated by regressing portfolio's excess return, $r_p - r_f$, by risk factor/factors specified in asset pricing model and the intercept of regression is the risk-adjusted alpha. The CAPM model is regressed by value-weighted market excess return averaging all NYSE, AMEX and Nasdaq stocks, $R_m - r_f$, and the coefficient (β_{Market}) represent stock's relative loading to the market risk. According to Fama and French (1993), the FF-3 model is regressed by market excess return, the size premium (SMB) calculated from the difference of average small stock portfolios and average big stock portfolios and the value premium (HML) calculated from the difference of average high book-to-market ratio portfolios and average low book-to-market ratio portfolios. The FFC-4 model, according to Carhart (1997), adds momentum factor (UMD), the difference of high and low cumulative returns from $t-11$ to $t-1$ before the month t evaluating portfolio performance) in addition to FF-3 model. If risk factor/factors can fully explain portfolio's excess return, the alpha is statistically indifferent from zero.

As with raw returns, risk-adjusted returns can be either equal- or value weighted in order to address potential abnormal returns driven by tiny and/or giant stocks. Compared with raw returns, risk-adjusted returns reflect the ways in which portfolio performance is related to existing risk factors, and reflects how anomalies can be explained by risk factors. In such cases, each anomaly is viewed as a significant risk-adjusted portfolio alpha. This chapter does not attempt to use the Fama-French 5-factor model as main risk-adjusted technique, as Chapter 5 and Chapter 6 is investigating firm's profitability anomaly that is closely related with one of the factors implied in the Fama-French 5-factor model. However, portfolio analyses in Chapter 4 is also examined under such model as a robustness test, and the results are consistent with main findings.

3.2 Individual Stock Analysis

3.2.1 Correlation of firm characteristics

A correlation of firm characteristics provides an intuitive conclusion about relationships between anomalies and other firm characteristics. The sign and significance of correlations between returns and anomalies give initial evidence about whether there is a connection between the two. The correlation may be measured in terms of Pearson's correlation or Spearman's rank correlation. However, given the existence of nonlinear relationships, coefficients of Spearman's rank correlation may deviate from the Pearson's correlation, and in such cases, the coefficient of regression analysis may be biased. This is thus commonly used as a cross-check with a portfolio's characteristics distribution as to whether there is a clear trend between two variables. The averaged correlation of two variables, A and B, is created from t-times rebalanced sample and then measured as follows:

$$\overline{corr(A,B)} = \frac{\sum_t corr_t(A,B)}{t} \quad (3.7)$$

The frequency of such rebalancing should be in line with the portfolio rebalance frequency.

3.2.2 Fama-MacBeth (1973) regression

The Fama-MacBeth regression is widely used in the cross-sectional analysis and was developed by Fama and MacBeth (1973) as a two-pass cross-sectional regression method to examine whether there is a linear relationship between expected returns and factor betas. Betas are estimated using time series regression in the first pass, and the relationships between returns and betas are estimated using a second pass cross-sectional regression. The use of estimated betas in the second pass introduces the classical errors-in-variables problem. As described by Cocharane (2005), in the first step, for each month t the excess returns of firm i (denoted as $R_{i,t+1} - r_{f,t+1}$ are regressed by factors $\lambda_n(N = 1,2,3 \ldots)$) which are observed at t and are assumed to determine stock returns:

$$R_{i,t+1} - r_{f,t} \;= \alpha_{i,t} + \lambda_{1,t}\beta_1 + \lambda_{2,t}\beta_2 + \cdots + \lambda_{n,t}\beta_n + \varepsilon_{i,t} \quad (3.8)$$

$$i = 1, 2, \ldots, I \text{ for each t}$$

$$n = 1, 2, \ldots, N$$

$i - firm$

$t - observing\ time\ period$

$\beta_n \ - factors\ related\ with\ r_{i,t} - r_{f,t}$

$\lambda_n - coefficient\ of\ factor\ \beta_n$

In the second step, the average value of $\hat{\alpha}_i$ and $\hat{\lambda}_n$ of the cross-sectional regressions is measured as:

$$\hat{\alpha}_i = \frac{\sum_{t=1}^{T} \hat{\alpha}_{i,t}}{T} \quad (3.9)$$

$$\hat{\lambda}_n = \frac{\sum_{t=1}^{T} \hat{\lambda}_{n,t}}{T} \quad (3.10)$$

The corresponding variance of the averaged value, $\hat{\alpha}_i$ and $\hat{\lambda}_n$, is then measured as:

$$Var(\hat{\alpha}_i) = \frac{\sum_{t=1}^{T} \left(\hat{\alpha}_{i,t} - \hat{\alpha}_i\right)^2}{T^2} \quad (3.11)$$

$$Var\left(\hat{\lambda}_n\right) = \frac{\sum_{t=1}^{T} \left(\hat{\lambda}_{n,t} - \hat{\lambda}_n\right)^2}{T^2} \quad (3.12)$$

The Fama-MacBeth regression usually reports the second step as final output for analysis. It allows tests to be designed to examine the power of pricing factors at the firm level. However, the researcher must be careful to ensure that the regression method does not highlight or mask any characteristics in the data that offer valuable information about the validity of the asset pricing model that is not included in the explanatory variable sets, β_n. Specifically, data snooping biases as discussed in Lo and MacKinlay (1990) must be avoided, as otherwise researchers could input only the desired factors and claim that these are what determines $R_{i,t} - r_{f,t}$.

3.2.3 Discussion of portfolio analysis and individual stock analysis

Many scholars have confirmed that the two mainstream research methods are compatible. Bali et al. (2016) particularly highlight that the coefficient of the Fama-MacBeth (1973) regression is comparable with returns from the long-short portfolio. The average coefficient estimates in Fama and MacBeth (1973) regression can, therefore, be interpreted as monthly returns on long-short trading strategies that trade on that part of the variation in each regressor that is orthogonal to every other regressor. A matrix algebra illustration of the commonality of the two methods is available in Footnote 3 of Ball et al. (2015), and in this thesis, their conclusion is the main theory supporting the validity of the use of two methodologies.

There are, however, certain advantages in using one method over some others. Bali et al. (2016) attribute the predominant metric of portfolio analysis to its nonparametric nature, which requires fewer sampling specifications than cross-sectional regression methods. Forming characteristic-based portfolios does not need a presumed distribution of a firm's characteristics, and allows observations with extreme values to be included alongside other companies; thus, any idiosyncratic risk that a single firm holds could also diversified in the portfolio. The drawbacks of portfolio analysis, according to Bali et al. (2016), include the limitation to the number of factors by which stocks may be sorted. If stocks are sorted by two factors and portfolios constructed at the intersection of the two factors' quintile breakpoints, a total number of 25 (5 times 5) portfolios are constructed. If the breakpoints are built on a decile basis, rather than a quintile basis, the corresponding number is 100 (10 times 10). If portfolio sorts are built based on three factors, and portfolios are formed at the intersection of decile breakpoints, the number of portfolios is 1,000 (10 times 10 times 10). This leads to concerns around whether some portfolios may not have a sufficient number of stocks to dilute distinctive characteristics, especially when the number of firms with specific information, e.g. firm's insider ownership (which will be discussed in Chapter 5), is small.

Cross-sectional regression analysis, meanwhile, allows a large set of explanatory variables to coexist. This enables research design to minimise the possibility of missing key variables, and to explore the pricing power of each variable, controlling for other firm characteristics. However, Bali et al. (2016) highlight three drawbacks that researchers should address when using cross-sectional analysis. The first is that cross-sectional regressions reflect the pervasive impact of the large number of small firms in the market. As the ordinary least square regression weights each observation equally, the weight on the micro-cap stocks, which make up roughly two-thirds of the market, but which represent less than 6% of the market by capitalisation, dominate the average coefficient results. The second drawback is that Fama-MacBeth regressions are also sensitive to outliers and impose a potentially unspecified parametric relation between the variables, making the economic significance of the results difficult to judge. The third drawback is that, given the skewed distributions and extreme observations for some firm characteristics, Fama-MacBeth regressions may not present unbiased results compared to portfolio tests, which provide potentially more robust results in terms of evaluating predictive ability.

4 LIMIT OF ARBITRAGE AND THE DISTRESS PUZZLE

4.1 Introduction

This chapter documents what lies behind the distress puzzle, a long, persistent negative return premium, is a set of significant limit of arbitrage effects. By using a comprehensive dataset that includes details of financially distressed firms based on U.S.-wide stocks in the main exchanges. The distress premium is captured and is found to be more concentrated in cases of high transaction cost stock portfolios, and concentrated in portfolios where arbitrage opportunities are restricted and those with high historical idiosyncratic volatility. Dissecting the distress puzzle shows that high distress risk firms with small market capitalization are the primary contributors to the premium, while small firms also tend to have high transaction costs, high idiosyncratic volatility, and high short-selling costs. In line with Fama and French (2008), the results were cross-checked using double-sort portfolio returns and the Fama-MacBeth regression. Consistent evidence of limit-of-arbitrage effects in the distress premium is demonstrated, as distress risk is positively related to expected return when the interaction effects of distress risk on high transaction costs and idiosyncratic volatility are controlled.

Firms with high financial distress risks generate abnormally low returns. Existing empirical evidence from Dichev (1998), Campbell et al. (2008), and Avramov et al. (2013) find a strong premium from a zero-cost portfolio that holding top 20% lowest distress risk stocks while short selling top 20% highest distress risk stocks cannot be explained by asset pricing models such as CAPM and the Fama-French 3-factor (FF-3) model. In addition, returns of those portfolios that are sorted by distress risk present a negative risk-return relationship: Low distress risk stocks earn high returns, while high distress risk stocks record low returns. These empirical findings compound the so-called "distress puzzle", as current theories are not able to provide satisfactory explanations for these results.

Firms that are at high risk of financial distress have several characteristics related to the limit of arbitrage effects, which leads to the main research hypothesis whether the distress puzzle exists due to arbitrage limits. Limit of arbitrage theory refers to the way in which transaction costs restrict the ability of traders to make profits from market mispricing, thus creating constant mispricing anomalies. This theory highlights that the assumption of a frictionless market, which is commonly used in risk-based asset pricing theories, is not in line with reality. Vassalou and Xing (2004) find that most distressed stocks are penny stocks. From a sample of 1,614 firms which eventually filed bankruptcy protection, defaulted, or were delisted for performance reasons, Campbell et al. (2008) note that the mean value of stock price was slightly over one dollar, and the average 3-month return volatility was almost twice the market level. Avramov et al. (2013) find the mean market capitalization of high financial distress risk firms to be 9 times smaller than that of solvent companies. From another perspective, Campbell et al. (2008) confirm the importance of market capitalization. They find that in their failure risk predictive model, the variable proxy for firm market capitalization is the most persistent variable with the power to predict the probability of financial distress over short and long forecasting horizons. Conrad et al. (2014) show that institutional ownership is negatively related to distress risk, and the top decile high distress risk firms have a mean value of institutional ownership of 12.5%, while the average value across the safest six deciles is over 30%. The spreads of firm's stock price, size and institutional ownership across high and low distressed firms suggest the existence of the distress puzzle is possibly due to high arbitrage limits in high distress risk firms, where anomaly exists but costs of correcting prices block potential arbitrage activities. This leads to our main research hypothesis if the distress puzzle is due to arbitrage limits.

Limit of arbitrage theory refers to the way in which transaction costs restrict the ability of traders to make profits from market mispricing, thus creating constant mispricing anomalies. This theory highlights that the assumption of a frictionless market, which is commonly adopted in risk-based asset pricing theories, is not in line with reality. Amihud (2002), Asquith et al. (2005), and Nagel (2005) contribute to the understanding of this topic by identifying stock illiquidity, short interest ratio, and institutional shareholders that represent the condition of arbitrage limits. They find that most asset pricing anomalies are more pronounced in stocks that have a significant limit of arbitrage properties. These findings argue that trading stocks using anomaly-driven strategies, contradictory to the implied hypothesis of EMH that transaction is frictionless and no transaction costs, are heavily influenced by those arbitrage limit effect than trading other stocks. Successful results in terms of explaining anomalies by limit of arbitrage theory can be found in Ali et al. (2003), where the value effect is strongly related to several limit-of-arbitrage effects, and Duan et al. (2010) who argue that the short interest ratio anomaly has no pricing power in low idiosyncratic volatility stocks. The research is thus designed by using proxies of transaction cost (bid-ask spread, dollar volume, Amihud (2002) illiquidity measure) and holding costs (idiosyncratic volatility) to explain the distress puzzle.

Indeed, a number of scholars claim to have resolved the distress puzzle. George and Hwang (2010) argue that there is an interactive effect between a firm's leverage and distress risk where distress risk is positively priced, as interaction variables are included in the Fama-MacBeth regression analyses. Garlappi et al. (2008) argue that the power of shareholder bargaining under high probability of financial distress implies a higher portion of the firm's value can be claimed. In their double-sort portfolio results, firm's distress risk at month $t-1$ is positively priced in the $t+1$ month returns controlling for firm's total assets, R&D expenditures and industry concentrations. Novy-Marx (2013) argues that the distress premium diminishes when gross profitability is used as a pricing factor, while Conrad et al. (2014) find that high distress risk firms are lottery-like, such that distressed firms record a subsequent extreme high return. They propose that the way to distinguish distressed firms and "Jackpot firms" is based on the return's idiosyncratic skewness, where firms with high idiosyncratic return skewness are likely to be Jackpots, while distressed firms do not demonstrate such patterns. A more interesting conclusion comes from Chava and Purnanandam (2010), which is that the distress premium was driven by extreme outliers of returns in the period 1980 to 1990. This implies that the distress puzzle is a time-specific mispricing phenomenon rather than a market-wide anomaly based on size and value premiums. Nevertheless, none of which presents a sound resolution to the negative distress risk-return relationship in the post-1980 period in both portfolio analysis and individual stock analysis.

This chapter contributes to solving the distress puzzle from the perspective of arbitrage. Starting with the computation of a firm's risk of financial distress, the failure probability introduced by Campbell et al. (2008) is estimated from a hazard model that contains predicting variables selected from financial reports and the capital market. The estimation, common to most papers citing CHS failure probability, is based on a comprehensive list of 2,610 financially distressed firms in the U.S. from 1963 to 2014. An independently run logit regression is used to obtain parameters for calculating the failure probability. This provides an up-to-date estimation of distress risks that the previous literature has not yet covered, and helps to avoid look-ahead bias by using information that investors should not have known on the date of observation. This leads to the discovery that the distress premium is not generated from outliers in 1980 to 1990 and that the premium is stronger than that observed by Campbell et al. (2008) when post-2003 stock returns are included.

The second contribution of this chapter is the elaboration of the concept of distress premium and its covariance with arbitrage opportunities. Following Asquith et al. (2005) as well as Li and Luo (2016), the distress risk premium measured as the monthly-rebalanced long-short portfolio return from holding the lowest 20% distress risk firms and short-selling the highest 20% distress risk firms, is positively related to firms' average monthly bid-ask spread, dollar volume, illiquidity ratio, and idiosyncratic volatility. This variation of distress risk premium in low and high arbitrage limit firms is even higher if portfolio return is risk-adjusted, in which the portfolio's Fama-French 3-factor alpha is 0.45%−1.03% per month in low arbitrage limit companies and is 1.51%-2.27% per month in high distress risk firms in the 1980-2014 sample period. The cross-sectional regression further supports the arbitrage limit theory hypothesis by showing a distinctive pricing power of failure probability between low and high arbitrage limit firms.

There are several complimentary aspects between this chapter and Da and Gao (2010), who find that the effect of clientele changes and short-term reversal drives the distress premium from monthly rebalanced portfolios where the illiquidity of stock is also considered to be a proxy for transaction costs. The same approach is used in this chapter to evaluate the relationship between two market phenomena. However, regressions show that the fundamental difference between this study and Da and Gao (2010) is that in their literature a positive distress risk-return pattern is observed; such a pattern does not exist in this research. Comparing a rough proxy using 1971 to 1999 U.S .equity market data, seven different limit-of-arbitrage characteristics were considered based on more comprehensive databases and the relationship over a longer time period, from 1981 to 2014.

4.2 Hypothesis Development

It is known from the earlier literature that arbitrage limit affects differences in expected returns across stocks. In the Shleifer and Vishny (1997) survey, they proposed the mechanism how costs of arbitrage in exploiting anomaly-related return premium can influence investor’s decision, and thus leaving mispricing phenomenon to remain. By arguing how implausible a frictionless market assumption in the asset pricing model could fit the reality, they present two sources that drive stock price deviating from fundamentals. The first is the source of noise, which may initially generate mispricing due to investor sentiments or impediments of trading to intuitions. The second source is the cost of arbitrage. If arbitrage trading is limited by some restrictions, then excess returns that cannot be explained by rational asset pricing models may exist and restrict arbitrage activities. Pontiff (1996) supplements the concept of arbitrage cost by identifying how transaction costs and holding costs affect arbitrage profits: Transaction costs like bid-ask spread occurs with each transaction, reducing the willingness of investors exploiting anomalies with high costs. Holding costs like portfolio’s idiosyncratic volatility constitute a risk exposure as they are the consequence of forming diversified portfolios with different stocks. Therefore, investors are less willing to hold assets for long-term. Thus, return anomalies are more pronounced with a high limit of arbitrage effect.

Although the relation of the distress puzzle and limit of arbitrage theory has not yet been empirically investigated, various research findings confirm that high distress risk firms have potential barriers in trading activities: Campbell et al. (2008) find distressed stocks, on average, have market value of equity which is over 10 times smaller than the average firm market value of equity in the market.

Novy-Marx and Velikov (2015) estimate the trading cost based on anomalies, and they find the trading cost based on long-short distress risk portfolio could, on average, explain 70.5% of the buy-and-hold distress premium. For firms with such a small size and high trading costs, whether its stocks can be traded and held frictionlessly is in doubt, as equity investments in distressed firms are not favoured by Absolute Priority Rule implied in the U.S. bankruptcy law. In the extreme case, the value of holding distressed stocks could be zero as it cannot be reclaimed until senior debtholders are satisfied. Therefore, even professional investors like institutional owners may lack interest in holding high distress risk stocks, or hold stocks to lending.

This research, inspired by the existing literature, forms the following hypotheses:

H1: *The abnormal return from long-short distress risk portfolios is positively associated with transaction costs/ holding costs.*

H1 is tested as follow: For every month t, all stocks are independently sorted by the measure of distress risk and the proxy of arbitrage limit effect, known at $t-1$ before the month of forming. Then the distress premium is characterised by the arbitrage limit effect. According to the literature, the distress premium in high arbitrage limit groups should outperform low arbitrage limit groups.

H2: *The predictive power of financial distress risk to the expected stock returns is more pronounced in firms with higher transaction costs/holding costs than others.*

H2 is tested by adopting Fama-MacBeth (1973) cross-sectional regressions: For each month t, all stock's monthly excess return is regressed by stock's distress risk proxy and the proxy of limit of arbitrage effect, known at $t-1$, and one interaction variable computed as the product of the two proxy variables, and then computed as the time-series averaged coefficients and time-series t-statistics throughout all month's cross-sectional regressions covered by the dataset. Existing literature implies that the coefficient of the interaction variable should be significantly different from zero, representing how distinctive the distress puzzle is presented in low and high arbitrage limit stocks.

4.3 Data and the Measures

The dataset is constructed as follows: All common shares (CRSP share code=10/11) that are listed in the NYSE/AMEX/NASDAQ from January 1980 to December 2014 are included. Financial firms (SIC code 6000-6999) are dropped. Distress returns are addressed by using the CRSP delisting return (CRSP code dlret) where available. In the event that the final return for the delisting return is unavailable, the last full month return information and date are used as the delisting return. In some cases, CRSP still reports a firm's stock return even after financial distress events have been observed. This can be due to 1) a re-emergence of a distressed firm; 2) the date of bankruptcy or default announcement being prior to the delisting events; or 3) a firm declaring bankruptcy or defaults, but continuing to trade stock in the market. For cases that match the above descriptions, the return from the month of the first financial distress event is used as the firm's delisting return, and all observations afterwards are dropped. In line with Campbell et al. (2008), all these delisting return adjustments represent a conservative estimation of returns from distressed firms and do not sharpen distress premium. The final dataset contains 2,271,552 firm-month observations for 408 months.

4.3.1 Campbell et al. (2008): Failure Probability

4.3.1.1 Model specification and data

The failure probability (FP) proposed by Campbell et al. (2008) is a predicting model that is heavily reliant on accounting information, though some market information is also utilised, to measure the risk of a firm being financially distressed. The probability is estimated as Shumway (2001) hazard model methodology, but FP has higher predicting power in long-term estimation by allowing the explanatory variables changes with time. This research subtracts the method of calculating FP because this creates the most accurate model for predicting distress risk using accounting-based information, according to Campbell et al. (2008) and Charitou et al. (2013).

The FP is estimated as follows: all explanatory variables (see Table 2 for detail) are constructed using accounting data from Compustat and market data from CRSP. These variables are inspired by early research such as Shumway (2001) as well as Hillegeist et al. (2004) and Campbell et al. (2008) and modify some variables with new calculation. The estimation also utilises a list of financially distressed firms from January 1963 to December 2014. The list of financially distressed firms includes U.S. bankruptcy initial filings from Thomson SDC Platinum, The UCLA-LoPucki Bankruptcy Research Database, Compustat, Moody's Default Research Database, and CRSP Event files from January 1963 to December 2014. All filings with common corporate identifiers and dates of declared bankruptcy, default, or performance-related delisting events are included. Duplicates are dropped, and the record with the earliest event date is stored. Given that this research will use accounting and market information to estimate the probability of failure and portfolio returns, only firms with traceable PEERMNO and GVKEY are retained. This final combined dataset contains 2,610 failure events. In the sample period in line with Campbell et al. (2008), the failure firm case is 2,077, a higher number than Campbell et al. reported due the backfilling of the original database.

Table 2 Predicting variables definition

Variable	Definition	Notes
PRICE	The log value of CRSP monthly closing price Note that CRSP reports negative stock price sometimes and the absolute value of price for calculation is taken.	CRSP code PRC Note all prices over \$15 are replaced as \$15 but its original value is used to calculate ME. Bid-ask average value is used when no closing price is available.
ME	Market capitalization is a number of shares outstanding times the closing price at the end of the month. For the market value of equity calculating MB, closing price and outstanding share is December-end information.	$ME_{i,\ t} = SHROUT_{i,\ t} \times PRC_{i,\ t}$
BE	The definition of book equity (BE) as total shareholders' equity plus deferred taxes and investment tax credit (Compustat item TXDITC) minus the book value of preferred stock (Compustat item PSTK). I prefer the shareholders' equity numbers as reported by Compustat (Compustat item SEQ). In case this data is not available, I calculate shareholders' equity as the sum of common and preferred equity (Compustat items CEQ and PSTK). If neither of the two is available, I define shareholders' equity as the differences between total assets and total liabilities (Compustat items ATand LT).	$BE = SEQ + TXDITC - PSTK$ $or\ BE = CEQ + PSTK + TXDICT - PSTK$ $or\ BE = AT - LT + TXDITC - PSTK$ Note that the BE is calculated based on the above sequence.
BEadj	Adding 10% of the difference between ME and BE.	$BE\ (adjusted)_{i,t} = BE_{i,t} + 0.1(ME_{i,t} - BE_{i,t})$ Note that if $BE\ (adjusted)_{i,t}$ is still negative after adjustment, I replace that native value as \$1.
TAadj	Total assets plus 10% of the difference between market equity value and book equity value.	$Total\ Assets\ (adjusted)_{i,t} = TA_{i,t} + 0.1(ME_{i,t} - BE_{i,t})$
RSIZE	Firm's market equity over the total S&P 500 market value	$RSIZE_{i,t} = \ln(\frac{ME_{i,t}}{Total\ S\&P\ 500\ Market\ Value_t})$
NITA	Net income over total assets	$NITA = \frac{NIQ}{TAadj}$
NIMTA	Net income over market value of total assets	$NIMTA = \frac{NIQ}{(ME + TL)}$
TLTA	Total Liability over total assets	$TLTA = \frac{TL}{TAadj}$
TLMTA	Total Liability over market value of total assets	$TLMTA = \frac{TL}{ME + TL}$
CASHMTA	Cash and short income over total market value of assets	$CASHMTA = \frac{CHEQ}{ME + TL}$

(Continue)

(Continued.)

EXRET	Gross excess return, S&P 500 return is value-weighted	$EXRET_{i,t} = \ln(1 + R_{i,t}) - Ln(1 + R_{S\&P\ 500,t})$
MB	The market value of equity (ME) over adjusted book value of equity (BEadj)	$MB_{i,t} = \frac{ME_{i,t}}{BE\ (adjusted)_{i,t}}$
SIGMA	Annualised 3-month rolling sample standard deviation. I assume the standard deviation is centered on zero, instead of centered around mean value given a time period. Return is calculated based on CRSP Daily Stock Files	$SIGMA_{i,t-1.t-3} = \sqrt{252 \times \frac{1}{N-1} \times \sum_{k \in \{t-1,t-2,t-3\}} r_{i,k}^2}$
NIMTAAVG	Time-weighted NIMTA	$NIMTAVG_{i,t-1,t-12} = \frac{1-\varphi^3}{1-\varphi^{12}}(NIMTA_{i,t-1,t-3} + \varphi \times NIMTA_{i,t-4,t-6} + \cdots + \varphi^9 \times NIMTA_{i,t-10,t-12})$ Where $\varphi = 2^{-\frac{1}{3}}$
EXRETAVG	Time-weighted EXRET	$EXRETAVG_{i,t} = \frac{1-\varphi}{1-\varphi^{12}}(EXRET_{i,t-1} + \varphi \times EXRET_{i,t-2} + \cdots + \varphi^{11} \times EXRET_{i,t-12}$ Where $\varphi = 2^{-\frac{1}{3}}$

All variables are winsorized at the 5/95 percentiles before regression. Outliers that are not in this range are therefore replaced by 5/95 percentile threshold values. To further examine whether MB, $PRICE$ and $SIGMA$ are not required for winsorize process, their original values are used within the regression and the outcome is significantly inconsistent with Campbell et al. (2008). The hazard model is then estimated by using winsorized explanatory variables.

At the beginning of a month t, the marginal probability of a firm i falling into financial distress, denoted by P , is estimated using a logit regression. This is known as the one-month model:

$$P\left(Y_{i,t} = 1|Y_{i,t-1} = 0\right) = \frac{1}{1+e^{-\alpha-\beta x_{i,t-1}}} \ (4.1)$$

In line with Campbell et al. (2008, 2011), $Y_{i,t}$ is the logit regression dependent variable, which equals to 1 if firm i falls into financial distress in month t, or 0 otherwise. Thus, the regression reflects the marginal probability if a firm file for financial distress in month *t* is $P\left(Y_{i,t} = 1|Y_{i,t-1} = 0\right)$. Here, $x_{i,t-1}$ is the vector of all explanatory variables measured at the end of the previous month. These predicting variables includes: $NIMTAAVG$, $TLMTA$, $EXRETAVG$, $SIGMA$, $RSIZE$, $CASHMTA$, MB, and $PIRCE$. In addition, the conditional probability that a firm will file for bankruptcy 12 months later ($t + 12$) is estimated using historical information from $t - 1$, given its assumed to be survival until month $t + 11$.

$$P\left(Y_{i,t+12} = 1|Y_{i,t+11} = 0\right) = \frac{1}{1+e^{-\alpha-\beta x_{i,t-1}}} \ (4.2)$$

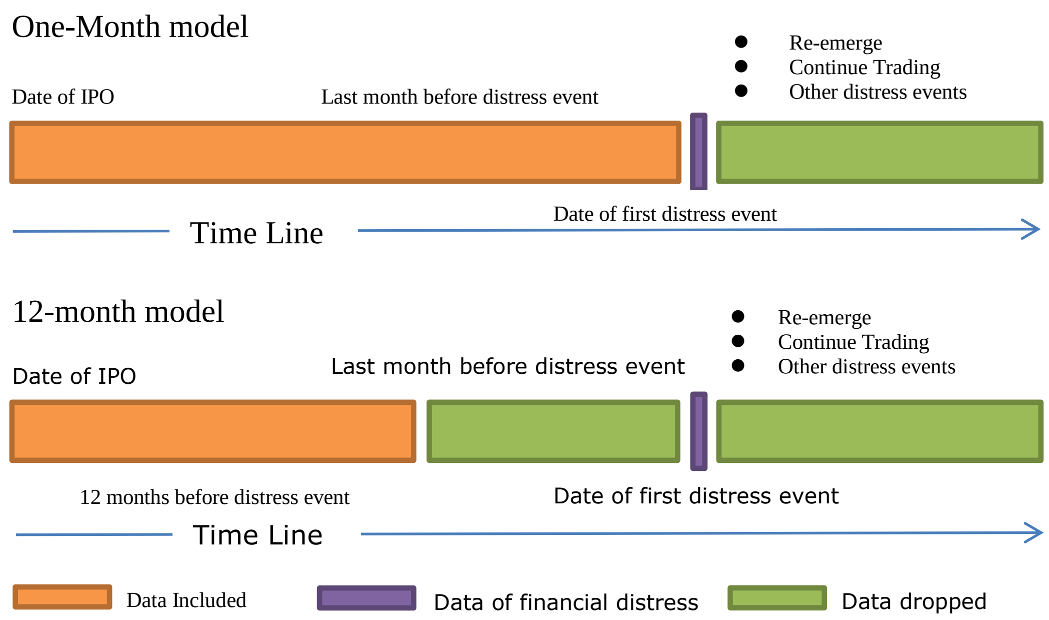

Figure 2 The one-month and 12-month failure probability predicting model

This figure illustrates how Campbell et al. (2008) failure probability is estimated in the panel dataset. The one-month model is estimated by using all available information set till one-month ahead of estimation $x_{i,t-1}$ as explanatory variables explain if firm i on month t is financially distressed $\left(\mathrm{Y_{i,t}} = 1|\mathrm{Y_{i,t-1}} = 0\right)$ or not $\left(\mathrm{Y_{i,t}} = 0|\mathrm{Y_{i,t-1}} = 0\right)$. For the 12-month model, the condition of the firm is estimated by 1-month lagged information set $x_{i,t-1}$ to estimate the conditional probability causing distressed $\left(\mathrm{Y_{i,t+12}} = 1|\mathrm{Y_{i,t+11}} = 0\right)$ or not $\left(\mathrm{Y_{i,t+12}} = 0|\mathrm{Y_{i,t+11}} = 0\right)$. All other firm-month observations after the first financial distress event occurring are dropped.

It is crucial to handle observations that enter into regression, and observations that are dropped from the database due to model setting requirements, which are the key difference between one-month model and 12-month model. Figure 2 plots the procedures and differences of estimating two models. For one firm at month t enters into regression, one-month model must observe all lagged independent variables $x_{i,t-1}$, in that month. For firms that eventually fall into financial distress, the model identifies the first date of distress event as the sole date of financial distress in the database, assigning $Y_{i,t} = 1$ in that month and zero otherwise. Most distressed firms stop reporting their financial statement and their stocks are delisted when a distress event occurs. But there are some exceptions wherein the estimation model drops them from the database and assume firms have not survived when a distress event occurs. In the estimation of the 12-month model, we also drop observations within 12 months of financial distress event. That is, for instance, Firm Alpha defaulted in September 1998, and eventually delisted in March 1999. The estimation of 12-month model drops observations from September 1997 and afterwards in the 12-month model even though the stock was still trading in the market for subsequent months, and using data that is updated to September 1997 to predict whether Firm Alpha would fall into financial distress in September 1998.

4.3.1.2 FP simulation outcomes

The replicating results are presented in Table 3. For each of the panel groups, the first row reports summary statistics of original values of predicting variables, taken from Campbell et al. (2008) and our replicating results in the same period are listed in the second row. The third row reports the summary statistics across the whole sample period.

Panel A of Table 3 reports the Entire Data Set, including all U.S. firm-monthly observations of healthy firms (active firms in the observing month), bankrupted firms (firms filed for Chapter 7 or Chapter 11 in the observing month) and failure firms (firms are delisted from current exchange due to performance-related reason; firms are rated as defaulted by S&P or by Moody's; firms are bankrupted in the observing month). Our replica in the same period (1963-2003) generally gives identical results as Campbell et al. (2008), and statistic characteristics of all variables are constant in the whole sample period (1963-2014). One might be interested in the inconsistency of variable's minimum and maximum statistics, where the full sample period gives a smaller value than the replica dataset. This is because the dataset in the different sample period is winsorized independently, thus with different volume of observations, summary statistics may vary due to the difference value of 5/95 percentile threshold in two sample periods.

Panel B of Table 3 reports summary statistics for Bankruptcy Group which only includes the firm-month observations which represent those firms that have filed for bankruptcy. Consistent with Shumway (2001) as well as Campbell et al. (2008, 2011), bankrupted firms have lower net incomes than the market average level. The mean/median value of profitability measure, $NITA$ and $NIMTA$ is -0.001/0.007 in 1963-2003 and is 0.000/0.006 in 1963-2014 for the Entire Data Set. For the bankrupted firms, the mean/median value of $NITA$ and

$NIMTA$ is -0.036/-0.029 and -0.024/-0.026 respectively, a drastic difference to the market level. Bankrupted firms are distinct from the market with other characteristics: they have high leverage (measured as $TLTA$ and $TLMTA$), negative stock returns ($EXRET$), small size ($RSIZE$), high return volatility ($SIGMA$), high Market-to-Book ratio and low stock price. For statistics in Panel C, those conclusions hold due to the large similarity in terms of accounting and marketing performance among distressed firms, regardless of which type of financial distress they are. The replica sample gives qualitative comparable results with Campbell et al. (2008) and maintains stable in the whole sample period, suggesting the backfill of bankrupted firms does not change the pattern of what the literature has identified.

Table 3 A comparison of failure probability predicting variable with Campbell et al. (2008)

This table lists summary statistics of the key variables for predicting firm's failure probability (FP). NITA is the ratio of firm's net income to total assets. NIMTA is the ratio of firm's net income to market-adjusted total assets. TLTA is the ratio of firm's total debt to total assets. TLMTA is the ratio of firm's total assets over market-adjusted total assets. EXRET is the firm's monthly stock return in excess of S&P 500 index return. RSIZE is the natural logarithm value of firm's market value of equity over S&P 500 listed firm size. SIGMA is the firm's annualised 3-month return volatility. CASHMTA is the ratio of firm's cash and short-term investments to market-adjusted total assets. MB is firm's market-to-book-ratio, following the adjustment suggested by Campbell et al. (2008). PRICE is the natural logarithm value of firm's stock price. The composition of variables is listed in Table 2. Each panel contains a group of summary statistics from Table II of Campbell et al. 2008 (p.2907), a replica using the same sample period, and a complete dataset covering all 1963-2014 firm-month observations. For each panel, all variables are independently winsorized at 5/95 percentiles.

Variable	NITA	NIMTA	TLTA	TLMTA	EXRET	RSIZE	SIGMA	CASHMTA	MB	PRICE
Panel A. Entire Data Set (Campbell et al. 2008), 1963-2003										
Mean	-0.001	0.000	0.506	0.445	-0.011	-10.456	0.562	0.084	2.041	2.019
Median	0.007	0.006	0.511	0.427	-0.009	-10.570	0.471	0.045	1.557	2.474
Std. Dev.	0.034	0.023	0.252	0.280	0.117	1.922	0.332	0.097	1.579	0.883
Min	-0.102	-0.069	0.083	0.036	-0.243	-13.568	0.153	0.002	0.358	-0.065
Max	0.039	0.028	0.931	0.923	0.218	-6.773	1.353	0.358	6.471	2.708
Observations	1,695,036									
Panel A2. Entire Data Set (Replica), 1963-2003										
Mean	-0.001	0.000	0.509	0.437	-0.010	-10.440	0.545	0.081	2.020	2.022
Median	0.007	0.006	0.514	0.420	-0.009	-10.564	0.476	0.045	1.479	2.464
Std. Dev.	0.033	0.021	0.249	0.274	0.115	1.913	0.322	0.092	1.585	0.869
Min	-0.101	-0.062	0.092	0.036	-0.238	-13.537	0.170	0.002	0.475	0.000
Max	0.039	0.028	0.931	0.911	0.213	-6.700	1.377	0.334	6.597	2.708
Observations	1,751,162									
Panel A3. Entire Data Set, 1963-2014										
Mean	-0.001	0.000	0.508	0.429	-0.009	-10.371	0.527	0.087	2.065	2.070
Median	0.007	0.005	0.510	0.401	-0.008	-10.472	0.443	0.049	1.540	2.546
										(Continue)

(Continued)										
Std. Dev.	0.033	0.021	0.252	0.276	0.110	1.896	0.307	0.095	1.578	0.839
Min	-0.100	-0.060	0.092	0.036	-0.230	-13.480	0.144	0.002	0.490	0.086
Max	0.040	0.027	0.930	0.911	0.204	-6.730	1.259	0.347	6.622	2.708
Observations	2,271,552									
Panel B1. Bankruptcy Group (Campbell et al. 2008), 1963-1998										
Mean	-0.054	-0.040	0.796	0.763	-0.115	-12.416	1.061	0.044	2.430	0.432
Median	-0.054	-0.047	0.872	0.861	-0.171	-12.876	1.255	0.021	1.018	-0.065
Std. Dev.	0.043	0.030	0.174	0.210	0.148	1.345	0.352	0.062	2.509	0.760
Observations	797									
Panel B2. Bankruptcy Group (Replica), 1963-1998										
Mean	-0.036	-0.024	0.703	0.631	-0.086	-11.956	0.930	0.056	3.297	0.788
Median	-0.029	-0.026	0.775	0.723	-0.105	-12.333	1.053	0.024	2.435	0.446
Std. Dev.	0.042	0.027	0.238	0.276	0.135	1.456	0.359	0.078	2.404	0.951
Observations	1,145									
Panel B3. Bankruptcy Group, 1963-2014										
Mean	-0.040	-0.027	0.682	0.620	-0.086	-12.145	1.020	0.072	3.199	0.870
Median	-0.030	-0.026	0.754	0.712	-0.108	-12.554	1.308	0.032	1.984	0.486
Std. Dev.	0.045	0.029	0.254	0.287	0.144	1.448	0.384	0.094	2.563	0.904
Observations	2,586									
Panel C1. Failure Group (Campbell et al. 2008), 1963-2003										
Mean	-0.059	-0.040	0.738	0.731	-0.105	-12.832	1.167	0.072	2.104	0.277
Median	-0.066	-0.047	0.821	0.842	-0.179	-13.568	1.353	0.029	0.751	-0.065
Std. Dev.	0.043	0.030	0.228	0.239	0.162	1.168	0.303	0.099	0.389	0.760
Observations	1,614									
Panel C2. Failure Group (Replica), 1963-2003										
Mean	-0.042	-0.029	0.707	0.646	-0.090	-12.068	0.954	0.061	3.300	0.832
										(Continue)

(Continued)										
Median	-0.032	-0.028	0.771	0.745	-0.119	-12.521	1.077	0.028	2.230	0.542
Std. Dev.	0.045	0.029	0.229	0.270	0.150	1.557	0.337	0.080	2.573	0.916
Observations	2,077									
Panel C3. Failure Group, 1963-2014										
Mean	-0.041	-0.027	0.711	0.653	-0.087	-11.995	1.057	0.066	3.235	0.891
Median	-0.030	-0.026	0.779	0.759	-0.116	-12.449	1.308	0.032	2.042	0.560
Std. Dev.	0.045	0.028	0.231	0.270	0.146	1.585	0.350	0.085	2.584	0.910
Observations	2,610									

4.3.2 Limit of arbitrage effect proxies

Inspired by Ali et al. (2003), Stambaugh et al. (2015) as well as Li and Luo (2016), this chapter adopts proxies of arbitrage limits below. Depending on the role that certain variables have played in the literature, these arbitrage limit proxies are categorised as transaction cost (stock's monthly average bid-ask spread, dollar volume, Amihud (2002)'s illiquidity measure) and holding cost (stock's monthly idiosyncratic volatility related with Fama-French three-factor model), as suggested by Asquith et al. (2005).

Bid-ask spread (BA): The difference between the quoted closing ask price (CRSP code ask) and closing bid price (CRSP code bid) over the bid-ask average value is calculated as (ask-bid)/(0.5*(ask+bid)). For missing prices of ask or bid, highest or lowest trading prices are used as an alternative. The variable is estimated on a daily basis, and reported as the average value in a given calendar month; this requires at least 15 effective observations in each month. According to the literature, BA should be positively priced in the expected stock returns and should be positively associated with the distress premium.

Dollar trading volume (DV): The number of shares traded (CRSP code vol) in a day times the closing price (CRSP code prc). If the closing price is missing, the bid-ask average is used. The variable is estimated on a daily basis, and reported as the average value in a given calendar month; this requires at least 15 effective observations each month. According to Amihud (2002), DV reflects stocks' trading volume with an interaction of stock price: stocks with low DV

are more sensitive by arbitrage activities, as large and frequent trading on these stocks can drive huge price drift comparing their limited stocks available for trading. Firms with low DV is a sign of high transaction costs. Therefore, based on our hypotheses the distress premium should be negatively related to DV.

Stock illiquidity ($\boldsymbol{ILLIQ}$): Defined as the average ratio of the daily absolute return (CRSP code ret) to the dollar trading volume (DV) on that day. Note that most research with cross-section of returns follows Amihud (2002), and states that $ILLIQ$ should be the average within a specific time period (denoted D):

$$ILLIQ_{adj} = \frac{1}{D}\sum_{d=1}^{D}\frac{|ret|}{DV} \quad (4.3)$$

$$D - Number\ of\ trading\ days\ in\ a\ month$$

$$ret - Daily\ stock\ return$$

$$DV - Dollar\ trading\ volume$$

In this research, the portfolios are rebalanced at the beginning of every month, so the number of trading days in one month is calculated, and at least 15 valid observations are required each month. The higher a firm's $ILLIQ$ is, the higher the stock transaction costs. Thus, the distress premium should be positively related to $ILLIQ$.

Idiosyncratic volatility ($\boldsymbol{IVOL}$): Idiosyncratic volatility is measured as the standard deviation of residual return from an asset pricing model. Given the failure of the CAPM to explain cross-sectional returns, and the ubiquity of the

FF-3 model in empirical financial applications, the focus is on idiosyncratic volatility measured relative to the Fama-French 3-factor model:

$$R_{i,t} - r_{f,t} = \alpha_{i,t} + \beta_{mkt} MKT_{i,t} + \beta_{SMB} SMB_{i,t} + \beta_{HML} HML_{i,t} + \varepsilon_{i,t} \quad (4.4)$$

Every month t the daily stock returns (CRSP Daily code ret) in excess of U.S. one-month t-bill rate $r_{f,t}$, is then regressed by MKT, SMB, and HML, all available on a daily basis from Professor Kenneth French's website. Idiosyncratic risk is thus defined as the standard deviation of the model-explained residual return $\varepsilon_{i,t}$, then multiplied by the square root of the total number of trading days (D) in the given month.

$$IVOL = Std.Dev(\varepsilon_{i,t}) \times \sqrt{D} \quad (4.5)$$

Similar to the $ILLIQ$, the distress premium is assumed to be positively related with $IVOL$.

4.3.3 Other variables

The proxy of distress risk is Campbell et al.'s (2008) failure probability (FP), and its estimation procedures are numerated in Section 3.4. Following the paradigm of asset pricing studies, this chapter also considers control variables below.

Stock Price: The closing price of a stock on the last trading day of a month (CRSP code prc); bid-ask average is used if no closing price is available.

Firm's size (ME): Measured by the value of a firm's market value of equity (CRSP code prc times $shrout$) in million dollars.

Firm's book-to-market ratio ($BEME$): Measured by the value of firm's Book-to-Market ratio. ME is the market capitalization, defined as the December-end closing price times shares outstanding in million U.S. dollars. BE is the shareholder's equity plus deferred taxes and investment credit using Davis, Fama, and French's (2000) estimating method. The definition of book equity (BE) as total shareholders' equity plus deferred taxes and investment tax credit (Compustat item $TXDITC$) minus the book value of preferred stock (Compustat item $PSTK$). I prefer the shareholders' equity numbers as reported by Compustat (Compustat item SEQ). In case this data is not available, I calculate shareholders' equity as sum of common and preferred equity (Compustat items CEQ and $PSTK$). If neither of the two is available, I define shareholders' equity as the differences of total assets and total liabilities (Compustat items AT and LT).

12-month Momentum ($MOM12$): The sum of stock returns (CRSP code ret) from the past 12 months to 1 month prior to the formation of a portfolio.

4.3.4 Summary statistics

Table 4 shows the summary statistics and correlations between all tested variables. The correlation is measured as time-series averaged cross-sectional correlation in terms of Spearman's ranking correlation. This is to describe better the relation of firm's distress risk and arbitrage limit in the cross-section dimension since these variables are skewed. The results show that distress risk strongly correlates with past 12-month returns (correlation=-0.324). This is in line with Campbell et al. (2008) and Garlappi et al. (2011), who note that high distress risk firms are associated with a negative momentum phenomenon. Distress risk is weakly related to book-to-market (correlation=0.039) equity but more strongly related to the firm's size (correlation=-0.161). The signs of correlation between all arbitrage limit factors to failure probability are consistent with the hypotheses by showing a positive correlation of FP and BA, $ILLIQ$ and $IVOL$ and negative correlation of FP and DV. All these signs support the hypothesis that arbitrage limit effect is positively related to the distress puzzle.

Table 4 Summary statistic of distress risk, firm characteristics and arbitrage limit factors

This table lists the time-series average Spearman's rank correlations across the main variables being investigated in this chapter. The data time period is from January 1981 to December 2014, a total number of 408 months. Data is from U.S.-incorporated firms with valid information for the test variables without SIC codes within 6000-6999. FP is measured as the month-end failure probability at t-1 measured as Campbell et al. (2008). BM is the firm's book-to-market ratio. ME is the log value of firm's market value of equity in million US dollars. MOM12 is the cumulative return of (t-12, t-2). BA is firm's monthly average bid-ask spread. DV is firm's monthly average dollar volume divided by 10^4. ILLIQ is firm's monthly illiquidity measure multiplied by 10^4. IVOL is firm's idiosyncratic volatility related to Fama-French 3-factor adjusted return. The detailed estimation of each variable is introduced in section 4.3.

	FP	BEME	ME	MOM12	BA	DV	ILLIQ	IVOL
Mean	0.061	0.669	1836.368	0.184	3.157	1277.628	2.814	0.029
P1	0.006	-0.363	4.774	-0.685	0.386	2.469	0.379	0.004
Median	0.031	0.559	199.859	0.070	2.288	330.556	2.186	0.024
P99	0.522	2.893	30584.94	2.622	14.130	18619.490	439.234	0.100
SD	0.115	1.446	8949.346	0.685	2.864	286.401	220.653	0.020
SKEW	9.492	12.229	15.235	4.975	287.598	28759.780	13.823	3.413
	FP	BEME	ME	MOM12	BA	DV	ILLIQ	IVOL
FP								
BEME	0.039							
ME	-0.161	-0.249						
MOM12	-0.324	-0.117	0.138					
BA	0.101	0.219	-0.573	-0.139				
DV	-0.094	-0.288	0.916	0.143	-0.676			
ILLIQ	0.135	0.264	-0.938	-0.15	0.697	-0.979		
IVOL	0.289	-0.025	-0.519	-0.106	0.413	-0.347	0.483	

4.4 Empirical Findings

4.4.1 Consistency with earlier literature

From January 1981 to December 2014, at the beginning of every year, all stocks in the full sample are sorted into ten decile groups according to their CHS failure probability (FP) that is estimated using historical information, which acts as a proxy for financial distress risk. This one-way sort generates t portfolios. The long-short portfolios, denoted as $Low - High$, represent a trading strategy whereby holding stocks in the 1st decile of distress risk (low distress risk firms) and shorting stocks in the 10th decile of distress risk (high distress risk firms) controlling for the effects of limit of arbitrage. In line with Fama and French (2008) and Hou et al. (2015), NYSE sample breakpoints are applied to the NYSE-AMEX-NASDAQ samples to further eliminate size effects.

The information used for sorting stocks is based on the price and market equity value of the last trading day in December, and the weight of each stock in the portfolio is therefore calculated by its previous December-end market value of equity. The sum of the stocks' market value of equity (ME) within a portfolio constitutes the market value of the portfolio. Thus the weight of each stock is the ratio of the stock's market value over the portfolio's value, as explained in the Chapter 3 *Research Methodology*. Every month, CRSP reports the stock's monthly holding period return, where stock's value-weighted return is calculated as its monthly holding period return times the stock's weight. The portfolio's value-weighted return is the sum of all stocks' value-weighted returns within the same portfolio.

Observations with negative book-to-market ratio are not removed from the sample because most financially distressed firms present negative book value of equity in their final life stages prior to delisting. About 2% of all firm-month observations have a negative book value of equity. Thus, removing those observations would mean removing firms that have high distress risks, which is counterintuitive when looking to explain this phenomenon. In accordance with Campbell et al. (2008) methodology, the negative book value of equity is replaced with the value of one dollar before the book-to-market value is calculated. For the same reason, only observations with the price per stock less than one dollar are excluded, rather than those of five dollars, to minimise market microstructure issues: the median stock price for distressed firms is just above one dollar.

Fama and French (2008), point out several methodological issues in terms of sorting portfolio returns on anomaly variables. When returns are estimated to be equal-weighted, a significant long-short portfolio return may reflect the pervasive nature of small firms. To address this issue, Table 5 reports value-weighted raw excess returns (portfolio's average monthly return minus 1-month U.S. T-bill rate), FF-3 alphas and FFC-4 alphas as risk-adjusted returns. The equal-weight returns are, however, still used as robustness checks but suppressed from the thesis in order to keep the main findings clear.

The results of this comparison are presented in Table 5. Three findings emerge from this presentation. First, the distress premium is more pronounced in terms of risk-adjusted returns, as the $Low - High$ portfolio's average FF-3 alpha is higher than its raw excess returns (1.45% per month against 0.62% per month).

Second, adjusting portfolio return by FFC-4 model reduces the hedge portfolio's performance. The average monthly FFC-4 alpha=0.51%, which is 83 bps lower than raw excess return and 94 bps lower than FF-3 alpha. This suggests that the momentum effect plays an important role in the distress puzzle, while FFC-4 the model cannot fully explain the distress puzzle since the FFC-4 alpha is still statistically significant (t=1.75). Finally, the results in Panel are generally consistent with Campbell et al. (2008), who present the average return from a low-high portfolio as 0.71% (Excess return), 1.65% (FF-3 alpha) and 1.06% (FFC-4 alpha) per month.

The latest research on asset pricing draws attention to the question of whether extremely low price stock, also known as "penny stocks", plays a critical role in understanding several anomalies relating to the theory of arbitrage limit. This view can be found from McLean and Pontiff (2016) as well as Li and Luo (2016). As the work of Campbell et al. (2008) drops stocks with a price below \$1.00, the effect of penny stocks has, therefore, not been examined. There is little evidence to confirm whether the distress puzzle is simply another aspect of the penny stock effect. To further investigate whether the overlooked penny stock effect in previous research impact on the distress puzzle, stocks are re-sorted using the sample, including stocks below \$1.00, but keeping all other procedures constant. The returns of portfolio that are sorted by all stocks including penny stocks are disclosed in the Panel B of Table 5.

The comparison of two sampling methods shows the following findings: Low distress risk portfolio yields higher average return than the reported return in

Panel A by 6 bps (value-weighted excess return), 5 bps (FF-3 alpha) and 25 bps (FFC-4 alpha) respectively. For the highest distress risk portfolio, the change of average return varies across three portfolio performance measures: the excess return maintains constant at -0.39% per month, while the FF-3 alpha increases by 4 bps and the FFC-4 alpha increases 20 bps than the corresponding Panel A results. The dramatic change of FFC-4 alpha is likely due to the high bid-ask bonus among penny stocks, an effect among small firms as Pontiff (1996) documented. For the long-short portfolio performance, the excess return is increased by 4 bps, the FFC-3 alpha increased by 1 bps and the FFC-4 alpha is reduced by 10 bps. Those findings confirm the fact that the distress puzzle is mostly due to the pricing failure of the Fama-French 3-factor model.

Table 5 Return of distress risk-sort decile portfolios (1981.1-2014.12)

At the beginning of every January from 1981 to 2014, all qualified stocks (nonfinancial firms, with valid FP, ME, BM, MOM12 and are traded on NYSE/AMEX/Nasdaq as common shares at the forming date) are independently grouped by failure probability (FP) from low to high. This generates 10 portfolios divided at every 10% of the spectrum of FP. Portfolios are rebalanced every year. Value-weighted monthly average returns in excess of 1-month T-bill rate (Excess Return) and alphas from Fama-French 3-factor model (FF-3 Alpha) as well as alphas from Fama-French-Carhart model (FFC-4 Alpha) for all 10 decile portfolios and long-short portfolios holding the low distress risk portfolio and short selling the high distress risk portfolio are shown. The t-statistics as adjusted by Newey-West standard error are reported below each row of return in parentheses.

Portfolios	1 Low Distress Risk	2	3	4	5	6	7	8	9	10 High Distress Risk	1-10 Low-High
Panel A. Drop $1 stocks, as Campbell et al. (2008)											
Excess Return	0.23	0.27	-0.06	-0.06	-0.02	-0.02	0.15	0.08	0.33	-0.39	0.62
	(1.30)	(2.59)	(-0.74)	(-0.73)	(-0.23)	(-0.15)	(0.91)	(0.47)	(1.24)	(-1.10)	(1.51)
FF-3 Alpha	0.30	0.39	0.04	0.01	-0.08	-0.12	-0.12	-0.29	-0.25	-1.15	1.45
	(1.96)	(4.18)	(0.52)	(0.06)	(-0.88)	(-1.04)	(-0.73)	(-1.73)	(-0.99)	(-3.62)	(3.78)
FFC-4 Alpha	0.14	0.27	0.09	0.12	0.06	0.15	0.22	0.09	0.33	-0.37	0.51
	(0.95)	(3.01)	(1.26)	(1.38)	(0.72)	(1.57)	(1.60)	(0.67)	(1.69)	(-1.53)	(1.74)
Panel B. Keep $1 stocks											
Excess Return	0.29	0.22	0.04	-0.06	0.01	-0.02	0.07	0.18	0.42	-0.39	0.68
	(1.72)	(1.83)	(0.50)	(-0.68)	(0.11)	(-0.19)	(0.42)	(0.99)	(1.29)	(-0.91)	(1.49)
FF-3 Alpha	0.35	0.36	0.17	0.04	0.02	-0.09	-0.12	-0.09	-0.10	-1.11	1.46
	(2.55)	(3.83)	(2.46)	(0.47)	(0.27)	(-0.75)	(-1.18)	(-0.54)	(-0.42)	(-3.26)	(3.38)
FFC-4 Alpha	0.25	0.26	0.21	0.18	0.21	0.16	0.27	0.34	0.67	-0.17	0.41
	(1.87)	(2.40)	(3.31)	(1.66)	(2.88)	(1.69)	(1.73)	(2.22)	(3.23)	(-0.47)	(0.91)

4.4.2 Portfolio characteristics of distress risk sorted stocks

In Panel A of Table 6, the average value of firm's distress risk, as well as three firm characteristics that are commonly viewed as key determinants of cross-sectional stock returns, are reported for each FP sorted decile portfolio. The average size of stocks in ten distress risk portfolios differs greatly, indicating that the effect of size causes dispersion. Firms in the highest distress risk portfolios have the smallest average size (509.0 million U.S. dollars) than other portfolios, suggesting those firms are more likely to be influenced by arbitrage limit. In line with Gomes and Schmid (2010), the spread of BE/ME is hump-shaped where the difference of lowest and highest distress risk portfolio is little. Consistent with the judgement of Campbell et al. (2008), high distress risk firms are associated with significant negative momentum effect, which can be seen as a monotonic downward value of $MOM12$ from 0.333 to -0.300 through ten distress risk-sorted portfolios.

Panel B of Table 6 reports the average value of firm's bid-ask spread (BA) in percentage, dollar-volume (DV) for every 10,000 units, Amihud's illiquidity ratio ($ILLIQ$) and idiosyncratic volatility related to FF-3 model. Amihud and Mendelson (1986) adopt the bid-ask spread as a measure of stock illiquidity, as price spread between demand and supply reflects the concession required for immediate sale. In their later research, dollar volume and illiquidity ratio are also used as proxies of market liquidity, and those measures are also adopted by Asquith et al. (2005), Fu (2009), and Li and Luo (2016). The average distress risk is positively related with bid-ask spread in all distress risk deciles, where the averaged BA is 1.606% in the first portfolio, and the value is slightly decreased in the subsequent 2 portfolios to 1.164%, then increased monotonically to 5.085% in the highest distress risk portfolio. The spectrum of averaged DV across failure probability sorted portfolio, like the reversed pattern of BA, is stated from 590.02 in the lowest distress risk portfolio and decreased to 308.05 in the highest distress risk portfolio. The spread of high and low illiquidity also positively relates to distress risk. In the lowest distress risk portfolio, the average $ILLIQ$ is 2.071, while the value is increased to 30.581 in the highest distress risk portfolio. The average $IVOL$ across distress risk portfolios also indicate that high distress risk firms have substantial holding cost (0.055 in the highest distress risk portfolio and 0.025 in the lowest distress risk portfolio). Pontiff (2006) demonstrates that idiosyncratic risk is the single largest cost faced by arbitrageurs. However, the idiosyncratic volatility-return pattern is contradictory: Ang et al. (2006) argue that the pattern is negatively related, yet Fu (2009) finds the pattern to be positive. The findings of this research confirm that rational investors hold fewer positions in stocks that have high idiosyncratic volatility. Consequently, there is less pressure for these stocks to be sold. Thus, firms with high idiosyncratic volatility have high holding costs. Overall, the spread of arbitrage limit variables across high and low distress risk firms indicate the potential cost from exploiting distress puzzle is enormous.

Panel C displays other firm characteristics of ten distress risk portfolios. Consistent with prior research, distress risk is negatively associated with the dividend-to-earnings ratio (Chava and Jarrow, 2004), networking capitals and size (Ohlson, 1980), positively associated with leverage (Avramov et al. 2013). In terms of arbitrage-related factors, distress risk is negatively related with institutional ownership (Campbell et al. 2008; Campbell et al. 2011, Conrad et al. 2014). Inspired by Asquith et al. (2005) who investigate the role of institutional ownership and short interest ratio as a pair of arbitrage effect variables, the average short interest ratio across decile distress risk portfolios are presented. The average distress risk is negatively associated with institutional ownership as well as short interest ratio, suggesting that any trading activities regardless of whether holding or shorting high distress risk stocks, are facing less supply of selling and demand of buying those stocks.

These results confirm the size-arbitrage limit relationship: small firms are mostly firms with the highest distress risk. In addition, a strong relationship between firm size and distress risk emerges: even when stocks are sorted only by distress risk and arbitrage factors, a clear pattern of high distress risk-small size is observable. However, Dichev (1998), as well as Campbell et al. (2998), find that firm's size does not explain the distress premium. Therefore, this research does not use size as an arbitrage limit proxy; rather sets it as one of the common risk factors that are determining the stock returns. To further minimise the potential effect of firm's size to the portfolio analyses, the return of portfolio is weighted by size (see Chapter 3 for the detailed estimation and discussion of value-weighted return), and further adjusted by Fama-French 3-factor models.

Table 6 Characteristics of ten portfolios sorted by failure probability

At the beginning of every month from January 1981 to December 2014, all stocks that are qualified for grouping portfolios stocks (nonfinancial firms with valid FP, lnME, lnBM, MOM12 and are traded on NYSE/AMEX/Nasdaq as common shares at the forming date) are sorted by failure probability (FP) from low to high. This generates 10 portfolios divided at every 10% of the spectrum of failure probability. Portfolios are rebalanced every month. SIZE is firm's market value of equity in million U.S. dollars at month $t-1$. Book-to-Makret Ratio is firm's book value of equity at fiscal year-end over market value of equity in December of $t-1$. FP is measured as the month-end failure probability at $t-1$ measured as Campbell et al. (2008). MOM12 is the cumulative return of (t-12, t-2). BA is firm's monthly average bid-ask spread. DV is firm's monthly average dollar volume divided by 10^4. ILLIQ is firm's monthly illiquidity measure multiplied by 10^4. IVOL is firm's idiosyncratic volatility related to Fama-French 3-factor adjusted return. The detailed estimation of each variable is introduced in section 4.3.

Portfolios	1	2	3	4	5	6	7	8	9	10
Panel A. Average Firm's Size, Book-to-Market Ratio, Momentum and FP										
Size (Million US Dollars)	1028.0	2486.9	3019.2	2877.0	2509.0	2006.1	1790.3	2378.7	1770.5	509.0
Book-to-Market Ratio	0.697	0.565	0.577	0.632	0.701	0.782	0.862	0.916	0.951	0.690
FP (%)	0.009	0.015	0.020	0.027	0.035	0.046	0.061	0.085	0.132	0.469
MOM12	0.333	0.321	0.279	0.230	0.193	0.156	0.123	0.076	-0.022	-0.300
Panel B. Transaction Cost and Idiosyncratic Volatility Measurements										
BA (%)	1.606	1.237	1.164	1.288	1.592	1.675	2.504	2.725	3.875	5.085
DV (10^4)	590.02	459.05	385.70	334.42	297.20	274.74	260.33	247.46	250.76	308.05
ILLIQ	2.701	1.869	2.137	2.216	2.429	3.025	4.404	5.370	9.259	30.581
IVOL	0.025	0.024	0.024	0.024	0.025	0.027	0.030	0.034	0.040	0.055
Panel C. Other Characteristics										
Dividends/Net Income	0.16	0.13	0.18	0.22	0.30	0.23	0.36	0.20	0.35	0.08

(Continued)

(Continued)										
Debt/Assets	0.05	0.10	0.14	0.18	0.22	0.25	0.28	0.31	0.35	0.45
NWC/Assets	0.14	0.14	0.14	0.13	0.12	0.11	0.10	0.09	0.07	0.01
Log(Assets)	4.35	4.91	5.18	5.34	5.43	5.46	5.45	5.30	5.12	4.86
Institutional Ownership	0.377	0.425	0.429	0.416	0.398	0.376	0.355	0.323	0.296	0.260
Short Interest Ratio	0.058	0.049	0.049	0.055	0.036	0.033	0.034	0.030	0.031	0.029

4.4.3 Double-Sorts portfolio analyses

Using the same sample period and sampling criteria, at the beginning of each month, all stocks in the full sample dataset are sorted into five quintile groups according to their FP, which acts as a proxy for financial distress risk. Independently, the stocks are sorted into five quintiles according to one of the limits of arbitrage effect variables mentioned earlier in this work. The intersection of breakpoints from two independent sorts generates 25 double-sorted portfolios. The Long-short portfolios denoted as $Low - High$, represent a trading strategy whereby holding stocks in the 1st quintile of distress risk and shorting stocks in the 5th quintile controlling for the effects of limit of arbitrage. Using the same methods, another five long-short portfolios are constructed to examine the arbitrage premium after controlling for distress risk. According to the suggestion made by Li and Luo (2016), because penny stocks are those with the highest sensitivity to arbitrage limit effect, penny stocks (price per share < one dollar) on the date of forming the portfolio remain in the database.

4.4.3.1 Trading costs and financial distress

The results in Table 7 show the monthly averaged returns of portfolio that are independently sorted by firm's failure probability and trading cost proxies. To correct the potential bias relating to firm's size, value-weighted FF-3 alpha is reported as the measure of portfolio performance. Given the fact in Table 6 that portfolio's average transaction costs are increased with portfolio's average distress risk in most cases. Stocks with a high bid-ask spread imply that a high cost to markets in terms of conducting transaction deals. Therefore, a bonus return is expected in these high bid-ask spread/low dollar volume/high illiquidity stocks and the bonus may result in the distress premium.

Panel A of Table 7 reports the double sort portfolio average returns by failure probability and bid-ask spread (BA). The distress premium, measured as the average monthly return from $Low - High$ distress portfolio, is higher and more significant when average BA is high. The highest performance of long-short distress risk portfolio is the one with highest average BA, yielding a monthly return at 1.85% (t=6.14) FF-3 alpha or 1.43% (t=4.69) without risk-adjust the procedure. Both performed better than the univariate portfolio results and defeat other four long-short distress risk portfolios. The phenomenon that FF-3 alpha is even higher than average excess return reflects the fact that the distress premium earns higher FF-3 risk-adjusted returns than excess returns. This finding is in line with the long-short decile portfolio performance reported in Table 5. When the average BA declines, the corresponding distress premium is reduced. In the lowest BA quintile, the value-weighted FF-3 Alpha reaches 0.84% (t=2.54), or is 0.38% (t=1.06) without risk-adjusting. Both are the worst performance among all the five long-short distress risk portfolios. In fact, the value-weighted distress premium in the first three BA quintiles is no longer significant, suggesting that the distress premium only exists in illiquid stocks. This finding is in line with the analysis using bid-ask spread in explaining cash holding anomaly, momentum effect, and idiosyncratic volatility puzzle (Li and Luo, 2016; Lesmond et al. 2004; Han and Lesmond, 2011) that the portfolio's performance from those anomalies are positively associated with high bid-ask spread and the premium is not significant among low bid-ask spread firms.

Breaking the composition of the distress premium into long position and short position, the portfolio sort further shows that the disappearance of the significant distress premium is mostly due to the sensitivity of firms with high FP, the short-side of premium. From the one side, the negative distress risk-return relationship is observed from all five BA-sorted rows. The performance of high distress risk firms is negatively affected with the average BA. From the low to high average BA quintile, the average portfolio performance worsen drastically, yielding from -0.31% per month in the lowest BA quintile to -0.79% per month in the second lowest BA quintile, and -1.14%, -1.49% and -1.10% per month respective to the subsequent three BA quintiles. On the other side, in the each quintile of BA spectrum, the low distress risk firms perform constantly well with a monthly excess return varying from 0.24%-0.75% and are relatively less affected by the variation of BA. This provides evidences that the premium of distress puzzle is mostly contributed by the short-side stocks in high BA stocks, which are high distress risk firms and associated with high transaction cost.

The effect of bid-ask spread does give a positive premium to high BA firms, but not as significant as those in high distress risk firms. In the 1st FP quintile, the $Low - High$ firms have a premium at -0.22% FF-3 alpha per month. This is in line with Amihud and Mendelson (1986) who find transaction cost like bid-ask spread is positively priced in the expected stock returns. When the average distress risk increases, the $Low - Higer$ return from other four BA quintiles are reversed to positive at 0.02%, 0.37%, 0.17% and 0.79% per month. The BA return premium is roughly increased from low to high distress risk quintile, but only premium in the 5th FP quintile is statistically different from zero (t=2.11). This further contradicts with arguments that liquidity risk is responsible to the distress puzzle (Da and Gao, 2010) as the underlying theory of liquidity risk requires a negative premium in such scenario.

Where the stock's Dollar Volume (DV) is used as the proxy variable for trading cost, a similar conclusion can be drawn as in the $FP - BA$ sorted analysis. Panel B of Table 7 presents the analysis results. A stock with low dollar volume implies low coverage in terms of market attention and low trading liquidity. Therefore, the distress premium exists since relatively few transactions are made that exploit arbitrage. The pattern of value-weighted $Low - High$ returns indicates that one of the distress puzzles, high distress risk-low equity return, is related to the stock's DV. The distress premium monotonically declines across the DV spectrum, as the excess return drops from 1.51% (t=4.28) to 1.03% (t=3.39) FF-3 alpha per month, or drops from 1.19% (t=3.22) per month to 0.43% (t=1.22) per month in terms of portfolio's average raw value-weighted return. In line with FP-BA sorted stocks, the disappearance of distress premium in terms of excess return is due to the relatively better performance of high distress risk firms with high DV. Although high distress risk firms generally underperform low distress risk counterparties, those with lower transaction costs (high DV) are more rewarding to investors.

These results are also in line with the general idea of Amihud and Mendelson (1986), who document a negative link between liquidity and average return, as in the short portfolio holding period BA and DV represent a market microstructure issue. Harris (1994) find returns on low-priced stocks are greatly affected by the minimum tick of \$1/8, which adds noise to the estimations of BA. Gervais et al. (2001) find past month trading volume contains future evolution of stock price. Those findings suggest that spread difference as a result of bid-ask quotes and dollar volume affects trading decisions and stock valuations from a completely different angle to liquidity risk in short holding periods. However, these findings do not support the view that liquidity risk is responsible to the distress puzzle, due to 1) the pricing power of dollar volume seems explained by FF-3 model, as none of five $DV\ Low - High$ premium is significantly different from zero, and 2) controlling the variation of BA, firms with high distress risk still underperform low distress risk firms with significant premium. The variation of distress premium across BA/DV quintiles should be, therefore, viewed as a result from costly arbitrage to high distress risk firms instead of bearing “liquidity risk”.

Panel C of Table 7 reports the average returns from distress risk and illiquidity ratio ($ILLIQ$) double sorted portfolios. Given the potential size effect in such portfolios, the focus remains on value-weighted portfolio returns. As predicted in an earlier chapter, when stock liquidity is relatively high, the distress risk premium is not significantly different from the baseline. Also, the first and second illiquidity quintile show corresponding $Low - High$ portfolio records of 1.03% and 1.08% average returns per month. When the illiquidity ratio increases, however, the distress premium increases drastically almost 50% to 1.95% (t=8.52) per month. The pattern of a positive relation between $ILLIQ$ and

$Low - High\ FP$ premium is, consistent with $FP - BA$ and $FP - DV$ sorts, showing that transaction cost has heavily influenced the distress puzzle.

Breaking down the source of distress premium from the long- and short-side further indicates that $ILLIQ$ affects distress premium radically symmetry. In the long-side (low distress risk) the average stock performance is positively related to stock illiquidity condition: low $ILLIQ$ stocks earn average monthly FF-3 alpha at 0.51% while high $ILLIQ$ firms earns 0.99%. In the short-side (high distress risk) the average stock performance is negatively related to $ILLIQ$, as most liquid stocks record monthly FF-3 alpha at -0.52% per month in average, and least liquid stocks earn -0.96% per month in average. In sum, consistent with the findings from previous analysis using different transaction cost proxies, two phenomena are observed: first, stock's illiquidity is positively priced in the return from low distress risk stocks. Second, in the high distress risk stocks, stock's illiquidity is negatively priced in the stock return.

Moreover, in three out of five distress risk quintiles, the average portfolios return increases with a portfolio's average illiquidity. This in line with the judgement of Amihud (2002) that illiquidity is compensated with high expected stock returns. However, this pattern is reversed in the highest distress risk quintile such that higher illiquidity portfolios record lower portfolio returns: the average zero-cost portfolio return from 0.48% per month drops to -0.44% per month (t=1.40), showing that liquidity risk is not the proper explanation to the distress puzzle. But since the magnitude of return, measured as the absolute value of portfolio return, is still associated with $ILLIQ$ positively, this return pattern could be viewed as after-cost expected return from investors.

Table 7 Portfolio returns from FP and transaction cost variable independent double-sorting

From January 1980 to December 2014, all qualified stocks (non-financial firms with valid FP, lnME, lnBM, MOM12 and are traded in NYSE/AMEX/Nasdaq as common shares at the forming date) are independently sorted by firm's distress risk measured by monthly failure probability (FP) and the proxy of transaction cost (measured as monthly bid-ask spread (BA) in Panel A; monthly dollar volume (DV) in Panel B and monthly Amihud (2002) illiquidity ratio (ILLIQ) in Panel C) then held for one month. The estimation of FP, BA, DV and ILLIQ is in section 4.3. This generates 25 portfolios, divided at every 20% of the distress risk spectrum from low to high and every 20% of the transaction cost spectrum in a similar manner. Low-High refers to a portfolio holding the top 20% most safe stocks (low FP) and shorting the riskiest 20% (High FP) within the same transaction cost variable quintile or refers to holding high transaction cost stocks and shorting low transaction cost stocks within the same FP quintile. The performance of the portfolio is measured as value-weighted Fama-French 3-factor alpha at percentage, and Newey-West (1987) adjusted standard error.

Panel A. FP-BA Group

Monthly Value Weighted Returns (%)

BA	Low FP	2	3	4	High FP	FP Low-High
Low BA	0.53	0.17	-0.00	-0.10	-0.31	0.84
	(3.62)	(2.19)	(-0.05)	(-0.66)	(-0.96)	(2.54)
2	0.41	0.15	-0.00	-0.27	-0.79	1.20
	(2.22)	(1.06)	(-0.01)	(-1.95)	(-3.05)	(3.76)
3	0.24	-0.33	-0.40	-0.33	-1.14	1.38
	(1.72)	(-2.16)	(-2.50)	(-1.91)	(-2.96)	(3.55)
4	0.46	-0.22	-0.55	-0.59	-1.49	1.95
	(2.57)	(-1.53)	(-2.72)	(-2.63)	(-6.02)	(6.45)
High BA	0.75	0.15	-0.37	-0.27	-1.10	1.85
	(3.33)	(0.75)	(-1.7)	(-0.77)	(-4.07)	(6.14)
BA Low-High	-0.22	0.02	0.37	0.17	0.79	
	(-0.84)	(0.08)	(1.44)	(0.43)	(2.11)	

(Continued)

(Continued)

Panel B. FP-DV Group

Monthly Value Weighted Returns (%)

DV	Low FP	2	3	4	High FP	FP Low-High
Low DV	0.95	0.44	0.34	0.54	-0.56	1.51
	(3.50)	(2.36)	(1.91)	(1.52)	(-2.15)	(4.28)
2	0.59	0.07	-0.01	-0.16	-0.89	1.48
	(5.57)	(0.64)	(-0.05)	(-1.11)	(-4.29)	(6.26)
3	0.32	0.06	-0.10	-0.18	-1.01	1.33
	(3.16)	(0.73)	(-1.23)	(-1.5)	(-4.92)	(5.34)
4	0.24	0.01	-0.05	-0.09	-0.69	0.93
	(2.24)	(0.06)	(-0.41)	(-0.91)	(-3.15)	(3.41)
High DV	0.48	0.11	-0.05	-0.15	-0.55	1.03
	(3.20)	(1.70)	(-0.69)	(-1.48)	(-1.94)	(3.39)
DV Low-High	0.47	0.33	0.39	0.68	-0.01	
	(1.39)	(1.58)	(1.92)	(1.90)	(-0.05)	

(Continued)

(Continued)

Panel C. FP-ILLIQ Group

Monthly Value Weighted Returns (%)

ILLIQ	Low FP	2	3	4	High FP	FP Low-High
Low ILLIQ	0.51	0.09	-0.00	-0.15	-0.52	1.03
	(3.49)	(1.44)	(-0.06)	(-1.56)	(-1.82)	(3.29)
2	0.28	-0.08	-0.15	-0.19	-0.80	1.08
	(2.30)	(-0.86)	(-1.24)	(-1.58)	(-3.15)	(3.52)
3	0.46	0.17	-0.19	-0.28	-0.97	1.43
	(3.27)	(1.38)	(-2.13)	(-2.75)	(-4.7)	(5.18)
4	0.53	0.26	0.03	-0.11	-0.98	1.51
	(4.61)	(1.80)	(0.21)	(-0.65)	(-4.72)	(6.01)
High ILLIQ	0.99	0.45	0.19	-0.15	-0.96	1.95
	(5.98)	(2.32)	(0.97)	(-0.78)	(-3.85)	(8.52)
ILLIQ Low-High	-0.48	-0.36	-0.19	0.00	0.44	
	(-2.32)	(-1.59)	(-0.91)	(0.01)	(1.40)	

Table 8 Portfolio returns from FP and transaction cost variable independent double-sorting

From January 1980 to December 2014, all qualified stocks (non-financial firms with valid FP, lnME, lnBM, MOM12 and are traded on NYSE/AMEX/Nasdaq as common shares at the forming date) are independently sorted by firm's distress risk measured by monthly failure probability (FP) and the proxy of holding cost, monthly idiosyncratic volatility (IVOL), then held for one month. The estimation of FP and IVOL is in section 4.3. This generates 25 portfolios, divided at every 20% of the distress risk spectrum from low to high and every 20% of the transaction cost spectrum in a similar manner. Low-High refers to a portfolio holding the top 20% most safe stocks (low FP) and shorting the riskiest 20% (High FP) within the same transaction cost variable quintile or refers to holding high transaction cost stocks and shorting low transaction cost stocks within the same FP quintile. The performance of the portfolio is measured as value-weighted Fama-French 3-factor alpha at percentage, and Newey-West (1987) adjusted standard error.

	Monthly Value Weighted Returns (%)					
IVOL	Low FP	2	3	4	High FP	FP Low-High
Low IVOL	0.42	0.26	0.11	0.13	-0.04	0.46
	(2.92)	(3.03)	(1.34)	(1.10)	(-0.17)	(1.87)
2	0.52	-0.02	-0.05	-0.30	-0.25	0.77
	(3.64)	(-0.23)	(-0.46)	(-2.45)	(-1.11)	(3.12)
3	0.45	0.19	-0.41	-0.53	-0.84	1.29
	(2.88)	(1.18)	(-2.39)	(-2.93)	(-2.75)	(3.52)
4	0.34	-0.08	-0.54	-0.70	-1.50	1.84
	(1.35)	(-0.37)	(-2.64)	(-2.92)	(-4.47)	(4.12)
High IVOL	-0.04	-0.79	-1.04	-1.06	-2.31	2.27
	(-0.17)	(-2.97)	(-3.74)	(-3.86)	(-6.68)	(6.03)
IVOL	0.46	1.05	1.15	1.19	2.27	
Low-High	(1.72)	(3.48)	(3.70)	(3.84)	(6.00)	

4.4.3.2 Idiosyncratic volatility and financial distress

Table 8 shows the pattern of the distress premium across idiosyncratic volatility ($IVOL$) quintiles. Based on the holding cost research documented by Pontiff (2006), distress premiums are expected to cluster where idiosyncratic volatility is high. Consistent with Pontiff's justification, value-weighted distress premiums generally increase when portfolio's average idiosyncratic volatility increases and the distress premium is concentrated in the High $IVOL$ quintile (2.27% per month, t=6.03), in sharp contrast to the premium in Low $IVOL$ firms (0.46% per month, t=1.83).

Idiosyncratic volatility also generates negative premiums that cannot be explained by asset pricing models, as reported in Ang et al. (2006 and 2009). In the last row of Table 8, all $IVOL\ Low - High$ portfolios across FP quintiles are negatively significant at 10% level or even higher, showing that controlling for FP, high $IVOL$firms underperform low $IVOL$ firms pervasively.

When holding costs matter, as the average $IVOL$ increases, the distress premium becomes even higher because the average return from high distress risk firms falls drastically, from -0.25% per month value-weighted excess return in the second $IVOL$ quintile -0.84% per month, -1.50% and -2.31% per month in the subsequent three quintiles. While firms with low distress risk generally have significant positive returns as 4 out of 5 portfolios in the low FP quintile have average return at 0.34%-0.52% per month, the change of distress premium is mostly driven by the short-side of the zero-cost portfolio. Thus, a combined reading of evidence presented in Table 7 and Table 8 suggests that the distress premium is disproportionately found in stocks. The stocks suffered from high transaction costs (proxied by high bid-ask spread, Amihud's illiquidity ratio and low trading volume), high holding costs (proxied by high idiosyncratic volatility related to $FF-3$ model) have recorded higher distress premium than stocks with low arbitrage costs, and the difference between high and low arbitrage limit effect stocks are statistically significant. If the distress premium is truly from bearing distress risk, controlling for such characteristics should not alter the scale of distress premium. In summary, the portfolio analysis shows that the distress premium is affected and is likely driven by arbitrage limit effect.

4.4.4 Robustness tests on portfolio sorts

4.4.4.1 Short-Selling constraints and financial distress

The results from Table 7 and Table 8 demonstrate that the major contributor of the distress puzzle is the short-side of the hedging portfolio, where high distress risk firms perform distinctively in low and high arbitrage limit conditions. Inspired by Nagel (2005) and Asquith et al. (2005), a further test of two short-selling constraint proxies are applied to test if arbitrage limit could explain distress puzzle: institutional ownership, representing the supply of short-selling stocks and short interest ratio, representing the demand for short-selling. Their effects, according to the literature, account for the abnormal return that is clustered in short-side of a zero-cost portfolio. As with other variables used as limit-of-arbitrage proxies, the return premium from low-high distress risk portfolio should decline in the event there is a corresponding increase in short-selling constraints.

Specifically, for institutional ownership-distress risk double-sorted portfolios, the equal-weight monthly distress premium is strongest in the top and bottom institutional ownership quintiles, at 1.79% and 0.66%, respectively. Additionally, the distress premium is only significant in the lowest institutional ownership quintile, at a 2.17% value-weighted per month. Again, the effect of size determines the insignificance of value-weighted distress premiums in the high institutional ownership quintile, where small firms account for the majority of firms in the portfolios with high institutional ownership. In addition, the value-weighted distress premium generally decreases from low to high institutional ownership quintiles, from 2.17% to -0.14% per month, which suggests that the ease of short selling significantly reduces the effect of arbitrage profits on the distress puzzle.

Although the distress premium from short interest ratio-distress risk double-sorted portfolios does not depict a clear pattern as is the case with institutional ownership portfolios, a significant equal-weighted distress premium is still observable in the highest short interest ratio quintile, at 1.32% per month. While the average value-weighted return in the same quintile is 0.75%; both values are statistically significant. In conclusion, the distress premium is negatively associated with institutional ownership as well as short interest ratio, indicating that institutions do not participate in trading high distress risk stocks. This is presumably the source of arbitrage limit among high distress risk stocks and explains why mispricing of FF-3 model is more severe in these stocks.

4.4.4.2 Robustness: Distress risk across limit of arbitrage in longer holding periods

If the limit of arbitrage effect conveys more information about short-term market impacts than fundamental conditions, then the distress premium is potentially not an anomaly within the efficient market hypothesis. Short-term market impact is unstable. Thus, the sign of distress premium switches more frequently, and its pricing power is not constant. The relationship between limit-of-arbitrage and distress risk was therefore tested to see whether it is driven by short-term market drift or by fundamental underlying market information. Campbell et al. (2008, 2011) and Hackbarth et al. (2015) all hold distress risk-related portfolios for a one-year period rather than only one month. Their methodologies are repeated here. The decrease in rebalancing frequency reduces the impact of turnover cost within the distress risk-hedge trading strategy, leaving the distress premium net of any potential cost due to trading. As seen in Table 1, high distress risk firms always have substantial high shorting-selling costs when measured as a monthly average value.

Annual holding portfolios are constructed using the same methodology as in the earlier sections, with the key difference that stocks were held for one year. The weight of stock returns included in the portfolio is determined by the portfolio formation date and remain constant over the following 12 months in terms of calculating the value-weighted returns. For the scope of the thesis, those results are omitted, as they are consistent with all finding sin monthly-rebalanced portfolios.

4.5 Cross-sectional Regression Analyses

4.5.1 Fama-MacBeth regression methodology

In order to examine whether the distress risk effect differs in different levels of arbitrage limit with and without control variables, the Fama-MacBeth (1973) regression method is employed as introduced previously introduced in section 3.2.2. The set of explanatory variables β_n, includes the proxy of firm's distress risk (FP), the proxy of firm's arbitrage limit effect ($Arbitrage\ Limit$) and a vector of the lagged control variable, denote $\boldsymbol{X_{i,t}}$, that are $lnME$, $lnBM$, and $MOM12$. $lnME$ is the natural logarithm of firm's ME at the end of June. $lnBM$ is the natural logarithm of the $BEME$. $MOM12$ is the cumulative compounded stock return over the last 12 months until month t. Specifically, the regression has the form as follows:

$$R_{i,t} - r_{f,t} = \lambda_0 + \lambda_1 FP_{i,t-1} + \lambda_2 Arbitrage\ Limit_{i,t-1} + \boldsymbol{\lambda_3}'\boldsymbol{X_{i,t-1}} + \varepsilon_{i,t} \quad (4.6)$$

Where

$$\boldsymbol{X_{i,t-1}} = \begin{bmatrix} lnME_{i,t-1} & lnBM_{i,t-1} & MOM12_{i,t-1} \end{bmatrix} \quad (4.7)$$

The regression tests whether the limit of arbitrage factors could weaken the predicting power of distress risk. If the coefficient of FP is no longer significant when $Arbitrage\ Limit$ also includes, one could conclude that the pricing power of distress risk is from stock's liquidity condition. In such case the distress puzzle is a manifesto of liquidity premium and can be explained by liquidity risk theory as argued by Da and Gao (2010). In a similar manner to prior research done by Avramov et al. (2009) and George and Hwang (2010), when $lnBM$ and $lnME$ are jointly entered into a Fama-MacBeth regression, $lnBM$ produces a positively priced expected return while $lnME$ has no significant pricing power. In addition, the pricing power of distress risk is not subsumed by value and size effects. As $lnBM$ refers to the effect of the value premium, and $ln\,ME$ refers to the effect of the size premium, when these are entered into the regression with FP, the coefficient of FP and its significance is enhanced. To further test the conclusion from Garlappi et al. (2008) and Garlappi and Yan (2011) that momentum profits can be explained by distress risk, momentum variables were added to the regression. $MOM12$ is the cumulative return from $t-12$ to $t-2$.

Moreover, a regression with an interaction term between firm's distress risk and arbitrage limit effect is added in order to examine whether there is an interaction effect between the two proxies, and to test whether there is a significant difference in pricing capacity of distress risk, depending on the firm's arbitrage limit status. The arbitrage limit variable is transformed as a dummy variable: when its value is below the market average value, it is set as 1 (high liquidity, low limit-of-arbitrage effect), and 0 for other cases (low liquidity, high limit-of-arbitrage). The value of the interaction variable thus equal to the FP when the firm's arbitrage limit value is above the market average level, and is zero otherwise. The significance of the interaction term depicts how the pricing power of distress risk deviates from low and high arbitrage limit firms.

$$R_{i,t} - r_{f,t} = \lambda_0 + \lambda_1 FP_{i,t-1} + \lambda_2 Arbitrage\ Limit_{i,t-1} + \lambda_3 Interaction_{i,t-1} + \boldsymbol{\lambda_4}'\boldsymbol{X_{i,t-1}} + \varepsilon_{i,t} \quad (4.8)$$

Where

$$\boldsymbol{X_{i,t-1}} = \begin{bmatrix} lnME_{i,t-1} & lnBM_{i,t-1} & MOM12_{i,t-1} \end{bmatrix} \quad (4.9)$$

To recap, equation (4.6) and (4.8) tests whether the distress puzzle can be explained by proposed proxies and test whether the liquidity risk theory or the limit of arbitrage theory is underlying. Then each λ are calculated in the second step as the average of all cross-sectional regression estimates through 1981 to 2014, or 408 months:

The corresponding standard error is then estimated from the difference between the averaged mean value and estimated value. Newey-West (1987) methods are adopted for this. For the selection of lag L, the estimation suggested by Stock and Watson (2011) is adopted:

$$L = 1.5 \times N^{\frac{1}{3}} \text{ (4.10)}$$

where L is the number of optimal lag and N is the total number of the observations used in the Newey-West estimation. Values of 1.5 and 1/3 were obtained from the Newey and West technique (1994), and hence the output of the sample is 11.25. However, using 11 or 12 as the optimal lag does not change the results.

4.5.2 FP, arbitrage limit, and cross-section of stock returns

The pricing power of distress risk is measured by the significance of the variable FP and the sign of FP ccoefficient indicates whether the distress risk-return relation is positive or negative. Using 1981 to 2014 U.S. market data, each month $t+1$ stock's monthly return over the one-month T-bill rate is regressed by distress risk factor measured by failure probability, one of the arbitrage limit proxies previously examined in the portfolio analysis section: bid-ask spread, dollar volume, illiquidity ratio and idiosyncratic volatility measured at t.

4.5.2.1 Trading costs and FP in the cross-sectional stock returns

In general, the distress risk is negatively priced expected stock returns. As reported in Table 9, the coefficient of FP is negative (-2.258, t=-1.41), and its significance is even higher when control variables enter into regressions (-3.828, t=-2.65). In Table 10, the coefficient of FP is -2.669 (t=-1.61) without control variable and -4.197 (t=-2.67) with control variable. The difference of FP coefficient and t-statistics is due to the different volume of samples. However, the quantitatively comparable results of FPin two samples show that the difference does not affect the persistence of the distress puzzle. The negative sign of FP is consistent with portfolio analysis results that distress premium is more pronounced after considering common risks that can explain stock returns. All proxies measuring market limit-of-arbitrage effect have a predicting power for expected returns. The results show that both BA and DV are priced in the expected return with the expected sign, as the coefficient of BA is 0.093 (t=2.78) and for DV the coefficient is -0.018 (t=-1.50). The significance of BA and DV is further increased with control variables together, at 0.114 (t=3.57) and -0.017 (t=2.39) respectively. This shows that the predicting power of bid-ask spread and dollar volume is independent to firm's size, book-to-market equity as well as past returns, and controlling for these variables further enhances the predicting power of the two transaction cost variables.

In the subsequent tests, the research now turns to evaluate the interaction effect between distress risk and transaction costs. The significance of FP is not reduced when BA or DV is in the regression simultaneously, providing evidence that the pricing power of distress risk does not represent an existing effect from trading costs in determining stock returns. In the $FP - BA$ group, the coefficients of FP and BA is -4.427 and 0.143 respectively. The coefficient is -3.933 for FP and 0.133 for BA with control variables. In the $FP - DV$ group, the coefficient for FP is -3.063 and for DV is -0.019 without control variable, and is -4.547 and -0.019 respectively with control variables. Compared with regressions where FP, BA, and DV is individually existing as regressor, the significance of these variables is increased in this context. These results provide evidence that in determining cross-sectional expected stock returns, the predicting power of liquidity, or liquidity risk does not substitute the pricing power of failure probability.

Finally, the research tests whether distress premium is concentrated in high transaction cost firms, which is one of the core arguments of whether the limit-of-arbitrage theory can explains distress puzzle. Regression analysis finds a significant return cluster in high bid-ask spread firms by showing significant $FP \times BA$ coefficients in Table 9. While the coefficient of FP is still significant ($\hat{\lambda}_2$=6.799, t=-3.72), the interaction variable ($\hat{\lambda}_3$) has a coefficient at 5.199, with a t-statics at 3.67. This gives straightforward evidence that the predicting power of distress risk is characterised by firm's bid-ask spread and the difference is over 3 standard errors from zero. The coefficient of interaction effect is quantitatively similar to the coefficient of FP, providing evidence that distress premium predominantly comes from high BA firms. The coefficient remains stable even when control variables are included where the coefficient of FP is -8.378 (t=-5.18) and for the interaction variable is 6.822 (t=5.46), proving that variation of FP's predicting power is not driven by omitting some key firm characteristics.

On the other hand, the interaction effect of $FP \times DV$, reported in Table 10, is not significant in the regression with or without control variables. The average coefficient of $\hat{\lambda}_3$ is 0.617 and is 2.073 where control variables are added;

neither is significant at 10% level. This is contrary to the arbitrage limit hypothesis as the coefficient should be significantly different from zero. Presumably this is caused due to the spurious correlation between dollar volume and firm's size, which Ali et al (2003) also point out. This explanation is supported by the significance of $lnME$. When DV and $lnME$ coexist in the regression, the coefficient of $lnME$ is statistically significant at 5% level, while $lnME$ is insignificant combining with BA. Since Campbell et al. (2008) has showed that the distress puzzle exits regardless of the firm size, the close relation between firm's dollar volume and size may therefore fail to characterise the pricing power of distress risk.

Table 9 Fama-MacBeth regressions with an interaction term between distress risk and bid-ask spread

For each month from January 1981 to December 2014, Fama-MacBeth (1973) cross-sectional regressions of monthly excess returns (CRSP monthly return over one-month T-bill rate) are run on a set of independent variables. $Distress\ Risk$ is measured as firm's failure probability (FP). The calculation of BA, $lnBM$, $lnME$ as well as $MOM12$ is in section 4.3.2 and the calculation of interaction variable is in section 4.5.2. The t-statistics, adjusted by the Newey-West standard error, are in parentheses. Panel A reports basic regressions and Panel B reports regressions with control variables. *denotes p<0.10, ** denotes p<0.05 and *** denotes p<0.01

Constant	FP	BA	Interaction	lnBM	lnME	MOM12	Observations	Avg. R^2
Panel A. Without Control Variables								
0.919***	-2.258						1475496	0.009
(3.54)	(-1.41)							
0.588**		0. 093***					1475496	0.008
(2.13)		(2.78)						
0.687***	-4.427***	0.143***					1475496	0.016
(2.80)	(-2.99)	(5.00)						
0.992***	-6.799***	0.149	5.199***				1475496	0.019
(4.06)	(-3.72)	(0.85)	(3.67)					
Panel B. With Control Variables								
1.924***	-3.828***			0.525***	-0.154***	0.629***	1475496	0.026
(4.50)	(-2.65)			(4.54)	(-2.93)	(3.04)		
0.893*		0.114***		0.528***	-0.034	0.726***	1475496	0.026
(1.69)		(3.57)		(4.66)	(-0.53)	(2.90)		
1.136**	-3.931***	0.133***		0.524***	-0.048	0.592***	1475496	0.030
(2.43)	(-2.78)	(3.96)		(4.61)	(-0.81)	(2.87)		
2.086***	-8.378***	-0.321***	6.822***	0.547***	-0.149***	0.622***	1475496	0.031
(4.85)	(-5.18)	(-2.63)	(5.46)	(4.83)	(-2.73)	(3.03)		

Table 10 Fama-MacBeth regressions with an interaction term between distress risk and dollar volume

For each month from January 1981 to December 2014, Fama-MacBeth (1973) cross-sectional regressions of monthly excess returns (CRSP monthly return over one-month T-bill rate) are run on a set of independent variables. $Distress\ Risk$ is measured as firm's failure probability (FP). The calculation of DV, $lnBM$, $lnME$ as well as $MOM12$ is in section 4.3.2 and the calculation of interaction variable is in section 4.5.2. The t-statistics, adjusted by the Newey-West standard error, are in parentheses. Panel A reports basic regressions and Panel B reports regressions with control variables. *denotes p<0.10, ** denotes p<0.05 and *** denotes p<0.01

Constant	FP	DV	Interaction	lnBM	lnME	MOM12	Observations	Avg. R^2
Panel A. Without Control Variables								
0.927***	-2.669						1460255	0.009
(3.56)	(-1.61)							
0.935***		-0.018					1460255	0.003
(2.81)		(-1.50)						
1.007***	-3.063*	-0.019*					1460255	0.012
(3.68)	(-1.88)	(-1.66)						
0.817***	-3.798	0.190	0.617				1460255	0.014
(3.22)	(-1.58)	(1.17)	(0.27)					
Panel B. With Control Variables								
1.943***	-4.197***			0.525***	-0.157***	0.621***	1460255	0.027
(4.48)	(-2.67)			(4.53)	(-2.94)	(3.00)		
1.870***		-0.017**		0.523***	-0.190**	0.764***	1460255	0.025
(3.23)		(-2.19)		(4.71)	(-2.40)	(3.26)		
2.227***	-4.547***	-0.019***		0.529***	-0.225***	0.641***	1460255	0.029
(4.72)	(-3.00)	(-2.65)		(4.68)	(-3.31)	(3.25)		
2.822***	-6.502***	-0. 601***	2.073	0.530***	-0.230***	0.639***	1460255	0.029
(5.23)	(-2.89)	(-3.97)	(1.26)	(4.66)	(-3.50)	(3.19)		

4.5.2.2 Interaction between Illiquidity and distress premiums

To test whether illiquidity is able to explain distress premium as it has been shown in section 4.4.3, following the same design, I added illiquidity and distress risk into the model where $lnBM$, $lnME$ and $MOM12$ are the risk factors that have been widely adopted in existing literature. Table 11 reports the results from Fama-MacBeth regression where distress risk and illiquidity ratio enter as explanatory variables individually where the coefficient of FP as well as $ILLIQ$ is negative and statistically significant at 1% level, so that stocks with high levels of distress risk, or stocks with high levels of illiquidity, earn lower returns than others. However, on its own, the illiquidity ratio is unable to account for distress risk's pricing power, or the negative relationship of distress risk-return by showing the significant FP coefficient (t=-3.51) where $ILLIQ$ (t=7.09) also enters regressions. These results are consistent when control variables are added.

The interaction variable of distress risk and illiquidity (denoted as $FP \times ILLIQ$), is built, following the same methods as $FP \times BA$ and $FP \times DV$. As reported in Table 11, there is a significant positive sign of $FP \times ILLIQ$ ($\hat{\lambda}_3$=5.742, t=2.95), and the standard error of this coefficient exceeds 3. This shows FP's stock price predicting power is significantly positively correlated with $ILLIQ$. This gives additional supportive evidence for the arbitrage limit effect and is consistent with distress risk-illiquidity double sort portfolios. The interaction variable carries information that the $ILLIQ$ does not carry. Therefore, adding $ILLIQ$ in the regression model does not change the scale of the coefficient of interaction variable. The pricing effect of FP and $FP \times ILLIQ$ together determine future return is even stronger where regression includes control variables ($\hat{\lambda}_4$7.829, t=5.02), suggesting that the difference of the distress puzzle is not a result from those well-documented firm factors.

Results from Table 12 show that as a measure of holding cost, idiosyncratic volatility also helps to explain the distress puzzle. The first regression shows that, in line with other models, distress risk is negatively priced to future returns ($\hat{\lambda}_1$=2.344, t=-1.45), and idiosyncratic volatility is negatively priced ($\hat{\lambda}_2$=-9.030, t=-1.24). When the interaction variable $FP \times IVOL$ enters into the regression alongside FP and $IVOL$, the interaction term is negative but not significant ($\hat{\lambda}_3$=1.739, t=1.18) and the significance of FP is enhanced (t=-2.03). When $lnME$, $lnBM$, and $MOM12$ enters regression as control variable, the interaction variable becomes significant ($\hat{\lambda}_3$ =3.650, t=2.89). The drift of FP, $IVOL$, and interaction variable significance is consistent with the characteristic of the distress puzzle and idiosyncratic volatility puzzle that both two factors are more pronounced controlling for firm's size, book-to-market ratio and momentum (see Campbell et al. 2008 and Ang et al. 2006).

Table 11 Fama-MacBeth regressions with an interaction term between distress risk and illiquidity

For each month from January 1981 to December 2014, Fama-MacBeth (1973) cross-sectional regressions of monthly excess returns (CRSP monthly return over one-month T-bill rate) are run on a set of independent variables. $Distress\ Risk$ is measured as firm's failure probability (FP). The calculation of $ILLIQ$, $lnBM$, $lnME$ as well as $MOM12$ is in section 4.3.2 and the calculation of interaction variable is in section 4.5.2. The t-statistics, adjusted by the Newey-West standard error, are in parentheses. Panel A reports basic regressions and Panel B reports regressions with control variables. *denotes p<0.10, ** denotes p<0.05 and *** denotes p<0.01

Constant	FP	ILLIQ	Interaction	lnBM	lnME	MOM	Observations	Avg. R^2
Panel A. Without Control Variables								
0.923***	-3.260*						1406851	0.009
(3.62)	(-1.92)							
0.667**		0.071***					1406851	0.007
(2.27)		(5.30)						
0.829***	-5.697***	0.087***					1406851	0.015
(3.30)	(-3.51)	(7.09)						
0.960***	-7.510***	0.394**	5.742***				1406851	0.017
(3.82)	(-3.92)	(2.07)	(2.95)					
Panel B. With Control Variables								
1.910***	-4.540***			0.516***	-0.149***	0.642***	1406851	0.028
(4.41)	(-2.85)			(4.50)	(-2.82)	(3.13)		
0.995*		0.059***		0.474***	-0.035	0.738***	1406851	0.026
(1.88)		(4.85)		(4.16)	(-0.55)	(2.98)		
1.323***	-5.421***	0.064***		0.474***	-0.056	0.579***	1406851	0.031
(2.90)	(-3.46)	(5.36)		(4.11)	(-0.99)	(2.87)		
1.886***	-8.518***	-0.221	7.829***	0.512***	-0.124**	0.587***	1406851	0.032
(4.01)	(-4.83)	(-1.33)	(5.02)	(4.48)	(-2.06)	(2.90)		

Table 12 Fama-MacBeth regressions with an interaction term between distress risk and idiosyncratic volatility

For each month from January 1981 to December 2014, Fama-MacBeth (1973) cross-sectional regressions of monthly excess returns (CRSP monthly return over one-month T-bill rate) are run on a set of independent variables. $Distress\ Risk$ is measured as firm's failure probability (FP). The calculation of $IVOL$, $lnBM$, $lnME$ as well as $MOM12$ is in section 4.3.2 and the calculation of interaction variable is in section 4.5.2. The t-statistics, adjusted by the Newey-West standard error, are in parentheses. Panel A reports basic regressions and Panel B reports regressions with control variables. *denotes p<0.10, ** denotes p<0.05 and *** denotes p<0.01

Constant	FP	IVOL	Interaction	lnBM	lnME	MOM	Observations	Avg. R^2
Panel A. Without Control Variables								
0.904***	-2.344						1459784	0.009
(3.46)	(-1.45)							
0.969***		-9.030					1459784	0.012
(4.27)		(-1.24)						
1.006***	-1.997	-6.753					1459784	0.017
(4.44)	(-1.50)	(-1.04)						
1.034***	-3.467**	-0.277	1.739				1459784	0.018
(4.50)	(-2.03)	(-1.37)	(1.18)					
Panel B. With Control Variables								
1.907***	-3.904***			0.532***	-0.153***	0.632***	1459784	0.027
(4.47)	(-2.65)			(4.52)	(-2.92)	(3.02)		
2.244***		-14.836***		0.479***	-0.187***	0.717***	1459784	0.028
(5.97)		(-2.63)		(4.83)	(-4.43)	(3.02)		
2.376***	-2.951**	-13.313**		0.487***	-0.196***	0.639***	1459784	0.031
(6.43)	(-2.27)	(-2.59)		(4.84)	(-4.66)	(3.23)		
2.299***	-6.102***	-0.538***	3.650***	0.502***	-0.193***	0.628***	1459784	0.030
(6.26)	(-4.09)	(-3.59)	(2.89)	(4.77)	(-4.47)	(3.09)		

4.5.3 Robustness tests on regression analyses

4.5.3.1 Does the Turn-of-Month effect explain the distress puzzle?

Da and Gao (2010) find that the distress premium is mainly driven by stocks among high distress risk stocks with poor return performance in recent months. They conclude that for a one-year holding period portfolio, highest 10% distress risk stocks earn an average return at 2.10% in the first month and drop to 1.52% per month in the second holding month, and then vanishes in subsequent months of the entire holding period. They also find that distress risk thus loses its predictive power for expected returns when the previous one-month return and illiquidity ratio enters the Fama-MacBeth regression. To test if the distress puzzle is related to the short-term reversal effect, the monthly excess return is then regressed on two short-term reversal variables as presented below:

Short-term Return Reversal ($\boldsymbol{R_{i,t-1}}$): The monthly return one month prior to the formation of a portfolio. According to Da and Gao (2010), this is negatively priced in the cross-sectional returns and overrules the pricing power of firm's distress risk.

Two-month Short-term Return Reversal ($\boldsymbol{R_{i,t-2}}$): The monthly return two months prior to the formation of a portfolio. According to Da and Gao (2010), this is negatively priced in the cross-sectional returns and reduces the coefficient of distress risk controlling for stock's illiquidity.

However, the results in Table 13 suggest that the Turn-of-Month effect does not account for the distress puzzle, as Da and Gao (2010) argue. In line with their argument, the Amihud illiquidity ratio ($ILLIQ$) is included alongside $lnBM$, $lnME$, $MOM12$, and remains significant considering the short-term reversal effect (Model 1 and Model 2). The $R_{i,t-1}$ (t=-9.22) and $ILLIQ$ (t=5.73) show strong predictive power in terms of each stock's expected return, but the pricing power of distress risk remains strong and stable that FP in all three models has a t-stat over 3.0. The previous month's return, R_{t-1}, does not subsume the predictive power of FP, and FP still retains a negative sign. Checking whether monthly returns from two months before the formation of the portfolio may provide additional information is also relevant in judging the conclusions drawn by Da and Gao (2010). The relevant results from Model 2 show that even returns from two-months (=-0.367, t=-1.20) prior to portfolio formation cannot explain the significance of the distress puzzle (=-0.319, t=-3.62), though the coefficient of FP is slightly reduced compared to the Model 1 (-0.319 against -0.325).

One possible explanation for the divergence of Da and Gao (2010) and the current results is that they use the default likelihood ratio to represent distress risk, a method taken directly from Vassalou and Xing (2004). This is used based on information from U.S. stocks from 1971 to 1999. However, here, the proxy of distress risk is the failure probability, in line with Campbell et al. (2008), and the data comes from U.S. stocks from 1981 to 2014. Campbell et al. (2008) prove that failure probability and DLI are generally negatively related to equity returns in the 1981 to 2003 period, which contradicts Da and Gao (2010). Furthermore, the current research suggests that the distress premium exists within longer holding periods and, as such, it is unlikely that a short-term return reversal could cause abnormal returns over a period of months.

Table 13 Fama-MacBeth regression on distress risk and turn-of-month effect

Each month t, stocks monthly excess return is regressed on lagged characteristics based on distress risk (FP), Amihud (2002) illiquidity ratio ($ILLIQ$), and control variables including firm's size ($lnME$), book-to-market ratio ($lnBM$), momentum ($MOM12$) using all NYSE, AMEX and NASDAQ common stocks as benchmark, and Model 1 and Model 2 adds short-term reversal variable (see section 4.5.5.1 for detail). T-statistics adjusted by the Newey-West standard error, are reported in parentheses. This dataset covers January 1981 to December 2014. *denotes p<0.10, ** denotes p<0.05 and *** denotes p<0.01.

	Benchmark	Model 1	Model 2
$lnBM$	0.491***	0.490***	0.492***
	(4.64)	(4.61)	(4.83)
$lnME$	-0.089*	-0.085*	-0.079*
	(-1.87)	(-1.81)	(-1.68)
$MOM12$	0.381***	0.369***	0.361**
	(2.83)	(2.61)	(2.49)
FP	-0.294***	-0.325***	-0.319***
	(-3.30)	(-3.54)	(-3.62)
$ILLIQ$	0.046***	0.048***	0.045***
	(5.73)	(6.00)	(6.40)
R_{t-1}		-3.683***	
		(-9.22)	
R_{t-2}			-0.367
			(-1.20)
Constant	-0.565	-0.825	-0.863
	(-0.56)	(-0.80)	(-0.86)
Observations	1347785	1347785	1347785
Adj R^2	0.031	0.037	0.032

4.5.3.2 Robustness: Do penny stocks matter?

Untabulated regression results also show that the pricing power of distress risk is not merely a tautology of penny stock effect. When penny stocks are removed from the dataset, that is, any firm-month observation that has a stock price below $1 is removed, the t-statistic of FP in the cross-sectional regression is ranging -3.46 and -3.53, a significant increase of t-statistics from the value range of -1.45 and -1.92 found in the previous sample where penny stocks were included. This strongly rejects the hypothesis that the penny stocks effect is a major contributor to the distress puzzle. In addition, the BA variable showed significant explanatory power in terms of explaining the pricing power of distress risk. When penny stocks are included, the results from the portfolio-level analysis and stock-level analysis are consistent. The coefficient sign of $IVOL$ also changes. In the analysis in Section 4.5.3, $IVOL$ is negatively related to stock returns, but in the new sample it is negatively related to stock returns, a result that is consistent with Ang et al. (2006). Thus, robustness analysis supports the hypothesis of the arbitrage limit playing a major role in explaining the distress risk anomaly, and it rejects the alternative explanation where penny stock effects drives most of the distress puzzle.

4.6 Default likelihood indicator, the distress puzzle and arbitrage limit effect

Default likelihood indicator (DLI) is another measure of distress risk, which Vassalou and Xing (2004), Campbell et al. (2008), Bharath and Shumway (2008) and Da and Gao (2010) has extensively discussed the estimation and implication in predicting distress event. Particularly, the distress puzzle in Vassalou and Xing (2004) is found as a significant return premium but the distress risk, proxied by DLI, is positively associated with stock returns under portfolio-level analysis in 1971-1999 period, a seemingly contradictory finding against Campbell et al. (2008) and several literatures.

To test if the arbitrage limit effect hypothesis also applies in the predicting power of DLI, the premium of distress risk should exist in the one-way sort portfolio. Table 14 reports the portfolio performance of ten DLI sorted portfolio, using the same forming method as Table 5. The univariate sort portfolio analysis depicts several aspects that deviate from FP portfolios. First, the relation between DLI and stock returns is still negative, which is not consistent with Vassalou and Xing (2004) or Da and Gao (2010). For equal-weight portfolio returns, the low distress risk portfolio earns 0.6% per month in average, and the premium maintains between 0.5% to 0.7% in the subsequent portfolios. The high distress risk portfolio breaks the stability, yielding only 0.09% per month equally-weighted. Adjusting portfolios with stock size relieves the poor performance of high distress risk portfolio, but the negative distress risk-return pattern still holds.

The second finding is regarding the distress premium. The distress risk premium measured as equally weighted excess return is at 0.548% per month or 1.390% per month as $FF - 3$ alpha, both are statistically significant at 1% level. However, value-weight portfolio performance is far less pronounced and is only 0.184% (excess return) and 0.555% ($FF - 3$ alpha) respectively. The drastic reduction of distress risk premium from equal-weight to value-weight shows that firm's size is associated with the DLI-driven premium, but unlike Campbell et al. (2008) that value-weight distress premium is still significant, the premium from DLI sorted portfolio does not pass the 5% significant threshold.

Though DLI presents a different picture as FP, they still have some commonalities: The $FF - 3$ alpha is higher than its raw excess return, regardless whether portfolio performance is equally weighted or value weighted. Dissecting the factor loading of the distress premium, the average DLI is positively associated with market risk factor loadings, and negatively associated with size factor loadings. The relation between DLI and HML factor loading is hump-shaped, but the difference between high and low DLI is statistically significant. The premium has an exceptionally high loading of size factor (-0.790, t=-12.85), suggesting that the distress premium is closely related to size effect, and value-weight performance measures are able to subsume its premium scale. In short, the factor loading analysis confirms that both FP and DLI can result in a higher risk-adjusted performance than its raw return, but size effect has higher impact on the premium that driven by DLI.

Table 14 Return of Distance-to-Default-sort decile portfolios (1981.1-2014.12)

At the beginning of every January from 1981 to 2014, all qualified stocks (nonfinancial firms, with valid DD, ME, BM, MOM12 and are traded on NYSE/AMEX/Nasdaq as common shares at the forming date) are independently grouped by default likelihood indicator (DLI) from low to high. This generates 10 portfolios divided at every 10% of the spectrum of DLI. Portfolios are rebalanced every year. Both Equal-weighted (EW) and Value-weighted (VW) monthly average returns in excess of 1-month T-bill rate (Excess Return) and alphas from Fama-French 3-factor model (FF-3 Alpha) for all 10 decile portfolios and long-short portfolios holding the low distress risk portfolio and short selling the high distress risk portfolio are shown. The FF-3 factor loadings of EW FF-3 alpha are reported in panel B. The t-statistics as adjusted by Newey-West standard error are reported below each row of return in parentheses.

Portfolios	1 Low DLI	2	3	4	5	6	7	8	9	10 High DLI	1-10 Low-High
Panel A. Portfolio Performance											
EW Excess Return	0.640	0.518	0.847	0.535	0.728	0.726	0.635	0.534	0.656	0.092	0.548
	(3.22)	(1.85)	(3.36)	(2.08)	(2.78)	(2.77)	(2.23)	(1.50)	(1.76)	(0.21)	(2.81)
EW FF-3 Alpha	0.192	-0.175	0.192	-0.155	0.026	-0.063	-0.220	-0.529	-0.484	-1.198	1.390
	(3.15)	(-1.37)	(1.76)	(-1.52)	(0.25)	(-0.56)	(-1.59)	(-2.82)	(-2.08)	(-4.15)	(3.95)
VW Excess Return	0.507	0.551	0.560	0.354	0.306	0.397	0.320	0.302	0.390	0.323	0.184
	(1.83)	(1.79)	(1.96)	(1.24)	(1.07)	(1.33)	(0.98)	(0.87)	(1.02)	(0.69)	(0.77)
VW FF-3 Alpha	0.365	0.149	0.210	0.090	-0.015	0.051	-0.080	-0.121	-0.045	-0.190	0.555
	(1.99)	(1.52)	(2.53)	(1.03)	(-0.16)	(0.54)	(-0.57)	(-0.76)	(-0.20)	(-0.57)	(1.93)
Panel B. Fama-French 3-factor loading											
MKT	0.852	0.908	0.944	1.001	1.046	1.057	1.106	1.123	1.095	1.155	-0.303
	(19.87)	(42.02)	(49.93)	(49.73)	(48.06)	(43.96)	(33.71)	(30.40)	(20.72)	(14.90)	(-3.14)
SMB	0.510	0.605	0.611	0.776	0.787	0.868	0.961	1.082	1.163	1.300	-0.790
	(8.19)	(20.13)	(23.18)	(26.29)	(24.90)	(24.86)	(20.17)	(20.18)	(15.16)	(11.54)	(-12.85)
HML	0.150	0.131	0.114	0.120	0.219	0.243	0.277	0.270	0.325	0.395	-0.245
	(2.28)	(4.13)	(4.05)	(3.87)	(6.59)	(6.61)	(5.52)	(4.79)	(4.02)	(3.33)	(-1.87)

Since the premium relating to DLI depicts a pattern different from FP, this subsection tests only the predicting power of DLI in the firm-level analysis, which is, in line with Da and Gao (2010) who use cross-sectional regression to explain the distress puzzle. Given that the DLI premium is higher in equal-weight portfolio, the predicting power of DLI should be significant. The cross-sectional regression is conducted, similar to equation (4.6) and (4.8), as follows:

$$R_{i,t} - r_{f,t} = \lambda_0 + \lambda_1 DLI + \lambda_2 Arbitrage\ Limit_{i,t-1} + \boldsymbol{\lambda_3}'\boldsymbol{X_{i,t-1}} + \varepsilon_{i,t} \quad (4.10)$$

$$R_{i,t} - r_{f,t} = \lambda_0 + \lambda_1 DLI + Arbitrage\ Limit_{i,t-1} + \lambda_3 Interaction_{i,t-1} + \boldsymbol{\lambda_4}'\boldsymbol{X_{i,t-1}} + \varepsilon_{i,t} \quad (4.11)$$

Where

$$\boldsymbol{X_{i,t-1}} = \begin{bmatrix} lnME_{i,t-1} & lnBM_{i,t-1} & MOM12_{i,t-1} \end{bmatrix}$$

In line with section 4.4, the proxy of $Arbitrage\ Limit$ is stock monthly BA, DV, $ILLIQ$,and $IVOL$ respectively. The equation (4.10) is to test if the predicting power of DLI is diluted by arbitrage limit effect, and (4.11) tests if the predicting power of DLI is statistically different between stocks with low and high arbitrage limit effect. Since regression analysis in section 4.5 has found that the predicting power of distress risk is associated with $\boldsymbol{X_{i,t-1}}$, the regressions without control variables are omitted. The empirical results are disclosed in Table 15.

The total observation is less than the sample in section 4.4. Due to the estimation of DLI requires at least one-month period consecutive daily returns and strictly requires financial ratios from Annual Compustat Fundamental files, according to Vassalou and Xing (2004), the sample volume is reduced by approximately half a million observations in the same period. However, the reduction does not systematically affect the analysis. The coefficient of three control variables, $lnME$, $lnBM$, $MOM12$, is maintained in terms of coefficient scale and significant level, showing their consistency with earlier literature and analyses in earlier sections.

The relation between DLI and arbitrage limit effect is different from Campbell et al. (2008) failure probability. Unlike FP that its predicting power is almost unrelated with arbitrage limit proxies, the predicting power of DLI is influenced by these effects directly. When BA is proxied as arbitrage limit effect, the coefficient of $\hat{\lambda}_1$is reduced statically and economically from -0.843 (t=-2.02) to -0.190 (t=-0.38). Considering its interaction effect, the predicting power of distress risk is eventually positively priced in the cross-sectional stock returns ($\hat{\lambda}_1$=0.384, t=0.99). The reduction also emerges in panel B (DV as proxy), panel C ($ILLIQ$ as proxy) and panel D ($IVOL$ as proxy), though the coefficient of DLI remains significant where DV and $ILLIQ$ enters into analyses. Overall, the regression analysis finds that the predicting power of DLI is consistent with Hypothesis 3 that liquidity condition matters the distress puzzle.

The deviation is, based on Hackbarth et al. (2015) as well as Da and Gao (2010), has several possible explanations. The first possible explanation is the change of bankruptcy legal environment in the post-1980 period, resulting that the relation distress risk and equity return is reverted from positive to negative. This explanation is consistent with the portfolio analysis in the univariate sort by DLI, and presents a resolution of our inconsistent findings relating to Vassalou and Xing (2004). However, further analysis including a breakpoint analysis is required before documenting the change of legal environment is responsible to the empirical findings in this section, which is pending further investigation.

The second possible explanation is that the change of short-term liquidity condition, especially turn-of-the-month effect has attributed to the distress puzzle. Thus, the predicting power of DLI is reduced. This is supported with regression analysis reported in Da and Gao (2010), who find DLI loses its significance when short-term liquidity condition enters into regression. In such case, one needs to discuss that if FP contains additional information that DLI does not reflect. Since the distress premium associated with DLI are not significant as shown in Table 14, this explanation is just numerated and left for further discussion once new evidence of DLI is available.

Table 15 Fama-MacBeth regressions with an interaction term between DD and arbitrage limit effects

For each month from January 1981 to December 2014, Fama-MacBeth (1973) cross-sectional regressions of monthly excess returns (CRSP monthly return over one-month T-bill rate) are run on a set of independent variables. Distress Risk is measured as firm's distance-to-default (DLI). The calculation of IVOL, lnBM, lnME as well as MOM12 is in section 4.3.2 and the calculation of interaction variable is in section 4.5.2. The t-statistics, adjusted by the Newey-West standard error, are in parentheses. Panel A reports basic regressions and Panel B reports regressions with control variables. *denotes p<0.10, ** denotes p<0.05 and *** denotes p<0.01

Constant	DLI	Arbitrage Limit	Interaction	lnBM	lnME	MOM12	Observations	Avg.R2
Panel A. BA as Proxy								
3.526***	-0.843**			0.466***	-0.038	0.545**	945952	0.026
(3.60)	(-2.02)			(4.24)	(-0.88)	(2.20)		
1.078		6.804		0.397***	0.055	0.682**	945952	0.027
(1.12)		(1.35)		(3.92)	(0.98)	(2.58)		
3.408***	-0.190	8.306		0.404***	0.049	0.683**	945952	0.029
(3.50)	(-0.38)	(1.54)		(3.94)	(0.89)	(2.55)		
1.030	0.384	0.096	-0.320	0.409***	0.013	0.701**	945952	0.033
(0.91)	(0.90)	(0.99)	(-1.23)	(3.93)	(0.26)	(2.60)		
Panel B. DV as Proxy								
3.521*	-0.843**			0.468***	-0.040	0.551**	935940	0.025
(3.52)	(-2.01)			(4.24)	(-0.88)	(2.24)		

(Continue)

(Continued.)

1.120		-0.016		0.458***	-0.023	0.542**	935940	0.025
(1.36)		(-1.58)		(4.34)	(-0.46)	(2.17)		
1.347*	-0.832**	-0.050		0.469***	-0.040	0.536**	935940	0.027
(1.69)	(-2.01)	(-1.03)		(4.31)	(-0.81)	(2.17)		
1.044	-0.607*	-0.022	-1.018**	0.465***	0.002	0.559**	935940	0.033
(1.24)	(-1.68)	(-1.28)	(-2.52)	(4.27)	(0.030)	(2.32)		
Panel C. ILLIQ as Proxy								
3.526***	-0.847**			0.479***	-0.044	0.541**	945952	0.026
(3.60)	(-2.03)			(4.32)	(-1.01)	(2.21)		
1.748*		0.102		0.466***	-0.043	0.550**	945952	0.027
(1.95)		(1.43)		(4.32)	(-0.75)	(2.31)		
3.710***	-0.648**	0.128*		0.475***	-0.053	0.545**	945952	0.029
(3.37)	(-2.19)	(1.81)		(4.28)	(-0.92)	(2.26)		
3.434***	-0.782	0.070	-0.706	0.478***	-0.095	0.546**	945952	0.031
(3.33)	(-1.27)	(0.41)	(-1.57)	(4.23)	(-1.30)	(2.28)		

(Continue)

(Continued.)

Panel D. IVOL as Proxy

3.340**	-0.843**			0.468***	-0.036	0.545**	938967	0.025
(2.82)	(-2.02)			(4.24)	(-0.89)	(2.19)		
2.794***		-13.413***		0.388***	-0.115**	0.484**	938967	0.030
(4.03)		(-4.64)		(4.08)	(-2.78)	(2.06)		
2.862***	-0.387	-12.924***		0.394***	-0.121***	0.475**	938967	0.031
(4.13)	(-1.02)	(-4.76)		(4.04)	(-2.90)	(1.99)		
2.942***	-0.464	-0.250**	-0.843**	0.389***	-0.127***	0.478**	938967	0.034
(4.27)	(-0.36)	(-2.57)	(-2.43)	(3.98)	(-3.02)	(2.01)		

4.7 Conclusions

A number of rational asset pricing theories have tried to explain the distress puzzle, that is, the question of why distress risk is negatively priced in terms of expected returns, and why investors have left such arbitrage opportunities for decades. Complex models that include firm characteristics such as the cost of financial distress, return skewness, or shareholders' bargaining power has explained where the predicting power of distress risk comes from, but none have explained the two questions above in full. Fama and French (2008) document that if the return premium of an anomaly is concentrated in the short-side of a zero-cost portfolio, the premium is unlikely to achieve rather as a realistic return due to the arbitrage costs and the difficulty of short-selling stocks. That is, mispricing in high-distress risk stocksexists, but such mistakes in prices do not imply easy profits. Investors may observe arbitrage opportunities, but they may have difficulty in seeking counterparties for trading, be unable to borrow stocks for short selling, or be unable or unwilling to bear the risk that their portfolios become less diversified.

As equipped by the arbitrage limit theory, this study presents original results that show how the theory could explain the distress puzzle. Indeed, distress risk can predict expected returns, as the risk contains pricing information that is related to systematic risk as documented by Dichev (1998), Fama and French (1996), and Kapadia (2011). However, the premium that arises as a result of hedging distress risk is associated with various constraints. Distressed stocks are generally small, and frequently display high bid-ask spreads and low trading volumes that add costs to be traded in the market. The pervasive illiquidity condition among high distress risk stocks further blocks arbitrage activities, as there are fewer investors and market makers participating in those stocks. D'Avolio (2002) finds that less than 1% of stocks have loan fees larger than 1% per annum. Those stocks are tiny in size, with a low price per stock and less liquidity; these are also characteristics of high distress risk stocks. In this research, a number of variables are investigated to show that market arbitrage limit levels significantly explain the distress puzzle, providing evidence that supports the arbitrage limit theory.

Indeed, in line with earlier research on the limit of arbitrage that stocks are seemingly mispriced when arbitrage limit is high, the distress premium primarily results from high distress risk stocks that are being underpriced in relation to other stocks with similar distress risk but easy to arbitrage. Garlappi and Yan (2011) argue that high distress stocks have a strong negative momentum effect during their final life stage, showing that high distress risk stocks have influenced by negative momentum. However, the recovery of equity returns from bankrupted firms is a violation of the US bankruptcy "Absolute Priority Rule" (Hackbarth et al. 2015), which ensures that institutional equity holders will have strong bargaining powers against debt holders and can, therefore, expect to claim more value for their investments if more of the firm's stock is held by the institution. This chapter presents empirical findings that extend the Garlappi and Yan (2011) conclusion that among firms with low cost for conducting transactions and holdings, the distress risk puzzle is explainable by Fama-French 3-factor models.

The limitations of this research are several. In particular, this paper investigates only one type of distress risk, and thus the conclusion remains to be tested on other distress risk measures such as Distance-to-Default (Vassalou and Xing, 2004) and O-score (Avramov et al. 2013). Further research could start from the position of using alternative distress risk measures to test the arbitrage limit theory.

5 PROFITABILITY, INSIDER OWNERSHIP, AND CROSS-SECTIONAL STOCK RETURNS

5.1 Introduction

The latest documented anomaly, firm profitability, can explain a series of asset pricing anomalies at the cross-section level (Novy-Marx, 2013; Fama and French, 2015; Fama and French, 2016), but has a return premium that cannot be explained by rational assets pricing models such as the Fama-French 3-Factor Model or CAPM. As profitability is directly linked to firm performance and earnings, high profitability firms should outperform unprofitable firms, as noted by Novy-Marx (2013) and Ball et al. (2015). However, the current research suggests that the profitability premium is not a risk factor that affects all firms in the market; hence, it cannot systematically determine the expected cross-sectional stock return. A firm's profitability is also influenced by its structure of insider ownership, leading to the return of profitability premium varying across a range of levels of insider ownership. This paper, therefore, explores the link between firm's insider ownership and profitability anomalies, offering novel empirical evidence about the asset pricing implications of firm's corporate governance.

According to financial theory, assets that have riskier payoffs should earn higher returns, on average, to compensate investors for bearing the increased risk (Schwert, 2003). Not all risk affects the payoffs in such a way, however. When markets are perfect and frictionless, investors require compensation for bearing systematic risks that cannot be diversified away, and thus the profitability premium is a type of anomaly that violates economic theory. As it seems to create a market-wide return pattern that rewards from bearing less systematic risk. Ball et al. (2015) find long-short top/bottom 10% operating profitability stocks earn 0.35% per month in excess of the one-month T-bill rate, with a significant negative systematic risk factor loading that is positive for market risk. Novy-Marx (2013) finds that using a similar portfolio formation method for the top/bottom 10% gross profitability firms generates a 0.29% per month excess return. These findings suggest that the premium from profitability trading strategies is not the result of bearing high levels of market risk.

A review of the literature offers a plausible explanation for the profitability anomaly by taking firm's agency cost into account: a good governance is associated with firm's subsequent high profitability. According to Cremers and Nair (2005), good governance mechanism reduces the agency cost by guiding manager's decision making with internal control: allowing them to hold firm's stock so that they can behave on behalf of shareholders, and external control as well: large institutions can access firm's decision making by playing the role of blockholders. Hence, firms with high insider holding levels, which are a documented sign of high levels of corporate governance, could outperform those with low insider holdings. It is well-documented in the corporate finance area that firm's profitability can be predictably determined by its corporate governance structure. Gompers et al. (2013) and Bebchuk et al. (2009) find that good (poor) governance is related to high (low) subsequent stock return and they observe an averaged value-weighted return of 0.71% to 1.16% per month from holding the top 10% good governance stocks and short selling the bottom

10% poor governance stocks. In terms of the pricing power of insider holdings, Zack (2011) find that trades made by insiders, in general, beat the market by 0.35% per month in the 1978 to 2005 period. Also, a long-short portfolio constructed by holding stocks that insiders buy and selling stocks that insiders sell generate a 1.48% monthly return. Cremer and Ferrell (2014) believe that the relationship between corporate governance and profitability became stable only after 1985 due to a series of exogenous structure changes in the U.S. legal system to protect shareholder's rights. Harford et al. (2008) also confirm the profitability-governance relationship by testing it with different proxies of profitability and governance indices. Their findings are in line with Shleifer and Vishny (1997), who note that institutional shareholders and high ownership concentrations reduce a firm's agency costs, leading to better firm performance.

Empirical research on corporate governance investigates the mechanisms that reduce the agency costs between a firm's shareholders and managers. According to the theoretical models proposed by Jensen (1986) and Stulz (1990), agency costs are the free cash flows that managers are able to access and use to fund projects and acquisitions that come with costs to shareholders. One of the predicted conclusions is that agency costs will eventually reduce the welfare of shareholders if corporate governance is absent. Laws and contracts between shareholders and managers are the most common corporate governance arrangements to reduce agency costs. However, the influential survey by Shleifer and Vishny (1997) produced the argument that large investors represent another channel of control rights within the firm and can, therefore, act as a defence in addition to legal protection for shareholders. The large shareholders, generally institutional shareholders, takeover activists or defenders, and large creditors concentrate voting rights and free cash flows that were originally allocated to individuals. Thus, agency costs are reduced where large investors exist. Depending on the ways that managers are monitored, Cremers and Nair (2005) categorise corporate governance into internal governance and external governance. Internal governance reflects how shareholders are active in a firm's decision and external governance mechanisms and reflect how the market is related to a firm's corporate governance mechanisms. This categorization further advances relevant research methods by considering sophisticated governance mechanisms in empirical analyses. Thus, this research offers conjectures on two existing topics: stock return-profitability relationships and profitability-corporate governance relationships.

Taking work by Cremers and Nair (2005) and Lilienfed-Toal and Ruenzi (2014) into account, this research adopts several insider ownership proxies to test whether the profitability premium is associated with: CEO ownership and top five executive managers' ownership represent internal insiders, as they have access to a firm's cash flow distribution decisions, and are supposed to be positively incentivised by the governance structure. Institutions also treat certain non-employees as insiders, especially those who own large shares of the firm and can be called "blockholders". They also have access to a firm's investment and free-cashflow distribution decisions. Institutional ownership and institutional ownership concentration are used as proxies for external insiders. In this chapter, the current research's findings are discussed in order to demonstrate that a firm's insider holding information, in terms of CEO holdings, the top five executive managers' holdings, institutional holdings, or institutional ownership concentration, can explain the firm's gross profitability anomaly, proposed by Novy-Marx (2013), and the operating profitability anomaly suggested by Ball et al. (2015).

The findings are summarised as follows: Firstly, the main conclusions from Novy-Marx (2013) and Ball et al. (2015) are replicated by using the methodology within their research, and then these findings are extended over a longer period of data. Thus, the gross profitability anomaly is found to generate a 0.351% monthly excess return and the operating profitability anomaly generates a 0.376% monthly excess return. Both of these are value weighted and statistically significant at the 10% level. In the 1963 to 2015 sample, returns from a long/short portfolio of the top/bottom deciles of profitability stocks earn 0.388% (operating profitability) and 0.378% (gross profitability), both statistically significant. This provides supportive evidence for the existence of profitability anomaly in the sample.

As the availability of information on insider ownership is limited to S&P 1500 listed firms, cross-sectional regression at firm level may not fully reflect the interaction of profitability and insider ownership, especially since the available observations are mostly from large companies. One challenge faced by this research is finding a suitable governance index with sufficiently large numbers of observations. Typically, research on corporate governance uses relatively small data sets. For example, Core et al. (1999) test the relationship between manager compensation and firm performance using a three-year sample of 495 firm-year observations, while Gompers et al. (2003) examine the relationship between governance and stock returns using a 10-year sample of 3,241 firm-year observations. Similarly, the number of firm-year observations in Harford et al. (2008) research is 11,645, and Novy-Marx (2013) examined profitability and stock returns using 210,000 firm-year observations in the 1963 to 2010 period. Additionally, if a candidate agency cost indicator does not represent a reliable proxy market-wide, then the analysis results are not reliable.

To address potential biases, all stocks are independently sorted by their profitability and insider holdings; the data is then examined to determine whether the profitability anomaly is concentrated where insider holding tends to be highest. The results support the hypothesis that the profitability premium from long-short portfolio on firm's profitability is positively associated with firm's average insider ownership. Thus returns from the profitability anomaly are more pronounced within high insider holding firms. This finding is robust by taking different measures of insider ownership to explain the anomaly associated with firm's gross profitability and operating profitability.

Then, the relationship between profitability anomalies and insider holdings is examined at firm-level by Fama-MacBeth regression to test whether the predicting power of GPTA/OPTA is distinguished with insider ownership. The results show that returns from two profitability trading strategies cluster where the proxies of insider holding, institutional ownership and ownership concentration, are higher than the market average level. This suggests that the abnormal return is associated with firms where more stocks are held by insiders than other types of stock holders. However, this interaction may result from compensatory factors arising from other common risk factors such as book-to-market ratio, size, and momentum.

This chapter, although its research objects are firm's profitability and insider ownership, is differs from previous research especially Core et al. (1999) and Harford et al. (2008) in several ways. First, this chapter is seeking explanation of an abnormal stock return pattern that is believed to associated with firm's gross profitability and operating profitability. Therefore, this research does not cover other profitability measures such as net income to total assets, sales growth, and return on equity because they are not identified as an anomaly. Second, our research is cross-sectional analysis, and explanatory variables are lagged information with at least one-month gap in order to predict stock returns. The model setting means the issue of endogeneity, especially the endogeneity related with time-series analysis does not plays a critical issue in the research. Third, this ultimate goal of research is understanding stock return predictability but not finding the mechanism of firm's profitability.

This chapter also differs from previous research that investigate anomalies with various corporate governance indicators. The relationship between firm's profitability, insider ownership is investigated at the cross-sectional level, which differs from the testing of abnormal returns caused by earnings announcement related to corporate governance such as changes of managers, changes in blockholders, or changes in accounting standards within an event window (see La Porta et al. 1997), or explaining analysts' forecast errors about firm's profitability (Giroud and Mueller, 2011). Additionally, though Gompers et al. (2003) and Bebchuk et al. (2009) find that corporate governance generates a premium on returns at the cross-sectional level and they provide no explanation for these findings. This chapter seeks to fill this blank by discovering the relationship between governance and other common risk factors identified by Fama and French (1993, 1996).

5.2 Further Motivations and Hypothesis Development

Novy-Marx (2013) explains that the premium from high profitability firms outperform low profitability firms based on the dividend discount model, following the hypothesis by Fama and French (2008) that all anomalies should offer "at least rough proxies for expected cash flows" (p.1675). The dividend discount model is defined as; stock price equals the present value of its cumulative expected dividends over time. Harford et al. (2008) find that shareholder rights are positively related to industry-adjusted profitability. This implies that the equation holds if corporate governance is related to profitability, as in Novy-Marx (2013), who assumes that gross profitability is a proxy for expected dividends. In light of this, the relation between firm's profitability and corporate governance can be generalised as follow.

Denote *M* as firm's market value of equity, the relationship between earning, book equity is expressed as:

$$M_t = \sum_{\tau=0}^{\infty} \frac{\mathrm{E_t}[\mathrm{Y}_{t+\tau} - \mathrm{dB}_{t+\tau}]}{(1+r)^{\tau}} \quad (5.1)$$

Where $\mathrm{Y_t}$ is the time-t earnings, $\mathrm{dB_t} \equiv \mathrm{B_t} + \mathrm{B_{t-1}}$ is the change in book equity, which results from the earning being retained in the firm, and r is the required rate of return on expected dividends. Assuming $\mathrm{M_t}$, $\mathrm{Y_t}$, $\mathrm{dB_t}$ and $\mathrm{r_t}$ are exogenous, holding all else equal, higher valuations imply lower expected returns. That is, value firms should outperform growth firms, and profitable firms should outperform unprofitable firms. Those properties can be viewed when the function is re-written as stock return on the left-hand side of the equation:

$$r = exp\left(\frac{\mathbf{E}_\mathrm{t}[\mathrm{Y_{t+\tau}} - \mathrm{dB_{t+\tau}}]}{M_t}\right) - 1 \text{ (5.2)}$$

Harford et al. (2008) find shareholder rights are positively related to Industry-adjusted profitability. This finding implies the equation 5.2 holds with a positive sign on its first-order condition.

$$\mathbf{E}_\mathrm{t}[\mathrm{Y_{t+\tau}} - \mathrm{dB_{t+\tau}}] = f(Governance, \mu_{it}) \text{ (5.3)}$$

The function holds if corporate governance is truly related with profitability, which Novy-Marx (2013) assume the gross profitability proxies expected dividends. Since this chapter is using $Governance_t$ to predict profitability on $t+1$, the model is less affected by endogeneity problem related with expected profitability.

Empirically, the relationship between corporate governance and stock returns is viewed and tested under the framework of firm performance research. Starting with Gompers and Metrick (2001), who argue that increasing institutional ownership from 1980 resulted from a demand for particular firm characteristics. Past institutional ownership can be seen to be positively related to stock returns. Gompers et al. (2003) tested the relationship in more detail, using the G-Index, a rating of high shareholder rights, as a proxy of governance. They found that corporate governance is positively predictive of future stock return, and they attribute this finding to the significant marginal relationship, whereby weak governance causes poor firm performance, and hence, poor stock return. Core et al. (1999) find that CEO compensation as a cost of the agency could explain annual buy-and-hold stock returns. Their findings are further supported by Lilienfeld-Toal and Ruenzi (2014), who find CEO ownership to be related to stock market performance, and who attribute pricing power to the incentives of insiders in a firm's governance mechanism.

Hypothesis 1: *Firms with high profitability have high levels of insider ownership.*

Gompers et al. (2003) note that Democracy Portfolios, which are composed of high corporate governance firms with G-indices less than 5, have higher net profit margins, return on equity, and sales growth that Dictator Portfolios, which contain firms with G-Index over 14. Harford et al. (2008) find firm's G-Index also positively links to high return-on-assets. The profitability-corporate governance relationship is predicted to be stable and to hold when proxies are replaced by other candidate variables.

Hypothesis 2: *Returns from high profitability firms are driven by those firms with high levels of insider ownership, controlling for variations from other factors.*

If firm's agency costs are negatively associated with firm's expected profitability, then the pricing power firm's profitability should perform differently in high and low insider ownership firms. Firms' profitability and dividends are significantly related to corporate governance, as empirically shown in GIM (2003) and Harford et al. (2008). The hypothesis implies that the interaction of insider ownerhsip and profitability should reduce predictive power and its significance in the cross-sectional test.

5.3 Data and Research Methods

All monthly stock returns and firm's S&P industry classifications are obtained from CRSP, with annual accounting data from the Compustat Annual File to build the dataset for research. Accounting information is lagged six months from the fiscal year-end month. The combined dataset includes all firms traded on the NYSE, Amex, and NASDAQ, and excludes securities other than ordinary common shares. Delisting returns are taken from CRSP where available. If a delisting return is missing, but it is recognised as a performance-related delisting event in CRSP (CRSP Delisting code 400, 550-585), a return of -30% is used. Any observation containing missing market values of equity, missing book-to-market ratio, missing profitability (gross profitability or operating profitability), the missing book value of total assets in the current month's return, or missing returns from the prior one-year period is removed from the dataset. Financial firms (SIC code 6000-6999) are also excluded. The final dataset contains firm-month observations that meet the above criteria from June 1980 to December 2015, including 1,501,724 firm-month observations across 426 months. Profitability breakpoints for constructing ten decile portfolios are based on all NYSE samples of ordinary shares with valid stock prices, MEs, and profitability measures. Following the convention of asset pricing studies, this chapter uses firm's size, book-to-market equity ratio and past 12-month returns as common pricing factors that determining stock returns, and the calculation is consistent with Chapter 4.3.

5.3.1 Firm's profitability

Gross Profitability ($GPTA$): Gross profitability is defined in line with Novy-Marx (2013) as total revenue (Compustat Annual item: $REVT$) minus cost of goods sold (Compustat Annual item: $COGS$), then divided by total assets (Compustat Annual item: AT). The measure is assuming a total of six months later of the firm's fiscal year-end month to ensure accounting information is fully known to the market. That means, if a firm's fiscal year ends in December, the profitability shall be known in June. This setting also means that if a firm's fiscal year ends in January-June and the portfolio is constructed using end-of-June information, the profitability shall be used for constructing portfolios in the next year.

Operating Profitability ($OPTA$): Operating profitability is defined by Ball et al. (2015), as total revenue (Compustat Annual item: $REVT$) minus cost of goods sold (Compustat Annual item: $COGS$) and sales, general, and administrative expenses (Compustat Annual item: $XSGA$), plus research and development expenses (Compustat Annual item: XRD) if available, then divided by total assets (Compustat Annual item: AT). Similar to the measure of GPTA, the estimation requires six months lagged after firm's fiscal year-end month.

5.3.2 Insider Ownership Measures

Depending on the type that how managers are monitored, Cremers & Nair (2005) categorise corporate governance mechanism into internal governance and external governance. Internal governance reflects how shareholders are active in firm's decision and external governance reflects how market is related to firm's corporate governance mechanism. Nikolov and Whited (2014) discussed the ownership categorised as managerial ownership and external ownership such as institutions as blockholders. They find both channels have its independent power in the corporate governance mechanism. This categorisation further polishes relevant research methods by considering sophisticated governance mechanism in empirical analyses and is used in this chapter. The term "internal insider" reflects managerial ownership. Jensen (1986) argues that managers have information that shareholders are difficult to obtain, as insiders managers have incentive in fulfilling their own benefits. The term "external insider" reflects institution who holds a portion of firm and therefore, are able to influence the decision of firm strategies (Shleifer and Vishny, 1997). Because institutions, especially those who presents the board of direct as blockholders, are able to obtain firm's information from its role of insider, thus the impact of institutional ownership are named as external insiders.

This chapter recognises the categorification is intuitive and has some limitations. First, even if the relation between insider ownership and profitability premium exits, managerial ownership and institutional ownership may contribute to the relation independently, in which the categorification "insider ownership" may not suitable to distinguish the effect separately. Second, if the relation reflects how corporate governance alters firm's profitability, then other measures of corporate governance rather than insider ownership should, following the similar argument, affect profitability premium as well. To alleviate these concerns, this chapter discusses the empirical results carefully and lists all possible explanations for discussion and uses additional governance proxies in the section 5.6 as further investigation.

5.3.2.1 Internal insider ownership

CEO Ownership (CEO): Lilienfeld-Toal and Ruenzi (2014) find that high CEO ownership stocks generally outperform low CEO ownership stocks, and historical CEO ownership positively determines firm profitability as measured by ROE. In the online appendix, the authors provided a subsample using Compustat ExecuComp data that replicated their main findings and they confirm that the sample has similar characteristics in terms of the CEO ownership anomaly.

In this study, CEO ownership is defined by the executive who has the highest stock ownership at the end of the fiscal year. Stock ownership is defined as the shares held by executives (ExecuComp item $SHROWN$) minus restricted stocks (ExecuComp item $STOCK\_UNVESTED$) and options (ExecuComp item $OPTION\_NUM$) over the total common shares outstanding (Compustat Annual item $CSHO$). ExecuComp backfills ownership information by including ownership information one year prior to the firm being listed in S&P 1500, for the given fiscal year (ExecuComp item $YEAR$) This is converted into calendar years and two-year lagged CEO ownership is then used to value sort portfolios. Thus, if a firm reports CEO ownership in 2004, this value is then used to sort stocks in 2006. According to literatures, CEO should be positively related to the profitability premium.

Insider Ownership ($INSIDER$): To test corporate governance's explanatory power on the profitability anomaly, insider ownership is measured per Harford et al. (2008) and Kim and Lu (2011). Based on the percentage of common shares held by top five executive officers over the total common shares outstanding at the fiscal year end date (Compustat Execucomp item $Shrown\_excl\_opts\_pct$). The ranking of officers in a firm is ordered by the sum of salary and bonuses received in the fiscal year (Compustat Execucomp item $EXECRANKANN$). If $EXECRANKANN$ is missing and there are fewer than five executives recorded in the firm for a given fiscal year, their stocks are summerized. As $Insider$

uses information from annual reports, a six-month lag from the fiscal-year end month to the month that information is available to the public is assumed. According to the literature, $Insider$ should be positively related to the profitability premium as CEO.

5.3.3 External insider ownership

Institutional Ownership (IO): This is calculated as the total number of shares (in millions) held by institutions as reported on the Thomson Reuters 13-F file database, divided by the total number of shares outstanding on the CRSP monthly file (CRSP code $SHROUT$ times 1,000 in order to accommodate the unit of Thomson Database variable). Institutional holding data is from the actual 13F Forms filed to the SEC on a quarterly basis (calendar quarter ends) by institutional money managers, as per Asquith et al. (2005).

Stocks recorded in Thomson 13-F database are originally assigned with CUSIP-8, which this study converts to PERMNO using CRSP Tools. For each PERMNO, the total number of shares held by institutions is the sum of shares owned by all institutions at each quarter-end month. CRSP cumulative adjustment factors (CRSP code $CFASSHR$) are used to adjust the total number of shares outstanding at the month-end (Thomson code $FDATE$) to compensate for corporate events such as stock splits. IO is measured every quarter-end date, and the most recent IO value is matched to each firm-month observation. For observations with a short interest report month t, the changing lengths of calendar months mean that they may be matched with an IO of month t, month t − 1, or month t − 2. This research assumes IO should be positively related with profitability premium.

Institutional Ownership Concentration ($IO - HHI$): Grinstein and Michaely (2005) find that, alongside institutional holding, institutional ownership concentration is another governance proxy. When most institutional ownership is held by fewer institutions, firms are more likely to adopt anti-takeover decisions, reducing dividend payouts. Thus, institutional ownership concentration is negatively related to a firm's agency cost and implies a weak governance structure.

In line with this, the institutional concentration ratio used in this research is defined by the Herfindahl index of the top five institutions from Thomson Reuters 13-F files.

$$Institutional\ Concentration = \sum_{i=1}^{5} \left(\frac{Instutition\ Holding\ Stocks}{Total\ Institutional\ Holding\ Stocks}\right)^2 \quad (5.4)$$

5.3.4 Summary Statistics

Table 14 reports the average of cross-sectional correlations of all mentioned variables. All insider ownership measures have the same sign of correlation as displayed in the portfolio sorts. Both $GPTA$ and $OPTA$ are positively correlated with CEO, while $Insider$ and IO and are negatively correlated with $IO - HHI$. The correlation between CEO and $Insider$ is 0.833, which is most likely due to the fact that the CEO is virtually always the largest insider owner among a firm's top executives. The correlation between $GPTA$ and $GPTA$ is 0.564, suggesting that alongside their commonality of representing a firm's profitability, they also carry additional information that distinguishes them.

Table 16 Correlation matrix of firm's profitability, corporate governance and firm characteristics

The matrix below gives the time series averaged summary statistics and Spearman's rank correlation between the main variables. GPTA is the gross profitability of total assets following Novy-Marx (2013). OPTA is the operating profitability of total assets following Ball et al. (2015). ME is the market capitalisation in million US dollars. BE/ME is the book-to-market ratio following Davis and the Fama and French (2000) estimation. CEO is the percentage of shares held by the top executive over total common shares outstanding. INSIDER is the insider ownership percentage as the sum of common shares owned by the top 5 executive managers over total common shares outstanding. IO is the institutional ownership, which is the number of total shares held by institutions over total common shares outstanding. IO-HHI is the top 5 institutional ownership concentrations following the Herfindahl index. The dataset is composed based on all firm-month observations from June 1980 to December 2015, a total month of 426.

	GPTA	OPTA	ME	BEME	MOM12	CEO	INSIDER	IO	IO-HHI
Mean	0.411	0.113	2034.993	0.870	0.152	3.763	3.736	0.372	0.239
P1	-0.046	-0.608	3.271	0.033	-0.755	0.000	0.001	0.004	0.020
Median	0.369	0.136	197.620	0.604	0.049	0.593	0.307	0.359	0.156
P99	1.291	0.483	37815.840	4.906	2.532	38.109	41.675	0.877	0.940
SD	0.289	0.255	10011.370	1.460	0.678	8.387	8.722	0.365	0.225
SKEW	1.129	-8.068	14.026	13.174	4.538	5.154	4.723	1.742	1.661
	GPTA	**OPTA**	**ME**	**BEME**	**MOM12**	**CEO**	**INSIDER**	**IO**	**IO-HHI**
GPTA									
OPTA	0.564								
ME	0.020	0.140							
BEME	-0.212	-0.339	-0.123						
MOM12	0.136	0.201	0.140	-0.115					
CEO	0.096	0.018	-0.037	-0.012	0.046				
Insider	0.105	0.010	-0.038	-0.009	0.041	0.833			
IO	0.040	0.093	-0.092	-0.094	-0.030	0.291	0.293		
IO-HHI	-0.010	-0.206	-0.141	0.219	0.018	-0.138	-0.142	-0.328	

5.4 Insider Ownership and the Profitability Anomaly

5.4.1 Portfolio formation

The question of whether there is a difference of insider ownership across portfolios formed by firms with different level profitability is first examined.

To mimic the findings of Novy-Marx (2013) and Ball et al. (2015), monthly stock returns and firms' S&P industry classifications are obtained from CRSP, and the annual accounting data obtained from the Compustat Annual File. Accounting information is lagged by six months from the fiscal year-end month. The CRSP-Compustat combined dataset includes all firms traded on the NYSE, Amex and NASDAQ, and excludes securities other than ordinary common shares (CRSP assign common shares with a code 10 or 11). Delisting returns are taken from CRSP where available. Following Shumway and Warther (1999), if a delisting return is missing and it is recognised as performance related delisting in CRSP (CRSP Delisting code 400, 550-585), a return of -30% is used. Any observation containing a missing market value of equity, missing book-to-market ratio, missing profitability (gross profitability or operating profitability), the missing book value of total assets current month's return, or missing returns from the prior one-year period is removed from the dataset. Financial firms (SIC code 6000-6999) are also excluded.

The final dataset contains firm-month observations that qualify according to the above criteria during the period July 1980 to December 2015. The stocks are sorted in to ten portfolios based on the deciles of the profitability proxy at the beginning of July 1980 then rebalanced on the end of June the next year. Profitability breakpoints for constructing the decile portfolios are based on all NYSE samples of ordinary shares, with valid share prices, MEs, and profitability measures. Firm characteristics are reported as their time-averaged cross-sectional mean values in order to reveal the differences between portfolios at a given time.

Both the equal and value weighted portfolio monthly returns are reported. Novy-Marx (2013) and Ball et al. (2015) discovered that anomalous returns from the profitability hedging portfolio are made worse by the use of the FF-3 model, and thus the FF-3 adjusted return is also used. The excess risk-adjusted return, known as the Fama-French 3-factor alpha, $\alpha_{i,t}$, by regressing monthly stock excess return as equation (3.5). All variables apart from $R_{i,t}$ are taken from Kenneth French's website and estimated on a monthly basis.

5.4.2 The gross profitability anomaly and operating profitability anomaly

As this research uses a different sample period (1980.7 to 2015.12) than Novy-Marx (2013), who used samples from 1963.7 to 2010, or Ball et al. (2015), whose research was based on a 1963.7 to 2013.12 sample database, it is naturally important to verify whether a profitability anomaly is still observable in the sample period before performing more detailed analysis. Two well-covered pieces of research by Schwert (2003) and Mclean and Pontiff (2016) document that the predictive power of several anomalies or returns generated from anomaly-driving trading strategies has disappeared or weakened since they have been recognised and extensively examined by academia. Therefore, the association of a profitability anomaly to insider ownership may be driven by other unobserved factors that are not included in the sample period.

The results displayed in Table 15 confirm the existence of two profitability anomalies in the period 1980 to 2015. In Panel A of Table 15, returns from the high-low portfolio are seen to be 0.429% per month equal-weighted and higher for the value-weighted return at 0.767% per month. Both figures are statistically insignificant. The value-weighted return appearing higher than the equal-weighted return happens because small firms in the low or high gross profitability portfolios contribute to the return significantly, which implies a strong size effect affecting portfolio returns. Both high and low gross profitability portfolios record a lower return when value-weighted; in particular, the return from the low gross profitability firm drastically declines from 0.996% to 0.020% per month.

When returns are adjusted by the Fama-French three-factor (FF-3) model, the average monthly FF-3 alphas for the high-low portfolio are 0.421% and 1.184%, equal or value weighted terms respectively. The value-weighted FF-3 alpha is higher than the excess value-weighted return for the high-low portfolio by about 0.4% per month. This is in line with Novy-Marx's (2013) finding that the gross profitability anomaly cannot be explained by the FF-3 model, but is in fact made worse.

Panel B of Table 15 lists the portfolio returns of operating profitability sorted portfolios. Returns from the high-low portfolio are 0.265% (t=0.65) and 0.758%

(t=1.68) per month in excess of the one-month T-bill rate for equal and value weighted terms respectively. For the Fama-French 3-factor adjusted return, the monthly alphas for the portfolio are 0.4% and 1.358% per month, similar to the high-minus gross profitability portfolio, which indicates that the Fama-French 3-factor model cannot explain the anomalous return.

Thus, the two profitability anomalies exist when the returns are adjusted by the Fama-French 3-factor model. The raw excess return is marginally significant only when profitability is value-weighted. However, returns from the high profitability portfolio are generally significant and increase alongside profitability on average. Thus, some characteristics may also increase (or decrease) with the distribution of a portfolio's average firm profitability; in this context, insider ownership could characterise profitability anomalies.

Table 17 The profitability premium

The final dataset contains non-financial firm-month observations qualified by select criteria from June 1980 to December 2015. Stocks are sorted into ten portfolios based on deciles of profitability proxies at the beginning of July 1980 (for CEO and Insider variables, July 1994), then rebalanced on the end of June the following year. Panel A reports ten gross profitability (GPTA) sorted portfolio returns, and Panel B reports operating profitability (OPTA) sorted portfolio returns. EW Excess Return refers to equal-weight monthly average returns in excess of the one-month T-bill rate, and VW Excess Return refers to value-weight monthly average returns in excess of the one-month T-bill rate. EW FF-3 Alpha refers to equal-weight monthly Fama-French 3-factor model alpha, and VW FF-3 Alpha refers to value-weight monthly Fama-French 3-factor model alpha. The t-statistics, with Newey-West adjusted standard error, are reported in parentheses.

Panel A. GPTA Portfolio Statistics											
Portfolio	Low	2	3	4	5	6	7	8	9	High	High-Low
EW Excess Return	0.996	0.727	0.710	0.713	0.928	1.049	1.140	1.181	1.256	1.425	0.429
	(1.35)	(1.50)	(2.09)	(2.00)	(2.37)	(2.24)	(2.78)	(2.89)	(2.98)	(3.23)	(1.03)
VW Excess Return	0.020	0.924	0.408	0.414	0.518	0.609	0.874	0.507	0.624	0.786	0.767
	(0.03)	(2.53)	(1.31)	(1.36)	(1.53)	(1.97)	(2.53)	(1.25)	(1.69)	(2.52)	(1.84)
EW FF-3 Alpha	0.142	-0.426	-0.137	-0.267	-0.143	-0.116	0.114	0.202	0.327	0.563	0.421
	(0.33)	(-2.10)	(-0.73)	(-1.66)	(-0.84)	(-1.01)	(0.88)	(1.64)	(2.25)	(3.69)	(1.72)
VW FF-3 Alpha	-0.776	0.204	-0.424	-0.394	-0.347	-0.177	0.094	-0.154	0.177	0.408	1.184
	(-2.18)	(1.03)	(-2.34)	(-2.77)	(-2.38)	(-1.41)	(0.58)	(-0.98)	(1.26)	(3.85)	(3.19)

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Panel B. OPTA Portfolio Statistics

EW Excess Return	1.085	0.906	1.030	1.020	1.039	1.186	1.087	1.206	1.163	1.350	0.265
	(1.52)	(1.95)	(2.58)	(2.69)	(2.80)	(3.27)	(3.07)	(3.31)	(3.04)	(2.88)	(0.65)
VW Excess Return	-0.029	0.394	0.203	0.623	0.689	0.698	0.392	0.819	0.658	0.729	0.758
	(-0.04)	(0.84)	(0.50)	(1.59)	(1.96)	(2.06)	(1.28)	(2.45)	(2.14)	(1.97)	(1.68)
EW FF-3 Alpha	0.091	-0.140	-0.036	-0.063	-0.048	0.183	0.072	0.249	0.270	0.531	0.440
	(0.27)	(-0.80)	(-0.25)	(-0.46)	(-0.34)	(1.36)	(0.64)	(1.71)	(2.29)	(2.63)	(1.19)
VW FF-3 Alpha	-0.916	-0.624	-0.721	-0.456	-0.146	-0.085	-0.347	0.106	0.012	0.444	1.358
	(-2.17)	(-2.00)	(-4.03)	(-2.32)	(-0.97)	(-0.44)	(-2.15)	(0.75)	(0.10)	(3.64)	(3.98)

5.4.3 Firm characteristics of profitability sorted portfolios

Table 16 lays out the characteristics of the ten gross-profitability sorted portfolios. Panel A of Table 16 reports each portfolio's average gross profitability, size, and book-to-market ratio. This shows that the lowest gross profitability portfolio (portfolio 1) has small firms, with a mean size of US$277 million, while the highest gross profitability portfolio (portfolio 10) has large firms with an average size of US$1,473 million. In terms of book-to-market ratio, firms in the low gross profitability portfolio have a generally higher ratio than those in the high gross profitability portfolio, with averages of 0.794 and 0.623 respectively. It is notable that the fundamental factors, particularly firm size, are not associated with gross profitability in linear terms. The lowest gross profitability portfolio has an exceptionally low average firm size, but the size jumps by over four times to the second lowest gross profitability portfolio, which has an average firm size of US$1,147 million. The spread of average size and book-to-market ratio indicates that a long-short portfolio that retains portfolio 10 and short sells portfolio 1 will carry a significant larger risk premium, which is in line with one-way sort portfolio analysis in section 5.3.1.

Panel B of Table 16 reports on each firm's average internal and external insider ownership across all portfolios. Firms in the lowest profitability portfolio have low insider ownership and high institutional ownership concentrations, while firms in the highest profitability portfolio have high insider ownership and low institutional ownership concentrations. For the low profitability portfolio, the average CEO, $Insider$, IO, and $IO - HHI$ are 3.837%, 3.020%, 20.9%, and 36.9% respectively. For the highest profitability portfolio, those indicators are 5.285%, 5.008%, 37.9%, and 24.9% on average, respectively. Since the low and high gross profitability firms also depicts a variation of insider ownership, the variation of insider ownership may help to explain the profitability premium.

Panel C of Table 16 lists other firm characteristics that are frequently discussed in the related literature. The lowest profitability portfolio has higher levels of cash holding, higher R&D expenditure, and fewer total assets than the high profitability firms. In terms of leverage and capital expenditure, there seems to be no significant difference between low and high profitability portfolios.

Table 17 reports on the characteristics of the ten $OPTA$ sorted portfolios in a similar manner to Table 16. The spread of average firm size and book-to-market ratio exists and is higher than the spread in Panel A of Table 16. The average firm size in portfolio 1 is $154 million, while in portfolio 10 it is $3,674 million. The average book-to-market ratio is 0.832 and 0.419 for portfolios 1 and 10, respectively. The variation of average ME as well as $BEME$ among low and high $OPTA$ decile portfolio indicates that a long-short portfolio that retains portfolio 10 and short sells portfolio 1 will carry a significant larger risk premium associated with size and value effect.

Panel B of Table 16 lists firms' common internal and external insider ownership across portfolios. Similar to the findings about gross-profitability decile portfolios, the average difference in insider ownership between high and low operating profitability portfolios is significant (4.375%, 4.283% and 19.3% for

CEO, $Insider$, and IO in a low operating profitability portfolio, and 4.845% 4.546%, and 45.5% correspondingly in a high operating profitability portfolio). Also, the average difference made by institutional ownership concentration is positive (0.369 versus 0.249). These results suggest the co-existence of the variation of firm's operating profitability and firm's insider ownership, which could be used to further examine the operating profitability premium.

For other firm characteristics that are reported in Panel C of Table 16, there is a spread of firm's average leverage, R&D expenditure, and total assets among low and high operating profitability portfolios, but no distinction between firms' average capital expenditure and cash holdings.

Table 18 Characteristics of ten portfolios sorted by gross profitability

The final dataset contains non-financial firm-month observations qualified by select criteria from June 1980 to December 2015. Stocks are sorted into ten portfolios based on deciles of profitability proxies at the beginning of July 1980 (for CEO and Insider variables, July 1994), then rebalanced on the end of June the following year. Profitability breakpoints for constructing decile portfolios are based on an all-NYSE sample of ordinary shares, with valid stock prices, MEs and profitability measures. GPTA is the gross profitability of total assets following Novy-Marx (2013). ME is the market capitalisation in million US dollars. BE/ME is the book-to-market ratio following Davis and the Fama and French (2000) estimation. CEO is the percentage of shares held by the top executive over total common shares outstanding. INSIDER is the insider ownership percentage as the sum of common shares held by the top 5 executive managers over total common shares outstanding. IO is the institutional ownership, which is the total shares held by institutions over total common shares outstanding. IO-HHI is the top 5 institutional ownership concentrations, following the Herfindahl index.

Portfolio	1 (Low Profitability)	2	3	4	5	6	7	8	9	10 (High Profitability)
Panel A. Portfolio Characteristics										
GPTA	0.050	0.121	0.151	0.184	0.227	0.274	0.327	0.392	0.489	0.774
ME	277	1147	1398	1577	1720	1631	1679	1902	1772	1473
BE/ME	0.794	0.997	0.983	0.986	0.879	0.885	0.523	0.767	0.706	0.623
Panel B. Insider Ownership										
INSIDER	3.837	3.231	2.742	3.169	3.270	3.263	2.868	3.367	3.797	5.285
CEO	3.020	2.995	2.479	2.437	2.785	3.095	2.519	3.264	3.586	5.008

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IO	0.209	0.291	0.344	0.380	0.397	0.400	0.401	0.401	0.399	0.379
IO-HHI	0.369	0.332	0.288	0.254	0.242	0.243	0.236	0.237	0.234	0.249
Panel C. Firm Characteristics										
Debt/Assets	0.163	0.248	0.282	0.300	0.282	0.259	0.234	0.208	0.184	0.144
Capital Expenditures/Assets	0.087	0.077	0.083	0.083	0.081	0.072	0.069	0.061	0.058	0.063
Cash/Assets	0.396	0.222	0.184	0.145	0.139	0.141	0.143	0.157	0.164	0.180
R&D/Assets	0.228	0.105	0.187	0.155	0.111	0.075	0.071	0.073	0.091	0.067
Log(Total Assets)	3.496	4.533	4.942	5.283	5.349	5.199	5.067	4.875	4.781	4.446

Table 19 Characteristics of ten portfolios sorted by operating profitability

The final dataset contains non-financial firm-month observations qualified by select criteria from June 1980 to December 2015. Stocks are sorted into ten portfolios based on deciles of profitability proxies at the beginning of July 1980 (for CEO and Insider variables, July 1994), then rebalanced on the end of June the following year. Profitability breakpoints for constructing decile portfolios are based on an all-NYSE sample of ordinary shares, with valid stock prices, MEs and profitability measures. GPTA is the gross profitability of total assets following Novy-Marx (2013). ME is the market capitalisation in million US dollars. BE/ME is the book-to-market ratio following Davis and the Fama and French (2000) estimation. CEO is the percentage of shares held by the top executive over total common shares outstanding. Insider is the insider ownership percentage as the sum of common shares held by the top 5 executive managers over total common shares outstanding. IO is the institutional ownership, which is the total shares held by institutions over total common shares outstanding. IO-HHI is the top 5 institutional ownership concentrations, following the Herfindahl index.

Portfolio	1 (Low Profitability)	2	3	4	5	6	7	8	9	10 (High Profitability)
Panel A. Portfolio Characteristics										
OPTA	-0.065	0.069	0.097	0.119	0.137	0.156	0.174	0.197	0.231	0.323
ME	154	694	831	967	1232	1659	2032	2100	2587	3674
BE/ME	0.832	1.134	1.058	0.964	0.835	0.767	0.673	0.530	0.534	0.419
Panel B. Insider Ownership										
INSIDER	4.375	4.640	3.807	3.725	3.601	3.646	3.324	3.438	4.258	4.845

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(Continued)										
CEO	4.283	3.891	3.402	3.294	3.207	3.057	3.112	3.633	3.749	4.546
IO	0.193	0.311	0.360	0.395	0.410	0.430	0.445	0.448	0.454	0.455
IO-HHI	0.420	0.324	0.284	0.245	0.230	0.212	0.196	0.185	0.176	0.173
Panel C. Firm Characteristics										
Debt/Assets	0.186	0.251	0.270	0.271	0.253	0.239	0.215	0.187	0.155	0.108
Capital Expenditures/Assets	0.066	0.055	0.058	0.059	0.064	0.067	0.071	0.076	0.079	0.083
Cash/Assets	0.274	0.148	0.121	0.114	0.119	0.124	0.130	0.145	0.175	0.239
R&D/Assets	0.151	0.079	0.049	0.057	0.045	0.064	0.051	0.057	0.074	0.110
Log(Total Assets)	3.291	4.582	4.981	5.112	5.225	5.275	5.329	5.267	5.145	4.900

5.4.4 Profitability premiums and internal insiders

To test the proposed hypotheses, following the methodology introduced by Fama and French (2008), all qualified stocks that have met the criteria in section 5.3.2 are now independently sorted by firm's profitability. They are measured at the end of June into five quintile groups, and by its June-end internal insider holding level into five quintile groups. The intersection of group breakpoints thus generates 25 portfolios including firms sorted with similar average profitability as well as internal insider's holding level. These portfolios are constructed at the beginning of July and held for one year, in line with one-way sort portfolio analysis.

To remain within the scope of this thesis, only value-weighted portfolio Fama-French 3-factor alpha is reported to account for the fact that a portfolio's excess return is driven by other common risk factors documented in previous literature. However, the complete analysis covers both equal-weighted and value-weighted portfolio average excess return and FF-3 alpha. Returns for double sort portfolios selected by firm's gross profitability ($GPTA$) and CEO ownership (CEO) are presented in the Panel A of Table 18. The gross profitability premium, which is measured as the long-short portfolio return and listed in the column "GPTA High-Low", is positive, suggesting the pervasive existence of gross profitability among the market. This is in line with Novy-Marx (2013), who finds the market-wide phenomenon that high profitability firms outperform low profitability firms in general. The profitability premium is statistically significant in four out of five CEO ownership quintiles. The monthly value-weighted Fama-French 3-factor alpha for gross profitability premium in the lowest CEO quintile is 0.86%, and it is 1.06% in the middle CEO quintile 1.35% in the highest CEO quintile, giving evidence that the profitability anomaly is more pronounced in high CEO ownership firms, though the pattern is not perfect in linear. The insider ownership premium, measured as the long-short CEO portfolio in each $GPTA$ quintile, is negative in four out of five $GPTA$ quintiles, and is only significant in low $GPTA$ quintile. This indicates that the premium from insider ownership sorted by CEO, documented by Lilienfeld-Toal and Ruenzi (2014), is driven by the correlation between CEO ownership variable with firm's fundamental factors that also have pricing power to future stock returns. The equal-weighted portfolio excess return gives consensus in finding that the positive CEO ownership exists, but only in high $GPTA$ quintiles.

A broader definition of internal insider ownership does not change the finding that the gross profitability premium is higher in high internal insider ownership firms. Independent sorting of stocks by gross profitability and top executives' ownership ($INSIDER$) also supports our finding, confirming the positive relationship between profitability and insider ownership. The results in Panel B of Table 18 depict that the bottom, medium and top 20% firms characterised by $INSIDER$, have an average monthly $GPTA$ premium at 0.86%, 0.91% and 1.26% per month value weighted FF-3 alpha. The gross profitability premium has similar pattern as the results from $GPTA$-CEO double sorts, especially the premium in top and bottom insider ownership quintile. This is due to the similarity of firms' insider ownership structure. Firms with high CEO ownership usually have high top managers' ownership as the CEO is one of the top managers in a firm. This is confirmed by the high spearman's ranking correlation between the two variables, which is 0.833% in Table 13.

The positive profitability-insider relationship also emerges in terms of operating profitability-CEO ownership and operating profitability-top executive's ownership. In Panel C of Table 18, the average returns from profitability high-low portfolios from the bottom 20%, mid 20%, and top 20% CEO ownership quintile are with value-weighted returns of -0.07%, 1.77%, and 1.47% FF-3 alpha. The profitability premium is strikingly low for low CEO ownership, resulting in a gap of return over 1% in monthly returns. The reduction of $OPTA$ premium is due to the fluctuation of low $OPTA$ firms, in which some firms outperform the others, despite of their low operating profitability. Panel D of Table 18 reports on an independent portfolios sort by operating profitability and top executives' ownership ($INSIDER$), where similar findings to the gross profitability and top executives' ownership are exhibited. The portfolios' monthly average value-weighted profitability premiums from low to high $INSIDER$ quintiles are 0.86%, 0.92%, and 1.20%. These results indicate a positive relationship between the operating profitability anomaly and insider ownership.

5.4.5 Profitability premium and external insiders

Returns from an independent sort of firms by gross profitability and outsider internal ownership, measured as institutional ownership (IO) show no supporting evidence for the assumed positive relationship to stock returns. The results in the Panel A of Table 19 show that the gross profitability premium generally declines with the increase of institutional ownership. The bottom, mid, and top 20% of IO quintiles record monthly value-weighted profitability premiums at 1.15%, 0.73%, and 0.60% respectively. It is seemingly a contradiction of the proposed hypothesis that high insider ownership should be rewarded with higher returns than low insider ownership firms. Decomposing the $OPTA$ premium in the three IO quintiles, the long-side portfolios are performed indifferently, yielding at 0.21%-0.28% per month. While the short-side portfolio is different: the monthly return is -0.87%, -0.52% and -0.39%, positively related to its institutional ownership. This shows that in low operating profitability firms, investors suffer less in higher insider ownership than low insider ownership firms.

Where the insider proxy is replaced by the concentration of institutional holders ($IO - HHI$), the portfolio analysis shows that the gross profitability premium is negatively associated with ownership concentration. Given the results in the Panel B of Table 19, the bottom, mid, and top 20% $IO - HHI$ quintiles have monthly returns of 0.76%, 0.53%, and 0.51% value-weighted returns. Although portfolio returns generally decline as ownership concentration increases, low gross profitability firms with high ownership concentrations have substantially lower average returns than any other firms, when profitability is controlled for.

Thus, the return premium is concentrated on firms with high ownership concentration but low gross profitability.

When operating profitability replaces gross profitability, the average returns from profitability- IO sorted stocks show a positive profitability-insider ownership relationship and those results are disclosed in Panel C of Table 19. The High-Low operating profitability portfolio has monthly value-weighted returns at 0.26%, 0.76%, and 0.64%. This increase in profitability premium is due to the relatively low portfolio returns from high institutional ownership firms. Replacing external insiders with institutional ownership concentration ($IO - HHI$), as presented in the Panel D of Table 18. The increase of the operating profitability premium across low to high ownership concentration, is not driven by the same mechanism of $GPTA$- $IO - HHI$ group, as the average portfolio returns in low $OPTA$ group seems negatively related to the increase of ownership concentration, leading to a positive $OPTA$-$IO - HHI$ pattern. This should be carefully interpreted as the ownership information not only reflects the agency behaviour but also signalling for the stock liquidity related to arbitrage activities, as discussed in Edelen et al. (2016) investigation.

Table 20 Profitability premium and internal insider ownerships

From July 1980 to December 2015, stocks independently sorted by firm's profitability (measured as GPTA in Panel A and B; OPTA in Panel C and D) and the proxy of internal shareholders (measured as CEO in Panel A and Panel C; Insider in Panel B and Panel D) then held for one year. This generates 25 portfolios, divided at every 20% of the profitability spectrum from low to high and every 20% of the insider ownership spectrum in a similar manner. High-Low refers to a portfolio holding the top 20% most profitable stocks (High) and shorting the bottom 20% (Low) within the same insider ownership quintile or refers to holding high insider ownership stocks and shorting low insider ownership firms within the same profitability quintile. The performance of the portfolio is measured as value-weighted Fama-French 3-factor alpha at percentage, and Newey-West (1987) adjusted standard error.

Panel A. GPTA-CEO Ownership Group

Monthly Value Weighted Returns (%)

CEO	Low GPTA	2	3	4	High GPTA	GPTA High-Low
Low CEO	-0.28	0.07	0.17	0.21	0.58	0.86
	(-1.77)	(0.49)	(1.01)	(0.14)	(0.92)	(3.12)
2	-0.35	0.01	0.13	0.12	0.37	0.72
	(-3.1)	(0.33)	(0.73)	(0.18)	(0.14)	(2.32)
3	-0.77	-0.49	0.07	-0.02	0.29	1.06
	(-2.93)	(-0.51)	(0.52)	(-1.31)	(1.08)	(2.85)
4	-0.36	-0.10	-0.08	0.30	-0.04	0.32
	(-0.87)	(-1.96)	(0.07)	(0.72)	(-0.40)	(0.66)
High CEO	-0.8	-0.18	-0.09	0.43	0.54	1.35
	(-3.23)	(-1.63)	(-1.47)	(0.52)	(0.62)	(3.50)
CEO High-Low	-0.51	-0.24	-0.25	0.22	-0.03	
	(-1.72)	(-0.84)	(-1.04)	(0.68)	(-0.10)	

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Panel B. GPTA-INSIDER Ownership Group

Monthly Value Weighted Returns (%)

INSIDER	Low GPTA	2	3	4	High GPTA	GPTA High-Low
Low INSIDER	-0.41	-0.01	0.22	0.16	0.45	0.86
	(-2.29)	(-0.08)	(1.19)	(1.24)	(2.89)	(3.41)
2	-0.51	0.54	0.15	0.08	0.43	0.94
	(-1.75)	(0.93)	(0.25)	(0.15)	(2.27)	(3.37)
3	-0.63	0.12	-0.31	0.31	0.28	0.91
	(-2.50)	(0.43)	(-1.29)	(1.50)	(1.55)	(3.04)
4	-0.16	-0.16	0.23	0.25	0.05	0.21
	(-0.68)	(-0.80)	(1.02)	(0.89)	(0.21)	(0.70)
High INSIDER	-0.74	0.15	-0.16	0.52	0.52	1.26
	(-1.70)	(0.52)	(-0.66)	(1.82)	(2.01)	(2.73)
INSIDER High-Low	-0.32	0.16	-0.38	0.36	0.07	
	(-0.84)	(0.60)	(-1.47)	(1.26)	(0.22)	

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(Continued)

Panel C. OPTA-CEO Ownership Group

Monthly Value Weighted Returns (%)

CEO	Low OPTA	2	3	4	High OPTA	OPTA High-Low
Low CEO	0.36	-0.28	0.26	0.12	0.29	-0.07
	(0.51)	(-1.28)	(1.42)	(0.83)	(2.58)	(-0.10)
2	-2.07	-0.07	-0.25	0.17	0.25	2.33
	(-2.71)	(-0.29)	(-1.11)	(1.15)	(1.21)	(3.13)
3	-1.46	-0.49	-0.29	-0.23	0.31	1.77
	(-2.21)	(-1.57)	(-1.25)	(-1.07)	(1.56)	(2.73)
4	0.18	-0.35	-0.21	0.01	0.01	-0.16
	(0.27)	(-0.81)	(-0.63)	(0.06)	(0.05)	(-0.26)
High CEO	-0.89	-0.22	0.05	-0.13	0.58	1.47
	(-1.36)	(-0.74)	(0.16)	(-0.65)	(2.14)	(2.33)
CEO High-Low	-1.25	0.06	-0.21	-0.24	0.29	
	(-1.46)	(0.18)	(-0.68)	(-1.22)	(0.95)	

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Panel D. OPTA- INSIDER Ownership Group

Monthly Value Weighted Returns (%)

INSIDER	Low OPTA	2	3	4	High OPTA	OPTA High-Low
Low INSIDER	-0.53	0.01	0.06	0.24	0.30	0.83
	(-2.61)	(0.07)	(0.50)	(1.84)	(2.18)	(3.39)
2	-0.29	-0.24	0.49	0.40	0.37	0.66
	(-0.76)	(-0.46)	(1.26)	(1.59)	(1.52)	(1.49)
3	-0.49	-0.34	-0.31	0.08	0.44	0.92
	(-1.64)	(-1.22)	(-1.51)	(0.34)	(1.85)	(3.44)
4	-0.36	0.17	0.03	-0.10	0.34	0.56
	(-1.31)	(0.91)	(0.15)	(-0.46)	(1.28)	(1.72)
High INSIDER	-0.51	0.05	-0.14	0.05	0.69	1.20
	(-1.36)	(0.20)	(-0.46)	(0.21)	(2.51)	(2.72)
INSIDER High-Low	0.02	0.04	-0.20	-0.19	0.39	
	(0.35)	(0.11)	(-1.48)	(-1.53)	(0.21)	

Table 21 Profitability premium across external insider ownerships

From July 1980 to December 2015, stocks independently sorted by firm's profitability (measured as GPTA in Panel A and B; OPTA in Panel C and D) and the proxy of internal shareholders (measured as CEO in Panel A and Panel C; Insider in Panel B and Panel D) then held for one year. This generates 25 portfolios, divided at every 20% of the profitability spectrum from low to high and every 20% of the insider ownership spectrum in a similar manner. High-Low refers to a portfolio holding the top 20% most profitable stocks (High) and shorting the bottom 20% (Low) within the same insider ownership quintile or refers to holding high insider ownership stocks and shorting low insider ownership firms within the same profitability quintile. The performance of the portfolio is measured as value-weighted Fama-French 3-factor alpha at percentage, and Newey-West (1987) adjusted standard error.

Panel A. GPTA-Institutional Ownership Group

Monthly Value Weighted Returns (%)

IO	Low GPTA	2	3	4	High GPTA	GPTA High-Low
Low IO	-0.87	0.91	-0.41	-0.27	0.28	1.15
	(-2.49)	(0.63)	(-1.80)	(-0.87)	(1.07)	(3.73)
2	-1.16	-0.58	-0.36	0.19	0.39	1.55
	(-3.58)	(-2.82)	(-1.53)	(0.76)	(1.95)	(4.67)
3	-0.52	-0.22	-0.09	-0.05	0.22	0.73
	(-2.14)	(-1.23)	(-0.52)	(-0.35)	(1.33)	(2.54)
4	-0.11	-0.19	-0.13	-0.00	0.22	0.33
	(-0.62)	(-1.09)	(-0.83)	(-0.03)	(2.06)	(1.53)
High IO	-0.39	-0.19	-0.21	-0.10	0.21	0.60
	(-2.08)	(-1.24)	(-1.6)	(-0.84)	(1.84)	(3.16)
IO High-Low	0.48	-1.10	0.20	0.17	-0.06	
	(1.33)	(-0.76)	(0.83)	(0.54)	(-0.23)	

(Continued)

(Continued)

Panel B. GPTA-Institutional Ownership Concentration Group

Monthly Value Weighted Returns (%)

IO-HHI	Low GPTA	2	3	4	High GPTA	GPTA High-Low
Low IO-HHI	0.00	0.11	0.34	0.57	0.76	0.76
	(0.02)	(1.31)	(1.81)	(3.38)	(3.25)	(3.24)
2	0.16	-0.07	0.04	0.27	0.54	0.39
	(1.27)	(-0.54)	(0.39)	(2.41)	(2.65)	(2.15)
3	-0.06	-0.54	0.14	0.25	0.46	0.53
	(-0.55)	(-3.55)	(1.06)	(1.96)	(2.67)	(2.50)
4	-0.24	-0.28	-0.16	0.10	0.39	0.63
	(-1.77)	(-1.37)	(-1.09)	(0.65)	(1.95)	(3.18)
High IO-HHI	-0.51	-0.62	0.13	-0.07	-0.02	0.51
	(-2.53)	(-3.17)	(0.44)	(-0.38)	(-0.09)	(2.46)
IO-HHI High-Low	-0.51	-0.73	-0.21	-0.63	-0.74	
	(-2.54)	(-3.74)	(-0.70)	(-3.18)	(-3.26)	

(Continued)

(Continued)

Panel C. OPTA-Institutional Ownership Group

Monthly Value Weighted Returns (%)

IO	Low OPTA	2	3	4	High OPTA	OPTA High-Low
Low IO	-0.24	-0.02	0.24	-0.05	0.02	0.26
	(-0.28)	(-0.05)	(0.75)	(-0.16)	(0.06)	(0.31)
2	-1.00	-0.76	-0.43	0.32	0.44	1.44
	(-3.37)	(-3.5)	(-1.98)	(1.60)	(2.12)	(4.37)
3	-0.76	-0.38	0.22	0.25	0.01	0.76
	(-3.10)	(-1.73)	(1.29)	(1.70)	(0.03)	(2.88)
4	-0.84	-0.16	-0.10	0.05	0.09	0.93
	(-3.02)	(-0.98)	(-0.6)	(0.37)	(0.68)	(3.28)
High IO	-0.45	-0.24	-0.12	-0.07	0.19	0.64
	(-2.22)	(-1.41)	(-1.03)	(-0.59)	(1.74)	(3.60)
IO High-Low	-0.21	-0.22	-0.36	-0.02	0.17	
	(-0.24)	(-0.72)	(-1.19)	(-0.09)	(0.51)	

(Continued)

(Continued)

Monthly Value Weighted Returns (%)

IO-HHI	Low OPTA	2	3	4	High OPTA	OPTA High-Low
Low IO-HHI	-0.09	0.10	0.31	0.42	0.59	0.65
	(-0.39)	(0.71)	(1.71)	(1.75)	(2.49)	(1.88)
2	-0.03	0.11	-0.11	0.19	0.43	0.45
	(-0.13)	(0.89)	(-1.1)	(0.81)	(2.41)	(1.45)
3	-0.50	-0.13	-0.20	0.27	0.34	0.84
	(-1.83)	(-1.06)	(-1.55)	(1.28)	(1.58)	(2.11)
4	-0.76	-0.14	-0.09	0.09	0.37	1.13
	(-1.95)	(-0.98)	(-0.56)	(0.54)	(1.34)	(3.22)
High IO-HHI	-1.21	-0.08	0.01	-0.18	-0.06	1.26
	(-3.19)	(-0.46)	(0.05)	(-0.95)	(-0.30)	(3.19)
IO-HHI High-Low	-1.10	-0.18	-0.30	-0.24	-0.65	
	(-2.04)	(-0.15)	(-0.61)	(-1.07)	(-2.47)	

5.5 Cross-sectional regression on profitability and insider ownership

5.5.1 Regression analysis

As there is a variation of insider ownership between low and high profitability portfolios, a test of whether such a variation can explain profitability anomalies was undertaken by conducting cross-sectional regressions on each stock's excess monthly returns with profitability and insider ownerships.

A regression without control variables ($lnME$, $lnBM$ and $MOM12$) is estimated following the cross-sectional regression for function 5.3. A regression with control variables is estimated following the same regression for function 5.4. For each function, the monthly stock return of firm i(R_i) in excess of the one-month Treasury Bill rate (R_f) is regressed by $Profitability$, a variable representing the firm's profitability lagged for one month. Then by $Insider$, a variable representing the firm's corporate governance proxy, and by the two variables together, and by the two variables and their interaction variables, lagged for one month.

$$R_{i,t} - r_{f,t} = \lambda_0 + \lambda_1 Profitability + \lambda_2 Insider\ Ownership + \boldsymbol{\lambda_3}' \boldsymbol{X_{i,t-1}} + \varepsilon_{i,t} \quad (5.5)$$

Where

$$\boldsymbol{X_{i,t-1}} = \begin{bmatrix} lnME_{i,t-1} & lnBM_{i,t-1} & MOM12_{i,t-1} \end{bmatrix} \quad (5.6)$$

5.5.2 Profitability and insider ownership interaction effects

If the pricing power of profitability and insider ownership in the cross-sectional student return is positively related, there may be an interactive effect that causes firms with high (low) profitability and high (low) insider ownership to have higher returns than other firms.

To verify this, Table 20 to Table 23 test whether insider ownership is associated with a gross profitability anomaly. If such an interaction effect exists, the interaction variable, represented by the coefficient of $Profitability \times Insider$ (noted as $Interaction$ below), should be distinct from zero.

$$R_{i,t+1} - r_{f,t+1} = \lambda_0 + \lambda_1 Profitability + \lambda_2 Insider\ Ownership + \lambda_3 Interaction_{i,t} + \boldsymbol{\lambda_4}'\boldsymbol{X_{i,t}} + \varepsilon_{i,t+1} \quad (5.7)$$

Where

$$\boldsymbol{X_{i,t}} = \begin{bmatrix} lnME_{i,t} & lnBM_{i,t} & MOM12_{i,t} \end{bmatrix} \quad (5.8)$$

There is no observable interaction effect between gross profitability and internal insiders, though CEO ownership is positively related to stock return. A unit change in CEO ownership results in an approximate 0.01% increase in expected monthly return. Though the economic change is marginal, it is statistically significant at the 10% level. The pricing power of CEO ownership is presumably due to its correlation with other fundamental firm characteristics that can predict stock returns. When control variables are added, the significance of CEO ownership drops. The gross profitability is also significantly positively related to expected returns at the 5% level. Adding control variables does not change the significance of $GPTA$, suggesting that GPTA carries pricing power for future stock return in addition to size, value, and momentum effects. However, the coefficient of interaction variable is positive but insignificant, which does not provide persuasive evidence for the hypothesis being tested or support the intuitive findings in earlier sections. For Insider ownership, the coefficient of interaction effect is larger than that of CEO ownership, but it remains insignificant. The coefficient of $INSIDER$ remains significant across all regressions in Table 21, suggesting that the pricing power of insider ownership is not due to missing fundamental risk factors in the model, nor spurious correlations with profitability.

In terms of external insider ownership, the interaction effect on gross profitability appears stronger. Table 22 reports the results of a regression of gross profitability and IO. The coefficient of $Interaction$ is significant but takes a negative sign: the coefficient is -1.573% with a t-statistic of -2.92. This suggests that an increase of the gross profitability anomaly is related to lower institutional ownership. Both $GPTA$ and IO are, as expected, positively priced with expected stock returns and are significant at the 10% level. Thus the negative interaction may result from other behaviour of institutions, such as the preference for low past profitability stocks to exploit, the so-called "lottery" stocks, or the preference for high liquidity stocks, which are usually large firms. Such preferences for specific, rather than general stocks, may hedge the portfolios of high level corporate governance firms. Table 23 reports on the interaction of gross profitability with $IO-HHI$, the concentration of institutions. The interaction of ownership concentration is negative and significant, with a coefficient of 0.832% and t-statistic of 1.76. All interaction effects are subsumed when $lnME$, $lnBM$ and $MOM12$ are added to the regression. However, this suggests that the variation of profitability premium among low and high insider ownership is related to those fundamental firm specifics.

Table 22 Fama-MacBeth regressions with interaction term between gross profitability and CEO ownership

For each month from January 1980 to December 2015, Fama-MacBeth (1973) cross-sectional regressions of monthly excess returns (CRSP monthly return over the one-month T-bill rate) are estimated for a set of independent variables: The proxy of firm's profitability (GPTA), the proxy of firms' internal insider (CEO), the interaction of firm's profitability to high/low in internal insider ownership (Interaction), and firm's size (lnME), book-to-market equity (lnBM) and past returns (MOM12). The t-statistics, adjusted by Newey-West standard error, are in parentheses. Panel A reports basic regressions and Panel B reports regressions with control variables. *denotes p<0.10, ** denotes p<0.05 and *** denotes p<0.01.

Constant	GPTA	CEO	Interaction	lnBM	lnME	MOM12	Observations	Avg. R2
Panel A. Without Control Variables								
0.683	0.792**						302948	0.007
(1.49)	(2.42)							
0.977**		0.010*					302948	0.002
(2.52)		(1.69)						
0.671	0.773**	0.007					302948	0.008
(1.47)	(2.39)	(1.25)						
0.715	0.672*	-0.004	0.022				302948	0.008
(1.56)	(1.90)	(-0.31)	(0.97)					
Panel B. With Control Variables								
1.680	0.789**			0.034	-0.095	0.349	302948	0.043
(1.40)	(2.43)			(0.27)	(-1.38)	(0.76)		
2.112*		0.006		-0.110	-0.068	0.350	302948	0.039
(1.77)		(1.07)		(-1.57)	(-0.59)	(0.77)		
1.623	0.780**	0.004		-0.091	0.035	0.348	302948	0.044
(1.33)	(2.40)	(0.73)		(-1.31)	(0.28)	(0.76)		
1.673	0.691**	-0.005	0.018	-0.092	0.032	0.350	302948	0.046
(1.37)	(2.01)	(-0.45)	(0.85)	(-1.32)	(0.26)	(0.76)		

Table 23 Fama-MacBeth regressions with interaction term between gross profitability and insider ownership

For each month from January 1980 to December 2015, Fama-MacBeth (1973) cross-sectional regressions of monthly excess returns (CRSP monthly return over the one-month T-bill rate) are estimated for a set of independent variables: The proxy of firm's profitability (GPTA), the proxy of firms' internal insider ownership(INSIDER), the interaction of firm's profitability to high/low in internal insider ownership (Interaction), and firm's size (lnME), book-to-market equity (lnBM) and past returns (MOM12). The t-statistics, adjusted by Newey-West standard error, are in parentheses. Panel A reports basic regressions and Panel B reports regressions with control variables. *denotes p<0.10, ** denotes p<0.05 and *** denotes p<0.01.

Constant	GPTA	INSIDER	Interaction	lnBM	lnME	MOM12	Observations	Avg. R2
Panel A. Without Control Variables								
0.750*	0.622**						275599	0.007
(1.71)	(2.08)							
0.962**		1.179**					275599	0.002
(2.53)		(2.40)						
0.733*	0.586**	1.022**					275599	0.008
(1.66)	(1.99)	(2.30)						
0.732*	0.591*	1.020	-0.183				275599	0.010
(1.65)	(1.85)	(1.05)	(-0.10)					
Panel B. With Control Variables								
1.904*	0.665**			0.030	-0.107*	0.103	275599	0.046
(1.86)	(2.24)			(0.29)	(-1.91)	(0.21)		
2.203**		0.842*		-0.049	-0.116**	0.107	275599	0.041
(2.19)		(1.95)		(-0.48)	(-2.04)	(0.22)		
1.785*	0.654**	0.770*		0.036	-0.100*	0.099	275599	0.047
(1.72)	(2.21)	(1.86)		(0.35)	(-1.76)	(0.20)		
1.798*	0.641**	0.590	0.164	0.035	-0.100*	0.101	275599	0.048
(1.73)	(2.04)	(0.65)	(0.10)	(0.33)	(-1.77)	(0.21)		

Table 24 Fama-MacBeth regressions with interaction term between gross profitability and institutional ownership

For each month from January 1980 to December 2015, Fama-MacBeth (1973) cross-sectional regressions of monthly excess returns (CRSP monthly return over the one-month T-bill rate) are estimated for a set of independent variables: The proxy of firm's profitability (GPTA), the proxy of firms' external insider (IO), the interaction of firm's profitability to high/low in external insider ownership (Interaction), and firm's size (lnME), book-to-market equity (lnBM) and past returns (MOM12). The t-statistics, adjusted by Newey-West standard error, are in parentheses. Panel A reports basic regressions and Panel B reports regressions with control variables. *denotes p<0.10, ** denotes p<0.05 and *** denotes p<0.01.

Constant	GPTA	IO	Interaction	lnBM	lnME	MOM12	Observations	Avg. R2
Panel A. Without Control Variables								
0.705**	0.641***						1301374	0.003
(2.25)	(3.52)							
0.661		0.528					1301374	0.008
(1.64)		(1.58)						
0.612	0.653***	0.007					1301374	0.011
(1.52)	(3.59)	(0.34)						
0.434	1.146***	0.727*	-1.573***				1301374	0.012
(1.03)	(3.93)	(1.80)	(-2.92)					
Panel B. With Control Variables								
1.195**	0.702***			0.475***	-0.094*	0.598**	1301374	0.026
(2.31)	(3.83)			(4.18)	(-1.70)	(2.36)		
1.573***		1.582***		0.446***	-0.244***	0.760***	1301374	0.027
(3.15)		(5.98)		(3.90)	(-4.23)	(2.84)		
1.293**	0.642***	1.069***		0.438***	-0.195***	0.634**	1301374	0.030
(2.45)	(3.36)	(4.48)		(3.74)	(-3.25)	(2.45)		
1.249**	0.763***	1.184***	-0.298	0.435***	-0.195***	0.632**	1301374	0.031
(2.32)	(2.69)	(4.11)	(-0.61)	(3.72)	(-3.25)	(2.44)		

Table 25 Fama-MacBeth regressions with interaction term between gross profitability and ownership concentration

For each month from January 1980 to December 2015, Fama-MacBeth (1973) cross-sectional regressions of monthly excess returns (CRSP monthly return over the one-month T-bill rate) are estimated for a set of independent variables: The proxy of firm's profitability (GPTA), the proxy of firms' external insider (IO-HHI), the interaction of firm's profitability to high/low in external insider ownership (Interaction), and firm's size (lnME), book-to-market equity (lnBM) and past returns (MOM12). The t-statistics, adjusted by Newey-West standard error, are in parentheses. Panel A reports basic regressions and Panel B reports regressions with control variables. *denotes p<0.10, ** denotes p<0.05 and *** denotes p<0.01.

Constant	GPTA	IO-HHI	Interaction	lnBM	lnME	MOM12	Observations	Avg. R2
Panel A. Without Control Variables								
0.705**	0.664***						1143916	0.003
(2.25)	(3.55)							
0.661		-0.420					1143916	0.007
(1.64)		(-1.31)						
0.612	0.652***	-0.083					1143916	0.010
(1.52)	(3.52)	(-0.25)						
0.434	0.449**	-0.388	0.833*				1143916	0.012
(1.03)	(2.52)	(-1.01)	(1.76)					
Panel B. With Control Variables								
1.195**	0.733***			0.478***	-0.092	0.669**	1143916	0.028
(2.31)	(3.87)			(4.03)	(-1.64)	(2.56)		
1.573***		-1.508***		0.475***	-0.225***	0.775***	1143916	0.027
(3.15)		(-5.41)		(4.03)	(-3.32)	(2.82)		
1.293**	0.708***	-1.116***		0.463***	-0.179**	0.643**	1143916	0.031
(2.45)	(3.72)	(-3.69)		(3.88)	(-2.58)	(2.43)		
1.249**	0.718***	-1.133***	0.091	0.463***	-0.179**	0.642**	1143916	0.032
(2.32)	(3.58)	(-3.70)	(0.19)	(3.87)	(-2.58)	(2.43)		

Regression on firms' excess returns to operating profitability and insider ownership gives similar results as to gross profitability and insider groups. When monthly stock excess return is regressed by $OPTA$ solely, its significance varies across internal and external insider groups, as Cremers and Nair (2005) documents (t=1.36 in CEO group and t=1.26 in $Insider$ group; t=2.04 in IO group and t=2.20 in $IO - HHI$ group). This suggests that the pricing power of operating profitability is less strong in this sample than the market sample. Recall that the source of CEO and $Insider$ is from Execucomp that only traces US S&P 1500 indexed firms and the variation of operating profitability among these firms may less sensitive to the stock returns. When control variables are included, as reported in Panel B of Table 24-Table 27, the significance of $OPTA$ is increased and the coefficient is quantitatively similar regardless the insider ownership group ($\widehat{\lambda_1}$=1.786 in CEO group, $\widehat{\lambda_1}$=1.868in $Insider$ group; $\widehat{\lambda_1}$=1.919 in IO group and $\widehat{\lambda_1}$=1.987 in $IO - HHI$ group).

Together with $OPTA$, the significance of CEO (t=1.92) is higher than $GPTA$ with CEO (t=1.25). However, the interaction variable is still not significant, as the coefficient of $OPTA \times CEO$ is 0.071 (t=0.88). Controlling firm's size, book-to-market equity and momentum further dilutes the pricing power of CEO ownership, as its t-stat drops to 1.02. This shows the pricing power of internal insiders is related to these well-documented factors and does not represent a systematic pricing factor. In light of this, the interaction effect of insider ownership and operating profitability may also not be systematically significant. The regression analysis supports this view by showing a decline of the coefficient of $OPTA \times CEO$ where control variables are added (=0.003, t=-0.01). When internal insider is proxied by $Insider$, the coefficient of $OPTA \times INSIDER$ is -0.424 without control variable and is -0.596 with control variable. Although the coefficient is economically large, it failed to pass the t-static significant threshold due to the relatively small sample size and less time period is covered. For the external insider group, the interaction effect is only significant when the insider proxy is related to institutions, and only when size, book-to-market ratio, and momentum are not included in the regression. The sign is also unexpectedly negative. These facts suggest that both $GPTA$ and $OPTA$ carry similar factor loadings to insider ownership variables.

5.5.3 Summary

The positive profitability-insider ownership relationship is not pervasive among the empirical evidence presented in this section. Only institutional ownership has a positive interaction effect with operating profitability in the cross-sectional stock return regression. All other tests either do not provide decisive evidence (no significant results, or results that are no longer significant when control variables are included) for the existence of an interaction effect or demonstrate an interaction effect that is contrary to the hypothesis. The alternate hypothesis, that profitability premium are more pronounced where insider ownership is high also does not receive sufficient supporting evidence.

In addition, it seems that the observation of two internal measures, CEO and $INSIDER$ do not represent an unbiased sample of the U.S. market. Previous research has repeatedly confirmed a strong positive relationship between returns and $lnBM$ and returns and $MOM12$, and a weakly negative relationship between returns and $lnME$. In the current research, the coefficients for $lnBM$ are insignificant when an anti-takeover variable enters the regression, and the coefficients of $Mom12$ are significant at the 10% level. The coefficient of $lnME$is significant at the 10% level. This inconsistent factor loading suggests that the sample of internal insiders is not an unbiased fraction of the market.

Information related to these controversial findings and inconsistencies with the hypotheses can be found in Edelen et al. (2016), who find evidence that institutions have an inability to trade stocks due to legal regulations on holding periods and short-sale constraints. These unobserved restrictions may distort the interactions of insider ownership and preference with profitability. In addition, Cremers and Nair (2005) argue that two-step cross-sectional regression for testing the interaction of governance and other firm characteristics is affected by a firm's idiosyncratic risk and therefore results in "very low power due to the noise in estimating the firm-specific alpha" (p.2873). Following their suggestions, portfolio analysis is used to reduce the effects of idiosyncratic risk and potential bias from skewed variables and outliers.

Table 26 Fama-MacBeth regressions with interaction term between operating profitability and CEO ownership

For each month from January 1980 to December 2015, Fama-MacBeth (1973) cross-sectional regressions of monthly excess returns (CRSP monthly return over the one-month T-bill rate) are estimated for a set of independent variables: The proxy of firm's profitability (OPTA), the proxy of firms' internal insider (CEO), the interaction of firm's profitability to high/low in internal insider ownership (Interaction), and firm's size (lnME), book-to-market equity (lnBM) and past returns (MOM12). The t-statistics, adjusted by Newey-West standard error, are in parentheses. Panel A reports basic regressions and Panel B reports regressions with control variables. *denotes p<0.10, ** denotes p<0.05 and *** denotes p<0.01.

Constant	OPTA	CEO	Interaction	lnBM	lnME	MOM12	Observations	Avg. R2
Panel A. Without Control Variables								
0.764	1.355						302948	0.007
(1.64)	(1.36)							
0.977***		0.010**					302948	0.002
(2.85)		(2.02)						
0.735	1.350	0.010*					302948	0.009
(1.57)	(1.35)	(1.92)						
0.800*	1.005	-0.004	0.071				302948	0.010
(1.66)	(0.90)	(-0.22)	(0.88)					
Panel B. With Control Variables								
2.160**	1.786**			0.028	-0.128**	0.325	302948	0.041
(2.03)	(2.17)			(0.21)	(-2.03)	(0.63)		
2.113*		0.065		-0.068	-0.110	0.350	302948	0.039
(1.88)		(1.02)		(-0.56)	(-1.62)	(0.67)		
2.076*	0.782**	0.046		0.029	-0.126*	0.324	302948	0.044
(1.90)	(2.40)	(0.72)		(0.22)	(-1.89)	(0.63)		
2.103*	0.778**	0.038	-0.003	0.024	-0.121*	0.323	302948	0.044
(1.90)	(2.29)	(0.26)	(-0.01)	(0.19)	(-1.87)	(0.63)		

Table 27 Fama-MacBeth regressions with interaction term between operating profitability and insider ownership

For each month from January 1980 to December 2015, Fama-MacBeth (1973) cross-sectional regressions of monthly excess returns (CRSP monthly return over the one-month T-bill rate) are estimated for a set of independent variables: The proxy of firm's profitability (OPTA), the proxy of firms' internal insider (Insider), the interaction of firm's profitability to high/low in internal insider ownership (Interaction), and firm's size (lnME), book-to-market equity (lnBM) and past returns (MOM12). The t-statistics, adjusted by Newey-West standard error, are in parentheses. Panel A reports basic regressions and Panel B reports regressions with control variables. *denotes p<0.10, ** denotes p<0.05 and *** denotes p<0.01.

Constant	OPTA	Insider	Interaction	lnBM	lnME	MOM12	Observations	Avg. R2
Panel A. Without Control Variables								
0.798*	1.098						273660	0.007
(1.68)	(1.26)							
0.962**		1.179**					273660	0.002
(2.53)		(2.40)						
0.762	1.089	1.145**					273660	0.008
(1.60)	(1.25)	(2.34)						
0.750	1.151	1.241	-0.424				273660	0.010
(1.55)	(1.21)	(1.18)	(-0.09)					
Panel B. With Control Variables								
2.150**	1.868***			0.067	-0.126**	0.088	273660	0.044
(2.16)	(2.86)			(0.68)	(-2.27)	(0.18)		
2.203**		0.842*		-0.049	-0.116**	0.107	273660	0.041
(2.19)		(1.95)		(-0.48)	(-2.04)	(0.22)		
2.006**	1.860***	0.852**		0.06	-0.117**	0.083	273660	0.045
(1.99)	(2.84)	(1.98)		(0.77)	(-2.10)	(0.17)		
1.981*	1.913***	0.975	-0.596	0.077	-0.116**	0.086	273660	0.046
(1.96)	(2.70)	(0.97)	(-0.13)	(0.78)	(-2.08)	(0.18)		

Table 28 Fama-MacBeth regressions with interaction term between operating profitability and institutional ownership

For each month from January 1980 to December 2015, Fama-MacBeth (1973) cross-sectional regressions of monthly excess returns (CRSP monthly return over the one-month T-bill rate) are estimated for a set of independent variables: The proxy of firm's profitability (OPTA), the proxy of firms' external insider (IO), the interaction of firm's profitability to high/low in external insider ownership (Interaction), and firm's size (lnME), book-to-market equity (lnBM) and past returns (MOM12). The t-statistics, adjusted by Newey-West standard error, are in parentheses. Panel A reports basic regressions and Panel B reports regressions with control variables. *denotes p<0.10, ** denotes p<0.05 and *** denotes p<0.01.

Constant	OPTA	IO	Interaction	lnBM	lnME	MOM12	Observations	Avg. R2
Panel A. Without Control Variables								
0.732*	1.239**						1096691	0.005
(1.87)	(2.04)							
0.816**		0.245					1096691	0.009
(1.99)		(0.70)						
0.721*	1.231***	0.051					1096691	0.011
(1.66)	(2.60)	(0.17)						
0.646	1.977***	0.438	-2.388*				1096691	0.013
(1.43)	(2.70)	(0.93)	(-1.65)					
Panel B. With Control Variables								
1.349***	1.919***			0.466***	-0.133**	0.779***	1096691	0.026
(2.70)	(4.51)			(4.40)	(-2.58)	(3.36)		
1.552***		1.323***		0.412***	-0.222***	0.739***	1096691	0.026
(3.17)		(5.63)		(3.97)	(-4.33)	(3.18)		
1.497***	1.702***	1.191***		0.416***	-0.246***	0.738***	1096691	0.029
(3.03)	(4.12)	(5.32)		(4.03)	(-5.05)	(3.22)		
1.542***	1.449**	0.850**	1.967	0.431***	-0.245***	0.745***	1096691	0.030
(3.03)	(2.29)	(2.42)	(1.51)	(4.18)	(-5.08)	(3.27)		

Table 29 Fama-MacBeth regressions with interaction term between operating profitability and ownership concentration

For each month from January 1980 to December 2015, Fama-MacBeth (1973) cross-sectional regressions of monthly excess returns (CRSP monthly return over the one-month T-bill rate) are estimated for a set of independent variables: The proxy of firm's profitability (OPTA), the proxy of firms' external insider (IO-HHI), the interaction of firm's profitability to high/low in external insider ownership (Interaction), and firm's size (lnME), book-to-market equity (lnBM) and past returns (MOM12). The t-statistics, adjusted by Newey-West standard error, are in parentheses. Panel A reports basic regressions and Panel B reports regressions with control variables. *denotes p<0.10, ** denotes p<0.05 and *** denotes p<0.01.

Constant	OPTA	IO-HHI	Interaction	lnBM	lnME	MOM12	Observations	Avg. R2
Panel A. Without Control Variables								
0.731**	1.224**						1005886	0.004
(2.03)	(2.20)							
0.901***		-0.117					1005886	0.008
(3.28)		(-0.36)						
0.662**	1.343***	0.111					1005886	0.011
(2.02)	(2.78)	(0.40)						
0.741**	0.839	-0.033	2.353*				1005886	0.012
(2.25)	(1.49)	(-0.41)	(1.82)					
Panel B. With Control Variables								
1.300***	1.987***			0.470***	-0.128**	0.755***	1005886	0.026
(2.61)	(5.26)			(4.09)	(-2.48)	(2.84)		
2.066***		-1132***		0.500***	-0.178***	0.725***	1005886	0.027
(3.60)		(-3.72)		(3.87)	(-2.70)	(2.67)		
1.923***	1.879***	-1021***		0.452***	-0.207***	0.726***	1005886	0.029
(3.29)	(4.98)	(-3.35)		(3.92)	(-3.24)	(2.71)		
1.872***	2.512***	-0.829***	-1.68	0.462***	-0.215***	0.724***	1143916	0.031
(3.25)	(5.34)	(-2.72)	(-1.18)	(4.02)	(-3.29)	(2.71)		

5.6 Further Tests of Firm's Profitability and Corporate Governance

If the interaction of firm's insider ownership and profitability anomaly is driven by the mechanism of corporate governance, other proxies, such as anti-takeover provision (see Gompers et al. 2003), manager salaries (see Harford et al. 2008) should predict the profitability premium via the same channel. This section pays special attention to the two possible channels as previous literature has documented a pricing power determining stock return from annually rebalanced portfolios sorted by the two variables (Gompers et al. 2003; Bebchuk et al. 2009), and are widely discussed in subsequent research (see Bebchuk et al. 2013, Gao, 2015)

Since the availability of G-Index and E-Index is limited to several years, leaving a gap of approximately 2-3 years between the update time. Following Bebchuk et al. (2013) this research assumes there is no change of two variables in the gap period. Given IRRC information is a summation of existing information from the market, this research assumes the information is available at the month of initial publication, which is September 1990, July 1993, July 1995, February 1998, November 2000, February 2002, January 2004, and January 2006 respectively. After the last IRRC publication, both G-Index and E-Index information remain unchanged until December 2006. This adjustment allows to examining stock return in a continuous time period from September 1990 to December 2006, which is 195 months.

5.6.1 Governance Proxies

$G - Index$: Gompers et al. (2003) compute the G-Index as an indicator of firm manager's power by a series of information from Corporate Takeover Defences by Investor Responsibility Research Centre (IRRC). The index range is from 1 to 19, while higher index value refers to higher manager's power, and lower shareholder's rights. Due to the limit of availability, G-Index only covers Standard & Poor's 500 listed firms as well as annual firm list covering firms that included in Fortune, Forbes and Business Week in the years 1990, 1993, 1995, 1998, 2000, 2002, 2004, and 2006. The data is from Professor Andrew Metrick's website (visit the web-link[1] in the footnote for details).

The original source of $G - Index$ is matched with TICKER, which contains 14,000 ticker-year observations. The index is merged with CRSP stock header file to match all TICKERs to PERMNO and GVKEY in order to merge $G - Index$ with accounting information, fiscal and calendar date and stock returns. Since firms with dual-class stocks have distinctive stockholder rights than ordinary firms, those firms are removed from database as GIM (2003). The identifier of dual-class is by G-Index database (dual class: 0 no;1 yes). I do not use CRSP Share Class identifier (CRSP code SHRCLS) as most stocks are labelled with blank. The total number of observations with PERMNO and no dual-class stock is 13,823, and 270 of which its PERMNO is linking with multiple market TICKER. I manually correct all those

[1] http://faculty.som.yale.edu/andrewmetrick/data.html

cases to ensure all observations are correctly matched thus give a total 13,613 observations.

$\boldsymbol{E-Index}$: Using the same original source from IRRC, $E-Index$ measures a similar methodology but has a value range from 0 to 6. Higher $E-Index$ indicates higher manager power which is similar to $G-Index$. Due to the limit of availability, $\mathrm{E-Index}$ only covers firms in the year of 1990, 1993, 1995, 1998, 2000, 2002, 2004, and 2006.

The data is provided by Professor Lucian Bebchuk from Harvard University (visit the web-link [2]in the footnote for details) and match all TICKER with corresponding GVKEY and PERMNO, following the same method addressing $G-Index$.

$\boldsymbol{Salary}$: The ratio of top manager's salary is measured by the top five managers' granted stock options using Black-Scholes value (Compustat Execucomp item $option\_awards\_blk\_value$), where ranking information is the same as $Insider$, divided by the total compensation of stock option, salary, and bonus they have received. If option's Black-Scholes value is missing, option's fair value that reported to SEC (Compustat Execucomp item $option\_awards\_fv$) is applied. Since $Salary$ uses information from annual reports, this research assumes a six-

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[2] http://www.law.harvard.edu/faculty/bebchuk/data.shtml

month lag from the fiscal-year end month to the month that information is available to the public.

5.6.2 Profitability premium and governance proxies

Return for double sort portfolio by gross profitability ($GPTA$) and G-Index ($G-Index$) is presented in Table 30. The profitability premium is positive in four out of five G-Index quintiles. This is in line with Novy-Marx (2013) that high profitability firms outperform low profitability firms in general. Another finding from Novy-Marx is profitability premium is marginally significant when return is not risk-adjusted. This research confirms this finding as only the third $G-Index$ quntile records profitability premium with a significant sign (t=2.04). To account for considerations that excess return is driven by other common risk factors that have been documented by previous literature, value weighted $FF-3$ alpha is reported. The conclusion remains similar with raw excess return. Good governance (low $G-Index$ quintile) is associated with positive portfolio risk-adjusted return, yielding 0.35% per month, and as hypothesised, weak governance is associated with negative portfolio return at -0.10% per month. However, the pattern of G-Index and GPTA premium is not monotonic.

Compared with G-Index, E-Index seems more correlated with stock return and firm's profitability premium. Although the relation between profitability and E-Index is not a monotonic pattern as well, profitability premium is positive in low $E-Index$ quintile but is negative in high $E-Index$ quintile and cannot subsume by Fama-French 3-Factor model. The governance premium is stronger than $G-Index$. These findings are roughly supporting the view that good governance (low $G-Index$ and low $E-Index$) is associated with higher profitability.

When profitability is measured by operating profitability ($OPTA$), the conclusion does not change. The pattern of $OPTA$ premium with three governance proxies confirms the good governance (low $G-Index$, low $E-Index$, and high $Salary$) is associated with higher profitability. The positive profitability-return pattern is observed and is significant in both GPTA and OPTA sorts. The positive corporate governance-return pattern is clearer than $G-Index$ as 3 out of 5 profitability quintiles records a negative High − Low premium and are significant in several quintiles

However, the interpretation of findings in Table 30 are strictly restricted due to the lack of sample volume and time span. Comparing with Novy-Marx (2013), using 1963-2010 period U.S. stock observation, the dataset used in Table 30 is restricted to the 1990-2006 period, and according to the instruction of IRRS as well as Gompers et al. (2003), only S&P 1500 stocks are included for computing anti-takeover index. Whether there is any bias is still pending further discussion.

Table 30 Profitability Premium and Governance Proxies

From July 1990 to December 2006, stocks within the same profitability are independently sorted by its gross profitability (GPTA) and operating profitability (OPTA) respectively and one measure of corporate governance (see section 5.6.1 for detail), then hold for one year. This generates 5 portfolios with every 20% of the profitability spectrum from low to high. Panel A reports value weighted portfolio FF-3 alpha (in percentage) of GPTA premium, Panel B reports OPTA premium and corresponding t-statistics as panel A, both are with Newey-West adjusted standard error.

G-Index		E-Index		Salary	
		Panel A. GPTA Group			
Low G-Index	0.351	Low E-Index	0.377	Low Salary	0.983
	(0.91)		(1.09)		(2.00)
2	0.450	2	0.728	2	0.400
	(1.31)		(2.66)		(1.25)
3	0.487	3	0.736	3	0.479
	(2.04)		(2.64)		(1.55)
4	0.430	4	0.828	4	0.555
	(1.54)		(1.60)		(1.79)
High G-Index	-0.112	High E-Index	-0.214	High Salary	1.741
	(-0.47)		(-0.89)		(6.25)
		Panel B. OPTA Group			
Low G-Index	0.823	Low E-Index	1.144	Low Salary	0.614
	(1.94)		(2.97)		(1.23)
2	1.721	2	1.32	2	0.826
	(2.97)		(4.01)		(4.71)
3	1.386	3	1.307	3	1.679

(Continue)

(Continued.)

	(3.39)		(0.12)		(3.59)
4	1.433	4	0.835	4	0.500
	(3.82)		(2.07)		(1.35)
High G-Index	0.776	High E-Index	0.083	High Salary	1.654
	(1.55)		(0.12)		(4.71)

5.7 Conclusion and Discussion

The relation between firm's profitability and insider ownership has helped to explain the profitability premium which is firstly proposed by Novy-Marx (2013) and further explored by Ball et al. (2015) as well as Fama and French (2015). Firms with high profitability are associated with high insider ownership as can be observed in the portfolio-level analysis. Controlling for the level of firm's internal insider ownership (measured as firm's CEO and $INSIDER$), the monthly average $GPTA$ and $OPTA$ premium is 0.86% in the lowest 20% insider ownership firms and is 12.6-1.47% in high insider ownership firms. This is consistent with the literature arguing firm's agency costs have significant predicting power to profitability, since insiders are more heavily influential than any other stakeholders as a key mechanism of corporate governance to reduce agency costs. As for the external insider ownership, the average $OPTA$ premium is also increased controlling for the institutional ownership (IO).

However, as summarised in section 5.5.3, the predictive power of firm's profitability does not diverge from low and high insider ownership firms in the cross-sectional regression analysis. This is contradictory to the conclusion from portfolio analysis, where the profitability premium is positively associated with average insider ownership. Therefore, hypothesis H2 has been rejected.

Using insider ownership as a proxy of governance has limitations in various prospects, as this research has recognised. Though Shleifer and Vishny (1997) argue that firm is performing better with high institutional ownerships because institutions are able to monitor manager behaviour and have an influence in free cash-flow distribution, Chen et al. (2007) find this assert is conditional upon several conditions.

First, institutions may not behave as good-duty supervision as hypothesized in theories. Chen et al. (2007) find only institutions that are independent and focus on long-term investing are more active in their role of supervision. Their further analysis finds that mixing long-term independent institutions with other institution types together distorts the predicting power of institutional ownership to firm performance. The mixed finding of institutional ownership, as this chapter has presented, may result from such phenomenon.

Second, the source of institutional ownership provided by Thomson Reuters has potential quality issues. The Thomson Reuters 13-F filling database is the original source calculating institution ownership. However, Asquith et al. (2005) observe that the ownership could over 100% for some firms in a specific period. Though firms that are under heavy short-selling may result in a scenario that institutional ownership is over 100% because all common shares are held by institutions and are short-sold. But the number of outliers is apparently much more than such an extreme case. Recently the Wharton Research Data Services (WRDS) has suspended the subscription of Thomson Reuters 13-F filling database for similar reasons (visit the web-link[3] in the footnote for details). This research recognises this notice and is ready to re-estimate the institutional ownership once high-quality institutional ownership database is available.

Third, this explanatory power of institutional ownership may result from other channels. Because the presence of institutions has also improved market efficiency by creating liquidity and reduces the bid-ask spread, the institutional ownership is also being viewed as a proxy of liquidity effect in literatures such as Ali et al. (2003) and Conrad et al. (2014). Since the channels of pricing stock returns are various and are largely under discovery, a significant relation between institutional ownership and profitability. Therefore, further analysis that could identify the co-founding effect of the two possible explanations is required.

Why do firm-level analysis and portfolio-level analysis arrive at such different conclusions? Lilienfeld-Toal and Ruenzi (2014) argue that high levels of stock holding incentivise insiders, leading them to behave as value-creating shareholders. Insider ownership, therefore, does not represent a missing risk factor within asset pricing theory, but rather may contain information related to a firm's other fundamental characteristics. In cases like this, insider ownership is a proxy of existing firm fundamental information, which explains why the interaction effect is no longer significant when a firm's size, book-to-market ratio, and past returns are included in the regression. For the portfolio analysis, as stocks are independently

[3] https://wrds-www.wharton.upenn.edu/pages/support/research-wrds/research-note-regarding-thomson-reuters-ownership-data-issues/

sorted by profitability and insider ownership, the portfolio subsumes firms' idiosyncratic risks. In such case, the portfolio analysis creates a clearer picture of the relationship between the two factors of interest than cross-sectional analysis.

6 PROFITABILITY PREMIUM, FIRM'S DISTRESS RISK AND STOCK RETURNS

6.1 Introduction

Two profitability-related factors, distress risk and profitability, play a significant role in understanding the cross-sectional stock return and the universe of asset pricing. Distress risk is measured as the probability of whether a firm is expected to become financially distressed, suffering from bankruptcy, default, or being performance-related delisted from the exchange. It has drawn considerable scholarly attention, as distress risk has been raised as an explanation for several well-documented anomalies by researchers, including Fama and French (1993), Kapadia (2011), and Avramov et al. (2013). Firm profitability, measured as the ratio of a firm's gross profits (or operating profits) over its total assets, are drawn directly from a firm's financial report. It has strong power in terms of determining stock returns. Novy-Marx (2013) argues that the variation of firm's profitability is an underlying source of value premiums. These findings contribute to understanding market efficiency by their power to predict stock returns, and it is possible to explain several other market anomalies by using these factors within analyses.

The pricing power of a firm's profitability, according to Novy-Marx (2013), is because profitability represents a firm's expected cash flow which determines the firm's rate of return demanded by investors. This judgement originated from the conceptual justification of Fama and French (2008), who argue that variations in firms' cross-sectional profitability, given the same stock prices, cause the different rate of stock returns. In this chapter, following the same logic, investors should also take distress risk into account, as distress risk means that the expected cumulative dividends displays a probability that cannot be fully claimed by equity investors. When a firm is in distress, the U.S. bankruptcy acts mean that equity investors have only a residual claim to the firm's value. Therefore, distress risk alters the expected stock return according to the potential loss of expected earnings, and high distress risk firms are historically associated with lower profitability and reluctant to pay dividends, as studied by Altman (1968). Also, this variation of distress risk may help to explain the profitability premium, the return pattern that is associated with firm's profitability ratio. The relation between firm's profitability and financial distress, according to Fama and French (2000), can be concluded as follows: "… and the prospect of failure or takeover gives firms with low profitability incentives to allocate asset to more productive uses" (p.161).

Interestingly, there has been no research investigating the relationship between firm profitability and distress risk and their interactions in terms of explaining the variation of returns across stocks. This is perhaps surprising, as the existing literature has documented the relationship between them consistently. Altman (1968) finds that firm' past profitability helps investors distinguish between the healthy firm and distressed firms, and further proposes a discriminating model that can be used to measure a firm's distress risk using profitability alongside several firm specifications. This finding is further examined and supported by Campbell et al. (2008), who find that a firm's past profitability has predictive power for the likelihood of financial distress up to 120 months ahead. On the other side, Fama and French (2006) document the fact that a firm's one-year lagged distress risk, measured by Ohlson's O-score, has predictive power for the firm's expected profitability in a cross-sectional analysis. These conclusions suggest that both return premiums are in fact driven by common factors embedded in distress risk and profitability.

In line with these justifications, this chapter adopts three financial distress measures to test whether the profitability anomaly can be explained via the correlation between the two factors. The three distress risk measures are chosen from available most-cited literature: Firm's failure probability (Campbell et al. 2008), firm's Distance-to-Default (Bharath and Shumway, 2008), and Firm's O-score (Franzen et al. 2006). These measures are representative as they are commonly used in asset pricing literatures such as Novy-Marx (2013), Hou et al. (2015), Pointiff and McLean (2016), and their validity in predicting financial distress risk has been scrutinised in Blöchlinger (2012) and Charitou et al. (2013). Before these variables are used to conduct analysis, all three distress risk measures are cross-checked with literature to ensure the measure is representing a credible replica of the targeting literature. Also, the measure of firm's gross profitability (Novy-Marx ,2013) and operating profitability (Ball et al. 2015) are cross-checked as well, in which section 5.4.2 has presented the replication in detail.

There is a convincing evidence arising from portfolios sorted on two profitability measures where a variation of distress risk exists across all portfolios. Particularly, in low profitability portfolios where the average return monotonically declines with the increase of distress risk, creating a significant variation of portfolio returns between high and low profitability firms. The firm-level analysis confirms the existence of an interaction effect between the two factors, and the profitability premium is more pronounced in high distress risk firms. These findings contribute to work combining the two pricing powers into a single framework.

This chapter presents novel findings of the profitability anomaly in relation with firm's distress risk. When profitability is present in the ten decile portfolios, all three distress risk measures monotonically decline with the increase in average gross profitability (measured as $GPTA$) as well as in operating profitability (measured as $OPTA$). Ranking stocks by profitability and distress risk independently further emphasises this relationship by showing the profitability premium, measured either as the excess return over the one-month T-bill rate or the Fama-French three-factor alpha, generally increases as the portfolio's average distress risk increases. The difference of average profitability premium between low and high distress risk firms could be as high as 1.30% per month. These findings are further supported by firm-level analysis, where Fama-MacBeth regressions show a significant interaction effect between a firm's profitability and distress risk in terms of pricing expected stock returns, and the explanatory power of firm's profitability is significantly different among low and high distress risk firms.

6.2 Hypothesis Development

In the attempt of understanding characteristics of firm's profitability, Fama and French (2006) find firm's strength (ability to survive), measured as O-score, a bankruptcy predictor, has significant power that negatively determined firm's profitability ratio, measured as firm's earning to total assets. This is consistent with the judgement of Altman (1984) who argues that financial distress occurs with indirect costs to firm's profits. In exploring how financial distress affects firm's performance, Altman (1984) further finds that firm's expected profits, measured by ten-year average profits, are reduced by 6.6% to 10.5% from three years before the firm is distressed, representing the cost of financial distress implied in firm's distress risk. This is in line with the legal requirement: Due to legislation requirement that distressed firms are not allowed to pay dividends, investors will receive less payoff as expected in such circumstance.

Though one might argue that since firm's distress risk and profitability is interactive, the finding of Fama and French (2006) does not represent a true economic relationship that firm's profitability is affected by the historical information. Opler and Titman (1994) address this issue by using distress industry as a dummy variable controlling its effect on firm's profitability, and they find financial distress still affects firm's performance, including sale growth and profitability, as distressed industry is suffering severe asset sale declining, employment loss and negative investment growth, which is in line with the argument of Altman (1986). Thus, this chapter investigates the return premium caused by firm's profitability by considering whether firm's distress risk can better characterise them. The lead-lag effect of firm's distress risk and profitability in the literature suggests the following hypothesis that this chapter is going to test.

If the profitability premium is solely driven by firm's profitability, then the lead-lag effect in profitability and distress risk shall be observed as a positive relation between firm's distress risk and profitability premium. Empirically, in the portfolio-level analysis, one should expect the profitability premium varies in accordance with portfolio's average distress risk.

Hypothesis 1: *The profitability premium is positively associated with firm's distress risk.*

The relationship of profitablility premium and firm's distress risk can only be true if the profitability premium is driven by the profitability itself, instead of other factors behind the profitability. Thus this research has designed a cross-sectional test, to discover whether the pricing power of profitability exists in the firm level analysis, and to what extent this pricing power is divergent by firms with high/low distress risk. In this test, it is expected that the pricing power of a firm's profitability positively and significantly determines the cross-sectional stock returns, and the pricing power is higher in firms with higher distress risk against low distress risk firms.

Hypothesis 2: *The predicting power of firm's profitability to the cross-sectional stock return is significantly different in firms with low/high distress risk.*

6.3 Data and Summary Statistics

This chapter is using a sample of 1980-2015 non-financial U.S. firms' common shares traded on NYSE, AMEX, and NASDAQ. The dataset does not contain firm data prior to 1980 due to the lack credibility data in estimating firm's distress risk, as mentioned by Campbell et al. (2008). Data is obtained from Compustat Annual file, Compustat Quarterly file, CRSP monthly stock file, and the combined dataset is used to calculate variables listed below. Delisting returns are taken from CRSP where available. If a delisting return is missing, but it is recognised as performance-related delisting event in CRSP (CRSP Delisting code 400, 550-585), a return of -30% is used the same way as Shumway and Warther (1999) and Bharath and Shumway (2008) did. Based on the convention in asset pricing studies, firms with SIC codes 6000-6999 are removed, along with stocks that are not common shares traded on the NYSE/AMEX/NASDAQ. Firm's market value of equity (ME), book-to-market equity ratio ($BEME$) and 12-month momentum (MOM12) are estimated following the methodology in section 4.3, and any observation missing value of such variables in given month does not remain in the database.

The final dataset contains 1,393,517 firm-month observations across June 1980-December 2015 that meet all the above criteria and have at least one valid distress risk measure.

6.3.1 Distress risk measures

Failure Probability ($\boldsymbol{FP}$): Campbell et al. (2008, 2011) find that their hazard model presents better predicting power than most existing distress risk models. It is measured by time-weighted firm net income to market value of total assets, time-weighted stock excess returns, market-to-book ratio, debt-to-total assets, price, return volatility and relative size to the S&P 500 market. The measure has been widely adopted in recent research (Conrad et al. 2014; Stambaugh et al. 2016). The detailed estimation is presented in section 4.3.1.

Distance-to-Default ($\boldsymbol{DD}$): Vassalou and Xing (2004) first introduced this measure as a way to understand size and value premiums in cross-sectional stock returns. Campbell et al. (2008, 2011) and Bharath & Shumway (2008) also contributed to the model by setting some parameters as fixed values.

The importance of estimating of DD in the context of Bharath and Shumway (2008) methodology lies in the market value of firm's assets as well as its volatility in the matching period of its debt structure, which are assumed in a framework of European call option and the implied value is derived by the option pricing model. The probability of financial distress, P, is equal to

$$P = \mathrm{N}\left(-\frac{\ln(\frac{V}{F})+(\mu-0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}\right) \text{(6.1)}$$

$$\sigma_V = \frac{\sigma_E E}{(E+F)} \text{(6.2)}$$

$$\sigma_E = \left(\frac{V}{E}\right)\frac{\partial E}{\partial V}\sigma_V \text{(6.3)}$$

where

$$\sigma_E = Historical\ return\ on\ equity$$
$$\sigma_V = Volatility\ of\ asset$$

$$E = \ The\ market\ value\ of\ the\ firm's\ equity$$
$$F = \text{The face value of the firm's debt}$$
$$V = Current\ market\ value\ of\ asset$$
$$\text{r} = \text{The ongoing risk} - \text{free rate}$$
$$\mu = Estimate\ of\ the\ expected\ annual\ return\ of\ the\ firm's\ assets$$
$$T = Debt\ maturity, set\ as\ 1\ year$$

The estimation of σ_E theoretically follows the third equation. However, for the convenience of calculation, Bharath and Shumway (2008) use the equation (6.2) equation to gain an approximate value of σ_V. The value of firm's debt is the sum of firm's debt in current liabilities (Compustat annual file item $dlct$) and long-term debt (Compustat annual file item: dlt) with a weight of 50%. Moreover, the parameter μ is equal to firm's cumulative return over the previous year before estimating.

$\boldsymbol{O-score}$**:** A factor model measuring a firm's distress risk, invented by Ohlson (1980). Dichev (1998) as well as Griffin and Lemmon (2002) find it to be related to market risk and has pricing power to determine expected stock returns. This measure is further polished by Franzen et al. (2007) by considering how a firm's R&D expenditure affects a firm's capital structure and future earnings and, ultimately, the firm's distress risk. Ultimately, the firm's distress risk is measured as O-score. This research follows the methodology of Dichev (1998), Franzen et al. (2007) and Blöchlinger (2012) by taking the O-score to predict firm's distress risk. High O-score firm means the firm is riskier in terms of being financially distressed than low O-score firms.

The O-Score model is calculated as follows:

$$O - score = -1.32 - .407 \times Size + 6.03 \times \frac{Liabilities}{Total\ assets} - 1.43 \times \frac{Working\ Capital}{Total\ assets} + 0.0757 \times \frac{Current\ Liabilities}{Current\ Assets} - 2.37 \times \frac{Net\ income}{Total\ assets} - 1.83 \times \frac{Operating\ Funds}{Total\ Liabilities} + 0.285 \times Dummy_{Past\ performance} - 1.72 \times Dummy_{Net\ assets} - 0.521 \times Adjust_{ratio} \quad (6.4)$$

where $Size$ is the log of total assets (Compustat Annual File item at); $Working\ Capital$ is firm's current assets (Compustat Annual File item ca); $Current\ Liabilities$ is firm's current liabilities (Compustat Annual File item cl); $Operating\ Funds$ is firm's pre-tax income (Compustat Annual File item pi) plus depreciation (Compustat Annual File item dp) $\text{Dummy}_{Past\ performance}$ equals 1 when the firm has negative net income (Compustat Annual File item ni) in the 2 prior years, 0 else; and $\text{Dummy}_{Net\ assets}$ is 1 if firm's total assets minus total liabilities (Compustat Annual File item lt) is less than zero, 0 else.

$Adjust_{ratio}$in equation (6.4) captures the effects of adjustments to the estimation, which is represented by

$$Adjust_{ratio} = \frac{net\ income_t - net\ income_{t-1}}{net\ income_t + net\ income_{t-1}} \quad (6.5)$$

6.3.2 Summary statistics

To deliver a comparable result with earlier chapters, this chapter also estimates firm's gross profitability ($GPTA$), operating profitability ($OPTA$), size, book-to-market ratio and momentum variables as the method introduced in section 5.3. The final dataset drops any firm-month observation that 1) has missing values of $GPTA$ at June-end; 2) has missing values of $OPTA$ at June-end; 3) has missing values of ME at December-end in the last year; 4) has missing value of BE at June-end; 5) has missing values of stock price at June-end.; 6) has no valid distress risk measure at June-end. This leaves 1,175,825 firm-month observations that meet all criteria. Compared with the dataset used in Chapter 5, there is a reduction of dataset volume by about 20%, due to the dataset used in this chapter requires at least one valid measure of firm's distress risk at the end of June, which requires substantial accounting information from firm's financial reports, where missing values on specific factors sometimes take place.

Table 29 reports the time-averaged cross-sectional summary statistics and Spearman's rank correlation between all variables. In line with Altman (1968), Ohlson (1980), Shumway (2001), as well as Campbell et al. (2008), all distress risk measures are negatively correlated with firm's profitability. Three distress risk measures are positively correlated with each other with a correlation coefficient of 43.0%-46.3%, a quantitatively comparable value implying these variables value distress risk with similar magnitude, though the estimation of each distress risk measure is distinctive.

Table 31 Summary statistics of firm's profitability, distress risk and firm characteristics

The matrix below gives the time series-averaged summary statistics and Spearman's rank correlation between the main variables. GPTA is the gross profitability of total assets following Novy-Marx (2013). OPTA is the operating profitability of total assets following Ball et al. (2015). ME is the market capitalisation in million US dollars. BE/ME is the book-to-market ratio following Davis and the Fama and French (2000) estimation. Three distress risk measures are: 1) DD is the Distance-to-Default following Bharath and Shumway (2008); 2) O-score measured as Franzen et al. (2007); 3) Failure Probability (FP) as Campbell et al. (2008). Other considered variables are capital expenditure to total assets, cash flow to total assets, debt to assets and R&D to total assets. The dataset is composed based on all firm-month observations from June 1980 to December 2015, a total month of 426.

Variable	GPTA	OPTA	ME	BEME	DD	O-Score	FP	Capital Exp./at	Cash/at	Cash flow/at	Debt/at	R&D
Mean	0.411	0.118	1604.880	0.519	0.086	-1.883	0.084	0.068	0.170	0.011	0.228	0.077
P1	-8.056	-80.500	0.128	-74.134	0.000	-267.993	0.000	-0.152	-0.018	-17.092	0.000	-0.382
Median	0.369	0.139	92.929	0.546	0.002	-2.661	0.030	0.044	0.088	0.064	0.188	0.036
P99	4.853	5.847	715599	1263.100	1.000	921.460	5.001	2.354	1.000	3.321	6.789	10.755
SD	0.278	0.299	10740	30.785	0.206	8.416	0.209	0.081	0.200	0.275	0.233	0.146
SKEW	0.992	-135.744	21.405	-214.432	2.616	42.391	7.995	3.867	1.640	-13.667	3.420	16.451
	GPTA	OPTA	ME	BEME	DD	O-Score	FP	Capital Exp./at	Cash/at	Cash flow/at	Debt/at	R&D
GPTA												
OPTA	0.535											
ME	-0.044	0.352										
BEME	-0.080	-0.132	-0.283									
DD	-0.082	-0.343	-0.546	0.218								
O-Score	-0.179	-0.436	-0.447	0.021	0.463							
FP	-0.190	-0.386	-0.124	-0.007	0.461	0.430						

(Continued)

(Continued)											
Capital expenditure/at	0.131	0.268	0.100	-0.046	-0.093	-0.059	-0.188				
Cash/at	-0.024	0.016	0.067	-0.204	-0.192	-0.143	-0.253	-0.078			
Cash flow/at	0.379	0.740	0.387	-0.082	-0.390	-0.478	-0.362	0.271	-0.075		
Debt/at	-0.173	-0.163	-0.068	0.004	0.321	0.374	0.365	0.002	-0.450	-0.150	
R&D/at	0.076	0.183	-0.053	-0.233	0.022	-0.014	-0.065	-0.058	0.375	-0.129	-0.284

6.4 Profitability Premium and Distress Risk

6.4.1 Gross profitability premium and distress risk

Stocks in the beginning of July of every year during sample period (1980-2015), are independently sorted by firm's profitability and by distress risk, and split into quintiles. Twenty five portfolios are constructed based on the intersection of the two factor's quintile breakpoints, and these portfolios are held for one year. Firm profitability is measured by gross profitability ($GPTA$) and operating profitability ($OPTA$) respectively, and both are calculated based on the previous fiscal year's annual report. Distress risk is measured by firm's failure probability (FP), Distance-to-Default (DD), and O-score ($O-score$) respectively. To maintain consistency with the literature, the DD and $O-score$ are calculated based on information known at the end of June, while FP is taken from the value at the beginning of January. This means that all distress risk variables used in the portfolio analysis have at least a one-month lag to the date of portfolio formation. All firms without valid profitability and distress risk proxy or that contains missing data required to compute firm's size, book-to-market ratio, or past year's returns are dropped before forming portfolios.

The profitability premium from buying high profitability stocks and shorting low profitability stocks ($High-Low$ portfolio) remains strong even after controlling for a firm's distress risk. For the stock group ranked by $GPTA$ and FP, the value-weighted monthly $FF-3$ alpha is 0.432%, 0.295%, 0.543%, 1.365%, and 1.702%

per month from low to high distress risk quintile. The premium is statistically significant at the 5% level for four out of five distress risk quintiles, which suggests that the profitability anomaly is not explainable by common risk factors that are embedded in the $FF-3$ model.

The profitability anomaly tends to be less significant in the low distress risk quintiles, especially when using the value-weighted Fama-French 3-factor alpha, which in the second quintile is insignificant (t=1.46). This suggests that, although controlling for distress risk, the profitability premium is still significant in most quintiles and abnormal returns seemingly cluster in the high distress risk quintiles. The cluster emerges with the increase of average distress risk suggesting that further supporting evidence should be sought. The distress risk premium seems concentrated within the lower $GPTA$ quintiles, where value-weighted portfolio monthly returns are significant (t=-4.62). Since low profitability firms are less able to survive in financial distress (Altman, 1968), this result is consistent with earlier literature.

When distress risk is proxied by $O-score$, the profitability premiums across remain significant in most $O-score$ quintiles. From the lowest distress risk quintile to the highest, the average profitability premiums are 0.702%, 0.815%, 1.035%, 0.903%, and 1.847% per month. All results are statistically significant except for the lowest $O-score$ quintile (t=1.69), which suggests that the positive profitability premium is robust and tends to increase with distress risk. The upward trend of profitability premiums related to distress risk remains observable, and features strong t-statistics.

When distress risk is measured by Distance-to-Default (DD), the $GPTA$-DD sorted portfolios record average monthly equal-weighted gross profitability premiums of 0.777%, 1.308%, 1.322%, 1.534%, and 1.329% for low distress risk quintile and each subsequent, all significant at the 1% level. The value-weighted monthly returns generally reduce this premium, particularly in the lowest and highest quintiles of DD, to 0.493%, 1.056%, 1.094%, 0.915%, and 0.550%. Again, the differences between equal-weight and value-weight results provide some evidence that the profitability premium is partially driven by firm size. Only the mid-range DD quintiles have a significant premium, which implies that the distribution of profitability premiums is hump-shaped when controlling for DD.

Portfolios based on long-short DD firms generate negative distress risk premiums as measured by FP and $O-score$. Equal-weighted portfolio returns monotonically increase with a firm's average profitability, with averages at -0.748%, -0.367%, -0.253%, -0.220% and -0.196% per month from low to high $GPTA$ quintiles. However, only the distress risk premium from the lowest $GPTA$ quintile is significant (t=2.19). When these premiums are value-weighted, all returns are statistically significant at the 10% level and they are -0.763%, -1.064%, -0.605%, -0.575%, and -0.706% per month. The value-weighted distress premium no longer has a positive relationship with firm profitability; this conclusion holds even where those premiums are measured as Fama-French 3-factor alphas.

Table 32 Portfolio returns from gross profitability and distress risk double sort

From July 1980 to December 2015, stocks within the same profitability are independently sorted by gross profitability (GPTA) and distress risk proxy and then held for one year. Five portfolios are generated by dividing at every 20% of the profitability spectrum from low to high and at every 20% of the distress risk spectrum. High-Low refers to a portfolio holding the top 20% profitable stocks (High) and shorting the bottom 20% (Low) within the same distress risk quintile or refers to holding good Distress Risk stocks and shorting bad Distress Risk firms within the same profitability quintile. Panel A reports GPTA and failure probability sorted portfolio value weighted average monthly risk-adjusted returns (in percentage terms) by Fama-French 3-factor model and corresponding t-statistics, with Newey-West adjusted standard error, Panel B reports the value-weighted Fama-French 3-factor alphas and corresponding t-statistics of GPTA-Distance-to-Default sorted portfolios, and Panel C reports the same information of GPTA-O-score sorted portfolios.

Panel A. Failure Probability as distress risk measure

Monthly Value Weighted Returns (%)

Failure Prob. (FP)	Low GPTA	2	3	4	High GPTA	GPTA High-Low
Low FP	0.12	0.24	0.17	0.17	0.55	0.43
	(0.44)	(2.09)	(0.81)	(0.73)	(2.46)	(2.88)
2	-0.12	0.05	-0.02	0.34	0.17	0.30
	(-0.43)	(0.41)	(-0.07)	(1.89)	(0.83)	(1.46)
3	-0.16	0.06	-0.05	0.37	0.39	0.54
	(-0.54)	(0.37)	(-0.33)	(2.41)	(2.32)	(2.09)
4	-0.82	0.23	0.30	0.30	0.55	1.37
	(-4.06)	(1.28)	(2.50)	(2.42)	(5.22)	(3.31)
High FP	-1.07	-0.49	0.18	0.36	0.63	1.70
	(-5.40)	(-2.15)	(1.92)	(3.68)	(6.72)	(2.49)
FP High-Low	-1.19	-0.73	0.01	0.19	0.08	
	(-4.62)	(-2.42)	(0.79)	(1.54)	(1.40)	

(Continued)

(Continued)

Panel B. Distance-to-Default as distress risk measure

Monthly Value Weighted Returns (%)

Distance-to-Default (DD)	Low GPTA	2	3	4	High GPTA	GPTA High-Low
Low DD	-0.49	-0.09	0.06	0.32	0.42	0.91
	(-1.58)	(-0.71)	(0.53)	(2.90)	(4.40)	(3.83)
2	-1.13	-0.26	0.18	-0.22	0.11	1.24
	(-4.56)	(-1.80)	(1.43)	(-1.52)	(0.66)	(4.32)
3	-1.44	-0.58	-0.43	-0.10	-0.24	1.21
	(-4.68)	(-3.33)	(-2.39)	(-0.53)	(-1.47)	(3.89)
4	-1.36	-0.71	-0.63	-0.37	-0.34	1.02
	(-3.85)	(-3.58)	(-3.02)	(-1.82)	(-1.62)	(3.17)
High DD	-1.86	-1.60	-1.29	-0.99	-1.06	0.80
	(-3.15)	(-5.11)	(-3.83)	(-3.08)	(-2.82)	(2.50)
DD High-Low	-1.37	-1.51	-1.35	-1.31	-1.49	
	(-2.22)	(-4.79)	(-5.03)	(-3.78)	(-4.66)	

Panel C. O-score as distress risk measure

(Continued)

(Continued)

Monthly Value Weighted Returns (%)

O-Score	Low GPTA	2	3	4	High GPTA	GPTA High-Low
Low O-Score	-0.38	0.18	0.23	0.15	0.33	0.70
	(-2.08)	(1.19)	(2.03)	(1.47)	(2.94)	(3.12)
2	-0.34	-0.03	0.19	0.18	0.47	0.82
	(-2.2)	(-0.3)	(1.87)	(1.71)	(3.47)	(3.30)
3	-0.63	-0.06	-0.28	0.23	0.40	1.04
	(-3.68)	(-0.51)	(-1.62)	(1.63)	(3.03)	(4.08)
4	-0.71	-0.70	-0.38	-0.00	0.20	0.90
	(-3.13)	(-3.83)	(-2.15)	(-0.03)	(1.11)	(4.01)
High O-Score	-1.96	-1.68	-1.13	-0.67	-0.11	1.85
	(-8.14)	(-5.04)	(-4.34)	(-2.72)	(-0.46)	(4.35)
O-Score High-Low	-1.58	-1.85	-1.36	-0.82	-0.43	
	(-4.79)	(-3.48)	(-4.06)	(-3.88)	(-2.13)	

6.4.2 Operating profitability premium and distress risk

Using the same portfolio analysis method as used in the $GPTA$-Distress risk double sorts, stocks are independently sorted by their operating profitability ($OPTA$) and a proxy of distress risk into five quintiles to investigate premiums from the resulting 25 portfolios.

The monthly average operating profitability premium monotonically increases with a firm's distress risk. When distress risk is proxied by FP, value-weighted portfolio FF-3 alphas are 0.975%, 1.198%, 1.007%, 0.855%, and 1.353% per month from low to high distress risk quintiles. The increasing premium across distress risk quintiles suggests that the profitability premium is positively related to distress risk, as per the $GPTA - FP$ sorted portfolios. The relatively low $OPTA$ premium in the 4^{th} FP quintile is because its premium has been accounted for in Fama-French 3-factors, where the $OPTA$ premium measured as portfolio's excess return increases monotonically with FP. This is in line with Ball et al. (2015) finding that operating profitability carries more pricing power related to firm's size and book-to-market ratio than gross profitability in determining stock returns.

The spread of $OPTA$ long-short portfolio premiums is even wider when distress risk is proxied by the $O - score$. In the lowest $O - score$ quintile, the profitability premium is 0.284% per month with a t-statistic of 1.27, and the monthly premium increases to 0.815% in the 2^{nd} $O - score$ quintile, 0.831% in the 3^{rd} $O - score$

quintile and finally reaching 1.702% in the highest $O - score$ quintile. The profitability premium is extremely large and significant in the highest distress risk quintile, where it yields over 1.40% per month higher than low distress risk firms. In summation, the tabulated results show the operating profitability premium is only significant at the 5th $O - score$ quintle. This gives further evidence that the profitability premium is strongly affected by distress risk.

Finally, DD is used as a proxy of distress risk and then the stocks are sorted independently by DD and $OPTA$. An interesting pattern is revealed, as the profitability premium no longer remains significant at the highest distress risk quintile. The $High - Low$ profitability portfolio at the 5th distress risk quintile has an average return of 0.376% (t=0.95) value-weighted. Comparing this with the increasing profitability premium from low to high distress risk quintiles in previous results, operating profitability premiums show no such pattern. The portfolio's FF-3 alpha further supports the previous findings by showing no clear pattern of profitability premiums related to distress risk in equal-weighted results. Additionally, no significant profitability premiums in the highest distress risk quintile. Both of these findings are contradictory to previous results.

By looking at portfolio returns in each distress risk quintile, the relation between distress risk and profitability premium is further dissected. The positive relation between operating profitability premium to the average portfolio's distress risk measured by FP and $O - score$ is heavily influenced by low profitability firms. Those firms are grouped as the short-side of long-short portfolio and those firms perform exceptionally low when portfolio's average distress risk is high. The variation of low and high distress risk portfolio returns in the low operating profitability group (the first column of the five-by-five groups) is 0.532% when FP proxies distress risk and is 1.908% when $O-score$ is proxying distress risk. While in the high operating profitability group (the fifth column of the five-by-five groups), the variation of portfolio return is relatively small. These findings imply that the pricing power of firm's profitability may be sensitive to firm's distress risk level.

Table 33 Portfolio returns from operating profitability and distress risk double sort

From July 1980 to December 2015, stocks within the same profitability are independently sorted by operating profitability (OPTA) and distress risk proxy and then held for one year. Five portfolios are generated by dividing at every 20% of the profitability spectrum from low to high and at every 20% of the distress risk spectrum. High-Low refers to a portfolio holding the top 20% profitable stocks (High) and shorting the bottom 20% (Low) within the same distress risk quintile or refers to holding good Distress Risk stocks and shorting bad Distress Risk firms within the same profitability quintile. Panel A reports OPTA and failure probability sorted portfolio value weighted average monthly risk-adjusted returns (in percentage terms) by Fama-French 3-factor model and corresponding t-statistics, with Newey-West adjusted standard error, Panel B reports the value-weighted Fama-French 3-factor alphas and corresponding t-statistics of OPTA-Distance-to-Default sorted portfolios, and Panel C reports the same information of OPTA-O-score sorted portfolios.

Panel A. Failure Probability as distress risk measure

Monthly Value Weighted Returns (%)

Failure Prob. (FP)	Low OPTA	2	3	4	High OPTA	OPTA High-Low
Low FP	-0.52	-0.03	0.22	-0.03	0.45	0.98
	(-2.38)	(-0.12)	(1.43)	(-0.21)	(2.99)	(3.98)
2	-0.89	-0.15	0.08	0.16	0.31	1.20
	(-3.44)	(-0.81)	(0.63)	(1.55)	(3.71)	(3.68)
3	-0.82	-0.37	-0.07	0.08	0.19	1.01
	(-3.45)	(-2.47)	(-0.50)	(0.84)	(1.45)	(2.87)
4	-0.88	-0.32	-0.27	-0.13	-0.02	0.86
	(-3.14)	(-2.47)	(-1.74)	(-0.80)	(-0.10)	(2.73)
High FP	-1.05	-0.82	-0.11	-0.12	0.30	1.35
	(-3.63)	(-3.70)	(-0.55)	(-0.47)	(0.91)	(3.02)
FP High-Low	-0.53	-0.79	-0.33	-0.09	-0.15	
	(-1.60)	(-2.19)	(-1.32)	(-0.26)	(-0.38)	

(Continued)

(Continued)

Panel B. Distance-to-Default as distress risk measure

Monthly Value Weighted Returns (%)

Distance-to-Default (DD)	Low OPTA	2	3	4	High OPTA	OPTA High-Low
Low DD	-0.20	-0.18	0.10	0.20	0.31	0.51
	(-0.65)	(-1.19)	(0.75)	(2.21)	(4.14)	(1.84)
2	-0.84	-0.52	-0.18	0.05	-0.06	0.78
	(-2.63)	(-2.88)	(-1.14)	(0.47)	(-0.39)	(1.96)
3	-1.31	-0.78	-0.49	-0.34	-0.16	1.15
	(-4.50)	(-3.33)	(-3.22)	(-2.10)	(-0.99)	(3.23)
4	-1.74	-0.66	-0.57	-0.59	-0.23	1.51
	(-5.22)	(-3.13)	(-2.79)	(-3.13)	(-1.07)	(3.14)
High DD	-1.65	-1.23	-1.21	-1.55	-1.28	0.38
	(-3.53)	(-3.98)	(-4.32)	(-4.15)	(-3.06)	(0.95)
DD High-Low	-1.45	-1.05	-1.31	-1.75	-1.58	
	(-3.37)	(-3.09)	(-5.23)	(-5.43)	(-4.49)	

Panel C. O-score as distress risk measure

Monthly Value Weighted Returns (%)

O-Score	Low GPTA	2	3	4	High GPTA	GPTA High-Low

(Continued)

(Continued)						
Low O-Score	-0.05	-0.23	0.30	0.11	0.23	0.28
	(-0.24)	(-1.33)	(2.11)	(-4.68)	(2.93)	(1.27)
2	-0.56	-0.18	0.01	0.16	0.26	0.82
	(-2.23)	(-1.34)	(0.05)	(0.91)	(2.68)	(2.77)
3	-0.65	-0.34	-0.14	0.07	0.18	0.83
	(-2.33)	(-2.35)	(-1.14)	(1.90)	(1.25)	(2.44)
4	-0.86	-0.38	-0.39	-0.47	-0.25	0.62
	(-3.31)	(-2.14)	(-2.24)	(0.52)	(-1.27)	(1.69)
High O-Score	-1.96	-1.53	-1.32	-1.21	-0.26	1.70
	(-7.10)	(-5.72)	(-4.68)	(-2.34)	(-1.02)	(5.11)
O-Score High-Low	-1.91	-1.29	-1.61	-1.32	-0.49	
	(-7.00)	(-4.67)	(-5.00)	(-4.03)	(-1.92)	

6.5 Cross-sectional Regression Analysis

6.5.1 Fama-MacBeth regression design

Cross-sectional regression is used to examine further two findings arising from the portfolio analysis: the interaction effect between the profitability anomaly and distress risk; and the fact that the profitability premium is higher where a firm's distress risk is high. A set of cross-sectional regressions is designed such that for each month $t+1$, stock excess return over U.S. one-month T-bill rate, denote $r_i - r_f$, is regressed by firm's profitability and distress risk at month t, along with the product of the two variables, representing their interaction:

$$R_{i,t} - r_{f,t} = \lambda_0 + \lambda_1 Profitability_{i,t-1} + \lambda_2 Distress\ Risk_{i,t-1} + +\boldsymbol{\lambda_3}'\boldsymbol{X_{i,t-1}} + \varepsilon_{i,t} \quad (6.6)$$

Where

$$\boldsymbol{X_{i,t-1}} = \begin{bmatrix} lnME_{i,t-1} & lnBM_{i,t-1} & MOM12_{i,t-1} \end{bmatrix} \quad (6.7)$$

Following the logic used in the portfolio analysis, a test is also performed to check whether the interaction effect is caused by omitted risk variables. To control the omitted risk variable issue, following Fama and French (2008), $lnME$, lnBM, and $MOM12$ are used as control variables. The proxy of distress risk, failure probability (FP), Distance-to-Default (DD), and O-score ($O - score$), respectively are used in the regression analysis.

To ensure all cross-sectional analyses are comparable, before performing the regression, all observations that have missing values of $lnME$, $lnBM$, or $MOM12$ are dropped. That means that the same dataset is used for regressions with and without the control variables. Thus, the total number of observations is consistent between the two groups where the same profitability and distress risk proxy is used. To address outlier observations with extreme value, all variables are winsorised at 1 percentile level. If an interaction effect exists, a statistically significant coefficient $\hat{\lambda}_3$, should appear within the regression. Furthermore, if such an interaction effect is not due to correlation with existing risk factors, $\hat{\lambda}_3$ should remain significant after control variables are included.

6.5.2 Does distress risk explain the profitability anomaly?

To set a benchmark that could compare results with various profitability measures and distress risk measures, firm's monthly excess return is regressed solely by the firm's profitability variable, and solely by the firm's distress risk variable. One would expect that the coefficient sign of $Profitability_{i,t}$ should keep being positive and significant, and the coefficient sign of $Distress_{i,t}$ should keep being negatively significant. Those results are disclosed in the first and second regression in Table 32-Table 37. The coefficient of $GPTA$ is 1.062 in Table 32, and is 1.182 in Table 33, 1.156 in Table 34, and all coefficients are statistically significant with a t-statistic over 5.0. The coefficient of $OPTA$, is 2.478 in Table 35, and is 2.793 in Table 36 and 2.390 in Table 37. All of which have a t-statistics over 4.5. These consistent results verify that the analyses does not suffer from a biased sample due to missing values of distress risk measures, and the significance of two profitability variables are in line with the finding of Ball et al. (2015). Meanwhile, three distress risk measures are all negatively priced in the cross-sectional expected returns with t-statistics over 2.0. This is also in line with earlier findings of the distress risk puzzle such as Campbell et al. (2008) and Bharath and Shumway (2008). The value of coefficient and significance of both firm's profitability and distress risk measures is even more pronounced when $lnME$, $lnBM$, and $MOM12$ enters into regression, suggesting the pricing power of firm's profitability and distress risk is beyond these well-documented firm characteristics.

If the profitability anomaly is simply a tautology of the distress puzzle, then the coefficient may lose its significance when firm's profitability and distress risk enter into regression simultaneously. The third regression in Table 32-Table 37 tests such hypothesis by regressing firm's excess return with firm's profitability and distress risk. In the $GPTA - FP$ group, the coefficient of $GPTA$ is increased about 8 basis points while the coefficient of FP decreases significantly by 97 basis points, and its significance drops proportionally. The $OPTA - FP$ group has a similar pattern as $GPTA - FP$, where the coefficient of FP declines 129 basis points after the $OPTA$ variable enters regression. A more severe drop of significance emerges where distress risk is measured by $O - score$. The coefficient of $O - score$ is marginally significant with $GPTA$, with a t-statistics of 1.79, and the coefficient is no longer significant with $OPTA$. However, the significance of DD variable remains stable co-existing with firm's profitability, where $GPTA$ and DD are all statistically significant at 1% level and so does in $OPTA$ and DD. In short, the significance of profitability is not absorbed by distress risk variable.

To test whether the profitability premium is mostly clustered among high distress risk firms, the distress risk variable is replaced with a dummy variable, which represents when a firm's distress risk is above the average value of the entire market. Thus, the interaction effect proxy is either zero or equal to the value of $Profitability_{i,t-1}$. Cross-sectional regressions are run as previously. If distress risk contributes to the power of a firm's profitability, then the average coefficient of the interaction variable will represent the fraction that high distress risk accounts for.

$$R_{i,t} - r_{f,t} = \lambda_0 + \lambda_1 Profitability_{i,t-1} + \lambda_2 Distress\ Risk_{i,t-1} + \lambda_3 Interaction_{i,t-1} + \boldsymbol{\lambda_4}' \boldsymbol{X_{i,t-1}} + \varepsilon_{i,t} \quad (6.8)$$

Where

$$\boldsymbol{X_{i,t-1}} = \begin{bmatrix} lnME_{i,t-1} & lnBM_{i,t-1} & MOM12_{i,t-1} \end{bmatrix} \quad (6.9)$$

Due to the form of $Distress\ risk$ has changed, the value of average coefficient of distress risk dummy does not directly comparable with regressions conducted using actual value. However, the significance of distress risk variable should be quantitatively similar, and it is in the analyses. The average adjusted R^2 is quantitatively similar also, ranging from 0.7% to 1.2% for regressions without control variables and 2.7% to 3.1% for regressions with control variables.

The interaction of $GPTA$ and FP shows that high distress risk accounts for a fraction of gross profitability predicting power. The value of $\hat{\lambda}_3$ is 0.408 with control variables, and is 0.540 without control variables. Both results are statistically significant at the 1% level. This implies that the average return from high profitability and high distress risk firms is higher than the average return from low distress risk but high profitability firms. For the $GPTA - O - score$ sample, the interaction effects shows the predicting power of $GPTA$ is more pronounced in high $O - score$ firms, but the variation is correlated with other firm characteristics, as the significance of interaction is positive but less significant When $lnME$, $lnBM$ and $MOM12$ are added in the regression as control variables. The interaction of $OPTA - FP$ has coefficients of 2.025% and 1.081% per month and both are statistically significant. However, there is no significant return cluster at high distress risk for $OPTA - O - score$ groups; the coefficient of interaction variable here is not significant. The interaction effect has no significant explanatory power for either the $GPTA - DD$ group or the $OPTA - DD$ group, which is consistent with the interaction effect analysis using actual values. Given that all distress risk measures are highly positive-skewed, using monthly mean values as the threshold for constructing dummy variables, it further supports the findings that the profitability anomaly is concentrated in a small fraction of firms and does not represent a systematic risk that is linearly related to expected stock returns.

Table 34 Regression analysis for gross profitability and failure probability

This table lists Fama-MacBeth regression analysis for gross profitability (GPTA) and distress risk. In every month, each firm's monthly stock return (CRSP code ret) over the one-month Treasury bill rate is regressed by firm profitability, distress risk, and the control variables. All variables, excluding return, are winsorized at the1 percent level. This table presents time-series averages of regression coefficients and Newey-West adjusted t-statistics with 12 lags. The sample period contains observations from July 1980 to December 2015, a total 426 months.

Intercept	GPTA	FP	Interaction	lnME	lnBM	MOM12	Observations	Avg.R2
0.203	1.062***						1175825	0.003
(0.61)	(6.07)							
0.862***		-3.896***					1175825	0.006
(3.35)		(-2.66)						
0.354	1.140***	-2.923*					1175825	0.009
(1.26)	(6.00)	(-1.96)						
0.375	0.989***	-0.483***	0.540***				1175825	0.008
(1.27)	(5.35)	(-2.95)	(2.91)					
0.167	1.374***			0.028	0.509***	0.510**	1175825	0.025
(0.35)	(6.94)			(0.67)	(5.12)	(2.45)		
1.079***		-4567***		-0.013	0.426***	0.445**	1175825	0.025
(2.73)		(-3.46)		(-0.32)	(4.27)	(2.18)		
0.462	1.280***	-3655***		0.005	0.497***	0.407**	1175825	0.029
(1.12)	(6.84)	(-2.93)		(0.14)	(4.94)	(2.06)		
0.441	1.165***	-0.501***	0.408**	0.012	0.507***	0.434**	1175825	0.028
(1.03)	(6.30)	(-3.33)	(2.41)	(0.30)	(5.01)	(2.15)		

Table 35 Regression analysis for gross profitability and Distance-to-Default

This table lists Fama-MacBeth regression analysis for gross profitability (GPTA) and distress risk. In every month, each firm's monthly stock return (CRSP code ret) over the one-month Treasury bill rate is regressed by firm profitability, distress risk, and the control variables. All variables, excluding return, are winsorized at the1 percent level. This table presents time-series averages of regression coefficients and Newey-West adjusted t-statistics with 12 lags. The sample period contains observations from July 1980 to December 2015, a total 426 months.

Intercept	GPTA	DD	Interaction	lnME	lnBM	MOM12	Observations	Avg.R2
0.225	1.182***						889997	0.003
(0.70)	(5.85)							
0.762***		-0.012***					889997	0.005
(2.73)		(-2.92)						
0.268	1.158***	-0.011***					889997	0.008
(0.87)	(5.84)	(-2.61)						
0.375	1.144***	-0.607***	0.210				889997	0.009
(1.27)	(5.62)	(-3.03)	(0.65)					
0.149	1.360***			0.023	0.507***	0.559**	889997	0.027
(0.30)	(6.59)			(0.52)	(5.17)	(2.53)		
0.952**		-0.014***		-0.018	0.443***	0.551**	889997	0.026
(2.17)		(-4.38)		(-0.45)	(4.55)	(2.47)		
0.331	1.328***	-0.012***		0. 002	0.518***	0.504**	889997	0.029
(0.71)	(6.52)	(-4.02)		(0.04)	(5.21)	(2.31)		
0.388	1.336***	-0.618***	0.056	-0.005	0.520***	0.510**	889997	0.030
(0.85)	(6.38)	(-3.87)	(0.18)	(-0.12)	(5.26)	(2.32)		

Table 36 Regression analysis for gross profitability and O-score

This table lists Fama-MacBeth regression analysis for gross profitability (GPTA) and distress risk. In every month, each firm's monthly stock return (CRSP code ret) over the one-month Treasury bill rate is regressed by firm profitability, distress risk, and the control variables. All variables, excluding return, are winsorized at the1 percent level. This table presents time-series averages of regression coefficients and Newey-West adjusted t-statistics with 12 lags. The sample period contains observations from July 1980 to December 2015, for 426 total months.

Intercept	GPTA	O-score	Interaction	lnME	lnBM	MOM12	Observations	Avg.R2
0.297	1.156***						1122397	0.004
(0.93)	(5.87)							
0.697**		-0.073***					1122397	0.005
(2.18)		(-2.62)						
0.288	1.026***	-0.049*					1122397	0.008
(0.87)	(5.28)	(-1.75)						
0.523**	0.772***	-0.368***	0.6352***				1122397	0.007
(1.97)	(4.22)	(-2.62)	(4.05)					
0.321	1.286***			0.004	0.440***	0.510**	1122397	0.025
(0.68)	(6.72)			(0.09)	(4.60)	(2.55)		
0.978**		-0.088***		-0.060	0.315***	0.568***	1122397	0.024
(2.24)		(-3.77)		(-1.63)	(3.27)	(2.76)		
0.434	1.125***	-0.053**		-0.028	0.399***	0.509**	1122397	0.027
(0.97)	(6.16)	(-2.35)		(-0.75)	(4.09)	(2.52)		
0.545	1.078***	-0.251**	0.2686*	-0.014	0.423***	0.506**	1122397	0.027
(1.28)	(5.53)	(-2.05)	(1.76)	(-0.34)	(4.31)	(2.51)		

Table 37 Regression analysis for operating profitability and failure probability

This table lists Fama-MacBeth regression analysis for operating profitability (OPTA) and distress risk. In every month, each firm's monthly stock return (CRSP code ret) over the one-month Treasury bill rate is regressed by firm profitability, distress risk, and the control variables. All variables, excluding return, are winsorized at the1 percent level. This table presents time-series averages of regression coefficients and Newey-West adjusted t-statistics with 12 lags. The sample period contains observations from July 1980 to December 2015, a total 426 months.

Intercept	OPTA	FP	Interaction	lnME	lnBM	MOM12	Observations	Avg.R2
0.379	2.478***						1175825	0.005
(1.09)	(4.65)							
0.862***		-3.896***					1175825	0.006
(3.35)		(-2.66)						
0.502*	2.200***	-2.637**					1175825	0.009
(1.66)	(4.91)	(-2.04)						
0.537*	1.738***	-0.368***	2.025***				1175825	0.009
(1.73)	(4.18)	(-2.62)	(3.88)					
0.692	3.046***			-0.055	0.450***	0.569***	1175825	0.025
(1.51)	(6.92)			(-1.43)	(4.62)	(2.67)		
1.079***		-4.567***		-0.013	00426***	0.445**	1175825	0.025
(2.73)		(-3.46)		(-0.32)	(4.27)	(2.18)		
0.894**	2.816***	-2.997**		-0.066*	0.444***	0.480**	1175825	0.028
(2.23)	(7.35)	(-2.54)		(-1.81)	(4.48)	(2.38)		
0.878**	2.517***	-0.362***	1.081**	-0.062*	0.439***	0.507**	1175825	0.028
(2.12)	(6.46)	(-2.76)	(2.40)	(-1.68)	(4.48)	(2.45)		

Table 38 Regression analysis for operating profitability and Distance-to-Default

This table lists Fama-MacBeth regression analysis for operating profitability (OPTA) and distress risk. In every month, each firm's monthly stock return (CRSP code ret) over the one-month Treasury bill rate is regressed by firm profitability, distress risk, and the control variables. All variables, excluding return, are winsorized at the1 percent level. This table presents time-series averages of regression coefficients and Newey-West adjusted t-statistics with 12 lags. The sample period contains observations from July 1980 to December 2015, 426 total months.

Intercept	OPTA	DD	Interaction	lnME	lnBM	MOM12	Observations	Avg.R2
0.347	2.793***						889997	0.006
(1.00)	(4.80)							
0.762***		-0.012***					889997	0.005
(2.73)		(-2.92)						
0.382	2.678***	-0.008**					889997	0.009
(1.16)	(4.97)	(-2.12)						
0.420	2.530***	-0.469***	0.635				889997	0.010
(1.30)	(4.86)	(-2.97)	(0.84)					
0.645	3.481***			-0.064	0.460***	0.620***	889997	0.027
(1.39)	(7.55)			(-1.61)	(4.88)	(2.76)		
0.952**		-0.014***		-0.018	0.443***	0.551**	889997	0.026
(2.17)		(-4.38)		(-0.45)	(4.55)	(2.47)		
0.796*	3.378***	-0.011***		-0.080**	0.470***	0.570**	889997	0.029
(1.81)	(7.57)	(-3.71)		(-2.11)	(4.92)	(2.58)		
0.855**	3.340***	-0.567***	0.136	-0.085**	0.474***	0.573**	889997	0.030
(1.97)	(7.74)	(-4.35)	(0.19)	(-2.27)	(4.99)	(2.57)		

Table 39 Regression analysis for operating profitability and O-score

This table lists Fama-MacBeth regression analysis for operating profitability (OPTA) and distress risk. In every month, each firm's monthly stock return (CRSP code ret) over the one-month Treasury bill rate is regressed by firm profitability, distress risk, and the control variables. All variables, excluding return, are winsorized at the 1 percent level. This table presents time-series averages of regression coefficients and Newey-West adjusted t-statistics with 12 lags. The sample period contains observations from July 1980 to December 2015, 426 total months.

Intercept	OPTA	O-score	Interaction	lnME	lnBM	MOM12	Observations	Avg.R2
0.458	2.390***						1122397	0.005
(1.35)	(4.77)							
0.697**		-0.073***					1122397	0.005
(2.18)		(-2.62)						
0.464	2.462***	0.007					1122397	0.007
(1.39)	(6.01)	(0.27)						
0.677**	1.044**	-0.278*	2.413***				1122397	0.009
(2.52)	(2.06)	(-1.66)	(2.93)					
0.810*	3.060***			-0.077**	0.396***	0.564***	1122397	0.025
(1.81)	(7.47)			(-2.07)	(4.15)	(2.77)		
0.978**		-0.087***		-0.060	0.315***	0.568***	1122397	0.024
(2.24)		(-3.77)		(-1.63)	(3.27)	(2.76)		
0.796*	3.221***	0.012		-0.075**	0.403***	0.546***	1122397	0.026
(1.83)	(8.78)	(0.56)		(-2.07)	(4.16)	(2.67)		
0.874**	2.665***	-0.081	0.653	-0.079**	0.386***	0.547***	1122397	0.027
(2.29)	(6.21)	(-0.58)	(1.03)	(-2.20)	(4.11)	(2.69)		

6.6 Conclusions

This chapter, together with Chapter 5, outlines the profitability premium and its relations to several firm characteristics, and provides empirical evidence showing how profitability premium relates to another risk factor, firm's distress risk. A significant interaction between firm profitability and distress risk in determining expected stock returns during the 1980 to 2015 period is observed. To verify these findings with reference to the existing literature, several distress risk measures that are used in Franzen et al. (2007) and Bharath and Shumway (2008) research are used. Combining these techniques with Campbell et al.'s (2008) failure probability, this research covers several measurements of distress risk, including accounting-based predictors, market-based predictors, and hybrid predictors. The average distress risks across one-way sorted profitability portfolios are similar, where distress risk is negatively associated with firm's profitability. Thus, the findings of this research are unlikely to be the result of spurious correlations or model misspecification.

The findings support the view that firm profitability and distress risk influence each other, as documented by scholars like Altman (1968) and Olson (1980). Investors interpret high distress risk as a negative impact factor in terms of a firm's future profitability. Thus, the distress risk-expected return relationship is more pronounced in low profitability firms. When a firm's profitability is high, the impact of distress risk is less important, as the positive strong profitability gives sufficient expectation for high dividend payouts, leading to a positive expected return for those stocks. In fact, the $GPTA - FP$ and $OPTA - FP$ portfolio sorts show that, when a portfolio's average profitability is high, investors are willing to take on additional distress risk, although they do demand higher expected returns for such portfolios. The value-weighted returns for portfolios formed by high $GPTA$ and high FP are 1.97% per month, or 1.296% per month for high $OPTA$ and high FP portfolios. Compared to the baseline return of 0.358% per month (see Ball et al. (2015)) for $High - Low\ GPTA$ hedge portfolio returns, controlling for distress risk significantly increases the performance of profitability long-short portfolios.

Additionally, cross-sectional regressions produce findings consistent with portfolio analysis. The interaction effect between profitability and distress risk is positively priced to expected stock returns and is statistically significant in most samples. The pricing power of firm profitability is also partially clustered in high distress risk firms: the difference of the pricing power of profitability variable is at 25% to 43% in high distress risk firms versus low distress risk firms, a statistically significant variation.

The findings suggest several areas for potential future research. Firstly, there is some evidence that distress risk explains a firm's profitability pricing power, but the current results do not allow the details of the mechanism by which the interaction of a firm's profitability and distress risk works to be ascertained in detail. Previous research has suggested economic endogeneity between firm profitability and distress risk, and this has been exploited as a proposed explanation for the empirical results. It is therefore natural to demand a more precise econometric analysis to discover if there is a causality effect between the two factors. This would also allow investigation of whether the term-structure of distress risk, as shown in Table 4 of Campbell et al. (2008), further contributes to the pricing power of profitability.

The second outstanding issue relates to the results found when using Distance-to-Default as distress risk proxy. Here, the measure does not explain the two profitability anomalies: the profitability premium does not concentrate in firms with high DD, and the interaction of profitability and DD is not statistically significant in the cross-sectional regression analyses. One potential explanation is that high DD firms have some characteristics that differ from high FP or high $O-score$ firms. This would reconcile the finding that the average $High-Low$ portfolio returns in the highest distress risk quintile are not significant in the 5-by-5 independent portfolio sorts. Another possible explanation is the bid-ask bonus on penny stocks. Those stocks have high distress risk alongside extreme illiquidity conditions (see Chapter 4). Thus, most research drops stocks that have closing prices below one dollar before conducting analysis.   This may contribute to providing a solution to this issue as penny stocks were retained in the models examined in this chapter to maintain the consistency of the sampling method used by Novy-Marx (2013) and Ball et al. (2015).

7 CONCLUSION

7.1 Findings

This thesis has scrutinised two return anomalies: firm's distress risk and firm's profitability in determining stock returns cross-sectionally. The research seeks to explain stock return premiums that are driven by these factors. The first chapter, *Limit of Arbitrage and the Distress Puzzle* finds the distress risk premium is clustered in stocks of high transaction cost and holding cost. When double-sorting firms are based on these factors and distress risk, the average value-weighted distress premium increases from 0.62% per month to 1.35%-2.17% per month in the top 20% high limit-of-arbitrage effect firms. Furthermore, it is observed that the interaction of distress risk with stock's illiquidity ratio, short-selling constraints and idiosyncratic volatility further characterises the predicting power of distress risk.

The second chapter, *Profitability, Insider Ownership and Cross-sectional Stock Returns,* examines how profitability anomalies are related to firm's insider ownership in terms of determining cross-sectional stock returns in the U.S. market. Portfolio-level analyses discover that firms with lower agency costs, as proxied by various forms of insider ownership, are associated with high expected stock returns, in line with Gompers et al. (2003). Additionaly, firm's insider ownership is positively related to profitability premium in the 1980-2015 U.S. stock market sample. The interactive relationship between firm's profitability and insider ownership can explain stock returns and the profitability premium at stock-level analyses. However, this empirical evidence is sensitive to additional risk factors and sample volume.

The third chapter, *Profitability Premium, Firm's Distress Risk and Stock Returns,* links the two empirical findings by documenting a robust relation between the two pricing factors. This research finds significant interaction effects of firm's profitability as well as distress risk in co-determining stock returns cross-sectional. In line with the findings of Altman (1968) and Fama and French (2006) that firm's past information of profitability predicts future distress and vice versa. It is also found that the predicting power of firm's profitability is partially clustered with firms having high distress risk, in which the difference of the power can be as large as 2.4 standard errors from zero. These findings, combined with earlier chapters, shed a light on exploring the two fundamental pricing factors under a unified framework.

7.2 Limitations

Given the growing literature that questions the research paradigm of empirical asset pricing research, this thesis has some limitations, whilst the best effort has been made to cover potential research bias, and robustness check has been conducted to ensure the coherent of findings. One might argue that the method of Fama-MacBeth (1973) regression overstates the significance of the average slope of tested pricing factors, which is raised by Peterson (2009) who also suggests several empirical techniques to minimize the potential bias in estimating variable's covariance. Besides, all portfolio analyses are constructed using two variables' independent sort method and have not considered the dependent sort methods, which present more meaningful results if researchers are interested in. For example, whether controlling for distress risk can further amplify/weaken the pricing power of profitability ratio.

The empirical findings are also restricted due to the limited availability of data. This particularly affects the results of research in Chapter 5. As noted by Bebchuk et al. (2013), finding a good proxy of agency cost is difficult in terms of two aspects: First, the mechanism how agency cost affects cross-sectional stock returns is still an ongoing debate, where no asset pricing models have been derived to prove the agency cost is covariate with stochastic discount factor. Second, even in the U.S. stock market where academia has investigated for decades, firms with full disclosure of corporate governance status are limited to those listed firms that are indexed by S&P or covered by IRRC. These firms only cover a small fraction of the market. Since the thesis's research object is two market-wide phenomena, the availability of data may restrict the interpretation of empirical findings.

In addition, in Chapter 6 one of the distress risk measures, Distance-to-Default (DD) has no explanatory power to the profitability anomaly, which is contradictory to the proposed hypothesis. It could be arguable that, according to Campbell et al. (2008), DD is a distress risk measurement that is less accurate than logit estimation model. But this argument could stand only if a systematic comparison of those measures is proposed. Another possible explanation is that DD is heavily influenced by short-term stock information, which contains noisy information that distorts the true distress risk information that DD is delivering.

Therefore, the averaged value of DD in a long estimation window is more suitable for tests in annually rebalanced portfolios, or the portfolio could be rebalanced monthly to fit the market condition timely.

Moreover, this thesis has not yet contributed to understanding asset pricing by presenting new asset pricing models. Given the extensive research on investigating the distress puzzle and profitability premium, one might present a multi-factor asset pricing model and compare the explanatory power with other more prestigious models. These discussed limitations could be the topic for future research.

7.3 Future Works

The extension of Chapter 4 *Limit of Arbitrage and the Distress Puzzle* can start with using other distress risk measures such as O-score and Z-score which has been mentioned in the research methodology chapter (See Avramov et al. (2013) and George and Hwang for the discussion of using O-score and Z-score in the asset pricing research). The extension of using other distress risk measures can further depict the whole picture of distress risk and limit of arbitrage and further reduce any potential bias of selecting distress risk proxy.

Future research related to Chapter 5 can test whether alternative interpretation is more suitable to explain the imperfect explanation of the profitability premium and insider ownership. For instance, Edelen et al. (2016) find the relation between institutional ownership to market anomalies is also subject to costly arbitrage and faulty earnings expectations, which are also popular explanations to anomalies in the literature. The change of institutional ownership is better in capturing the behaviour of institutional ownership than the static percentage of shares held by institutions. Besides, one may collect and re-estimate the analysis using additional corporate governance data and blockholder information from other sources. As documented in Chapter 5, the limited availability of this information from EXECUCOMP and Thomson Reuters has restricted the analysis to present robust findings. Moreover, there are other mechanisms that show how governance mechanism affects stock returns. For instance, Hou and Robinson (2006) argue that industry competition may also result in a variation of firm's profitability. Given research like Giroud and Mueller (2011), Abdioglu et al. (2015) have controlled the industry effect to examine the variation of firm's corporate governance. The difference of industry may be an alternative explanation on why insider ownership is related to the profitability premium phenomenon.

Future research related to Chapter 6 can start from modelling the economic relation between distress risk and profitability and incorporating them under a unified asset pricing framework, similar to the way Novy-Marx (2013) adopted a dividend-discount model or the way Garlappi and Yan (2011) or George and Hwang (2010) used a stochastic discount factor model. For the empirical research area, one should address the insignificance of DD in explaining the profitability premium by considering alternative estimating methods to the option-implied model, or using a longer time-averaged DD to avoid random variation in the short-term. Given the finding from Chapter 4 that high distress risk firms are also difficult to arbitrage, the effect of arbitrage limit and size effect should be considered in conducting empirical research in order to present the full picture of the two anomalies.

8 BIBLIOGRAPHY

ABDIOGLU, N., KHURSHED, A. & STATHOPOULOS, K. 2015. Firm innovation and institutional investment: the role of the Sarbanes–Oxley Act. European Journal of Finance, 21, 71-92.

ACHARYA, V. V. & PEDERSEN, L. H. 2005. Asset pricing with liquidity risk. Journal of Financial Economics, 77, 375-410.

AGARWAL, V. & TAFFLER, R. 2008. Comparing the performance of market-based and accounting-based bankruptcy prediction models. Journal of Banking & Finance, 32, 1541-1551.

AGARWAL, V. & TAFFLER, R. 2008. Does financial distress risk drive the momentum anomaly? Financial Management, 37, 461-484.

AGGARWAL, R., SCHLOETZER, J. D. & WILLIAMSON, R. 2016. Do corporate governance mandates impact long-term firm value and governance culture? Journal of Corporate Finance.

ALI, A., HWANG, L.-S. & TROMBLEY, M. A. 2003. Arbitrage risk and the book-to-market anomaly. Journal of Financial Economics, 69, 355-373.

ALTMAN, E., RESTI, A. & SIRONI, A. 2004. Default recovery rates in credit risk modelling: a review of the literature and empirical evidence. Economic Notes, 33, 183-208.

ALTMAN, E. I. 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. Journal of Finance, 23, 589-609.

AMIHUD, Y. 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets, 5, 31-56.

AMIHUD, Y. & MENDELSON, H. 1986. Asset pricing and the bid-ask spread. Journal of Financial Economics, 17, 223-249.

ANG, A., HODRICK, R. J., XING, Y. & ZHANG, X. 2006. The cross-section of volatility and expected returns. Journal of Finance, 61, 259-299.

ANG, A., HODRICK, R. J., XING, Y. & ZHANG, X. 2009. High idiosyncratic volatility and low returns: International and further US evidence. Journal of Financial Economics, 91, 1-23.

ASQUITH, P., PATHAK, P. A. & RITTER, J. R. 2005. Short interest, institutional ownership, and stock returns. Journal of Financial Economics, 78, 243-276.

AVRAMOV, D., CHORDIA, T., JOSTOVA, G. & PHILIPOV, A. 2009. Credit ratings and the cross-section of stock returns. Journal of Financial Markets, 12, 469-499.

AVRAMOV, D., CHORDIA, T., JOSTOVA, G. & PHILIPOV, A. 2013. Anomalies and financial distress. Journal of Financial Economics, 108, 139-159.

BAKER, M. & WURGLER, J. 2006. Investor sentiment and the cross-section of stock returns. Journal of Finance, 61, 1645-1680.

BALI, T. G., ENGLE, R. F. & MURRAY, S. 2016. Empirical asset pricing: the cross section of stock returns, John Wiley & Sons.

BALL, R., GERAKOS, J., LINNAINMAA, J. T. & NIKOLAEV, V. V. 2015. Deflating profitability. Journal of Financial Economics, 117, 225-248.

BANZ, R. W. 1981. The relationship between return and market value of common stocks. Journal of Financial Economics, 9, 3-18.

BASU, S. 1977. Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. Journal of Finance, 32, 663-682.

BEAVER, W.H., 1968. Market prices, financial ratios, and the prediction of failure. *Journal of accounting research*, pp.179-192.

BEBCHUK, L., COHEN, A. & FERRELL, A. 2009. What matters in corporate governance? Review of Financial Studies, 22, 783-827.

BEBCHUK, L. A., COHEN, A. & WANG, C. C. 2013. Learning and the disappearing association between governance and returns. Journal of Financial Economics, 108, 323-348.

BHARATH, S. T. & SHUMWAY, T. 2008. Forecasting default with the Merton distance to default model. Review of Financial Studies, 21, 1339-1369.

BLACK, F. 1972. Capital market equilibrium with restricted borrowing. Journal of Business, 45, 444-455.

BLÖCHLINGER, A. 2012. Validation of default probabilities. Journal of Financial and Quantitative Analysis, 47, 1089-1123.

CAMPBELL, J. Y. 1996. Understanding risk and return. Journal of Political Economy, 104, 298-345.

CAMPBELL, J. Y., HILSCHER, J. & SZILAGYI, J. 2008. In search of distress risk. Journal of Finance, 63, 2899-2939.

CAMPBELL, J. Y., HILSCHER, J. D. & SZILAGYI, J. 2011. Predicting financial distress and the performance of distressed stocks. Journal of Investment Management 9, 20.

CARHART, M. M. 1997. On persistence in mutual fund performance. Journal of Finance, 52, 57-82.

CHAN, K. & CHEN, N. F. 1991. Structural and return characteristics of small and large firms. Journal of Finance, 46, 1467-1484.

CHARITOU, A., DIONYSIOU, D., LAMBERTIDES, N. & TRIGEORGIS, L. 2013. Alternative bankruptcy prediction models using option-pricing theory. Journal of Banking & Finance, 37, 2329-2341.

CHAVA, S. & JARROW, R. A. 2004. Bankruptcy prediction with industry effects. Review of Finance, 8, 537-569.

CHAVA, S. & PURNANANDAM, A. 2010. Is default risk negatively related to stock returns? Review of Financial Studies, 23, 2523-2559.

CHEN, N.-F., ROLL, R. & ROSS, S. A. 1986. Economic forces and the stock market. Journal of Business, 383-403.

COCHRANE, J. H. 2005. Asset Pricing, vol. 1. Princeton University Press, Princeton, NJ.

COMMITTEE, N. P. 2013. Understanding Asset Prices.

CONRAD, J., KAPADIA, N. & XING, Y. 2014. Death and jackpot: Why do individual investors hold overpriced stocks? Journal of Financial Economics, 113, 455-475.

CORE, J. E., HOLTHAUSEN, R. W. & LARCKER, D. F. 1999. Corporate governance, chief executive officer compensation, and firm performance. Journal of Financial Economics, 51, 371-406.

CREMERS, K. & NAIR, V. B. 2005. Governance mechanisms and equity prices. Journal of Finance, 60, 2859-2894.

CREMERS, M. & FERRELL, A. 2014. Thirty years of shareholder rights and firm value. Journal of Finance, 69, 1167-1196.

D'AVOLIO, G. 2002. The market for borrowing stock. Journal of Financial Economics, 66, 271-306.

DA, Z. & GAO, P. 2010. Clientele change, liquidity shock, and the return on financially distressed stocks. Journal of Financial and Quantitative Analysis, 45, 21.

DAH, M. A., FRYE, M. B. & HURST, M. 2014. Board changes and CEO turnover: The unanticipated effects of the Sarbanes–Oxley Act. Journal of Banking & Finance, 41, 97-108.

DANIEL, K., HIRSHLEIFER, D. & SUBRAHMANYAM, A. 1998. Investor psychology and security market under-and overreactions. Journal of Finance, 53, 1839-1885.

DAVIS, J. L., FAMA, E. F. & FRENCH, K. R. 2000. Characteristics, covariances, and average returns: 1929 to 1997. Journal of Finance, 55, 389-406.

DICHEV, I. D. 1998. Is the risk of bankruptcy a systematic risk? Journal of Finance, 53, 1131-1147.

DUAN, Y., HU, G. & MCLEAN, R. D. 2010. Costly arbitrage and idiosyncratic risk: Evidence from short sellers. Journal of Financial Intermediation, 19, 564-579.

EDELEN, R. M., INCE, O. S. & KADLEC, G. B. 2016. Institutional investors and stock return anomalies. Journal of Financial Economics, 119, 472-488.

ELTON, E. J. & GRUBER, M. J. 1977. Risk reduction and portfolio size: An analytical solution. Journal of Business, 50, 415-437.

FAMA, E. F. 1970. Efficient capital markets: A review of theory and empirical work. Journal of Finance, 25, 383-417.

FAMA, E.F. & MACBETH, J.D., 1973. Risk, return, and equilibrium: Empirical tests. *Journal of political economy*, *81*(3), pp.607-636.

FAMA, E. F. 1991. Efficient capital markets: II. Journal of Finance, 46, 1575-1617.

FAMA, E. F. & FRENCH, K. R. 1992. The cross-section of expected stock returns. Journal of Finance, 47, 427-465.

FAMA, E. F. & FRENCH, K. R. 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33, 3-56.

FAMA, E. F. & FRENCH, K. R. 1996. Multifactor explanations of asset pricing anomalies. Journal of Finance, 51, 55-84.

FAMA, E. F. & FRENCH, K. R. 1998. Value versus growth: The international evidence. Journal of Finance, 53, 1975-1999.

FAMA, E. F. & FRENCH, K. R. 2000. Forecasting profitability and earnings. Journal of Business, 73, 161-175.

FAMA, E. F. & FRENCH, K. R. 2006. Profitability, investment and average returns. Journal of Financial Economics, 82, 491-518.

FAMA, E. F. & FRENCH, K. R. 2008. Dissecting anomalies. Journal of Finance, 63, 1653-1678.

FAMA, E. F. & FRENCH, K. R. 2015. A five-factor asset pricing model. Journal of Financial Economics, 116, 1-22.

FAMA, E. F. & FRENCH, K. R. 2016. Dissecting anomalies with a five-factor model. Review of Financial Studies, 29, 69-103.

FRANZEN, L. A., RODGERS, K. J. & SIMIN, T. T. 2007. Measuring distress risk: The effect of R&D intensity. Journal of Finance, 62, 2931-2967.

FRENCH, K. R. 1980. Stock returns and the weekend effect. Journal of Financial Economics, 8, 55-69.

FRIEWALD, N., WAGNER, C. & ZECHNER, J., 2014. The Cross-Section of Credit Risk Premia and Equity Returns. *The Journal of Finance*, *69*(6), pp.2419-2469.

FU, F. 2009. Idiosyncratic risk and the cross-section of expected stock returns. Journal of Financial Economics, 91, 24-37.

GAO, N. 2015. The motives of cash reserve and bidder cash reserve effects. International Review of Financial Analysis, 37, 73-88.

GARLAPPI, L., SHU, T. & YAN, H. 2008. Default risk, shareholder advantage, and stock returns. Review of Financial Studies, 21, 2743-2778.

GARLAPPI, L. & YAN, H. 2011. Financial distress and the cross-section of equity returns. Journal of Finance, 66, 789-822.

GEORGE, T. J. & HWANG, C.-Y. 2010. A resolution of the distress risk and leverage puzzles in the cross section of stock returns. Journal of Financial Economics, 96, 56-79.

GERTNER, R. & SCHARFSTEIN, D. 1991. A theory of workouts and the effects of reorganization law. Journal of Finance, 46, 1189-1222.

GERVAIS, S., KANIEL, R. & MINGELGRIN, D. H. 2001. The high-volume return premium. Journal of Finance, 56, 877-919.

GIROUD, X. & MUELLER, H. M. 2011. Corporate governance, product market competition, and equity prices. Journal of Finance, 66, 563-600.

GODFREY, C. & BROOKS, C. 2015. The Negative Credit Risk Premium Puzzle: A Limits to Arbitrage Story.

GOMES, J. F. & SCHMID, L. 2010. Levered returns. Journal of Finance, 65, 467-494.

GOMPERS, P., ISHII, J. & METRICK, A. 2003. Corporate governance and equity prices. Quarterly Journal of Economics, 118, 107-156.

GOMPERS, P. A. & METRICK, A. 2001. Institutional investors and equity prices. Quarterly Journal of Economics, 116, 229-259.

GRIFFIN, J. M. & LEMMON, M. L. 2002. Book–to–market equity, distress risk, and stock returns. Journal of Finance, 57, 2317-2336.

GRINSTEIN, Y. & MICHAELY, R. 2005. Institutional holdings and payout policy. Journal of Finance, 60, 1389-1426.

GRUBER, M. J. & ROSS, S. A. 1978. The current status of the capital asset pricing model (CAPM). Journal of Finance, 33, 885-901.

HACKBARTH, D., HASELMANN, R. & SCHOENHERR, D. 2015. Financial distress, stock returns, and the 1978 Bankruptcy Reform Act. Review of Financial Studies, hhv009.

HAN, Y. & LESMOND, D. 2011. Liquidity biases and the pricing of cross-sectional idiosyncratic volatility. Review of Financial Studies, 24, 1590-1629.

HARFORD, J., MANSI, S. A. & MAXWELL, W. F. 2008. Corporate governance and firm cash holdings in the US. Journal of Financial Economics, 87, 535-555.

HARRIS, L. E. 1994. Minimum price variations, discrete bid–ask spreads, and quotation sizes. Review of Financial Studies, 7, 149-178.

HARVEY, C. R., LIU, Y. & ZHU, H. 2016. … and the cross-section of expected returns. Review of Financial Studies, 29, 5-68.

HAUGEN, R. A. & BAKER, N. L. 1996. Commonality in the determinants of expected stock returns. Journal of Financial Economics, 41, 401-439.

HERMALIN, B. E. & WEISBACH, M. S. 2012. Information disclosure and corporate governance. Journal of Finance, 67, 195-233.

HILLEGEIST, S. A., KEATING, E. K., CRAM, D. P. & LUNDSTEDT, K. G. 2004. Assessing the probability of bankruptcy. Review of Accounting Studies, 9, 5-34.

HIRSHLEIFER, D., TEOH, S. H. & YU, J. J. 2011. Short arbitrage, return asymmetry, and the accrual anomaly. Review of Financial Studies, 24, 2429-2461.

HOU, K. & LOH, R. K. 2016. Have we solved the idiosyncratic volatility puzzle? Journal of Financial Economics, 121, 167-194.

HOU, K. & ROBINSON, D. T. 2006. Industry concentration and average stock returns. Journal of Finance, 61, 1927-1956.

HOU, K., XUE, C. & ZHANG, L. 2015. Digesting Anomalies: An Investment Approach. Review of Financial Studies, 28, 650-705.

HWANG, B.-H. & LIU, B. 2012. Which Anomalies are More Popular? And Why. Unpublished working paper, Purdue University.

JAGANNATHAN, R. & WANG, Z. 1996. The conditional CAPM and the cross-section of expected returns. Journal of Finance, 51, 3-53.

JARROW, R. A. & LARSSON, M. 2012. The meaning of market efficiency. Mathematical Finance, 22, 1-30.

JENSEN, M. C. 1978. Some anomalous evidence regarding market efficiency. Journal of Financial Economics, 6, 95-101.

JENSEN, M. C. 1986. Agency costs of free cash flow, corporate finance, and takeovers. The American Economic Review, 76, 323-329.

KAPADIA, N. 2011. Tracking down distress risk. Journal of Financial Economics, 102, 167-182.

KIM, E. H. & LU, Y. 2011. CEO ownership, external governance, and risk-taking. Journal of Financial Economics, 102, 272-292.

KUMAR, A. 2007. Do the diversification choices of individual investors influence stock returns? Journal of Financial Markets, 10, 362-390.

LESMOND, D. A., SCHILL, M. J. & ZHOU, C. 2004. The illusory nature of momentum profits. Journal of financial economics, 71, 349-380.

LI, X. & LUO, D. 2016. Investor Sentiment, Limited Arbitrage, and the Cash Holding Effect. Review of Finance, rfw031.

LILIENFELD-TOAL, U. V. & RUENZI, S. 2014. CEO ownership, stock market performance, and managerial discretion. Journal of Finance, 69, 1013-1050.

LINTNER, J. 1965. The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. Review of Economics and Statistics, 13-37.

LO, A. W. & MACKINLAY, A. C. 1990. Data-snooping biases in tests of financial asset pricing models. Review of Financial Studies, 3, 431-467.

MALKIEL, B. G. 2003. The efficient market hypothesis and its critics. Journal of Economic Perspectives, 17, 59-82.

MARKOWITZ, H. 1952. Portfolio selection. Journal of Finance, 7, 77-91.

MCLEAN, R. D. & PONTIFF, J. 2016. Does academic research destroy stock return predictability? Journal of Finance, 71, 5-32.

MERTON, R. C. 1973. Theory of rational option pricing. The Bell Journal of economics and management science, 141-183.

NAGEL, S. 2005. Short sales, institutional investors and the cross-section of stock returns. Journal of Financial Economics, 78, 277-309.

NEWEY, W. K. & WEST, K. D. 1987. Hypothesis testing with efficient method of moments estimation. International Economic Review, 777-787.

NEWEY, W. K. & WEST, K. D. 1994. Automatic lag selection in covariance matrix estimation. Review of Economic Studies, 61, 631-653.

NOVY-MARX, R. 2013. The other side of value: The gross profitability premium. Journal of Financial Economics, 108, 1-28.

NOVY-MARX, R. & VELIKOV, M. 2015. A taxonomy of anomalies and their trading costs. Review of Financial Studies, 29, 104-147.

OHLSON, J. A. 1980. Financial ratios and the probabilistic prediction of bankruptcy. Journal of Accounting Research, 109-131.

OPLER, T. C. & TITMAN, S. 1994. Financial distress and corporate performance. Journal of Finance, 49, 1015-1040.

PETERSEN, M. A. 2009. Estimating standard errors in finance panel data sets: Comparing approaches. Review of Financial Studies, 22, 435-480.

PONTIFF, J. 1996. Costly arbitrage: Evidence from closed-end funds. Quarterly Journal of Economics, 111, 1135-1151.

PONTIFF, J. 2006. Costly arbitrage and the myth of idiosyncratic risk. Journal of Accounting and Economics, 42, 35-52.

ROLL, R. 1983. Vas ist das? Journal of Portfolio Management, 9, 18-28.

ROSS, S. A. 1976. The arbitrage theory of capital asset pricing. Journal of Economic Theory, 13, 341-360.

SCHWERT, G. W. 2003. Anomalies and market efficiency. Handbook of the Economics of Finance, 1, 939-974.

SHARPE, W. F. 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. Journal of Finance, 19, 425-442.

SHLEIFER, A. & VISHNY, R. W. 1997. The limits of arbitrage. Journal of Finance, 52, 35-55.

SHLEIFER, A. & VISHNY, R. W. 1997. A survey of corporate governance. Journal of Finance, 52, 737-783.

SHUMWAY, T. 1997. The delisting bias in CRSP data. Journal of Finance, 52, 327-340.

SHUMWAY, T. 2001. Forecasting bankruptcy more accurately: A simple hazard model. Journal of Business, 74, 101-124.

SHUMWAY, T. & WARTHER, V. A. 1999. The delisting bias in CRSP's Nasdaq data and its implications for the size effect. Journal of Finance, 54, 2361-2379.

STAMBAUGH, R. F., YU, J. & YUAN, Y. 2012. The short of it: Investor sentiment and anomalies. Journal of Financial Economics, 104, 288-302.

STAMBAUGH, R. F., YU, J. & YUAN, Y. 2015. Arbitrage asymmetry and the idiosyncratic volatility puzzle. Journal of Finance, 70, 1903-1948.

STOCK, J. H. & WATSON, M. 2011. Dynamic factor models. Oxford Handbook on Economic Forecasting.

STULZ, R. 1990. Managerial discretion and optimal financing policies. Journal of Financial Economics, 26, 3-27.

TANG, Y., WU, J. G. & ZHANG, L. 2014. Do anomalies exist ex ante? Review of Finance, 18, 843-875.

TYKVOVÁ, T. & BORELL, M. 2012. Do private equity owners increase risk of financial distress and bankruptcy? Journal of Corporate Finance, 18, 138-150.

TYKVOVÁ, T. & BORELL, M. 2012. Do private equity owners increase risk of financial distress and bankruptcy? Journal of Corporate Finance, 18, 138-150.

VAN DIJK, M. A. 2011. Is size dead? A review of the size effect in equity returns. Journal of Banking & Finance, 35, 3263-3274.

VASSALOU, M. & XING, Y. 2004. Default risk in equity returns. Journal of Finance, 59, 831-868.

ZACKS, L. 2011. The handbook of equity market anomalies: translating market inefficiencies into effective investment strategies, John Wiley & Sons.

ZMIJEWSKI, M. E. 1984. Methodological issues related to the estimation of financial distress prediction models. Journal of Accounting Research, 59-82.