

# Cross-Sectional Return Predictability: the Predictive Power of Return Asymmetry, Skewness and Tail Risk

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A thesis submitted for the degree of

*Doctor of Philosophy*

2016

## Acknowledgements

The PhD life is a journey, a process of self-improving and refining. During this process, I learnt how to read a paper, how to program, how to do research and how to solve a problem by myself. This experience was an unforgettable and precious journey in my life. Along this journey, I would like to express my special appreciation and great thanks to my supervisors, Dr. Xiafei Li and Dr. Thanaset Chevapatrakul. I would like to thank them for their contributions of time, ideas and exceptional guidance. Without their help and encouragement, I would not have made it in three years. Moreover, I want to thank Ning Gao from the University of Manchester for his invaluable input. Moreover, I would like to thank my father, my mother and my sister for their unconditional love, support and encouragement. I would also like to thank my friends in the Business School, my friends in China, as well as my flatmates during the three years. More importantly, special thanks to my girlfriend, Xue Qiu, for her understanding and support.

# **Abstract**

This thesis attempts to investigate the cross-sectional predictive power of return asymmetry, skewness and tail risk. It mainly consists of three empirical chapters on the relation between predictive patterns of the return distribution and expected stock returns.

In the first empirical chapter, I adopt a measure of asymmetry, originally proposed by Patil et al. (2012), which can be employed to characterise the shape of the entire distribution of asset returns instead of skewness. Empirical evidence on the relation between asset returns and the skewness of the return distribution is mixed. As skewness is primarily influenced by the tail behaviour of the return distribution, it is possible for two distributions with identical skewness to have quite different asymmetry. I will examine the relationship between this new measure and stock returns. My empirical analysis indicates that stocks with high return asymmetry exhibit low expected returns. The negative relation between return asymmetry and expected returns persists after I control for size, book-to-market, momentum, short-term return reversals, liquidity, idiosyncratic volatility and various skewness factors. My results are consis-

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tent with the findings from theoretical models such as those of Brunnermeier et al. (2007) and Barberis and Huang (2008).

In the second empirical chapter, I examine the default risk and financial crisis explanations for the market skewness risk effect and find that the effect is stronger among stocks with large size, high growth, and low default risk. This suggests that the positive skewness preference theory only holds for safe stocks. Moreover, the effect of market skewness risk on stock returns interacts with default risk significantly. Market skewness risk has explanatory power for stock returns only during the periods of good economic conditions. Additionally, the market skewness risk effect is not persistent. After the financial crisis of 2007-2008, the strong effect disappears.

In the last empirical chapter, I know that investors sometimes underweight the tail event. I then try to figure out this situation by examining the default risk and financial crisis explanations for the tail risk effect. I find that market size, book-to-market ratio, and default risk have large impact on the tail risk effect. Moreover, tail risk only has explanatory power for stock returns during the periods of good economic conditions. The results suggest that when investors hold stocks with small size, low growth, and high default risk, the tail risk tends to be ignored. The tail risk effect is not persistent. The significant tail risk effect also disappear after the financial crisis of 2007-2008.

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# Chapter 1

## Introduction

### 1.1 Motivations

Traditional asset pricing theory, Efficient Market Hypothesis (EMH), implies that prices fully reflect all available information in the stock market and investors cannot predict future returns. This is documented by Fama (1965) and Fama (1991). However, empirical studies provide a lot of evidence on the prediction of stock returns. Recent development in the return prediction suggests that cross-section of expected stock returns can be predicted by some factors (Banz (1981); Jegadeesh and Titman (1993); Fama and French (1993); Ang et al. (2006) and so on).

However, empirical studies have proved that the cross-sectional variation of expected returns cannot be fully explained by existing factors. There are still many undiscovered determinants of the cross-section of stock returns. Examining the effect of undiscovered determinates and existing pricing

factors on the cross-section of expected stock returns turns out to be quite important. This thesis suggests looking closely at the distribution of stock returns as potential determinants of the cross-section of expected returns. Specifically, I firstly propose a new predictable pattern of return distribution, namely, return asymmetry. Then I investigate the cross-sectional effect of two existing predictable patterns of return distribution, which are skewness risk and tail risk. Therefore, the motivations of this thesis can be illustrated from three strands:

First, people tend to use skewness to measure the asymmetry for a distribution and they find that skewness can be used to predict stock returns. Arditti (1967) shows that under very general assumptions, investors have a preference for assets whose return distributions are positively skewed. Afterwards, Rubinstein (1973), Kraus and Litzenberger (1976) and Harvey and Siddique (2000a) modify the capital asset pricing model (CAPM) by incorporating the effect of skewness of the return distribution in their models. The modifications made to the CAPM are grounded on an assumption that investors prefer stocks with positive skewness and so demand higher expected returns if they are to be persuaded to hold stocks with negative skewness.

Recent development in the literature suggests that the degree of asymmetry of an asset return distribution may be used to explain variations in asset returns. For example, Mitton and Vorkink (2007) find that idiosyncratic skewness can be used to predict stock returns after heterogeneous investor preference for skewness is incorporated in their model. Barberis and Huang (2008) demonstrate that when preferences are assumed to follow the cumulative prospect theory, which is a model for descriptive decisions under risk

and crisis, proposed by Tversky and Kahneman (1992), investors are found to prefer lottery-like securities which have small probabilities to generate extremely large returns in the future. Their findings imply that stocks with larger idiosyncratic skewness are predicted to have lower than average expected returns.

Although theoretical models developed during the past decades mostly agree on the effect of skewness on asset returns, empirical investigations of the models give mixed results. Using firm-level data, Boyer et al. (2009) find that the expected idiosyncratic skewness and stock returns are negatively correlated while Bali and Murray (2013) note that physical skewness<sup>1</sup>, measured as the skewness of daily returns over the past one year, fails to predict future stock returns. Idiosyncratic skewness is the skewness calculated from residuals of individual stock returns after adjusting some risk factors. Moreover, using intraday data to compute weekly realised skewness, Amaya et al. (2015) show that the third moment of return distribution is strongly negatively correlated with the cross-section of stock returns. In their paper, they also show that Boyer et al. (2009)'s results crucially depend on the skewness estimation window. While a number of researchers use physical skewness in their works, others estimate implied skewness from option prices. Conrad et al. (2013) suggest that risk-neutral skewness<sup>2</sup> is negatively related to stock returns whereas Rehman and Vilkov (2012) and Bali et al. (2014) both find positive relationship between *ex ante* skewness and future stock returns. As the skewness measure is heavily influenced by the behaviour at the tail of a density function, it comes as no

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<sup>1</sup>Physical skewness is skewness calculated from historical data.

<sup>2</sup>Risk-neutral skewness is skewness calculated from option data and this skewness can also be called *ex ante* skewness and implied skewness.

surprise that different researchers fail to agree on the relationship between skewness and asset returns. The contradictory results may stem from the fact that skewness's ability to describe the shape of a distribution is not adequate. As mentioned in Conrad et al. (2013), it is well known that outliers can significantly influence the skewness estimates; the impact of outliers are found to be even more pronounced on the third moment than on the first two moments. To make matter more complicated, skewness is found to be time-varying (Harvey and Siddique, 1999). Whether or not I can apply a new measure of asymmetry to a return distribution. I will fill this gap in my first empirical study.

Second, it has been long accepted that market-wide volatility is an important pricing factor. Recent evidence, however, has emerged that market-wide volatility, measured by higher moments of the return distribution, is also priced in the cross-section of expected returns. For example, Harvey and Siddique (2000a) find that conditional coskewness can explain idiosyncratic components in cross-section of expected returns. Boyer et al. (2009) document that expected idiosyncratic skewness also has an impact on asset prices. More interestingly, Chang et al. (2013) report that stocks with low market skewness risk<sup>3</sup> outperform stocks with high market skewness risk significantly, even after adjusting for Fama and French's (1993) three factors. Barberis and Huang (2008) and Brunnermeier et al. (2007) offer explanations based on the cumulative prospect theory and optimal beliefs. The negative relation, they argue, stems from the fact that investors overinvest in stocks with positive skewness and underinvest in stocks with negative

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<sup>3</sup>Market skewness risk is the sensitivity of stock returns to market skewness factor. Ex ante skewness proposed by Conrad et al. (2013) can not be viewed as skewness risk.

skewness.

Furthermore, a large body of studies show that skewness of return distribution is induced by asymmetric response of volatility to return shocks (Nelson (1991); Engle and Ng (1993), Zakoian (1994); Bekaert and Wu (2000); and Berd et al. (2007)). Black (1976) and Christie (1982) put "leverage effect" forward to explain the asymmetric volatility property of individual stock returns. Merton (1974) extends the Modigliani-Miller theorem and shows that leverage is highly related to default risk. Berd et al. (2007) and Engle (2011) further document that long-term negative skewness could cause massive defaults and high default correlations would increase the possibility of another negative return shock on asymmetric volatility. Moreover, Yuan (2005) develops a rational expectations equilibrium model that predicts an asymmetric market return distribution after negative shocks. These shocks, which are common during a financial crisis, often lead to asset price meltdown. He shows that the sensitivity of asset price to negative shocks increases when information asymmetry becomes severe and borrowing constraints are more binding. Adrian and Rosenberg (2008) show that market skewness risk is an indicator of the tightness of financial constraints. Several recent studies demonstrate that financial constraints are sensitive to the financial crisis of 2007-2008 (Campello and Chen (2010); Campello et al. (2011) and Calomiris et al. (2012)). To the best of my knowledge, none of the existing studies investigate the default risk and financial crisis explanations for the market skewness risk effect. I attempt to fill this gap.

Third, from the view of tail risk, Mandelbrot (1963) and Fama (1965) find that stock returns are not normally distributed and have heavy tails. This can be described by a power law. More recently, according to the model-free

approach by Carr and Madan (2001) and Bakshi and Madan (2000), Conrad et al. (2013) extract risk-neutral skewness for each stock and find that stocks with high implied skewness will generate lower returns in the future.<sup>4</sup> The second method is based on high-frequency data. Bollerslev and Todorov (2011) extract the expected jump tails by using high-frequency intraday returns and out-of-the-money options with short maturity. Their results show that the compensation for jump tail risk may lead to the historically large equity and variance risk premium.

Furthermore, investors evaluate risk in the financial market according to cumulative prospect theory documented by Tversky and Kahneman (1992). Under probability weighting, investors tend to overweight the tail event in their decision making. Barberis (2013) argues that the probability weighting also works for understanding the aggregate stock market. As a result of occasional large crashes, the aggregate stock market is negatively skewed. Kelly and Jiang (2014) use Hill et al. (1975)'s estimator from a large cross section of stock returns to capture large crashes. When the tail risk increases, investors prefer to hold stocks with low sensitivity to tail risk in order to hedge the large crashes. Then the stocks with high sensitivity to tail risk will be discounted more steeply. Therefore, probability weighting leads to a new prediction. However, Hertwig et al. (2004) point out that people are more likely to underweight tail events when they make decisions according to their experience. From the view of behaviour finance, Barberis (2013) states that the reason of Hertwig et al. (2004)'s findings might be because people use simple reasoning rather than experience. They argue that the prices

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<sup>4</sup>See, for example, Bakshi et al. (2003), Chang et al. (2013) and Bali and Murray (2013).

of stocks with high default risk have been beaten down. Therefore, these stocks have limited downside. Under their hypothesis, when investors hold stocks with high default risk, they tend to underweight the tail event. This means even when the market will experience a large crash, investors believe the distressed stocks have limited downside and they will underweight the tail event. Barberis (2013) also discusses that if an investor judges a tail event not likely to occur, he may ignore the tail risk in his decision making. My last empirical analysis tries to figure out whether the default risk has an impact on the effect of tail risk.

Moreover, Werner and Upper (2004) argue that the tail index of bond future is not stable over time and the changes of tail index may be on account of the Russia and LTCM crises. Gourio (2012) also points out that the variations in the probability of disaster have some connections with a significant fraction of business cycle dynamics. Therefore, I would like to find out whether the tail risk is underweighted during different economy conditions.

## 1.2 Research questions

I focus my research on the predictable patterns of stock return distributions, namely, return asymmetry, skewness risk and tail risk. In the first empirical chapter, I will apply an existing measure of asymmetry to stock market. In the last two empirical chapters, I will focus on the effect of default risk on the market skewness risk and tail risk. To guide my thinking, I would like to ask three sets of questions according to different topics:

- Can I apply a new measure of asymmetry to stock returns? How can I construct this factor in stock market? Can this asymmetry factor be used to explain the difference of returns across individual stocks? Whether the results are consistent with the theory. If this factor can be used to predict returns, can this effect be explained by other factors?
- Is market skewness risk related to default risk? What is the performance of the sensitivity to market skewness risk after adjusting for default risk? What is the effect of market skewness risk after financial crisis?
- Is tail risk related to default risk? What is the performance of the sensitivity to tail risk after adjusting default risk? What is the effect of tail risk after the financial crisis?

## 1.3 Empirical findings

To examine the first set of questions, I construct a new factor in the stock market based on the distribution of stock returns. I call it "return asymmetry". I estimate the asymmetry coefficient for each stock based on the method by Patil et al. (2012). Using portfolio sorts and cross-sectional regressions, I find that return asymmetry is negatively related to expected stock returns. The average raw and abnormal returns for portfolios with the highest values of return asymmetry are significantly lower than the average and abnormal returns for portfolios with the lower values of return asymmetry. The difference in returns is more pronounced for the equal-

weighted portfolios than the value-weighted portfolios and for the portfolios formed according to the asymmetry measure estimated over the last 60 months than the portfolios formed based on the return asymmetry measure computed over the last 12 months. Furthermore, my results are robust to different sample periods. I control for the effects of well-known pricing factors on the security returns by including the following variables in our analysis: firm's size, the book-to-market ratio, the momentum factor, the liquidity risk factor, the idiosyncratic volatility and the various skewness factors. Moreover, I also examine the cross-sectional relation between return asymmetry and expected security returns at the stock-level using the cross-sectional regression technique. My results show that, after popular pricing factors are controlled for, the strong negative relationship between return asymmetry and returns remains intact.

For the second group of research questions, I choose two proxies for default risk. Then I test the impact of default risk on the relationship between market skewness risk and stock returns by using two-way portfolio sorts and Fama and MacBeth (1973) cross-sectional regressions. Using the same sample period with Chang et al. (2013), I find a strong negative relationship between market skewness risk and expected returns. Moreover, the significant market skewness risk effect is concentrated among stocks with large market capitalizations, low book-to-market ratios, low default likelihood indicators, and low O-scores. Consistent with our hypothesis, the results from Fama and MacBeth (1973) cross-sectional regressions show that market skewness risk significantly interacts with default risk on expected returns. Using out-of-sample tests, I show that the strong return difference between stocks with low and high market skewness risk disappears after

### 1.3. EMPIRICAL FINDINGS

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the financial crisis of 2007-2008. In addition, market skewness risk is only priced during good economic periods, but is not priced during bad economic periods.<sup>5</sup>

For the third set of questions, I also choose O-score and default likelihood indicator as the proxies for default risk. Then I test the impact of default risk on the relationship between tail risk and stock returns by using two-way portfolio sorts and Fama and MacBeth (1973) cross-sectional regressions. I find that the relationship between tail risk and stock returns is positive and this is consistent with the results by Kelly and Jiang (2014). Moreover, the results also show that the tail risk premium is highly significant in the stocks with large market capitalizations, low book-to-market ratios, low default likelihood indicators, and low O-scores. However, the effect of tail risk disappears in the stocks with small market capitalizations, high book-to-market ratios and high default risk. I then use the sample period after the financial crisis of 2007-2008, which is from January 2008 to December 2014. My results show that the positive relationship between tail risk and stocks returns disappears. The financial crisis does have an impact on the tail risk effect. I also use expected market risk premium to define good times and bad times. The results from Fama and MacBeth (1973) cross-sectional regressions in different economy conditions show that the tail risk premium is insignificant during the bad times.

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<sup>5</sup>Good economic is the time period when expected market risk premium is lower than the mean value. Bad economic is the time period when expected market risk premium is higher than the mean value.

## 1.4 Potential contribution

This study provides new insight into the predictable patterns of distribution of stock returns, namely, return asymmetry, skewness risk and tail risk. I mainly focus on the test on the weak form Efficient Market Hypothesis. I apply a new measure of asymmetry to return distribution of the stock market. This new factor can be viewed as a new challenge against Efficient Market Hypothesis (EMH). Moreover, empirical studies help provide a better understanding on the importance of default risk in explaining the effect of market skewness risk and tail risk. Initiated by theoretical frameworks in Tversky and Kahneman (1992), Mitton and Vorkink (2007) and Barberis and Huang (2008), recent empirical studies provide some evidence on the relationship between skewness risk and stock returns (Chang et al. (2013); Conrad et al. (2013) and Bali and Murray (2013)), as well as the relationship between tail risk and stock returns (Kelly and Jiang (2014) and Bollerslev et al. (2013)). Chang et al. (2013) address that the relationship between skewness risk and stock returns is negative, while Kelly and Jiang (2014) argue that stocks with high sensitivity to tail risk tend to generate high returns in the future. Surprisingly, the impacts of default risk and financial crisis on the skewness risk effect and tail risk effect have not been examined. Moreover, skewness mainly captures the tail information of a distribution. There is little straightforward measure of asymmetry of return distribution. My study contributes to the literature in the following ways:

- The empirical study based on return asymmetry is the first to propose a straightforward asymmetry measure of stock return distribution. This new measure captures more information of a distribution compared

with the skewness measure. I highlight that this new measure can be used to predict future returns. Stocks with high return asymmetry will generate lower returns in the future. This is consistent with the theoretical findings by Barberis and Huang (2008). In addition, the effect of return asymmetry cannot be explained by other factors. These empirical findings enhance the understanding on the Effect Market Hypothesis (EMH) by contributing to the literature on the relationship between predictive variable and returns.

- The empirical study based on the impact of default risk on the skewness effect is the first in the literature to explore the default risk and financial crisis explanations for the market skewness risk effect. Empirical research provides little understanding of the economic source of the effect. I highlight the strong interaction effect between market skewness risk and default risk on expected stock returns. Additionally, my results suggest that the positive skewness preference theory of Kraus and Litzenberger (1976) only holds for stocks with large market value, high growth, low default risk, and during good economic conditions. This provides new insight into the positive skewness preference theory. Moreover, our results provide additional empirical evidence in support of the rational expectations equilibrium model developed by Yuan (2005).
- The empirical study based on the impact of default risk on the tail risk effect contributes to the literature that default risk have a large interaction with the effect of tail risk. There are few empirical studies examining this effect. I highlight that when investors hold stocks with small size, high book-to-market ratios and high default risk, the tail

risk tends to disappear. The empirical findings are consistent with the behavioural explanation by Barberis (2013). In addition, the strategy that long the stocks with lowest tail loadings and short the stocks with highest tail loadings does not always work when the default risk and economy conditions are taken into consideration.

## 1.5 Thesis structure

The remainder of the thesis proceeds as follows. In Chapter 2, I review the background of this thesis, which is Efficient Market Hypothesis (EMH). Then anomalies used against the hypothesis are reviewed. In this thesis, I only consider the predictable variables related to the distribution of stock returns: skewness risk and tail risk.<sup>6</sup> Various measures of skewness and tail risk will be illustrated. According to the studies in empirical Chapter 5 and Chapter 6, I also review the default risk and popular measures of default risk are introduced.

In Chapter 3, I discuss the methodologies used in my empirical studies. I explain the portfolio sorts and cross-sectional regressions in this chapter. The calculation of risk-adjusted returns is also presented in detail.

In Chapter 4, I propose a new measure of asymmetry in the stocks markets compared with skewness measure. I call this new factor "return asymmetry". I use simulations to distinguish the performance of skewness measure and

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<sup>6</sup>As the concept of "return asymmetry" comes from skewness literature, there are few literature studies on new asymmetry measure of returns. Therefore, I only review the two key predictive variables in this thesis.

asymmetry measure. My measure has been proved to have better performance than skewness. Then I use portfolio sort to examine the relationship between return asymmetry and expected stock returns. Then two-way portfolio sorts and cross-sectional regressions are applied to investigate the effect of asymmetry after I control for other factors.

Chapter 5 is based on research article which has been submitted to the peer-reviewed journal. The co-authors are Xiafei Li, Thanaset Chevapatrakul and Ning Gao. In this chapter, I test for the interaction between skewness risk and default risk and financial crisis in predicting cross-sectional expected returns. First of all, I use two-way portfolio sorts to test the performance of skewness risk in different levels of default risk groups. Then I define dummy variables based on default risk and examine the effect of skewness risk by using cross-sectional regressions after controlling for dummy variables as well as interactions. At last, I investigate the effect of skewness risk after financial crisis, during good times and bad times.

In Chapter 6, I examine the impact of default risk and financial crisis on the tail risk effect in the prediction of cross-sectional stock returns. Similar to the studies of skewness risk, I use two-way portfolio sorts to test the performance of tail risk in different levels of default risk groups. Cross-sectional regressions are employed to test the effect of tail risk when stocks have different levels of default risk. Lastly, I investigate the effect of tail risk after financial crisis, during good times and bad times.

In Chapter 7, I conclude the thesis. The limitations and future studies about the return asymmetry, skewness risk and tail risk are illustrated in this chapter.

# Chapter 2

## Literature Review

### 2.1 Efficient Market Hypothesis (EMH)

During the past 50 years, the efficient market hypothesis has been widely accepted by academic financial economists. The concept "Efficient Market" was proposed by Fama in 1965. In a stock market, if the prices of stocks fully reflect all available information, then this market is defined as an efficient market.

He suggests that an efficient market is a market in which there are a lot of rational, profit-maximizing investors, who participate in the competition actively (Fama, 1965). Fama (1965) insists that competition among investors can result in a situation: at one point of time, stock prices have already reflected the effects of information that have been released in the market as well as the news which markets expected to release in the future. This confirms his Efficient Market Hypothesis (EMH) put forward in 1970. Efficient

## 2.1. *EFFICIENT MARKET HYPOTHESIS (EMH)*

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Market Hypothesis implies that investors cannot predict the returns. In an efficient market, prices correctly reflect the information available to the market. Therefore, the investors cannot make abnormal returns. (Shefrin, 2007)

The efficient market hypothesis is associated with the hypothesis of random walk. The hypothesis emphasizes that stock market prices move randomly. Therefore future prices cannot be predicted. The theory was first presented by Kendall and Hill (1953). They provide the evidence of zero correlation in returns with exhibition of the distribution of Standard and Poor's Index in the period of five years. Samuelson (1965) argues that security prices randomly walk in competitive markets with rational risk-neutral participants. More importantly, Fama (1995) strongly supports the random walk hypothesis and he illustrates that the stock prices move without following any patterns.

Since these two hypotheses all imply that the returns are unpredictable, lots of scholars start to focus on this issue and try to test whether the market is efficient. Fama (1991) divides the tests on market efficiency into three parts: the first part is test for return predictability, this work includes the use of returns to predict future returns and forecasting return with factors such as dividend yields. The second test is event study. The work is to examine the reaction of prices to public information. The concept "event study" is first documented by Ball and Brown (1968) and used by Fama et al. (1969). The main idea of this method is averaging the cumulative returns of stocks over a specific time window before and after the event. The last test is on private information. It is to examine whether the investors have private information that has not been reflected in the stock prices. The private

information is also defined as inside information. (Fama, 1991)

The majority of literature is in terms of weak and semi-strong form efficient market hypothesis. Moreover, lots of evidence has been provided to challenge the Efficient Market Hypothesis. These evidences are called anomalies.

## 2.2 Anomalies

A lot of scholars find evidence against the EMH and the evidences are called anomalies. Shefrin (2007) suggests that the empirical patterns, which are puzzles from the perspective of market efficiency, are called anomalies. In early years, Basu (1977) demonstrates that price-earnings ratios are related to stock returns. Stocks with high price-earnings ratios underperform the stocks with low price-earnings ratios in the period of 15 years after 1965. However, Reinganum (1981) indicates that the P/E effect is as a result of model specification. Specifically, after he controls the firm size, the P/E effects disappear for NYSE and AMEX stocks. But the size effect is still significant even after controlling the P/E ratios. Banz (1981) is the first to identify the premium of size. He predicts that small NYSE companies tend to have larger risk adjusted returns than large NYSE companies in the long run.

Some other anomalies also provide some evidence on market inefficiency. The earliest one is long-term past returns, first identified by Bondt and Thaler (1985). They find a return reversal in long-term returns up to five years. Equities with high long-term past returns turn out to be worse performed. Bondt and Thaler (1985) attribute this result to price overreaction from the

prospect of behavioural finance, which will be illustrated in the next section. In contrast to long time past returns, Jegadeesh and Titman (1993) find that short-term past returns can also affect stock returns. Stocks with high past returns can usually have high returns for the next few months. Based on this theory, strategies that buy past winners and sell past losers can win an abnormal return. This anomaly is defined as momentum. Moreover, Lakonishok et al. (1994) insist that past sales growth and cash flow/price can both related to stock returns: stocks with high past sales growth tend to have low returns in the future and the cash flow/price ratio is positively related to average stock returns.

More recently, scholars find some new anomalies such as profitability, investment, accruals and stock issues. Haugen and Baker (1996) and Cohen et al. (2002) stress that companies with more profits tend to have higher stock returns. This profitability effect is confirmed by Novy-Marx (2013). He uses gross profits-to-assets to measure profitability and find that unprofitable firms generate lower stock returns than profitable firms. Another anomaly is investment. Titman et al. (2004) state that firms with more abnormal capital investment will generate lower mark-adjusted returns in the following five years. Both profitability effect and investment effect cannot be explained by standard factors such as size and book-to-market equity (Fama and French, 2015). Sloan (1996) is the first researcher to highlight that the accruals components of earnings have impact on stock returns and the relation is negative. Another anomaly documented by Daniel and Titman (2006) and Pontiff and Woodgate (2008) is stock issues. They both demonstrate that the stock issues are negatively linked to average stock returns.

Apart from anomalies, there are also many predictable factors which can be used to predict stock returns. In this thesis, I mainly focus on one anomaly (skewness) and one predictable factor (tail risk). Moreover, I will propose a new predictable variable in the stock market. The details will be discussed later.

Depending on the results of anomalies, all these patterns in returns support that the stock returns can be predicted, which is inconsistent with the EMH. Why do there exist anomalies? The question will be explained from two prospects: from the views of behavioural finance and the rational approach.

## **2.3 Explanations of anomalies**

### **2.3.1 Explanation of anomalies in behavioural finance**

The first way to explain the anomalies is from the behavioural point of view. As the limitations of the hypothesis of Efficient Market Hypothesis, behavioural finance provides a quite specific way to interpret the market inefficiency.

Fama (1998) defines that behavioral explanation on market inefficiency is on account of the imbalance between overreaction and underreaction. For example, investors may undervalue the companies with poor earnings in loser portfolios and overvalue companies with good earnings in winner portfolios. There is a wealth of literature about over or underreaction in terms of different anomalies. In early years, Bondt and Thaler (1985) test the long-term return anomalies and find that past winners tend to be

future losers. They attribute the effect of long-term reversals to investor overreaction. Specifically, past performance of companies has been given so much attention and regardless of the situation that earnings will revert to the mean. Other studies may prefer to concentrate on the interpretation through underreaction. For example, Ikenberry et al. (1995) investigate the long-term performance of the companies after the share repurchase announcements. They find that the companies tend to repurchase stocks on account of underreaction.

Considering the methods of behavioural finance in explaining the anomalies, there are three behavioural models used to discuss how the overreaction and underreaction occur when investors participate in the market.

**(i) BSV model.** Barberis-Shleifer-Vishny (BSV) model is constructed by Barberis et al. (1998) and assumes that the earnings follow a random walk. The investors show wrong cognition on the future returns, which contains two regimes. In regime A, investors are more likely to believe that the earnings will revert to the mean. This indicates that the investors will undervalue the price when earnings change because they think that the trend of earnings growth will not last long. In regime B, investors insist that the earnings will follow the trend. This implies that the price of stocks will over-react to the earnings changes.

Some empirical evidence has been provided on the two regimes. Momentum effect identified by Jegadeesh and Titman (1993) proves regime A. Long-term return reversals documented by Bondt and Thaler (1985) provide the evidence of regime B. Fama (1998) points out that the BSV model only covers anomalies such as post-earning drift, momentum, long-term

reversal, and cross-sectional predictability. Some other anomalies have been neglected.

**(ii) DHS model.** Similar to the BSV model, Daniel et al. (2004) propose Daniel-Hirshleifer-Subrahmanyam's (DHS) model which is based on the judgement biases between overreaction and underreaction. Fama (1998) suggests that the results predicted by DHS model are similar to the prediction from BSV model.

In DHS model, investors are divided into two types: informed and uninformed. Uninformed investors judge stock price without bias. Informed investors can determine the stock prices and they are affected by two cognition biases: overconfidence and biased self-attribution. Overconfidence makes the investors more confident on estimating the price based on their private information, while the biased self-attribution leads them to undervalue the public information especially when the public signals challenge their private information. The overreaction and underreaction to different signals could result in continuation of stock price in the short run and return reversals in the long run.

**(iii) HS model.** Both BSV model and DHS model assume that a single representative agent, who may have several cognitive biases, determines the asset prices. They then examine whether the biases are enough to present the continuation in the short run and reversals in the long run at the same time. However, Hong and Stein (1999) propose a new behavioural model which considers more about the interaction between different agents rather than psychology of the single representative agent.

They classify the agents into two types: "newswatchers" and "momentum

traders". The newswatchers forecast the asset prices depending on news they observed about the future conditions, while momentum traders care more about the historical price changes. If the private news diffuses gradually across the whole watchers, the prices will be below the fundamental price in the short run. This underreaction gives the signals that the momentum traders can get profits by following the momentum strategy. However, if the momentum traders implement simple strategies, their behaviours must result in overreaction in a long period of time. (Hong and Stein, 1999)

These three models are widely used to illustrate the stock returns in behavioural finance. Behavioural finance plays an important role in the stock market and helps understand performance of stocks especially when asset pricing models are not enough to explain stock returns. However, behavioural models are not precise enough to predict a linear relation (Fama and French, 2008). In the next part, asset pricing models will be introduced, which help explain the anomalies in the stock market with rational approach.

#### 2.3.2 Explanation of anomalies in a rational way

Rational approach to examine the market efficiency is based on the assumptions that returns are constant and prices follow a random walk. Scholars proposed various models to test the market efficiency by investigating the relations between returns and priced factors. In this section, five asset pricing models will be reviewed:

**(i) Capital asset pricing model.** The oldest asset pricing model documented by Sharpe (1964) and Lintner (1965) is the Capital Asset Pricing

Model (CAPM), using the covariance of the asset's return with market return to measure the equity risk. Evidence has been presented by Fama and MacBeth (1973) that Capital Asset Price Model (CAPM) has a good performance to explain equity returns.

However, Capital Asset Pricing Model (CAPM) is also challenged by a number of researchers. As the CAPM is the first asset pricing model and the systematic risk is measured by beta of the asset, Roll (1977) finds that the two parameter asset pricing model is hard to test and the only testable hypothesis is: the market is mean-variance efficient. But the relation between expected returns and systematic risk is unable to be tested independently. Fama and French (1992) state that estimated risk premium of market is not different from zero, which means there is no profit from bearing the systematic risk of CAPM. As the cross-sectional expected returns are weakly related to the betas, the relations between other variables and expected returns are strong. Overall, much evidence has been provided to demonstrate that the relation between expected returns and betas is low.

Aside from the argument on the market risk premium, there also exist some other factors, for example, size, earnings/price, cash flow/price, book-to-market equity, past sales growth, long-term past return and short-term past return, challenging the Sharpe-Lintner CAPM hypothesis that there are no other variables to explain the returns. Fama and French (1992) point out that the average return is strongly related to these factors. Specifically, the relation between size and return is negative and robust after including other factors. The return is positively related to book-to-market equity and the relation tends to persist compared with other variables. Moreover, the variable of traditional asset pricing model is impossible to explain the cross

section of average returns on common stocks (Fama and French, 1993).

Therefore, the traditional capital asset pricing model (CAPM) is not a perfect model to interpret the relation between risk and returns. Moreover, such CAPM anomalies point out that it is necessary to propose a new asset pricing model.

**(ii) Fama-French three-factor model.** As a result of the defects of CAPM, Fama and French (1993) discover five risk variables in explaining the returns in stocks and bonds. They find that the stocks sorted based on firm size and book-to-market equity can well explain the cross section of stock returns. Therefore, they expand the asset pricing model by incorporating size and book-to-market variables. Fama and French (1996) find that the three factors of Fama-French three-factor model can cover the effects of most anomalies except short term returns, which provide a better view on the relation between risk and returns by using time-series regression.

Additionally, the cross-sectional regressions with the size factor and book-to-market factor also better performed than CAPM (Fama and French, 1992). The good performance has also been admired by behaviouralists, of which the size and book-to-market factors capture much effect ignored by CAPM. But they associate the results with the investors' overreaction. Moreover, Kothari et al. (1995) find that beta risk carries a substantial risk premium.

Some other people suggest that the risk premiums from the three-factor model are on account of survivor bias and data snooping. Kothari et al. (1995) argue that the high book-to-market ratio portfolios tend to overstate the average returns as a result of including distressed firms. These kinds of firms with low market value are more likely to generate higher returns.

Therefore, the past result on book-to-market factor is because of selection bias of COMPUSTAT data. Barber and Lyon (1997) insist that survivorship bias and data snooping are not the reasons to explain the size or book-to-market premiums. Despite the debates on the three-factor model, it is still widely used as an alternative to the Sharpe-Lintner CAPM.

Fama and French (1996) illustrate that the Fama-French three-factor model can explain most of the anomalies such as size, book-to-market equity, earning/price, past sales growth, cash flow/price and long-term past returns. However, short-term returns cannot be captured by these three factors.

**(iii) Carhart four-factor model and Fama-French five-factor model.**

Carhart (1997) incorporates short-term return factor, defined as momentum, into the Fama-French three-factor model based on one-year momentum in stock returns documented by Jegadeesh and Titman (1993). The four-factor model captures four risk factors with low cross-correlations, which means that the multicollinearity does not have substantial impact on the coefficients of the model.

Moreover, the Carhart four-factor model reduces the average pricing errors when compared with CAPM and Fama-French three-factor model. Carhart (1997) also proves that the mean absolute error from four-factor model is only 0.14 which is smaller than errors from the other two models. This indicates that the cross-sectional returns can be well described by four-factor model. Nevertheless, there are still some other anomalies which cannot be explained by three-factor model: net stock issues, accruals, profitability, and asset growth, and momentum. Even when Carhart four-factor model is proposed, it only covers the effects of momentum. It is still meaningful to

construct a new model.

More recently, Fama and French (2015) propose a five-factor model including the additional profitability factor and investment factor compared with three-factor model. The profitability and investment are identified by Novy-Marx (2013) and Aharoni et al. (2013) respectively. However, the five-factor model fails to include the momentum factor. Fama and French (2015) explain that the size, book-to-market, profitability and investment are the most they can control at the same time. If the momentum factor is included, the poor diversification of the portfolios may be produced as a result of correlations among the variables.

GRS test of Gibbons et al. (1989) is applied to examine the five-factor model and shows that the model cannot capture the size, B/M, profitability and investment factors. However, the model exhibits a considerable description of average returns on diversified portfolios sorted on size and one or two of the other three factors. Moreover, this model implies that the relationship between HML and average returns is relatively weak. The effect of HML is captured by the other four factors, but the four-factor model still performs no better than the five-factor model.

Since the Fama-French five-factor model is quite a new model, there is little literature that studies testing the model. Empirical evidence needs to be provided on the application of this new model.

**(iv) Liquidity-augmented capital asset pricing model.** Apart from the popular factor models, some other scholars also present some other factor based asset pricing models. Liu (2006) proposes a new asset pricing model which is called liquidity-augmented capital asset pricing model and

he shows that liquidity is an important source of priced risk. He proposes a new liquidity measure which is the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months. This measure is better than other popular measures such as the liquidity risk by Pastor and Stambaugh (2001). While Pastor and Stambaugh (2001)'s measure only captures the price reaction to trading volume, Liu (2006)'s new measure captures multiple dimensions of liquidity such as trading speed, trading quantity, and trading cost, with particular emphasis on trading speed. This new measure can predict stock returns one or more years ahead.

His two-factor (market and liquidity) model can well explain the cross-section of stock returns. Moreover, this model captures the liquidity premium which is enhanced after adjusting for either the CAPM or the Fama-French three-factor model. It means that both the two models fail to explain the liquidity risk.

As asset pricing model develops quickly over these years, there is no one asset pricing model that is absolutely the best. Moreover, some other anomalies remain to be explained. However, all the asset pricing models introduced before have presented meaningful descriptions of the relationship between risk factors and equity returns. In the next part, three important predictive variables will be reviewed. These variables are found to be linked with stock returns. The empirical analysis of this thesis is on the basis of these popular variables.

## 2.4 Skewness risk

### 2.4.1 Introduction to skewness

Skewness is found to be a new anomaly and it is more like a risk characteristic of securities. Arditti (1967) points out that the third moment of the distribution is one kind of risk. It is clear that the second moment of distribution refers to variance and the third moment means skewness. In short, market skewness means that the distribution of returns does not follow a normal distribution. On the basis of studies by Arditti (1967), Scott and Horvath (1980) argue that higher values of even moments, for example, variance and kurtosis are associated with higher returns in the future, and vice versa. However, higher values of odd moments, for example, skewness are connected with lower expected returns.

Kraus and Litzenberger (1976) incorporate skewness into asset price model and propose the three-factor model. According to their model, the expected returns are affected by systematic variance as well as systematic skewness. The systematic risk cannot be diversified. After that, the model is widely used and tested with various methods. Lim (1989) uses generalized method of moments (GMM) approach to test the three-factor model based on monthly stock returns and concludes that systematic skewness is priced. Lee et al. (1996) re-examine the model by using multivariate testing and the results are in line with the study by Lim (1989). Moreover, they stress that co-variance is more important than co-skewness in explaining the stock returns. All the results prove that the model performs well.

Harvey and Siddique (1999) extend the GARCH(1,1) model by explicitly modelling conditional variance and skewness jointly. The results show that the co-skewness is important and the asymmetry in variance disappears after the inclusion of skewness. Harvey and Siddique (2000a) incorporate the conditional skewness into asset pricing model and find that conditional skewness can explain the cross-sectional variation in expected excess returns. At the same time, Harvey and Siddique (2000b) prove that conditional co-skewness is important and helps explain the time-variation of ex ante market risk premium. This effect is found to be more pronounced for world portfolio than for US portfolio. Lately, Vanden (2006) finds that the covariance and coskewness affect the market returns as well as option returns when his pricing kernel takes the index option into consideration. Chabi-Yo (2012a) supposes that pricing kernel relies on two factors: coskewness and volatility. He also tries to use investors' preferences to explain the risk premium of coskewness and market volatility.

According to the model of Kraus and Litzenberger (1976), unsystematic skewness should be diversified and thus cannot be used to predict returns. Unsystematic skewness is also called idiosyncratic skewness. Kane (1982) shows that investors may prefer skewness and thus they may not hold diversified portfolios. Simkowitz and Beedles (1978) insist that diversification is not necessarily desired for investors who make their decisions based on the first three moments of return distributions. Therefore, idiosyncratic skewness matters in the pricing of assets. Mitton and Vorkink (2007) introduce the heterogeneous preference for skewness into a rational model. Underdiversified investors are more likely to get positive skewed returns when compared with diversified investors. Furthermore, they suggest that the idiosyncratic

skewness can affect the prices, and the stocks selected by underdiversified investors often exhibit higher idiosyncratic skewness. In another example, Barberis and Huang (2008) demonstrate that the investors' decisions are on the basis of cumulative prospect theory. Participants prefer positive skewed assets, resulting in overpriced as well as negative excess market returns. Fu (2009) examines the relation between idiosyncratic volatility and cross section of stock returns. Then Boyer et al. (2009) continue to investigate the effects of expected idiosyncratic skewness and they find that there is a strong negative relationship between expected idiosyncratic skewness and stock returns.

While it is difficult to measure the skewness of future stock returns from historical data, recent studies tend to focus on the implied skewness extracted from option data. Conrad et al. (2013) compute option implied-skewness for each stock and find that stocks with higher skewness will generate lower returns in the future. Chang et al. (2013) extracted implied skewness from S&P 500 index options and they find that stocks with higher sensitivity to market skewness risk will have lower returns in the future. However, Xing et al. (2010) insist that risk-neutral skewness is positively linked to future stock returns.

According to the literature, the skewness can be defined into many kinds, for example, total skewness, co-skewness and idiosyncratic skewness. In next part, the classification of skewness based on the data used in the calculation will be outlined.

### 2.4.2 Classification of skewness

Firstly, this section classifies the skewness into two broad categories: realized skewness and implied skewness. And then the other kinds of skewness defined in other ways, which may be included in the two groups, are introduced. Next, the development on the skewness risk is sketched. Lastly, the weaknesses of the research on skewness are illustrated.

**(i) Realized skewness.** Realized skewness mainly refers to two kinds of skewness: the first one refers in particular to the realized skewness introduced by Neuberger (2012) and the second one is historical skewness. Neuberger (2012) defines a new skewness called realized skewness which is defined in the same way as realized volatility. The realized skewness is calculated from high-frequency data and the purpose is to measure the skewness of long-horizon returns precisely. However, the other so called realized skewness, which all refer to historical skewness, are different from the concept proposed by Neuberger (2012). The historical skewness is calculated by using the past equity returns, and this kind of skewness only contains the past information in the market without considering the future information. The findings of realized skewness by numbers of scholars will be illustrated as follows:

Kapadia (2006) shows three measurements of skewness calculated by using historical individual stock returns and points out that the cross-section skewness is a basic measure. Moreover, the negative relation between cross-section skewness and returns has been found by regressing the stock returns on skewness factor and Fama-French factors. Adrian and Rosenberg (2008) use the historical daily returns to compute the volatility which is

divided into two parts: short-run component and long-run component. The short-run component is regarded as market skewness risk. They find that the risk premium of market skewness risk turns out to be positive.

For other examples, see Lambert and Hübner (2013) and Kostakis et al. (2012) who all use historical data of stock returns to get the skewness factors. Another skewness called stochastic skewness is also historical skewness. It is past skewness with an exogenous shock. Bakshi et al. (2008) introduce the stochastic skewness and stochastic risk premiums generated from currency options in international economics. The results show that the risk premium is higher in Japan than those in US and UK. Moreover, when the negative shock occurred, the investors need a larger risk premium to compensate for this kind of risk. Investors only react to the downside jumps but neglect upside jumps. Chabi-Yo (2012a) suggests that the price of stochastic skewness is different from the systematic risk power such as coskewness.

**(ii) Implied skewness.** Implied skewness is usually computed under risk-neutral probability by using option data. Option price contains the information of investors' expectations. This kind of skewness has only been widely used in the last decade. For example, Xing et al. (2010) examine the relation between option implied skewness and individual stock returns and demonstrate the positive effect of the risk-neutral skewness, while Chang et al. (2013) investigate implied skewness based on index options and the results show that the stocks with high exposure to innovations in option implied skewness are associated with low returns.

Friesen et al. (2012) try to focus on what factors are influential in explaining

the skewness. The skewness is regarded as a dependent variable in cross-sectional regression. Belief heterogeneity is found to be negatively related to risk-neutral skewness. They figure out that some other variables such as option open interest, idiosyncratic volatility and stock trading volume are correlated with skewness.

Conrad et al. (2013) focus on the ex ante skewness based on equities' risk-neutral distribution. This kind of skewness can also be defined as risk-neutral skewness as option prices used. Option price contains the future expectation of investors, so the ex ante skewness and risk-neutral skewness are all implied skewness. Conrad et al. (2013) test the effects of ex ante skewness on the cross section of returns with a sample of options on individual stocks. The results indicate that the relation between ex ante skewness and returns is strongly negative, and the kurtosis is positively related to cross section of returns. Moreover, the effects persist even after controlling for other firm factors.

**(iii) Other skewness.** Skewness can also be classified with other standards. For example, based on the risk characteristic, skewness can be divided into systematic skewness and idiosyncratic skewness. Systematic skewness can also be defined as coskewness which means the third moment correlation between the individual stocks and market. The idiosyncratic skewness is calculated by using the residuals of the asset pricing model (Boyer et al., 2009). Therefore, idiosyncratic skewness can be diversified away when holding fully diversified portfolios. There are also some other skewness measures like conditional skewness. This section defines all these skewness as other types of skewness because these types of skewness can also be implied and realized depending on the data used for calculation.

Another important part of skewness is idiosyncratic skewness. Idiosyncratic skewness is also idiosyncratic risk. In the early years, scholars only regarded idiosyncratic volatility as idiosyncratic risk. Idiosyncratic volatility has been found to play a role in determining the returns (Ang et al. (2006); Spiegel and Wang (2005); Fu (2009); Bali and Cakici (2008)). Idiosyncratic skewness is similar to the idiosyncratic volatility as skewness is the third moment of distribution while volatility is the second moment. Therefore, idiosyncratic skewness can be priced in stock returns (Mitton and Vorkink (2007); Barberis and Huang (2008)). Boyer et al. (2009) examine the pricing implication of the idiosyncratic skewness using expected idiosyncratic skewness. They utilize the lagged skewness as well as standard firm-level variables to predict the skewness and find that expected idiosyncratic skewness is negatively linked to the average returns. The results are highly significant.

Feunou and Tédongap (2012) are the first to use stochastic volatility model with conditional skewness, and the model is defined as SVS model. The model overcomes the limitations of current discrete-time SV models in explaining the characteristics of asset returns by allowing the conditional asymmetries in the model. They find that their model performs better than GARCH model and stochastic volatility with jumps models (SVJ), which confirms the results by Carr and Wu (2007). Dovonon (2013) uses a conditionally heteroskedastic model proposed by Doz and Renault (2006) to capture the conditional skewness as well as leverage effect. Their finding also confirms the results by Harvey and Siddique (1999) that after incorporating conditional skewness, conditional volatility turns out to be less persistent.

Although there are many kinds of skewness, all these types of skewness can be defined as implied skewness and historical skewness based on whether

the data used is backward-looking or forward-looking.

**(iv) Comparison between implied skewness and historical skewness.** Historical skewness has been widely used for a long period of time, but using returns history has some drawbacks. Lambert and Hübner (2013) suggest that coskewness computed with historical returns lies in the trade-off problem caused by the choice between long time-series for precise estimation and short windows to obtain variation in skewness and kurtosis over time.

More recently, scholars have preferred to use implied skewness. Option implied skewness is forward-looking and captures the investors' expectations (Chang et al. (2013); Conrad et al. (2013)). Moreover, Conrad et al. (2013) also present that the option prices used to extract the skewness can solve the problem of using a long time series of returns especially when the payoff distribution of new companies need to be forecasted. However, not all stocks have options and hence using implied skewness could lead to a much smaller sample than other methods. Chang et al. (2013) suggest that the implied skewness calculated from a single day of option prices is appropriate for examining the conditional asset pricing models. Additionally, they also stress that implied higher moments are also risk-neutral moments and they are important risk factors.

Therefore, one of the empirical chapters in this thesis uses the methodology by Bakshi et al. (2003) to extract the option implied skewness factor. Next, the development on the skewness risk will be illustrated.

### 2.4.3 Development on the importance of skewness

**(i) Skewness and time series returns.** Early scholars try to incorporate the market coskewness into the capital asset pricing model and examine the relation between time-series stock returns and the third moment. As the volatility is the second moment of distribution and skewness is the third moment of distribution, they expand the investor's utility function in a Taylor series and neglect the moments, higher than the fourth moment, suggested with no economic significance. Kraus and Litzenberger (1976) first define the three-moment CAPM by applying the coskewness to CAPM. However, the empirical evidence from Friend and Westerfield (1980) shows that the three-moment model is not precise as they may only reflect the results in a particular time period as well as estimation approaches. Sears and Wei (1985) and Sears and Wei (1988) also extend the application on three-moment model and redefine the coefficient of the variables. They tend to explain the economic price of the skewness. Harvey and Siddique (2000b) suggest that the conditional skewness is influential in explaining the negative market risk premiums. The asset pricing model which includes the skewness factor performs better than CAPM for the world portfolio.

**(ii) Skewness and cross section of returns.** More recently, scholars also find that the skewness risk matters in the cross section of stock returns. Harvey and Siddique (2000a) use the excess return on both negative and positive skewness to proxy the conditional systematic skewness. Consequently, they discovered that the conditional systematic skewness is both statistically significant and economically significant in explaining the cross section of stock returns. When Annaert et al. (2013) study the extreme returns and

cross section of stock returns, they also focus on idiosyncratic skewness and coskewness and find that the negative relations between expected returns and both idiosyncratic skewness and coskewness are significant even after adding the extreme returns.

Lambert and Hübner (2013) and Kostakis et al. (2012) both study the coskewness and cross section of stock returns by applying Fama-French cross-sectional regression and find that the coskewness is negatively related to the returns. Lambert and Hübner (2013) mainly focus on the US market, while Kostakis et al. (2012) investigate the effect in the UK market and their approaches to calculate the skewness are quite different. However, the results are all significant even after controlling for the standard factors as well as the fourth moment of distribution.

Different from previous studies, Chang et al. (2013) employ the market-wide skewness extracted from Standard and Poor's 500 index options and the results show that the relation between the skewness and cross section of returns is negative, while the risk premium of kurtosis is positive. Moreover, the option-implied skewness is both statistically and economically significant even after various robustness checks. This new anomaly cannot be explained by other risk factors such as size, book-to-market equity, momentum, and volatility.

According to the literature of skewness, I will propose a new factor instead of skewness. The predictive power of this new factor will be illustrated in Chapter 4. Chapter 5 focuses on the skewness risk factor. I will examine the effect of option-implied market skewness in cross section of stock returns by incorporating other factors.

## 2.5 Tail risk

### 2.5.1 Introduction to tail risk

Over the past decade, a branch of studies have investigated the time-varying extreme event risk in financial markets and emphasize that heavy-tailed shocks help understand much asset pricing behaviour. The extreme event is also called "tail event" which represents rare, high-impact events. For example, the US financial crisis is one of the tail events during recent years. The extreme events lead to large crashes in financial markets.

In early years, Mandelbrot (1963) documents that large price changes occur often, which is inconsistent with predictions by the Gaussian. The large price changes reflect the "excessively peaked" character of price relatives. Fama (1965) also finds that the stocks returns are not normally distributed and are associated with heavy tails. This can be described by a power law. Additionally, Officer (1972) argues that stock return distributions incorporate some non-normal characteristics. More specifically, the distribution is "fat-tailed".

Another view on tail risk should be the investigation on the disasters in the equity market. Many studies have found evidence that the disasters matter in financial markets. Rietz (1988) points out that the equity premium puzzle can be solved after taking the large, unlikely market crashes into consideration. As a result of rare bad events in the market, he adds a low-probability, depression-like third state to the consumption asset pricing model in order to capture the effect of the crashes. The motivation is that risk-averse equity investors require a high return for bearing extreme

losses. On the basis of Rietz (1988)'s model, Barro (2006) uses the observed probability distribution for economic disasters in the twentieth century to calibrate the model. He also finds that the model can explain the high equity premium. Moreover, it also helps resolve why expected risk-free rate were low in the U.S. during wartime, such as in World War II.

However, Rietz-Barro hypothesis is usually accompanied by constant intensity of disasters. Gabaix (2012) apply a variable-intensity version of the disaster hypothesis and examine the effect of time-varying disaster intensity on stock and bond returns. This extended model helps resolve many finance puzzles and can be regarded as a simple benchmark for various problems in macroeconomics and finance. Following previous studies, Gourio (2012) incorporates time-varying risk premia in a business cycle model and considers the feedback from this premia to macroeconomic activities. Wachter (2013) also introduces a model with a time-varying disaster. All these studies provide a better understanding on the equity premium puzzle. Wachter (2013) also finds that the time-variation on the probability of a disaster is the reason for high market volatility and excess return predictability.

Another branch of related studies is from the view of modelling of extreme events with jump process. The most notable affine is investigated by Duffie et al. (2000). They derive a closed-form expression of an affine jump-diffusion process on affine asset pricing models. The class of transforms leads to an analytical treatment of many valuation and economic problems. Many studies focus on long-run risk extensions built on models with jump processes. Eraker and Shaliastovich (2008) incorporate fat-tailed endowment shocks and examine the equilibrium effect of volatility shocks on theoretical option price. They find that pricing stocks, bonds, and derivatives with

affine no-arbitrage models is possible. Bansal and Shaliastovich (2010) introduce a long-run risks type model and they point out that investors use cross-section of signals to learn about the expected growth. The combination of fluctuations in confidence risk and recency-biased expectations are the reason of asset market jumps. Bansal and Shaliastovich (2011) also argue that the market volatility can be used to predict jumps in returns. Their model reflects smooth Gaussian dynamics of income and dividends as well as large and low probability movements in equity prices, which is also based on long-run risks model. Another similar study is presented by Drechsler and Yaron (2011), generalized long-run risks model requires a time-varying variance premium and return predictability. Their results provide important evidence that transient non-Gaussian shocks play a role in the impact of agents' view of economic uncertainty and prices.

More recently, scholars have found that there is a large compensation for rare events. Bollerslev and Todorov (2011) identify and investigate a new Investor Fears Index to measure the large time-varying compensation for bearing the disasters in the market. Their results show that the compensation for disasters is one of the main reason for jump average equity and variance risk premia. Kelly and Jiang (2014) try to capture the tail risk by using tail index. They find that investors tend to use the stocks with low sensitivity to tail risk to hedge tail risk. The stocks with high loadings to tail risk are highly discounted. Therefore, they predict that stocks with high loadings to tail risk tend to have high returns in the future.

### 2.5.2 Classification of tail risk measures

Tail risk dynamics for stock returns can be measured with three approaches. Kelly and Jiang (2014) point out that as a result of infrequent nature of tail events, it is not feasible to estimate dynamic tail risk estimates in a univariate time series model. Therefore, the large dataset used in the estimation of dynamic tail risk is quite essential.

The first approach is based on option price data. Bakshi et al. (2003) and Carr and Madan (2001) extract risk-neutral skewness and kurtosis from the option price data. This method has been applied by many scholars such as Chang et al. (2013) and Conrad et al. (2013). Chang et al. (2013) estimate the implied moments from market level while Conrad et al. (2013) investigate the implied moments from stock level. They all find that option implied skewness has a strong explanation power on stock returns. Other option implied skewness studies are discussed in section 2.4. Backus et al. (2011) examine the distribution of consumption growth disasters by using index options. They argue that it is not easy to estimate the jump parameters from short historical data. Option data provide another short way to resolve the problem. This is because option data contain additional information about how market investors value extreme events. They find that disasters extracted from option prices have smaller probability compared to the prediction by Rietz (1988) and Barro (2006). There are similar studies such as Gao and Song (2015) who construct a time-varying rare disaster risk from out-of-the-money options to explain expected returns in the cross sections. The results show that assets with higher sensitivity to rare disaster risk generate lower expected returns, while assets with lower sensitivity

to rare disaster risk will have higher returns in the future. These results are consistent with the findings by Chang et al. (2013) and Conrad et al. (2013).

The second approach is based on high frequency return data. Bollerslev and Todorov (2011) extract the expected jump tails by using high-frequency intraday returns and out-of-the-money options with short maturity. Their results show that the compensation for jump tail risk may lead to historically large equity and variance risk premium. Bollerslev et al. (2013) find that jump tail risk deduced from high frequency data combined with variation in the diffusive volatility lead to "extreme" joint dependence. They also insist that the distribution of jumps are close to symmetric with heavy tails. By using this method, Bollerslev and Todorov (2014) suggest that there exists strongly significant temporal variation in both tails. This is more pronounced for left tail, which is associated with market distress and financial crisis.

The last approach is based on cross-section of data information. By applying Hill et al. (1975)'s estimator to cross-section of stock returns, it is possible to capture common variation in the tail risks for each firm. Chollete and Lu (2011) estimate daily tail index based on a power law distribution. They find that tail risk generates large returns in the stock market and this effect cannot be explained by other risk factors. The relationship between tail risk and stock returns is negative. Kelly and Jiang (2014) calculate the tail risk for each month based on the large cross-section of daily returns. They find that tail risk is highly persistent and this measure is highly correlated with implied skewness and kurtosis documented by Chang et al. (2013). This tail index can also be used to predict stock returns. Stocks with high

loading to tail risk tend to generate higher returns in the future. This result is consistent with the findings by Chollete and Lu (2011). The difference between methods used in these two studies is the frequency of tail risk estimated.

The approach based on option data has data limitations. Option data are usually available from 1996, which means the time period of data is restricted. The approach based on high frequency has the limitation of application. Some data had no high frequency data such as cash flow data. Compared with the previous two methods, the approach based on cross-section of data is much more straight forward. In the empirical part of this thesis, I will also apply Hill et al. (1975)'s estimator to a large cross-section of stock returns following the procedure by Kelly and Jiang (2014).

## **2.6 Default risk**

In this thesis, I will use default risk as the key control variable when I examine the effect of skewness risk as well as the effect of tail risk. Therefore, I will review the relationship between default risk and stock returns and some popular proxies of default risk.

### **2.6.1 Introduction to default risk**

Default risk is one kind of credit risk. It refers to the likelihood that a levered company fails to make the required payments on their debt obligations. This kind of risk is also known as distress risk and bankruptcy risk. In

recent years, many scholars have found that default risk is priced in equity returns. The research on default risk and stock returns can be classified into two groups. The first group of people insist that the default risk and stock returns are positively related, however, the other group of people stress that stocks with default risk can generate low returns.

Vassalou and Xing (2004) point out that default effect is a positive average return differential between high and low default risk stocks. It is especially pronounced in small size groups. The measure used in their study is called default likelihood indicators (DLI) which is a positive nonlinear function of its default probability. Chava and Purnanandam (2010) use two methods to measure default risk: the first one is default probability based on hazard rate model and the second measure is distance to default based on Merton (1974) model. They use implied cost of capital (ICC) as a proxy for expected return. They find that default risk is positively related to expected returns. They also test the relationship between default risk and realized stock returns and find that the relationship is considerably weaker.

Other scholars may think that the relationship between default risk and stock returns is negatively related. Dichev (1998) finds that there is a negative relationship between default risk and stock returns. He uses accounting model to construct Z-score and O-score and use realized return as the expected stock returns. Garlappi et al. (2008) use the Expected Default Frequency (EDF) of Moody's KMV model to measure default risk and try to investigate the relationship between default risk and stock returns. They stress that higher default risk is not associated with higher expected equity returns. They conclude that distressed companies with stronger shareholder advantage should have lower expected returns in the cross section.

From the past literature, I can find that there are many different kinds of measures of default risk. In the following section, I will review some measurements of default risk.

### 2.6.2 Measurement of default risk

In this section, I introduce four widely used measurements of default risk: Z-score, O-score, default spread and distance to default. The first two methods are both based on accounting model using accounting information. The default spread is calculated based on bond data. The fourth method is based on Merton (1974)'s model, which has become more popular in recent years.

**(i) Z-score and O-score.** The earliest quantitative method used to measure the credit risk of firms is Z-score proposed by Altman (1968a). In his paper, he attempts an assessment of corporate bankruptcy which is the quality of ratio analysis. The prediction of corporate bankruptcy is used as an illustrative case. Specifically, a set of financial and economic ratios will be considered in a bankruptcy prediction context wherein a multiple discriminant statistical methodology is employed. Altman (1968a) stresses that his Z-score predicts 24 out of 25 bankruptcy firms correctly.

However, Ohlson (1980) uses his sample of firms and finds that the prediction error-rate is larger compared with the rate reported in the study by Altman (1968a).

One of the most popular measurements of default risk is O-score presented by Ohlson (1980). He uses nine financial ratios to construct O-score. SIZE

is log total assets. TLTA is total liabilities divided by total assets. WCTA is working capital divided by total assets. CLCA is current liabilities divided by current assets. OENEG equals to one if total liabilities exceeds total assets, zero otherwise. NITA is net income divided by total assets. FUTL is funds provided by operations divided by total liabilities. INTWO equals to one if net income was negative for the last two years, zero otherwise. CHIN is intended to measure change in net income. However, a potential disadvantage of O-score model is that the model does not use any market transactions data of the firms. Ohlson (1980) proves that O-score model performs better than Z-score model.

Griffin and Lemmon (2002) examine the relationship between book-to-market equity, distress risk and equity returns by using the proxy proposed by Ohlson (1980). They find that the difference in returns between high and low book-to-market equity stocks is more than twice as large as the returns in other groups. They also find that firms with high distress risk have characteristics that make them more likely to be mispriced by investors. Moreover, firms with high distress risk exhibit the largest return reversals around earnings announcements.

Dichev (1998) uses both Z-score and O-score to test the relation between bankruptcy risk and subsequent returns and find that the bankruptcy risk is not rewarded by higher returns. In other words, firms with higher bankruptcy risk generate lower average returns.

However, Z-score and O-score are based on accounting models. They all use similar financial ratios which have similar likelihood of default to calculate the default indicator. These methods have been proved not accurate as

they miss the volatility of asset value which is crucial information about the firm's probability to default. Therefore, I outline some other methods.

**(ii) Default spread.** Another measurement of default risk is default spread. The default spread is usually calculated as the return differential between long-term BAA corporate bonds and long-term AAA bonds. Early scholars tend to use default spread to measure the default risk and find that it is related to equity returns.

Keim and Stambaugh (1986) construct bond market variable by using the spread between yields on low-grade corporate bonds and one-month treasury bills. They use this variable to measure default risk. They find that this bond market variable can predict returns on common stocks of companies of different sizes and long-term bonds of various default risks. Moreover, the returns on small size stocks and low-grade bonds are highly correlated in January. Campbell (1987) uses the term structure of interest rates to represent default spread and he proves that the term structure can predict excess stock returns in U.S. monthly data for the period 1958-1979 and 1979-1983.

However, Elton et al. (2001) stress that default spread calculated as the spread between spots rates and government bonds is unrelated to default risk. Nearly 85% of the spread can be explained as the systematic risk premium. Moreover, differential taxes can potentially be a major variable in accounting for the overall corporate. After that, scholars try to find another way to measure default risk, which is default probability.

**(iii) Default probability.** Default probability is the probability that the firms will be unable to service obligations. This measurement is based on

Merton (1974)'s model. Bohn and Crosbie (2003) point out that there are three main elements that determine the default probability of a firm: value of assets, asset risk and leverage. Z-score and O-score are calculated based on accounting model which only considers asset value and leverage of a firm. This misses the asset risk. Asset risk is a measure of a firm's business and industry risk. The value of the firm's assets is uncertain. Therefore, the volatility of asset value should be taken into consideration. Therefore, this method is mainly based on equity data which is quite different from the default spread by using the data from the bond market.

Many scholars pay much attention to modeling default risk by using the method distance to default. For example, Bharath and Shumway (2008) examine the accuracy of the Merton distance to default (DD) model. They suggest that Merton DD model does not produce many statistics for the probability of default. However, its functional form is very useful for predicting the defaults.

In recent years, scholars have found that default probability is related to equity returns. Vassalou and Xing (2004) are the first scholars to calculate default measures for individual firms using Merton (1974)'s option pricing model and connect the default risk with equity returns. They find that default risk is systematic and it is priced in the cross section of stock returns. Vassalou and Xing (2004) also point out that both size and BM effects can be viewed as defaults and this is particularly the case for the size effects. The size effect exists only within the portfolios with the highest default risk. In the highest default risk portfolios, the return difference between small and big firms is 3.82% per month. In the other four default risk risk portfolios, size effect are all insignificant. Different from Vassalou and Xing

(2004), Chava and Purnanandam (2010) also use the distance to default to measure default risk. However, they use implied cost of capital (ICC) instead of realized return. They finally find a positive relationship between expected stock returns and default risk.

In conclusion, there are many different measures of default risk and the relationship between default risk and stock returns still need to be investigated. All this literature helps us understand the risk and returns more clearly. I will use default probability as the key control factor in our empirical analysis.

## 2.7 Conclusion

In this chapter, I review the Efficient Market Hypothesis (EMH) and the evidence against the hypothesis. This evidence is called "anomalies". Moreover, the explanation of anomalies is illustrated in two aspects, namely, rational approach and asset pricing models. I also review various skewness measures and tail risk measures. These two factors are predictive variables, which can be used to predict asset returns. In general, most studies on stocks with high skewness risk tend to have low returns in the future, while the relationship between tail risk and expected returns is positive. The studies on skewness risk are also the research background of the empirical study in Chapter 4. Moreover, the two key factors are the basis of empirical studies of this thesis in Chapters 5 and 6. Further, I review default risk measures. This factor is used to examine the effect of skewness risk and tail risk.

# Chapter 3

## Methodology

This chapter will illustrate two main methodologies documented by Fama and French (2008) to identify anomalies. The first method is portfolio sorts and the other method is cross-sectional regressions. I will discuss the specific applications of different methodologies in the empirical chapters according to the different research questions.

### 3.1 Portfolio sorts

There is a branch of literature that uses portfolio sorts to study the predictable variables in the equity market. At first, sorts is used to sort stocks on a single factor characteristic such as pre-ranking beta (Jensen et al., 1972). The idea is proposed by Banz (1981) based on size. He sorts stocks into portfolios according to size and pre-ranking *beta*. After that, Fama and French (1992) sort portfolios based on different characteristics of *beta*, size, E/P, leverage, and book-to-market equity in order to evaluate the

relations between the average returns and anomalies. More recently, Fama and French (2008) optimize the sorts approach because sorts usually form equal-weight decile portfolios and microcaps tend to play an important role in portfolios, resulting in unexpected results. Sometimes equal-weight method can take place with value-weight method. However, value-weight method is influenced by a few big stocks. Consequently, Fama and French (2008) first sort portfolios on size and then sort on other firm characteristics. Size is divided into three groups which are microcaps, small stocks and big stocks. They also imply that sorts can simply illustrate how stock returns vary across one particular variable.

According to the portfolio sorts approach, I examine the performance of five portfolios based on different key factors in this thesis. In Chapter 4, 5 and 6, I use the sensitivities to market skewness risk, loadings to tail risk and return asymmetry to form portfolios, respectively. In general, at the end of each month  $t$ , all the stocks listed on NYSE, AMEX and NASDAQ are ranked on their key factors, and then are assigned to one of the five quintiles. Therefore, portfolio 1 denotes the stocks with the lowest value of the key factor and portfolio 5 represents the stocks with the highest value of the key factor. The portfolio sorts by key factors are based on CRSP breakpoints. However, the breakpoints for portfolio sorts by size and book-to-market value are different. Considering the stocks listed on NYSE are usually with larger size and these stocks have larger impact on the whole market compared with the stocks listed on AMEX and NASDAQ. Fama and French (1992) choose NYSE breakpoints rather than CRSP points. By using these breakpoints, the extreme portfolios contain not only tiny stocks. In our empirical studies, stocks sorted based on size and book-to-market

ratios are allocated to three portfolios based on NYSE breakpoint. I will examine the effect of key factors in these three portfolios.

I will use different weights when I calculate portfolio returns, which are equal-weighted (EW) and value-weighted (VW). For the equal-weighted approach, after forming portfolios at the end of each month  $t$ , I calculate equal-weighted return for each portfolio at the end of month  $t + 1$ . For value-weighted approach, after forming portfolios at the end of each month  $t$ , I calculate value-weighted return for each portfolio at the end of month  $t + 1$ . The weight for each stock  $i$  is the ratio of market value of the stock  $i$  to the total market value of the portfolio at the end of month  $t$ . In Chapter 4, we calculate equal-weighted returns and value-weighted for each asymmetry portfolios. Following Chang et al.'s (2013) method, I form quintile portfolios by sensitivities to market risk and calculate the value-weighted returns for each portfolio in Chapter 5. The value-weighted returns for skewness portfolios are not significant. According to Kelly and Jiang (2014)'s approach, I will sort all the stocks into quintile portfolios by loadings to tail risk and compute both equal-weighted and value-weighted returns for each portfolio in Chapter 6.

## 3.2 Abnormal return

After portfolio formation, I also investigate the abnormal returns. Abnormal returns are also called risk-adjusted returns. Risk-adjusted returns are the returns after removing the effect of common risk factors. In general, after getting all the post-returns for each portfolio, I regress the monthly returns

### 3.2. ABNORMAL RETURN

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on the risk factors for the whole sample. The alphas extracted from the regressions are the risk-adjusted returns. To confirm the effect of key factors, I use popular asset pricing models. For the capital asset pricing model (CAPM) proposed by Sharpe (1964) and Lintner (1965), I run the following model:

$$R_{p,t} - R_{f,t} = \alpha_{CAPM} + \beta_{p,mkt} (R_{m,t} - R_{f,t}) + \epsilon_{p,t} \quad (3.1)$$

where  $R_{p,t}$  is the return on portfolio  $p$  in month  $t$ .  $R_{f,t}$  is risk-free rate in month  $t$ .  $R_{m,t} - R_{f,t}$  is the market excess return, value-weighted return of all NYSE, AMEX and NASDAQ stocks.

For the Fama-French three-factor model (FF3) documented by Fama and French (1993), I run the following time-series regression:

$$\begin{aligned} R_{p,t} - R_{f,t} = & \alpha_{FF3} + \beta_{p,mkt} (R_{m,t} - R_{f,t}) + s_p SMB_t \\ & + h_p HML_t + \epsilon_{p,t} \end{aligned} \quad (3.2)$$

where  $SMB_t$  (Small-Minus-Big),  $HML_t$  (High-Minus-Low) are size factor in month  $t$  and the book-to-market factor in month  $t$ , respectively. Specifically, they are the differences between the returns on diversified portfolios of stocks with small and big market values, high and low book-to-market ratios.

For the Carhart four-factor model documented by Carhart (1997), I run the following regression:

### 3.2. ABNORMAL RETURN

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$$\begin{aligned} R_{p,t} - R_{f,t} = & \alpha_{Carhart} + \beta_{p,mkt} (R_{m,t} - R_{f,t}) + s_p SMB_t \\ & + h_p HML_t + m_p UMD_t + \epsilon_{p,t} \end{aligned} \quad (3.3)$$

where  $UMD_t$  (Up-Minus-Down) is momentum factor in month  $t$ , which is the difference between the returns on diversified portfolios of stocks with high and low past returns.

For the Fama-French five-factor model documented by Fama and French (2015), I run the following regression:

$$\begin{aligned} R_{p,t} - R_{f,t} = & \alpha_{FF5} + \beta_{p,mkt} (R_{m,t} - R_{f,t}) + s_p SMB_t \\ & + h_p HML_t + r_p RMW + c_p CMA_t + \epsilon_{p,t} \end{aligned} \quad (3.4)$$

where  $RMW_t$  (Robust-Minus-Weak) is operating profitability (OP) factor in month  $t$  and  $CMA_t$  (Conservative-Minus-Aggressive) is investment factor in month  $t$ . Specifically, they are the differences between the returns on diversified portfolios of stocks with robust and weak profitability, and low and high investment, respectively.

If an asset pricing model explains the portfolio returns, the intercept of the model should be insignificant, proving that the intercept equals zero.

### 3.3 Cross-sectional regression

Another approach to identify anomalies is cross-sectional regression documented by Fama and MacBeth (1973). The Fama and MacBeth (1973) cross-sectional regression is used to investigate the risk premiums of anomalies. The regression can be done in two steps: firstly, time series regressions are used to estimate the betas of different anomalies, and then second regressions are applied to test the coefficients of the betas. Fama and French (2008) think that the results from regression approach can be affected by microcaps because of their disproportional representation. As a consequence, they turn to consider the separate regressions on microcaps, small stocks and big stocks along with a group of all-but-microcap stocks.

In this thesis, I use Fama and MacBeth (1973) cross-sectional regressions based on individual stocks. In the last two empirical chapters, I first sort all the stocks into three portfolios based on selected control variables, then in each group of stocks, I run cross-sectional regressions by regressing the monthly returns on lagged key factor and control variables. The cross-sectional regression is as follows:

$$R_{i,\tau+1} - R_{f,\tau+1} = \lambda_0 + \lambda_1 Key + \boldsymbol{\lambda}'_2 \mathbf{X}_{i,\tau} + \epsilon_{i,\tau+1} \quad (3.5)$$

where  $R_{i,\tau+1}$  denotes the monthly raw return of stock  $i$  from July of year  $\tau$  to June of year  $\tau + 1$ .  $Key$  is the lagged key factor from June of year  $\tau$  to May of year  $\tau + 1$ .  $\mathbf{X}_{i,\tau}$  is the  $3 \times 1$  vector of the lagged control variables that are  $\ln(MV)$ ,  $\ln(B/M)$ , and  $MOM$ .  $\ln(MV)$  is the natural logarithm of firm's market value calculated with information available at the end of

June of year  $\tau$ .  $\ln(B/M)$  is the natural logarithm of the ratio of the book value of equity for the fiscal year ending in year  $\tau - 1$  divided by market value of equity at the end of December of year  $\tau - 1$ .  $MOM$  is the cumulative compounded stock returns over the last 6 months from June of year  $\tau$  to May of year  $\tau + 1$ .

Portfolio sorts and Fama and MacBeth (1973) regression are usually used at the same time in papers. This is because different methods have different advantages and could make up own shortages. More importantly, the two methods support the same results. Fama and French (2008) point out that the sorts are hard to interpret which risk factors have the unique effect on average returns. Moreover, sorts are not proper to investigate the relation between risk and returns with the form of function. The Fama and MacBeth (1973) cross-sectional regression provides good solutions. However, Fama and French (2008) emphasize that the observation problems may hide in cross-sectional regressions. This can be supported by the sort method since sorts can cross check the individual stocks and help find potential observation problems.

## 3.4 Conclusion

In this chapter, I review two widely used methodologies, which are portfolio sorts and cross-sectional regressions. These two methods are both used in the empirical Chapters 4, 5 and 6. I will change the applications of the two methods according to specific research topics. For example, I will apply two-way portfolio sorts in Chapter 5 and 6. Then cross-sectional

### 3.4. *CONCLUSION*

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regressions in different group of stocks will be examined. The details of the two methods will be illustrated in the following empirical studies.

## Chapter 4

# Return Asymmetry and the Cross Section of Stock Returns

### 4.1 Introduction

A large body of research on empirical asset pricing focuses on the relation between expected returns and the shape of the return distribution, characterised by its third moment: skewness. Among a number of early works in this area, Arditti (1967) shows that under very general assumptions, investors have a preference for assets whose return distributions are positively skew. Subsequently, Rubinstein (1973), Kraus and Litzenberger (1976) and Harvey and Siddique (2000a) extend the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) by incorporating skewness of the distribution of asset return in the CAPM. The theoretical modifications made to the CAPM are grounded on the assumption that investors prefer securities with positive skewness which possess a lottery-like property and thus demand higher expected returns if they are to be persuaded to hold assets with negative skewness.

Recent development in the theoretical research in this area suggests that

skewness of the return distribution can explain variations in the asset returns. For example, Mitton and Vorkink (2007) find that idiosyncratic skewness can be used to predict stock returns when the model incorporates heterogeneous investor preference for skewness. Barberis and Huang (2008) demonstrate that when preferences are assumed to follow the cumulative prospect theory of Tversky and Kahnemann (1992), investors are attracted to lottery-like securities which have small probabilities of generating extremely large returns in the future. Their findings imply that stocks with larger idiosyncratic skewness should have lower expected returns. Furthermore, based on a model of optimal beliefs, Brunnermeier et al. (2007) also arrive at a similar conclusion. An implication of their model suggests that investors overweight assets with positive skewness because of their natural tendency to be optimistic about the payout from their investments. As a result, they argue that positively skewed assets tend to have lower returns.

Despite the negative relation between skewness and expected returns predicted by theoretical models, empirical investigations carried out during the past decade show mixed results. For instance, using firm-level data, Boyer et al. (2009) use lagged volatility, lagged skewness and a number of firm characteristics to predict idiosyncratic skewness. They find that expected idiosyncratic skewness and stock returns are negatively related. Moreover, using intraday data to compute weekly realised skewness, Amaya et al. (2015) also show that the third moment of return distribution is negatively correlated with the cross-section of stock returns. Importantly, they demonstrate that results reported in Boyer et al. (2009) crucially depend on the estimation window of skewness. Bali and Murray (2013), however, note that skewness of daily returns calculated over the past one year fails

to predict future stock returns.

While the historical approach for calculating return skewness is widely adopted among researchers, a model-free measure of risk-neutral skewness, proposed by Bakshi and Madan (2000) and Bakshi et al. (2003), has recently gained much attention. This approach, which estimates skewness from option prices, is attractive because it mitigates the issues of measurement error in skewness associated with historical-based estimates. Among a number of empirical papers investigating the relation between *ex ante* risk-neutral skewness and stock returns, Conrad et al. (2013) find that the relation is negative when they calculate implied skewness for individual stocks. Chang et al. (2013) also find positive relation between sensitivities to innovations in market skewness risk and stock returns when they compute implied skewness risk from S&P 500 index options. However, Rehman and Vilkov (2012) and Bali et al. (2014) both report a positive relation. They both compute implied skewness for individual stock, which is the same as Conrad et al. (2013).

As a measure of the degree of asymmetry of a probability distribution, skewness has two issues. First, skewness is difficult to estimate precisely. The conventional measure of skewness is estimated from the standardised third sample moments following Pearson (1895). The measure is based on the sample mean and therefore is sensitive to outliers. The impact of outliers on the estimate of the third moment could be very large due to the effect of third power on the skewness measure. Employing a quantile measure of skewness, developed by Bowley (1901) and Hinkley (1975), Kim and White (2004), Conrad et al. (2013), and Ghysels et al. (2016) manage to eliminate the influence of outliers in financial data on estimates of the

third moment. Neuberger (2012) and Amaya et al. (2015) adopt a realised skewness measure using high-frequency data returns to capture the unbiased estimate of the true third moments.

Second, a large body of literature on statistical methods document that the conventional measure of skewness might not be a reliable measure of asymmetry under certain conditions.<sup>1</sup> Doksum (1975) proves that the classical measures of location could impose a measurement error due to asymmetry. Patil et al. (2012) argues that the measure of skewness is heavily influenced by tail behavior of a distribution and cannot capture the asymmetry of the entire distribution. Although several measures have been developed to capture asymmetry in the statistics literature, there is a lack of attention on asymmetry of stock returns in the finance literature.<sup>2</sup>

In this chapter, I develop a new measure of asymmetry in the stock returns for individual stocks. I adopt this measure of asymmetry, originally proposed by Patil et al. (2012), to examine the relation between return asymmetry and expected stock returns. In their article, Patil et al. (2012) discuss a necessary condition for a probability distribution function to be symmetric and demonstrate that their proposed measure of asymmetry can capture the degree of asymmetry of the distribution beyond the tail behaviour.

My study may have some connections with other studies on the asymmetry of financial markets. Ang and Chen (2002) focus on asymmetric correlations of stock returns with aggregate U.S. market indices and develop a new statistic for examining asymmetries in conditional correlations. They conclude that

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<sup>1</sup>Related papers include van Zwet (1964), Doksum (1975), Oja (1981), MacGillivray (1986), Critchley and Jones (2008), and Patil et al. (2012).

<sup>2</sup>See, for example, Doksum (1975), Boshnakov (2007), Critchley and Jones (2008), and Patil et al. (2012).

small stocks and value stocks tend to have more asymmetric movements. Hong et al. (2007) provide a test for asymmetry correlations and they find that both size and momentum portfolios are asymmetric. Bekaert and Wu (2000) examine asymmetric volatility at the firm and market level. They find support for a volatility feedback explanation of the asymmetry. However, these studies focus on the asymmetric relationship between individual stocks and market indices. My study considers the asymmetry in the individual's stock returns. This empirical research is similar in spirit to the work of Jiang et al. (2014) who also put forward two asymmetry measures based on (i) the probability difference of upside gains and downside risk of a stock and (ii) the entropy which is adapted from the Bhattacharya-Matsushita-Hellinger distance measure discussed in Racine and Maasoumi (2007). While both of their measures make use of information at the tail of the distribution beyond the third moment, ours takes into account the asymmetry of the distribution in its entirety. Moreover, compared to the measures proposed by Jiang et al. (2014), my measure is significantly more straightforward to estimate and does not require strict assumptions regarding the tail of the distribution.

As a preview of my empirical results, at the portfolio-level, I find that return asymmetry is negatively related to expected security returns. Portfolios containing securities with the highest values of return asymmetry generate significantly lower average excess and abnormal returns than portfolios constructed from securities with the lowest values of return asymmetry. The differences in the average excess and risk-adjusted returns are found to be more pronounced for equal-weighted portfolios than value-weighted portfolios. I also find that the return differences are larger when the

asymmetry measure is calculated using the 60-month window than when it is estimated using the 12-month windows. Furthermore, my results are robust to different sample periods according to the results from subperiod analysis. Consistent with the portfolio-level analysis results, using the two-step Fama and MacBeth (1973) approach to investigate the effect of return asymmetry on future returns at the individual stock level, the coefficient on the return asymmetry measure is found to be negative and statistically significant. The negative relation is also found to persist in the presence of popular factors such as size, book-to-market, momentum, liquidity risk, idiosyncratic volatility and skewness, implying that my asymmetry measure possesses explanatory power above and beyond that of the well-known factors.

Despite the different approaches used in the calculations of return asymmetry, Jiang et al.'s (2014) results are remarkably similar to ours. They also find that the relation between return asymmetry and future stock returns is negative. Their results show that stocks with high upside asymmetry generate lower future returns and skewness risk premium is not always found to be significant. They find that the average excess and risk-adjusted returns of the difference portfolio lies between 0.179% and 0.193% per month. As a preview of my main results, I can report that using my approach to calculate return asymmetry and form portfolios, compared to the results in Jiang et al. (2014), the long-short strategy generates even larger monthly excess returns of 1.20% and 1.72% depending on the estimation window used in the calculations of the asymmetry measure. While Jiang et al. (2014) form ten decile portfolios based on their measures of asymmetry, using my measure of asymmetry, I construct five quintile portfolios as well as decile

portfolios.

This empirical chapter provides a new review on the relationship between predictive variable and stock returns. My study is the first to apply Patil et al.'s (2012) method to financial markets. My measure is only based on the historical stock returns and helps to understand the predictive pattern of return distribution. Moreover, I provide a new evidence against the Efficient Market Hypothesis (EMH).

The rest of this chapter is organised as follows. Section 4.2 discusses the data used and methods to calculate return asymmetry and other control variables. Section 4.3 reports the empirical results by employing the portfolio sorts and cross-sectional regressions. Section 4.3 also describes the differences between skewness and return asymmetry and effect of return asymmetry after controlling for skewness factors. Section 4.4 concludes the chapter.

## 4.2 Measure of Asymmetry

### 4.2.1 Calculation of return asymmetry

To calculate the asymmetry measure for each security in my sample, I use the method described in Patil et al. (2012). At the end of each month, the measure of asymmetry of the return on a security, denoted  $Asym$ , is computed as follows:

$$Asym = \begin{cases} -\text{Corr}(f(R), F(R)) & \text{if } 0 < \text{Var}(f(R)) < \infty \\ 0 & \text{if } \text{Var}(f(R)) = 0 \end{cases} \quad (4.1)$$

## 4.2. MEASURE OF ASYMMETRY

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where  $\text{Corr}(\bullet)$  is the correlation function,  $f(R)$  and  $F(R)$  are the probability density function and the cumulative probability density function of the security return, respectively.

The value of the coefficient  $Asym$  ranges between  $-1$  and  $1$ . A return distribution is positively asymmetric when  $Asym > 0$ , negatively asymmetric when  $Asym < 0$  and symmetric when  $Asym = 0$ . Compared to other measures of asymmetry of the distribution of a random variable, Patil et al. (2012) note that their measure is more intuitive and can be calculated in a more straightforward manner.

Since the probability density function  $f(\bullet)$  and the cumulative probability density function  $F(\bullet)$  are unknown, they must be approximated. I employ a non-parametric smoothing approach, proposed by Rosenblatt et al. (1956) and Parzen (1962), to approximate both  $f(\bullet)$  and  $F(\bullet)$ . Consider the following probability density and cumulative density functions of the return on a stock:

$$\hat{f}(r) = \frac{1}{nh} \sum_{j=1}^n K\left(\frac{R_j - r}{h}\right) \quad (4.2)$$

$$\hat{F}(r) = \int_{-\infty}^r \hat{f}(u) du \quad (4.3)$$

where  $n$  is the number of the observations of  $\{R_j\}$ ,  $h$  is the bandwidth and  $K(\bullet)$  is a non-negative bounded kernel function. In this study, I employ the standard Gaussian kernel

$$K(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2}.$$

to fit the stock return distribution.

Since the choice of bandwidth estimation method crucially affects the accuracy of the nonparametric kernel density estimator, I employ the plug-in estimator of the asymptotically optimal bandwidth, suggested by Altman and Léger (1995), to estimate the bandwidth. Even though a number of bandwidth selection methods, such as the cross validation approach and Mallows's  $C_p$ , have been widely studied, modern plug-in approaches have been consistently proved to possess superior performance compared to traditional cross-validation techniques. Park and Marron (1990) show that the least-squares cross-validation technique has often been disappointing in many simulations as well as real data studies. Altman and Léger (1995) point out that leave-one-out cross-validation, which is a bias reduction technique, mimics the prediction problem and demonstrate superior performance of the plug-in methods in selecting the bandwidth. Chu et al. (2015) state that bandwidths selected using a plug-in approach perform well when simulated data are not uniform. For these reasons, I opt for the approach discussed in Altman and Léger (1995) to estimate the bandwidths of the kernels. Technical details of the method are described in Appendix A.

Let the investment horizon over which an investor is hoping to measure the asymmetry risk be  $T$  months. Furthermore, let  $S(t)$  denote the set of trading days from the first day of month  $t - (T - 1)$  through to the end of month  $t$  and let  $n$  denote the number of days in this dataset. Let  $U_{i,d} = \hat{f}(R_{i,d})$ ,  $V_{i,d} = \hat{F}(R_{i,d})$ ,  $\bar{U} = \sum_{d \in S(t)} U_{i,d}/n$  and  $\bar{V} = \sum_{d \in S(t)} V_{i,d}/n$  where  $\hat{f}(R_{i,d})$  and  $\hat{F}(R_{i,d})$  are the probability density function and the cumulative probability density function for stock  $i$  on day  $d$  computed following Eqs. (4.2) and (4.3), respectively. Using the above notations, I

can write Eq. (4.1) as:

$$Asym_{i,t} = -\frac{\sum_{d \in S(t)} U_{i,d} V_{i,d} - n \bar{U} \bar{V}}{\sqrt{\left(\sum_{d \in S(t)} U_{i,d}^2 - n \bar{U}^2\right) \left(\sum_{d \in S(t)} V_{i,d}^2 - n \bar{V}^2\right)}}. \quad (4.4)$$

where  $Asym_{i,t}$  denotes the asymmetry measure for stock  $i$  computed using all the daily return observations realised from the beginning of month  $t - (T - 1)$  until the end of month  $t$ . In order to improve the accuracy of the nonparametric kernel density estimator, at least 100 observations are required. Moreover, to ensure that the results are not sensitive to the number of observations employed in the calculation of the asymmetry measure, I use two different estimation windows, setting  $T = 12$  and  $T = 60$ .

### 4.2.2 Asymmetry vs. Skewness

Even though skewness can be used to measure the asymmetry of a distribution, it is mainly influenced by the tail behaviour of the distribution. This limitation suggests that the skewness measure can only capture part of the information about the degree of asymmetry of the distribution. As pointed out by Patil et al. (2012), the skewness and the asymmetry measures are not always consistent with each other as they observe that a more skewed distribution may exhibit less asymmetry. Using a simulation approach, Jiang et al. (2014) test the difference between skewness and asymmetry and find that two distributions with identical skewness turn out to have different asymmetry. In this section, I demonstrate that, using simulated data, my asymmetry measure can identify the degree of asymmetry which the conventional skewness measure cannot detect.

## 4.2. MEASURE OF ASYMMETRY

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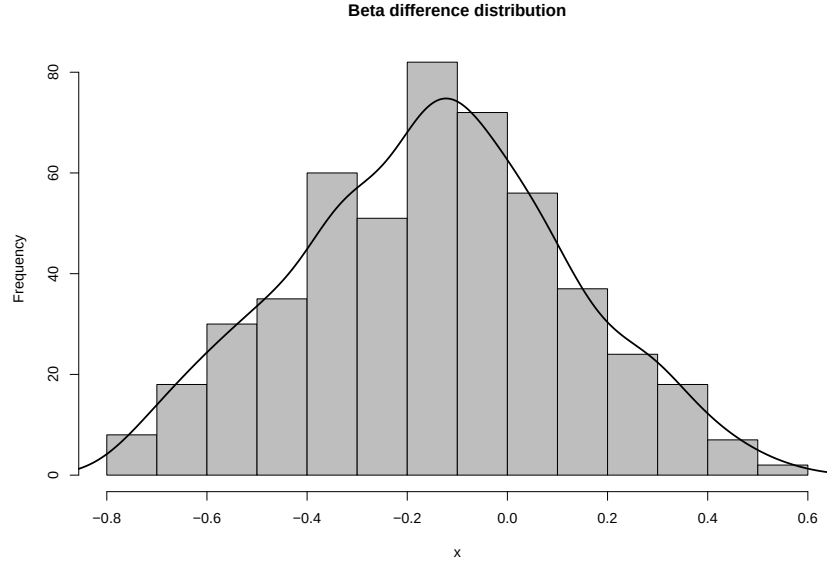


Figure 4.1: Distribution with negative asymmetry

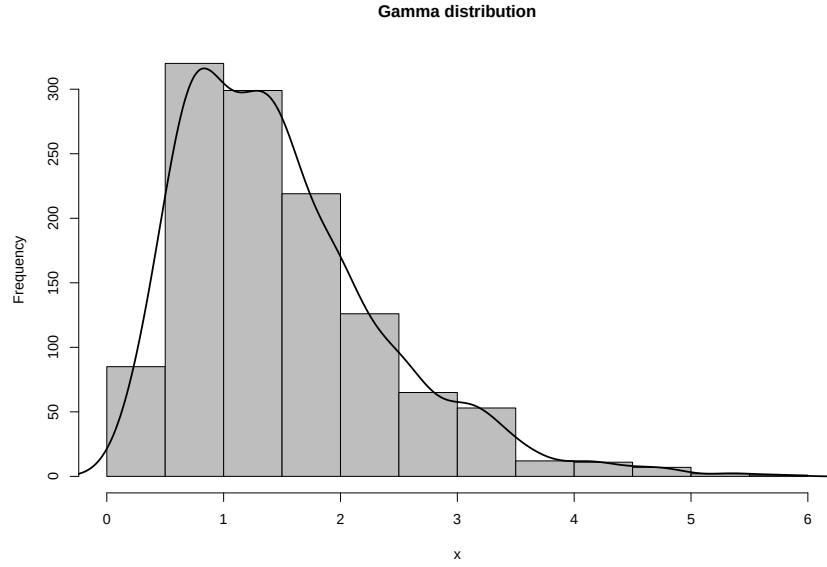


Figure 4.2: Distribution with positive asymmetry

Following Jiang et al. (2014), I simulate 500 observations from each of the following three distributions:  $N(120, 240)$ ,  $\chi^2(10)$  and  $\text{Beta}(1, 3.7)$  –

## 4.2. MEASURE OF ASYMMETRY

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Beta(1.3, 2.3).<sup>3</sup> While I know with certainty that  $N(120, 240)$  is symmetric and  $\chi^2(10)$  is asymmetric, it is not straightforward to conclude from visual inspection of Figure 4.1 whether or not  $\text{Beta}(1, 3.7) - \text{Beta}(1.3, 2.3)$  is symmetric. But, in fact,  $\text{Beta}(1, 3.7) - \text{Beta}(1.3, 2.3)$  is asymmetric with a slightly longer left tail. Figure 4.2 shows a gamma distribution with positive asymmetry. I can find that gamma distribution is not symmetric and it has a longer right tail.

With 500 observations drawn from one of the three distributions, I obtain a sample distribution. I then compute the skewness and the asymmetry measures of the sample distribution. The exercise is repeated 1,000 times for each of the distributions. The average values of skewness and my asymmetry measures are calculated along with their standard errors. I report the statistics in Table 4.1.

Table 4.1: Simulation and asymmetry test

This table reports the average values of skewness and my asymmetry measure. I randomly select 500 observations from the three distributions:  $N(120, 240)$ ,  $\chi^2(10)$  and beta difference distribution. Then I calculate the skewness and asymmetry for each sample. The average values are obtained from 1000 simulations.  $t$ -statistics are reported in parentheses. Statistical significance at the 10%, 5% and 1% levels is indicated using \*, \*\*, and \*\*\*, respectively.

|      | $N(120, 240)$      | $\chi^2(10)$         | $\text{Beta}(1, 3.7) - \text{Beta}(1.3, 2.3)$ |
|------|--------------------|----------------------|-----------------------------------------------|
| Skew | -0.0020<br>(-0.62) | 0.2334***<br>(65.78) | 0.0011<br>(0.40)                              |
| Asy  | -0.0013<br>(-0.64) | 0.1182***<br>(51.18) | -0.0657***<br>(-29.93)                        |

The  $t$ -statistics show that, based on both the skewness and the asymmetry measures, I fail to reject the null hypothesis of symmetry for  $N(120, 240)$

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<sup>3</sup>My choice of distributions from which data are simulated is identical to that of Jiang et al. (2014). This is done deliberately to show that both their results and my own are comparable.

at the 1% significance level. The results prove that the skewness measure and asymmetry measure are both equal to zero, indicating that the  $N(120, 240)$  is a symmetric distribution. I reject the null of symmetry for  $\chi^2(10)$  at the 1% significance level, indicating that  $\chi^2(10)$  is asymmetric. The skewness and the asymmetry measures perform well in both cases. For  $\text{Beta}(1, 3.7) - \text{Beta}(1.3, 2.3)$ , however, the skewness measure fails to capture the asymmetric characteristic of the distribution since I fail to reject the null hypothesis of symmetry. The average value of skewness is found to be 0.0011 with  $t$ -statistic of 0.40, suggesting that the skewness is zero. However, when my asymmetry measure is used to examine if the distribution is symmetric, the average value of the asymmetry measure is negative and statistically significant, implying that  $\text{Beta}(1, 3.7) - \text{Beta}(1.3, 2.3)$  is indeed asymmetric. Therefore, I can conclude that my asymmetry measure captures more information than the skewness measure.

## 4.3 Empirical Analysis and Results

In this section, I will describe the data and construction of control variables used in empirical analysis, which are in Sections 4.3.1 and 4.3.2 below. I begin my main analysis by first looking at portfolio characteristics in relation to my measure of return asymmetry. I then examine the relation between return asymmetry and expected stock returns by comparing returns across the five quintile portfolios into which stocks are sorted according to the values of the asymmetry measure. I also look at the return obtained from an investment strategy where securities in the highest asymmetry quintile portfolio are sold to fund the purchase of securities in the lowest

quintile portfolio. As a check for robustness, I also sort stocks into decile portfolios by return asymmetry. Moreover, I split the sample period into two subperiods (i.e., 1963–1988 and 1989–2014) and repeat the portfolio sort on both subsamples. And finally, I turn to the conditional two-way portfolio sort approach and the Fama and MacBeth (1973) cross-sectional regression technique to investigate the relation between return asymmetry and future stock returns after controlling for variables commonly thought to affect stock returns. All of my findings and discussions are reported in Sections 4.3.3–4.3.7.

#### 4.3.1 Data

My dataset contains returns on stocks of all the firms listed on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the NASDAQ.<sup>4</sup> The return series are downloaded from the Center for Research in Security Prices (CRSP) database. I adjust returns on delisted stocks following a widely used approach discussed in Shumway (1997). Specifically, if a delisting return is available in CRSP, I assign the delisting return to the missing return. If a delisting return is unavailable, I assign different values to the missing return according to the reason of delisting, indicated by the DLSTCD field. If the DLSTCD is 500, 520, from 551 to 574, 580 or 584, the missing return during that month equals  $-30\%$ . Otherwise, the missing return equals  $-100\%$ . The accounting information for firms in my dataset is obtained from the CRSP/Compustat Merged Database. Variables in a five-factor model of Fama and French (2015) including size, value, profitability,

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<sup>4</sup>I exclude from my sample all the stocks with prices lower than \$5 and greater than \$1000.

investment patterns and market excess returns are obtained from Kenneth French's website<sup>5</sup>. The Carhart's (1997) monthly return momentum factor and time series of the risk-free rate are also collected from Kenneth French's website. My dataset spans a period between January 1963 and December 2014. Normally, most scholars use a sample from June 1963. This is because AMEX stocks are included in the CRSP database starting in July 1962. Some variables examined in empirical asset pricing studies are computed using one year's worth of historical data. Therefore, the first month of those available variables is June 1963.

#### 4.3.2 Control variables

Numerous factors are found to affect security returns. In order to isolate the impact of my measure of return asymmetry on expected future stock returns from some of the well-known risk factors, the following control variables are included in my analysis: firm's size and book-to-market ((Fama and French, 1992) and (Fama and French, 1993)), the momentum factor (Jegadeesh and Titman, 1993), the short-term return reversal factor (Jegadeesh, 1990), the liquidity factor (Amihud, 2002) and idiosyncratic volatility (Ang et al., 2006). I also include three skewness measures in my analysis: total skewness, idiosyncratic skewness and co-skewness. This is to allow us to investigate if the asymmetry measure possesses an explanatory power beyond that of the skewness factors.

I calculate the size factor, denoted by *Size*, as the natural logarithm of the firm's market value at the end of each month. The book-to-market ratio

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<sup>5</sup>[http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\\_library.html](http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)

for year  $t$ , denoted by  $B/M$ , is the book value of equity for the fiscal year ending in year  $t - 1$  divided by the market value of equity at the end of December in year  $t - 1$ .<sup>6</sup> As described in Jegadeesh and Titman (1993), the momentum factor for a security, denoted by  $Mom$ , is its cumulative return over a period of eleven months ending one month prior to the portfolio formation month. Following Jegadeesh (1990) and Lehmann (1990), the short-term return reversal factor, denoted by  $Rev$ , is estimated as the return on the stock over the previous month. The liquidity factor of Amihud (2002), denoted by  $Liq$ , is measured using the average value of the ratio of the absolute daily stock return to its daily dollar trading volume in the one-month period:

$$Liq_{i,t} = \text{Average} \left( \frac{|R_{i,d}|}{Volume_{i,d}} \right) \quad (4.5)$$

where  $Liq_{i,t}$  is the liquidity factor for stock  $i$  in month  $t$ ,  $R_{i,d}$  and  $Volume_{i,d}$  are the daily return and dollar trading volume of stock  $i$  on day  $d$  in month  $t$ , respectively.<sup>7</sup> Trade volume is the total number of shares transacted for the stocks in a specific month. I scale the liquidity factor by a factor of 1000.

Following Ang et al. (2006), I calculate monthly idiosyncratic volatility, denoted  $Ivol_t$ , as the standard deviation of daily residuals which are estimated from the Fama-French three-factor model:

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<sup>6</sup>The book value of equity is the value of stockholders' equity plus the balance sheet's deferred taxes and investment tax credit less the book value of preferred stock.

<sup>7</sup>The NASDAQ volumes are adjusted according to Gao and Ritter (2010). Specifically, the value is divided by 2 prior to February 1, 2001. Between February 1, 2001 and December 31, 2001, the volume is divided by a factor of 1.8 and by 1.6 between 2002 and 2003.

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_i (R_{m,d} - R_{f,d}) + \gamma_i SMB_d + \delta_i HML_d + \varepsilon_{i,d} \quad (4.6)$$

where  $SMB_d$  and  $HML_d$  are daily size and book-to-market factors;  $R_{i,d}$ ,  $R_{m,d}$  and  $R_{f,d}$  are the daily return of stock  $i$ , the daily market return and the daily risk-free rate, respectively.<sup>8</sup>

In regard to the skewness measures, I adopt a rolling window of 60 months to calculate both total and idiosyncratic skewness. Following Bali et al. (2011), total skewness for security  $i$  in month  $t$ , denoted  $Tskew_{i,t}$ , is computed at the end of the month using daily returns realised during the previous 60 months:

$$Tskew_{i,t} = \frac{1}{S(t)} \sum_{d \in S(t)} \left( \frac{R_{i,d} - \bar{R}_i}{\hat{\sigma}_i} \right)^3 \quad (4.7)$$

where  $R_{i,d}$  is the return of stock  $i$  on day  $d$ ;  $\bar{R}_i$ ,  $\hat{\sigma}_i$  and  $S(t)$  are the sample mean, the sample standard deviation of  $R_{i,d}$  and the number of trading days in the 60-month estimation window, respectively.<sup>9</sup>

Idiosyncratic volatility and idiosyncratic skewness are calculated using the method discussed in Boyer et al. (2009). At the end of each month, I use the daily return data observed during the previous 60-month period to run the Fama-French three-factor model (see Eq. (4.6)). The idiosyncratic volatility

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<sup>8</sup>I also experimented with the residuals obtained from the CAPM and the Carhart's four-factor model to compute the idiosyncratic volatility as well as extending the estimation window to one year. I find that the effect of the idiosyncratic volatility remains unchanged.

<sup>9</sup>The first daily observation used in the estimation of total skewness is the first trading day of month  $t - 59$ ; the last daily observation is the last trading day of month  $t$ .

for stock  $i$  at the end of month  $t$ , denoted  $Ivol_{i,t}$ , is computed using the following equation:

$$Ivol_{i,t} = \sqrt{\frac{1}{S(t) - 1} \sum_{d \in S(t)} \varepsilon_{i,d}^2} \quad (4.8)$$

where  $\varepsilon_{i,d}$  is the residuals obtained from the regression in Eq. (4.6). The idiosyncratic skewness is calculated as follows:

$$Iskew_{i,t} = \frac{1}{S(t) - 2} \times \frac{\sum_{d \in S(t)} \varepsilon_{i,d}^3}{Ivol_{i,t}^3} \quad (4.9)$$

where  $Iskew_{i,t}$  is the idiosyncratic skewness for security  $i$  at the end of month  $t$  and  $Ivol_{i,t}$  is calculated as shown in Eq. (4.8).<sup>10</sup>

Finally, to calculate co-skewness, I follow the approach discussed in Harvey and Siddique (2000a). First, I run the following regression

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i (R_{m,t} - R_{f,t}) + \varepsilon_{i,t} \quad (4.10)$$

where  $R_{i,t}$ ,  $R_{m,t}$  and  $R_{f,t}$  are the monthly return of stock  $i$ , the monthly return on the CRSP value-weighted market index and the monthly risk-free rate at the end of month  $t$ , respectively. The risk-free rate used in the calculation of the excess return is the one-month Treasury bill rate. Then, for each stock in the sample, the co-skewness measure for stock  $i$  in month  $t$ , denoted  $Coskew_{i,t}$ , is estimated as follows:

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<sup>10</sup>I adjust the number of trading days by one for volatility and two for skewness as in the equations. I have similar results when I use alternative adjustment to  $S(t)$ .

$$Coskew_{i,t} = \frac{E[\varepsilon_{i,t} R_{m,t}^2]}{\sqrt{E[\varepsilon_{i,t}^2] E[R_{m,t}^2]}} \quad (4.11)$$

where  $\varepsilon_{i,t}$  is the residuals calculated from Eq. (4.10) above. Note that I use the daily returns during the previous 12 months to compute the security's co-skewness following Harvey and Siddique (2000a).

### 4.3.3 Return asymmetry and firm's characteristics

Panel A of Table 4.2 reports the descriptive statistics of the variables used in my analysis. The mean value of the return asymmetry measure is found to be 0.02 indicating that on average stocks in my dataset exhibit small positive return asymmetry. I can find that minimum value and maximum value is  $-0.01$  and  $0.05$ , respectively. The return asymmetry for all the stocks does not change dramatically. Are the returns of stocks across different asymmetry values different? In section 4.3.4, I will examine the effect of return asymmetry on the stock returns in spite of the narrow range of the value.

Table 4.2: Descriptive statistics

The table reports the mean, the standard deviation (SD), the minimum (MIN) and the maximum (MAX) values for variables used in the analysis in Panel A. The Spearman rank correlation coefficient is shown in Panel B. The sample includes all the common stocks traded on the NYSE, AMEX, and NASDAQ during a period between January 1963 to December 2014.

|                                           | <i>Asym</i> | <i>MV</i> | <i>B/M</i> | <i>Mom</i> | <i>Rev</i> | <i>Liq</i> | <i>Ivol</i> | <i>Tskew</i> | <i>Coskew</i> | <i>Iskew</i> |
|-------------------------------------------|-------------|-----------|------------|------------|------------|------------|-------------|--------------|---------------|--------------|
| <i>Panel A: Descriptive statistics</i>    |             |           |            |            |            |            |             |              |               |              |
| Mean                                      | 0.02        | 2377796   | 0.83       | 0.18       | 0.02       | 0.21       | 9.59        | 0.22         | -0.03         | 0.24         |
| SD                                        | 0.01        | 2188160   | 0.27       | 0.22       | 0.06       | 0.13       | 2.07        | 0.28         | 0.03          | 0.32         |
| MIN                                       | -0.01       | 329656    | 0.44       | -0.37      | -0.27      | 0.10       | 6.13        | -0.52        | -0.14         | -0.55        |
| MAX                                       | 0.05        | 9210423   | 2.10       | 1.03       | 0.25       | 0.52       | 19.25       | 0.77         | 0.05          | 0.86         |
| <i>Panel B: Spearman rank correlation</i> |             |           |            |            |            |            |             |              |               |              |
| <i>MV</i>                                 | 0.63        | 1.00      |            |            |            |            |             |              |               |              |
| <i>B/M</i>                                | -0.53       | -0.48     | 1.00       |            |            |            |             |              |               |              |
| <i>Mom</i>                                | 0.23        | 0.21      | 0.18       | 1.00       |            |            |             |              |               |              |
| <i>Rev</i>                                | 0.08        | 0.09      | 0.07       | -0.05      | 1.00       |            |             |              |               |              |
| <i>Liq</i>                                | -0.49       | -0.40     | 0.24       | -0.14      | -0.04      | 1.00       |             |              |               |              |
| <i>Ivol</i>                               | 0.02        | 0.05      | -0.18      | -0.10      | 0.14       | 0.41       | 1.00        |              |               |              |
| <i>Tskew</i>                              | 0.54        | 0.83      | -0.41      | 0.22       | 0.08       | -0.34      | 0.18        | 1.00         |               |              |
| <i>Coskew</i>                             | 0.05        | 0.13      | 0.00       | -0.05      | 0.00       | -0.21      | -0.36       | 0.22         | 1.00          |              |
| <i>Iskew</i>                              | 0.48        | 0.85      | -0.38      | 0.21       | 0.07       | -0.19      | 0.17        | 0.89         | 0.16          | 1.00         |

The Spearman rank correlation coefficients shown in Panel B, calculated using the time-series of cross-sectional averages of the variables, indicate that the measure of return asymmetry is positively correlated with size, total skewness and idiosyncratic skewness with correlation coefficients of 0.63, 0.53 and 0.48, respectively. The correlation coefficient between return asymmetry and the book-to-market ratio is found to be  $-0.53$ , suggesting that growth stocks tend to have positive return asymmetry. The correlation with the liquidity factor is also strong and negative. The results also indicate that although the asymmetry and the skewness measures can all be used to describe the shape of a return distribution, their information content differs as it can be observed from the low correlation between my measure of return asymmetry and the skewness measures. I can find that the correlation between total skewness and idiosyncratic skewness is 0.89. High correlation is on account of the calculations. The total skewness skewness is computed by using 60-month daily returns and the idiosyncratic skewness is calculated by using 60-month daily residuals of returns adjusted by Fama-French three factors.

Table 4.3 shows the mean values of the variables discussed earlier across the five quintile portfolios. Specifically, at the end of each month, stocks are sorted into five portfolios according to the asymmetry measure and then the mean values of the variables for each quintile portfolio are calculated. The reported means are time-series averages of the cross-sectional values. The statistics presented in Table 4.3 clearly exhibit a monotonically decreasing pattern for the mean values of the book-to-market ratio ( $B/M$ ), the measure of liquidity ( $Liq$ ), total skewness ( $Tskew$ ), and idiosyncratic skewness ( $Iskew$ ) as I move from Quintile portfolio 1 to Quintile portfolio 5. The findings

### 4.3. EMPIRICAL ANALYSIS AND RESULTS

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suggest that as the portfolio return asymmetry increases, the values of the aforementioned variables decline. Therefore, return asymmetry may have some connections with these factors. Could the effect of return asymmetry be explained by these factors? I will test the results after controlling for relevant variables. It is also worth noting that the results in Table 4.3 suggest that the measures of return asymmetry and skewness are not positively correlated.

Table 4.3: Characteristics of asymmetry portfolios

This table reports the mean values of firm's characteristics across asymmetry portfolios. At the end of each month, I sort stocks into five equal-weighted portfolios based on their return asymmetry (*Asym*) computed with 60-month estimation period. Quintile portfolio 1 contains stocks with the lowest 20% of *Asym* and quintile portfolio 5 contains the highest 20% *Asym*. The characteristics reported are market capitalization (*MV*), book-to-market ratio (*B/M*), momentum (*Mom*), short-term return reversal (*Rev*), liquidity (*Liq*), idiosyncratic volatility (*Ivol*), total skewness (*Tskew*), co-skewness (*Coskew*) and idiosyncratic skewness (*Iskew*). The sample includes all common stocks on the NYSE, AMEX, and NASDAQ for the period from January 1963 to December 2014. The reported means are time-series averages of the cross-sectional values.

|               | Quintile |         |         |         |         |
|---------------|----------|---------|---------|---------|---------|
|               | 1        | 2       | 3       | 4       | 5       |
| <i>Asym</i>   | -0.09    | -0.01   | 0.03    | 0.07    | 0.17    |
| <i>MV</i>     | 2180489  | 1701917 | 2037713 | 2535698 | 3431765 |
| <i>B/M</i>    | 1.08     | 0.91    | 0.80    | 0.71    | 0.67    |
| <i>Mom</i>    | 0.15     | 0.15    | 0.17    | 0.20    | 0.22    |
| <i>Rev</i>    | 0.01     | 0.01    | 0.01    | 0.02    | 0.02    |
| <i>Liq</i>    | 0.65     | 0.37    | 0.23    | 0.16    | 0.24    |
| <i>Ivol</i>   | 10.94    | 9.89    | 9.14    | 8.78    | 9.22    |
| <i>Tskew</i>  | 0.61     | 0.41    | 0.34    | 0.25    | 0.30    |
| <i>Coskew</i> | -0.03    | -0.03   | -0.03   | -0.02   | -0.02   |
| <i>Iskew</i>  | 0.60     | 0.42    | 0.36    | 0.29    | 0.34    |

#### 4.3.4 Univariate portfolio-level analysis

In this section, I report the findings from the univariate portfolio-level analysis. The procedure for sorting securities is as follows. At the end of each month, I sort securities into five portfolios based on the estimated asymmetry measures. Quintile portfolio 1 contains stocks whose asymmetry measures lie below the 20<sup>th</sup> percentile of the distribution of the measure of the return asymmetry while quintile portfolio 5 contains stocks whose measures of asymmetry belong to the highest quintile of the distribution. To ensure that my results are not sensitive to the estimation window used in the calculation of the asymmetry measures, two different estimation windows are adopted: 12-month and 60-month windows. As the weight of a stock in the portfolio can have a significant impact on the portfolio return, I experiment with two different stock weighting schemes: equal-weighting and value-weighting. The weight of a stock in the value-weighted portfolio is the stock's market value at the end of the period divided by the total market value. After all the five quintile portfolios are constructed, they are held for a period of one month during which daily returns are recorded. At the end of the holding period, the return asymmetry measures are re-calculated after rolling the estimation window forward by one month. The portfolios are then rebalanced based on the new asymmetry measures and the process is repeated.

In addition to computing average monthly excess returns from daily returns recorded during the one-month holding period after portfolio formation, I also estimate the portfolio risk-adjusted returns from the following asset pricing models: (i) the capital asset pricing model (CAPM) of Sharpe

(1964) and Lintner (1965); (ii) the Fama-French three-factor model (FF3) of Fama and French (1993); the Carhart's (1997) four-factor model; and the Fama-French five-factor model (FF5) of Fama and French (2015).

Moreover, in order to compare with the study by Jiang et al. (2014), I also sort stocks into decile portfolios based on the estimated asymmetry measures. Decile portfolio 1 contains stocks whose asymmetry measures lie below the 10<sup>th</sup> percentile of the distribution of the measure of the return asymmetry while quintile portfolio 10 contains stocks whose measures of asymmetry belong to the highest decile of the distribution. I also test results by using 12-month and 60-month estimation windows. Then, average return and risk-adjusted return are calculated.

#### 4.3.4.1 Portfolio sort based on the measure of return asymmetry

The results of the quantile portfolio sorts are shown in Table 4.4. Rows labelled "Average return" show the monthly excess returns obtained from investments in each of the quintile portfolios. I also report the portfolio risk-adjusted returns calculated from four asset pricing models shown above. The results are presented along rows labelled "CAPM alpha", "FF3 alpha", "Cahart alpha" and "FF5 alpha".

Table 4.4: Quintile portfolios sorted by return asymmetry

At the end of each month, I calculate the return asymmetry measure using daily returns during the previous 12 months (Panel A) and the previous 60 months (Panel B) following Patil et al. (2012). Then all the stocks are sorted into quintile portfolios. I calculate and report the post average return and abnormal return for each portfolio. The  $t$ -statistics based on Newey and West (1987) are reported in the parentheses. Statistical significance at the 10%, 5% and 1% levels is indicated using \*, \*\*, and \*\*\*, respectively. My sample includes all the common stocks traded on NYSE, AMEX, and NASDAQ for the period between January 1963 and December 2014.

| Sorting statistic                          | Quintile portfolio  |                    |                    |                   |                    |
|--------------------------------------------|---------------------|--------------------|--------------------|-------------------|--------------------|
|                                            | 1                   | 2                  | 3                  | 4                 | 5                  |
| <i>Panel A: 12-month estimation period</i> |                     |                    |                    |                   |                    |
| <i>Equal-weighted portfolios</i>           |                     |                    |                    |                   |                    |
| <i>Asym</i>                                | -0.09<br>(-4.89)*** | -0.01<br>(-1.56)   | 0.03<br>(2.63)***  | 0.07<br>(5.61)*** | 0.17<br>(11.07)*** |
| Average return                             | 3.03<br>(10.81)***  | 2.75<br>(10.59)*** | 2.35<br>(9.65)***  | 2.04<br>(8.43)*** | 1.84<br>(6.98)***  |
| CAPM alpha                                 | 2.09<br>(11.04)***  | 1.80<br>(9.42)***  | 1.39<br>(8.48)***  | 1.05<br>(7.15)*** | 0.79<br>(4.87)***  |
| FF3 alpha                                  | 1.82<br>(12.34)***  | 1.55<br>(11.20)*** | 1.17<br>(10.23)*** | 0.89<br>(9.71)*** | 0.74<br>(6.84)***  |
| Carhart alpha                              | 1.99<br>(12.15)***  | 1.69<br>(11.31)*** | 1.25<br>(10.22)*** | 0.94<br>(8.95)*** | 0.76<br>(6.08)***  |
| FF5 alpha                                  | 1.76<br>(11.88)***  | 1.51<br>(11.27)*** | 1.14<br>(10.43)*** | 0.90<br>(9.79)*** | 0.85<br>(7.64)***  |
| <i>(Continued)</i>                         |                     |                    |                    |                   |                    |

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| Sorting statistic                | Quintile portfolio   |                   |                   |                   |                    |
|----------------------------------|----------------------|-------------------|-------------------|-------------------|--------------------|
|                                  | 1                    | 2                 | 3                 | 4                 | 5                  |
|                                  |                      |                   |                   |                   | 1 – 5              |
| <i>Value-weighted portfolios</i> |                      |                   |                   |                   |                    |
| <i>Asym</i>                      | -0.08<br>(-14.29)*** | -0.01<br>(-1.81)* | 0.03<br>(3.05)*** | 0.07<br>(7.07)*** | 0.17<br>(18.83)*** |
| Average return                   | 1.10<br>(5.46)***    | 1.09<br>(6.17)*** | 1.08<br>(5.87)*** | 1.04<br>(5.31)*** | 0.97<br>(4.99)***  |
| CAPM alpha                       | 0.21<br>(2.75)***    | 0.21<br>(3.03)*** | 0.18<br>(4.00)*** | 0.13<br>(3.82)*** | 0.04<br>(0.76)     |
| FF3 alpha                        | 0.20<br>(2.51)**     | 0.19<br>(3.09)*** | 0.19<br>(4.16)*** | 0.13<br>(3.54)*** | 0.12<br>(2.34)**   |
| Carhart alpha                    | 0.24<br>(2.80)***    | 0.28<br>(4.00)*** | 0.23<br>(5.07)*** | 0.14<br>(3.62)*** | 0.10<br>(1.70)*    |
| FF5 alpha                        | 0.18<br>(2.09)**     | 0.16<br>(2.54)**  | 0.20<br>(4.69)*** | 0.12<br>(2.98)*** | 0.15<br>(2.76)***  |

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Panel B: 60-month estimation period  
Equal-weighted portfolios

|                |                    |                   |                   |                   |                   |
|----------------|--------------------|-------------------|-------------------|-------------------|-------------------|
| <i>Asym</i>    | -0.09<br>(-1.00)   | -0.01<br>(-0.64)  | 0.02<br>(1.40)    | 0.04<br>(2.81)*** | 0.10<br>(3.15)*** |
| Average return | 3.39<br>(10.87)*** | 2.54<br>(9.49)*** | 1.95<br>(8.31)*** | 1.67<br>(7.43)*** | 1.72<br>(7.93)*** |
| CAPM alpha     | 2.46<br>(9.43)***  | 1.60<br>(7.33)*** | 1.01<br>(6.11)*** | 0.72<br>(5.93)*** | 0.70<br>(5.80)*** |
| FF3 alpha      | 2.22<br>(11.49)*** | 1.36<br>(9.44)*** | 0.82<br>(8.39)*** | 0.59<br>(7.81)*** | 0.66<br>(7.98)*** |
| Carhart alpha  | 2.25<br>(11.20)*** | 1.43<br>(9.43)*** | 0.89<br>(9.22)*** | 0.65<br>(8.49)*** | 0.74<br>(7.93)*** |
| FF5 alpha      | 2.18<br>(11.30)*** | 1.29<br>(9.43)*** | 0.74<br>(8.46)*** | 0.55<br>(7.28)*** | 0.70<br>(7.93)*** |
|                |                    |                   |                   |                   | 1.48<br>(7.19)*** |

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| Sorting statistic                | Quintile portfolio  |                   |                   |                   |                    |
|----------------------------------|---------------------|-------------------|-------------------|-------------------|--------------------|
|                                  | 1                   | 2                 | 3                 | 4                 | 5                  |
|                                  |                     |                   |                   |                   | 1 – 5              |
| <i>Value-weighted portfolios</i> |                     |                   |                   |                   |                    |
| <i>Asym</i>                      | -0.07<br>(-4.34)*** | -0.01<br>(-1.21)  | 0.02<br>(2.33)**  | 0.04<br>(4.18)*** | 0.09<br>(10.91)*** |
| Average return                   | 1.77<br>(7.35)***   | 1.29<br>(6.66)*** | 1.09<br>(6.10)*** | 0.96<br>(5.19)*** | 0.94<br>(4.53)***  |
| CAPM alpha                       | 0.87<br>(6.15)***   | 0.41<br>(4.71)*** | 0.21<br>(2.93)*** | 0.10<br>(2.41)**  | 0.04<br>(0.69)     |
| FF3 alpha                        | 0.71<br>(5.93)***   | 0.30<br>(3.75)*** | 0.14<br>(2.03)**  | 0.08<br>(1.69)*   | 0.12<br>(2.79)***  |
| Carhart alpha                    | 0.79<br>(6.24)***   | 0.38<br>(4.32)*** | 0.21<br>(3.08)*** | 0.08<br>(1.84)*   | 0.11<br>(2.26)**   |
| FF5 alpha                        | 0.69<br>(5.29)***   | 0.25<br>(3.25)*** | 0.06<br>(0.88)    | -0.03<br>(-0.67)  | 0.11<br>(2.43)**   |
|                                  |                     |                   |                   |                   | 0.57<br>(3.91)***  |

The univariate portfolio analysis results presented in Panel A of Table 4.4 show a clear negative relation between return asymmetry and the expected stock returns when stocks in the portfolios are weighted equally. Quintile portfolio 1 generates the highest levels of average excess and abnormal returns while quintile portfolio 5 provides the lowest average returns. The average excess returns of the difference portfolio are shown in column labelled 1–5 equals 1.20% per month with the corresponding Newey and West’s (1987)  $t$ -statistic of 6.19. Furthermore, according the values of  $\alpha$  calculated from the CAPM, FF3, Carhart and FF5 models, the difference portfolio generates abnormal returns approximately between 0.91% and 1.30% per month. My results are comparable to those of Jiang et al. (2014) who also find that stocks with positive return asymmetry generate lower returns than stocks with negative return asymmetry. When portfolios are formed by weighting stocks based on their market values, however, the negative relation between the return asymmetry measure and the expected stock returns substantially weakens. The risk-adjusted returns for the difference portfolio are no longer statistically significant except when  $\alpha$  is estimated using the Carhart four-factor model.

When portfolios are sorted according to the return asymmetry measure, calculated using information on daily returns during the past 60 months, I observe a negative relation between return asymmetry and the expected stock returns across all the five quintile portfolios for both equal-weighted and value-weighted portfolios. It can be seen from the results in Panel B of Table 4.4 that as return asymmetry increases, both the excess and the abnormal returns decrease except the last portfolio. Moreover, the excess and the abnormal returns of the difference portfolio, shown under column

1–5, are all positive and statistically significant at the 1% significance level for both equal-weighted and value-weighted portfolios.

I also find that the average excess returns and the average abnormal returns of the difference portfolio of around 1.48%–1.77% per month for equal-weighted portfolios are much higher than those for the value-weighted portfolios of around 0.57%–0.83% per month. These observations are consistent with the results reported in Harvey and Siddique (2000a) who show that the skewness risk premium are largest for equal-weighted portfolios formed according to co-skewness.<sup>11</sup>

On the other hand, the results of the decile portfolio sorts are shown in Table 4.5. When I compute the equal-weighted return for each portfolio, the return differences for 12-month estimation window and 60-month estimation window are both highly positively significant, generating average return of 1.20% and 1.70% per month, respectively. My results exhibit better performance by using my asymmetry measure compared with the findings by Jiang et al. (2014). They only find 0.179% and 0.193% per month when they compute average return by using two different asymmetry measures. For the value-weighted portfolios, I cannot find significant effect of return asymmetry by using 12-month estimation window. The return differences for risk-adjusted returns remain highly significant. I can conclude that return asymmetry is negatively related to expected stock returns.

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<sup>11</sup>Harvey and Siddique (2000a) only report value-weighted portfolios in their paper. From personal correspondence with Campbell Harvey by Ang et al. (2006), the coskewness effect is more pronounced in equal-weighted portfolios than in value-weighted portfolios.

Table 4.5: Decile portfolios sorted by return asymmetry

At the end of each month, I calculate the return asymmetry measure using daily returns during the previous 12 months (Panel A) and the previous 60 months (Panel B) following Patil et al. (2012). Then all the stocks are sorted into decile portfolios. I calculate and report the post average return and abnormal return for each portfolio. The  $t$ -statistics based on Newey and West (1987) are reported in the parentheses. Statistical significance at the 10%, 5% and 1% levels is indicated using \*, \*\*, and \*\*\*, respectively. My sample includes all the common stocks traded on NYSE, AMEX, and NASDAQ for the period between January 1963 and December 2014.

| Sorting statistic                   | Decile portfolio   |                    |                    |                    |                    |                    |                   |                   |                   |                   |
|-------------------------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|-------------------|-------------------|-------------------|-------------------|
|                                     | 1                  | 2                  | 3                  | 4                  | 5                  | 6                  | 7                 | 8                 | 9                 | 10                |
| Panel A: 12-month estimation period |                    |                    |                    |                    |                    |                    |                   |                   |                   |                   |
| <i>Equal-weighted portfolios</i>    |                    |                    |                    |                    |                    |                    |                   |                   |                   |                   |
| Average return                      | 3.07<br>(10.45)*** | 3.04<br>(10.87)*** | 2.90<br>(10.80)*** | 2.62<br>(10.24)*** | 2.4<br>(9.65)***   | 2.31<br>(9.59)***  | 2.10<br>(8.70)*** | 1.99<br>(8.09)*** | 1.81<br>(7.44)*** | 1.86<br>(6.47)*** |
| CAPM alpha                          | 2.14<br>(10.72)*** | 2.09<br>(10.56)*** | 1.95<br>(9.84)***  | 1.66<br>(8.79)***  | 1.44<br>(8.34)***  | 1.34<br>(8.46)***  | 1.11<br>(7.38)*** | 0.99<br>(6.75)*** | 0.79<br>(5.48)*** | 0.79<br>(4.23)*** |
| FF3 alpha                           | 1.86<br>(11.47)*** | 1.81<br>(11.69)*** | 1.69<br>(11.53)*** | 1.43<br>(10.39)*** | 1.22<br>(10.04)*** | 1.13<br>(10.05)*** | 0.94<br>(9.77)*** | 0.85<br>(9.16)*** | 0.71<br>(7.45)*** | 0.78<br>(5.93)*** |
| Carhart alpha                       | 2.04<br>(11.49)*** | 1.99<br>(11.71)*** | 1.84<br>(11.46)*** | 1.56<br>(10.68)*** | 1.30<br>(10.20)*** | 1.21<br>(9.90)***  | 0.99<br>(9.54)*** | 0.89<br>(8.01)*** | 0.71<br>(6.56)*** | 0.83<br>(5.41)*** |
| FF5 alpha                           | 1.81<br>(11.15)*** | 1.75<br>(11.16)*** | 1.66<br>(11.82)*** | 1.37<br>(10.18)*** | 1.16<br>(10.14)*** | 1.13<br>(10.18)*** | 0.93<br>(9.85)*** | 0.89<br>(9.06)*** | 0.77<br>(8.04)*** | 0.95<br>(6.81)*** |
|                                     |                    |                    |                    |                    |                    |                    |                   |                   |                   |                   |

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| Sorting statistic                | Decile portfolio  |                   |                   |                   |                   |                   |                   |                   |                   |                   |
|----------------------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
|                                  | 1                 | 2                 | 3                 | 4                 | 5                 | 6                 | 7                 | 8                 | 9                 | 10                |
| <i>Value-weighted portfolios</i> |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |
| Average return                   | 1.10<br>(5.02)*** | 1.08<br>(5.15)*** | 1.15<br>(5.97)*** | 1.10<br>(6.36)*** | 1.04<br>(5.94)*** | 1.12<br>(5.61)*** | 1.04<br>(5.14)*** | 1.05<br>(5.43)*** | 0.99<br>(5.25)*** | 0.96<br>(4.45)*** |
| CAPM alpha                       | 0.22<br>(2.03)**  | 0.19<br>(1.90)*   | 0.27<br>(2.97)*** | 0.22<br>(2.81)*** | 0.14<br>(1.88)*   | 0.22<br>(3.55)*** | 0.13<br>(2.54)**  | 0.15<br>(3.10)*** | 0.08<br>(1.43)    | 0.00<br>(0.03)    |
| FF3 alpha                        | 0.19<br>(1.81)*   | 0.18<br>(1.72)*   | 0.23<br>(2.79)*** | 0.20<br>(2.82)*** | 0.11<br>(1.54)    | 0.24<br>(4.15)*** | 0.11<br>(2.21)**  | 0.15<br>(3.01)*** | 0.13<br>(2.26)**  | 0.10<br>(1.28)    |
| Carhart alpha                    | 0.22<br>(1.90)*   | 0.26<br>(2.47)**  | 0.34<br>(3.73)*** | 0.28<br>(3.61)*** | 0.18<br>(2.36)**  | 0.27<br>(4.65)*** | 0.13<br>(2.48)**  | 0.16<br>(2.64)*** | 0.12<br>(1.83)*   | 0.08<br>(0.82)    |
| FF5 alpha                        | 0.16<br>(1.38)    | 0.17<br>(1.55)    | 0.20<br>(2.30)**  | 0.16<br>(2.40)**  | 0.08<br>(1.19)    | 0.27<br>(4.79)*** | 0.07<br>(1.31)    | 0.16<br>(2.79)*** | 0.16<br>(2.72)*** | 0.15<br>(1.73)*   |
| (Continued)                      |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |

### 4.3. EMPIRICAL ANALYSIS AND RESULTS

(Continued)

| Sorting statistic                                                                  | Decile portfolio   |                    |                   |                   |                   |                   |                   |                   |                   |                   |
|------------------------------------------------------------------------------------|--------------------|--------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
|                                                                                    | 1                  | 2                  | 3                 | 4                 | 5                 | 6                 | 7                 | 8                 | 9                 | 10                |
| <p>Panel B: 60-month estimation period</p> <p><u>Equal-weighted portfolios</u></p> |                    |                    |                   |                   |                   |                   |                   |                   |                   |                   |
| Average return                                                                     | 3.56<br>(10.39)*** | 3.28<br>(10.88)*** | 2.73<br>(9.62)*** | 2.37<br>(9.28)*** | 2.09<br>(8.59)*** | 1.82<br>(7.91)*** | 1.72<br>(7.69)*** | 1.62<br>(7.10)*** | 1.58<br>(6.80)*** | 1.79<br>(6.67)*** |
| CAPM alpha                                                                         | 2.66<br>(9.15)***  | 2.34<br>(9.18)***  | 1.80<br>(7.45)*** | 1.43<br>(7.07)*** | 1.15<br>(6.30)*** | 0.88<br>(5.74)*** | 0.79<br>(6.09)*** | 0.66<br>(5.57)*** | 0.62<br>(5.12)*** | 0.80<br>(5.79)*** |
| FF3 alpha                                                                          | 2.42<br>(10.77)*** | 2.08<br>(11.13)*** | 1.55<br>(9.31)*** | 1.20<br>(9.28)*** | 0.95<br>(8.64)*** | 0.69<br>(7.39)*** | 0.64<br>(7.60)*** | 0.55<br>(7.35)*** | 0.56<br>(6.87)*** | 0.79<br>(7.40)*** |
| Carhart alpha                                                                      | 2.44<br>(10.45)*** | 2.13<br>(10.88)*** | 1.63<br>(9.29)*** | 1.26<br>(9.29)*** | 1.03<br>(9.21)*** | 0.77<br>(8.58)*** | 0.70<br>(7.99)*** | 0.60<br>(8.17)*** | 0.61<br>(6.88)*** | 0.89<br>(7.71)*** |
| FF5 alpha                                                                          | 2.43<br>(10.60)*** | 2.01<br>(10.81)*** | 1.48<br>(9.34)*** | 1.12<br>(9.19)*** | 0.88<br>(8.72)*** | 0.6<br>(6.99)***  | 0.58<br>(7.22)*** | 0.51<br>(6.55)*** | 0.55<br>(6.47)*** | 0.87<br>(7.76)*** |
|                                                                                    |                    |                    |                   |                   |                   |                   |                   |                   |                   |                   |

(Continued)

(Continued)

| Sorting statistic                | Decile portfolio  |                   |                   |                   |                   |                   |                   |                   |                   |                   |
|----------------------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
|                                  | 1                 | 2                 | 3                 | 4                 | 5                 | 6                 | 7                 | 8                 | 9                 | 10                |
| <i>Value-weighted portfolios</i> |                   |                   |                   |                   |                   |                   |                   |                   |                   |                   |
| Average return                   | 2.11<br>(8.05)*** | 1.70<br>(6.95)*** | 1.26<br>(6.55)*** | 1.41<br>(6.94)*** | 1.24<br>(6.61)*** | 0.98<br>(5.01)*** | 1.07<br>(5.47)*** | 0.91<br>(4.89)*** | 0.91<br>(4.63)*** | 0.98<br>(4.40)*** |
| CAPM alpha                       | 1.21<br>(6.04)*** | 0.79<br>(5.37)*** | 0.39<br>(3.59)*** | 0.54<br>(4.47)*** | 0.36<br>(2.72)*** | 0.10<br>(1.19)    | 0.22<br>(3.49)*** | 0.04<br>(0.65)    | 0.02<br>(0.38)    | 0.06<br>(0.71)    |
| FF3 alpha                        | 1.04<br>(7.18)*** | 0.60<br>(4.64)*** | 0.24<br>(2.64)*** | 0.39<br>(3.69)*** | 0.28<br>(2.65)*** | 0.01<br>(0.07)    | 0.16<br>(3.06)*** | 0.03<br>(0.48)    | 0.05<br>(1.02)    | 0.16<br>(2.22)**  |
| Carhart alpha                    | 1.11<br>(6.90)*** | 0.64<br>(5.11)*** | 0.36<br>(3.86)*** | 0.43<br>(3.68)*** | 0.37<br>(3.25)*** | 0.06<br>(0.68)    | 0.17<br>(2.64)*** | 0.02<br>(0.30)    | 0.06<br>(1.26)    | 0.13<br>(1.56)    |
| FF5 alpha                        | 1.06<br>(6.61)*** | 0.48<br>(3.70)*** | 0.21<br>(1.90)*   | 0.25<br>(2.15)**  | 0.20<br>(2.23)**  | -0.10<br>(-0.95)  | 0.06<br>(1.17)    | -0.09<br>(-1.20)  | 0.03<br>(0.55)    | 0.14<br>(1.82)*   |
|                                  |                   |                   |                   |                   |                   |                   |                   |                   |                   | 0.92<br>(4.95)*** |

#### 4.3.4.2 Subperiod analysis

In order to verify that the negative relation between the return asymmetry measure and future stock returns is not driven by a particular sample period, I split my sample into two subperiods: 1963–1988 and 1989–2014. For each subperiod, I form equal-weighted portfolios based on the measure of return asymmetry estimated at the end of each month using both 12- and 60-month estimation windows. Similar to the analysis performed on the entire sample, I hold portfolios for one month after formation and calculate monthly returns from the observed daily returns at the end of each month. The portfolios are rebalanced based on the new estimates of the asymmetry measure after the sample is rolled forward by one month. I repeat the process until I exhaust all the observations in the sample.

Panel A of Table 4.6 shows average monthly excess and risk-adjusted returns calculated from the asset pricing models (i.e., CAPM, FF3, Cahart and FF5) for the five quintile portfolios formed according to the return asymmetry measure estimated using the 12-month estimation window. The findings for the subperiods are identical to those of the entire sample. As I move from quintile portfolio 1 to quintile portfolio 5, increasing the measure of asymmetry, the average excess as well as risk-adjusted returns are found to decline in both subperiods. The differences of the excess returns between quintile portfolios 1 and 5 are estimated to be 1.69% per month with a  $t$ -statistic of 9.33 for the 1963–1988 subperiod and 0.73% per month with a  $t$ -statistic of 2.34 for the 1989–2014 subperiod. The average risk-adjusted returns for the difference portfolio are all positive and statistically significant in both subperiods.

Table 4.6: Portfolios sorted by return asymmetry in subperiods

We divide our sample period into two equal subperiods: 1963-1988 and 1989-2014. At the end of each month, we calculate return asymmetry for each stock using previous 12-month daily data (Panel A) and 60-month daily data (Panel B) with the method by Patil et al. (2012). I sort stocks into quintile portfolios using the same method and report post average returns. The t-statistics based on Newey and West (1987) are reported in the parentheses. Statistical significance at 10%, 5% and 1% levels is indicated by \*, \*\*, \*\*\* respectively.

| Outcome variable                                                                                              | Quintile portfolio |                   |                   |                   |                   |
|---------------------------------------------------------------------------------------------------------------|--------------------|-------------------|-------------------|-------------------|-------------------|
|                                                                                                               | 1                  | 2                 | 3                 | 4                 | 5                 |
| <p style="text-align: center;"><i>Panel A: 12 month estimation window</i><br/> <i>Subperiod 1963-1988</i></p> |                    |                   |                   |                   |                   |
| Average return                                                                                                | 3.18<br>(7.43)***  | 2.51<br>(6.45)*** | 2.02<br>(5.54)*** | 1.74<br>(4.76)*** | 1.50<br>(3.78)*** |
| CAPM alpha                                                                                                    | 2.25<br>(9.93)***  | 1.56<br>(7.04)*** | 1.07<br>(5.50)*** | 0.78<br>(4.33)*** | 0.52<br>(2.67)*** |
| FF3 alpha                                                                                                     | 1.82<br>(8.56)***  | 1.13<br>(7.33)*** | 0.70<br>(6.26)*** | 0.52<br>(5.56)*** | 0.36<br>(2.85)*** |
| Carhart alpha                                                                                                 | 2.08<br>(10.32)*** | 1.34<br>(8.43)*** | 0.78<br>(6.51)*** | 0.48<br>(5.07)*** | 0.23<br>(1.87)*   |
| FF5 alpha                                                                                                     | 1.88<br>(8.56)***  | 1.21<br>(8.17)*** | 0.75<br>(7.31)*** | 0.56<br>(6.14)*** | 0.40<br>(2.94)*** |
| <i>(Continued)</i>                                                                                            |                    |                   |                   |                   |                   |

*Continued)*

| Outcome variable | Quintile portfolio         |                   |                    |                    |                   |
|------------------|----------------------------|-------------------|--------------------|--------------------|-------------------|
|                  | 1                          | 2                 | 3                  | 4                  | 5                 |
|                  | <i>Subperiod 1989-2014</i> |                   |                    |                    |                   |
| Average return   | 2.88<br>(7.91)***          | 2.98<br>(8.74)*** | 2.66<br>(8.55)***  | 2.32<br>(7.48)***  | 2.15<br>(6.37)*** |
| CAPM alpha       | 1.96<br>(6.56)***          | 2.07<br>(7.05)*** | 1.73<br>(7.31)***  | 1.32<br>(6.25)***  | 1.03<br>(4.22)*** |
| FF3 alpha        | 1.82<br>(8.08)***          | 1.96<br>(9.28)*** | 1.64<br>(11.19)*** | 1.25<br>(10.85)*** | 1.06<br>(7.54)*** |
| Carhart alpha    | 1.96<br>(7.73)***          | 2.07<br>(8.93)*** | 1.72<br>(10.72)*** | 1.34<br>(11.18)*** | 1.15<br>(7.83)*** |
| FF5 alpha        | 1.74<br>(7.68)***          | 1.90<br>(9.03)*** | 1.60<br>(11.09)*** | 1.26<br>(10.90)*** | 1.20<br>(8.31)*** |

*(Continued)*

(Continued)

| Outcome variable                                                                  | Quintile portfolio |                   |                   |                   |                   |
|-----------------------------------------------------------------------------------|--------------------|-------------------|-------------------|-------------------|-------------------|
|                                                                                   | 1                  | 2                 | 3                 | 4                 | 5                 |
| <p><i>Panel B: 60 month estimation window</i><br/> <i>Subperiod 1963-1988</i></p> |                    |                   |                   |                   |                   |
| Average return                                                                    | 3.19<br>(6.79)***  | 2.13<br>(5.17)*** | 1.63<br>(4.19)*** | 1.45<br>(3.84)*** | 1.37<br>(3.36)*** |
| CAPM alpha                                                                        | 2.27<br>(7.44)***  | 1.22<br>(4.91)*** | 0.71<br>(3.65)*** | 0.54<br>(4.18)*** | 0.46<br>(3.15)*** |
| FF3 alpha                                                                         | 1.85<br>(8.66)***  | 0.84<br>(6.03)*** | 0.45<br>(4.23)*** | 0.38<br>(4.95)*** | 0.42<br>(4.23)*** |
| Carhart alpha                                                                     | 1.85<br>(8.48)***  | 0.89<br>(7.02)*** | 0.53<br>(5.00)*** | 0.40<br>(5.21)*** | 0.42<br>(4.19)*** |
| FF5 alpha                                                                         | 1.91<br>(9.29)***  | 0.90<br>(7.60)*** | 0.47<br>(4.59)*** | 0.40<br>(5.17)*** | 0.51<br>(4.23)*** |
|                                                                                   |                    |                   |                   |                   |                   |

(Continued)

(Continued)

| Outcome variable           | Quintile portfolio |                   |                    |                   |                   |
|----------------------------|--------------------|-------------------|--------------------|-------------------|-------------------|
|                            | 1                  | 2                 | 3                  | 4                 | 5                 |
|                            |                    |                   |                    |                   | 1-5               |
| <i>Subperiod 1989-2014</i> |                    |                   |                    |                   |                   |
| Average return             | 3.55<br>(8.53)***  | 2.85<br>(8.47)*** | 2.20<br>(7.97)***  | 1.84<br>(6.93)*** | 1.91<br>(6.57)*** |
| CAPM alpha                 | 2.67<br>(6.71)***  | 1.95<br>(6.01)*** | 1.29<br>(5.44)***  | 0.90<br>(4.94)*** | 0.90<br>(5.25)*** |
| FF3 alpha                  | 2.54<br>(8.26)***  | 1.81<br>(8.87)*** | 1.16<br>(9.79)***  | 0.80<br>(7.84)*** | 0.87<br>(7.38)*** |
| Carhart alpha              | 2.59<br>(8.25)***  | 1.89<br>(8.76)*** | 1.24<br>(10.54)*** | 0.89<br>(9.08)*** | 0.97<br>(7.87)*** |
| FF5 alpha                  | 2.51<br>(8.00)***  | 1.69<br>(8.76)*** | 1.03<br>(11.13)*** | 0.72<br>(8.18)*** | 0.90<br>(7.82)*** |
|                            |                    |                   |                    |                   | 1.62<br>(4.70)*** |

As can be seen in Panel B of Table 4.6, when the 60-month estimation window is used to calculate the return asymmetry measure, the declining pattern (except the last portfolio) in the average excess and risk-adjusted returns previously found when the return asymmetry measure is calculated using the 12-month estimation window remains largely unchanged except for quintile portfolio 5 where the excess and the risk-adjusted returns are slightly larger than the returns for quintile portfolio 4. Despite the slight increase in value, I note that returns for the difference portfolio are greater when the asymmetry measure is computed using the 60-month window compared to when it is computed using the 12-month window. Based on the results in both Panels A and B of Table 4.6, I conclude that securities with high (low) return asymmetry exhibit low (high) expected returns. Importantly, the relation between return asymmetry and the expected stock returns is not driven by a specific sample period.

#### 4.3.5 Portfolio sorts after controlling for other pricing factors

I already find that return asymmetry can be used to predict the stock returns. This effect is not driven by a specific sample period. However, can the effect be explained by other pricing factors. In this section, I focus on the relation between return asymmetry and stock returns after I control for well-known pricing factors that are documented to affect expected stock returns: size, book-to-market, momentum, short-term return reversal, liquidity, and idiosyncratic volatility. The methodology used in this section is bivariate dependent-sort. Compared with independent-sort methodology used in Chapter 5 and Chapter 6, dependent-sort analysis is usually used to

examine the relation between the second sort variable (return asymmetry in my case) and the outcome variable (expected return in my case), after controlling for some factors, while independent-sort enables to test this relation, as well as the relation between control factors and outcome variable. I will also use independent-sort in section 4.3.7.1 to examine the relation between return asymmetry and expected returns, as well as the relations between skewness variables and expected returns.

As an example of my approach, I control for the size effect by first sorting stocks into five quintile portfolios based on their market capitalisation, computed at the end of the portfolio formation month. Then within each size quintile portfolio, I sort securities into five portfolios according to the return asymmetry measure, calculated using daily return series during the previous 60 months. Asymmetry quintile portfolio 1 therefore contains stocks with the lowest return asymmetry while asymmetry quintile portfolio 5 contains stocks with the highest return asymmetry. The conditional sort procedure just described creates a set of asymmetry portfolios that are independent of firm size. It is worth noting that, for this exercise, stocks in each of the twenty-five portfolios are equally weighted.

Table 4.7 reports the mean values of the risk-adjusted returns computed using the Fama-French three-factor (FF3) model. For each of the asymmetry quintile portfolio, the averages are calculated across the five quintile portfolios formed based on each of the control variables.<sup>12</sup> Consistent with the results reported earlier, I find that after controlling for the effect of the firm's size, stock returns are observed to decline as return asymmetry

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<sup>12</sup>I also calculate the average excess returns, the CAPM alphas, the Carhart four-factor alphas and the Fama-Frech five-factor (FF5) alphas. The results (not reported in the study) follow the same pattern of those for FF3. They are available upon request.

increases. When I control for the size effect, the difference in the risk-adjusted returns between the low and the high asymmetry portfolios is approximately 0.25% per month with a Newey-West  $t$ -statistics of 1.90. The magnitude is found to be much lower than the return difference calculated when portfolios are formed according to the return asymmetry measure only. These findings show that return asymmetry may be related to the size effect and so variation in the return asymmetry measure within size-sorted portfolios is smaller.

Recall from the results in Table 4.2 that the return difference between quintile portfolios 1 and 5 for equal-weighted portfolios is higher than the difference for value-weighted portfolios. Compared to value weighting, equal weighting places relatively larger weights on small stocks. As small stocks tend to have higher returns, it is not unusual to find that equal-weighted portfolios perform better than value-weighted portfolios. However, based on the results reported in Table 4.7, I can conclude that market capitalisation does not explain the effect of return asymmetry on the expected security return since I observe that the difference in the risk-adjusted returns between quintile portfolios 1 and 5 is still statistically significant even after I control for the size effect.

Table 4.7: Portfolio sorts by return asymmetry after controlling for other factors

At the end of each month, I first sort stocks into five quintile portfolios according to each of the control variables: market capitalization (*Size*), the book-to-market ratio (*B/M*), the momentum factor (*Mom*), the short-term return reversal factor (*Rev*), the liquidity factor (*Liq*) and idiosyncratic volatility (*Ivol*). Then within each quintile portfolio, I further sort stocks into five quintile portfolios based on the return asymmetry measure, computed using daily return data during the previous 60 months. Quintile portfolio 1 contains stocks with the lowest *Asym* values; quintile portfolio 5 contains stocks with the highest *Asym* values. This table reports the Jensen's alphas calculated from the Fama-french three-factor model (FF3), averaged within the asymmetry quintile portfolios across the five quintile portfolios formed according to each of the control variables. The *t*-statistics reported in parentheses are calculated using the method discussed in Newey and West (1987). Statistical significance at the 10%, 5% and 1% levels is indicated by \*, \*\*, and \*\*\*, respectively. The sample includes all the common stocks on NYSE, AMEX, and NASDAQ for the period from January 1963 to December 2014.

| Control     | Quintile           |                    |                    |                    |                   |
|-------------|--------------------|--------------------|--------------------|--------------------|-------------------|
|             | 1                  | 2                  | 3                  | 4                  | 5                 |
| <i>Size</i> | 2.06<br>(10.93)*** | 2.04<br>(10.68)*** | 1.96<br>(10.32)*** | 1.92<br>(9.40)***  | 1.81<br>(9.56)*** |
| <i>B/M</i>  | 2.07<br>(11.05)*** | 1.26<br>(9.58)***  | 0.91<br>(9.14)***  | 0.78<br>(11.30)*** | 0.86<br>(9.62)*** |
| <i>Mom</i>  | 2.48<br>(10.72)*** | 1.57<br>(9.90)***  | 1.09<br>(8.61)***  | 0.76<br>(8.05)***  | 0.85<br>(8.54)*** |
|             |                    |                    |                    |                    | 1.63<br>(7.21)*** |

(Continued)

(Continued)

| Control     | Quintile           |                    |                    |                    |                    |
|-------------|--------------------|--------------------|--------------------|--------------------|--------------------|
|             | 1                  | 2                  | 3                  | 4                  | 5                  |
|             |                    |                    |                    |                    | 1-5                |
| <i>Rev</i>  | 2.45<br>(10.95)*** | 1.53<br>(9.31)***  | 1.06<br>(9.51)***  | 0.81<br>(10.44)*** | 0.87<br>(9.69)***  |
|             |                    |                    |                    |                    | 1.58<br>(7.49)***  |
| <i>Liq</i>  | 2.07<br>(12.63)*** | 1.39<br>(10.44)*** | 1.07<br>(10.24)*** | 0.91<br>(11.87)*** | 1.00<br>(10.08)*** |
|             |                    |                    |                    |                    | 1.07<br>(7.67)***  |
| <i>Ivol</i> | 2.88<br>(9.20)***  | 2.06<br>(9.99)***  | 1.53<br>(8.01)***  | 1.20<br>(8.12)***  | 1.27<br>(9.01)***  |
|             |                    |                    |                    |                    | 1.61<br>(5.82)***  |

As for the other control variables, I find that the strong negative relation between return asymmetry and stock returns remains intact after I control for the book-to-market ( $B/M$ ), the momentum ( $Mom$ ), the short-term return reversal ( $Rev$ ), the liquidity ( $Liq$ ) and the idiosyncratic volatility ( $Ivol$ ) effects. The results presented in Table 4.7 show that differences in the Fama-French three-factor alphas between quintile portfolios 1 and 5 lie between 0.25% and 1.63% per month. The differences are all statistically significant at the 1% significance level.

#### 4.3.6 Fama-MacBeth cross-sectional regression

In this section, I explore the effect of return asymmetry on expected returns at the individual-stock level by employing the Fama and MacBeth (1973) cross-sectional regressions. As pointed out by Fama and French (2008), the portfolio sort approach occasionally fails to capture the effect of the risk factor on security returns. Following Fama and MacBeth (1973), at the end of each month, I run the following cross-sectional predictive regression:

$$R_{i,t+1} - R_{f,t+1} = \lambda_0 + \lambda_1 Asym_{i,t} + \boldsymbol{\lambda}'_2 \mathbf{X}_{i,t} + \varepsilon_{i,t+1} \quad (4.12)$$

where  $R_{i,t+1}$  and  $R_{f,t+1}$  denote the excess return of stock  $i$  and the risk-free return in month  $t + 1$ , respectively;  $Asym_{i,t}$  is the measure of return asymmetry for stock  $i$  calculated at the end of month  $t$ ; and  $\mathbf{X}_{i,t}$  is a vector whose elements are the control variables whose values are observed in month  $t$ . Depending on the specification to be estimated, the elements in  $\mathbf{X}_{i,t}$  include the natural logarithm of size ( $\ln(MV)$ ), the natural logarithm of the book-to-market value ( $\ln(B/M)$ ), the momentum measure ( $Mom$ ),

the short-term return reversal factor ( $Rev$ ), the liquidity factor ( $Illiq$ ) and idiosyncratic volatility ( $Ivol$ ). The cross-sectional regressions are run from January 1963 to December 2014. All the  $t$ -statistics are computed using Newey and West (1987) HAC standard errors with twelve lags to correct for potential problems relating to autocorrelation and heteroscedasticity.

Table 4.8 reports the time-series averages of the slope coefficients  $\lambda_1$  and  $\lambda_2$  along with the corresponding  $t$ -statistics in parentheses. The univariate regression results presented along the first row show a negative and statistically significant relation between return asymmetry and the expected stock returns. The average slope calculated from monthly regressions of the realised returns on lagged return asymmetry equals  $-1.93$  with a  $t$ -statistic of  $-2.25$ .

The second row of Table 4.8 shows the estimated coefficients for a model which includes  $\ln(MV_{i,t})$  and  $\ln(B/M_{i,t})$  as additional regressors. The model corresponds to the three-factor model of Fama and French (1993). The third row shows the results for a specification which adds  $Mom_{i,t}$  to the model, corresponding to the four-factor model of Carhart (1997). The results reported in the second and the third rows show that the parameter of the return asymmetry measure is negative and statistically significant, suggesting that after controlling for the size, book-to-market and momentum effects, the predictive power of the asymmetry measure remains strong and statistically significant.

Table 4.8: Fama-MacBeth (1973) regressions

At the end of each month, I estimate the average coefficient from Fama and MacBeth cross-sectional regressions of monthly excess returns on a set of lagged predicted variables: return asymmetry (*Asym*) market capitalization ( $\ln(MV)$ ), book-to-market ratio ( $\ln(B/M)$ ), momentum (*Mom*), short-term return reversal (*Rev*), liquidity (*Liq*) and idiosyncratic volatility (*Ivol*).  $\ln(MV)$  is the natural logarithm of market capitalization calculated with information at the end of June of year  $t$  from CRSP,  $\ln(B/M)$  is log book-to-market ratio of the book value of equity for the fiscal year ending in year  $t - 1$  divided by market equity at the end of December of year  $t - 1$ , the calculation of other factors are unchanged. The t-statistics based on Newey and West (1987) are reported in the parentheses. Statistical significance at 10%, 5% and 1% levels is indicated in the bold face and by \*, \*\*, \*\*\* respectively. The sample includes all common stocks on the NYSE, AMEX, and NASDAQ for the period from January 1963 to December 2014.

| Constant          | <i>Asym</i>        | $\ln(MV)$          | $\ln(B/M)$        | <i>Mom</i>        | <i>Rev</i>          | <i>Liq</i>         | <i>Ivol</i>       |
|-------------------|--------------------|--------------------|-------------------|-------------------|---------------------|--------------------|-------------------|
| 1.02<br>(4.05)*** | -1.93<br>(-2.25)** |                    |                   |                   |                     |                    |                   |
| 0.67<br>(0.89)    | -1.63<br>(-1.76)*  | 0.04<br>(0.72)     | 0.19<br>(2.96)*** |                   |                     |                    |                   |
| 0.71<br>(0.99)    | -1.78<br>(-2.18)** | 0.02<br>(0.45)     | 0.19<br>(3.13)*** | 0.57<br>(2.65)*** |                     |                    |                   |
| 2.68<br>(3.90)*** | -1.46<br>(-1.85)*  | -0.10<br>(-2.28)** | 0.19<br>(3.27)*** | 0.40<br>(1.97)**  | -4.56<br>(-8.37)*** | 0.09<br>(-2.97)*** | 0.05<br>(3.98)*** |

The last row of Table 4.8 shows the results for the model which includes *Rev*, *Liq* and *Ivol* as additional predictors. The regression results indicate that even after controlling for these additional factors, the negative effect of the return asymmetry measure on the expected stock returns remains strong and statistically significant at the 10% significance level. The parameters on all the control variables, except the idiosyncratic volatility, have the correct signs and are statistically significant. My findings that the idiosyncratic volatility has a positive impact on future stock returns are in line with Fu (2009) but are not consistent with the findings reported by Ang et al. (2006). Using exponential GARCH models, Fu (2009) shows that idiosyncratic volatilities are time-varying and suggests that the negative relation between idiosyncratic volatility and stock returns uncovered by Ang et al. (2006) is largely explained by the return reversal of a subset of small stocks with high idiosyncratic volatilities.

#### 4.3.7 Return asymmetry and skewness

In this section, I further explore whether the explanatory power derived from the return asymmetry measure and skewness is the same. My goal is to test if the effect of return asymmetry on security returns can indeed be explained by the skewness factors. To achieve the objective, I employ independent two-way portfolio sorts and the Fama-MacBeth approach.

##### 4.3.7.1 Two-way portfolio sorts

To separate the effect of return asymmetry from the effect of skewness, I examine the returns generated from portfolios independently formed based

on return asymmetry and each of the three skewness factors: total skewness, co-skewness and idiosyncratic skewness. The asymmetry measure, the total skewness and the idiosyncratic skewness are estimated using the same rolling window method described in Sections 4.2 and 4.3.2. The portfolio sorting procedure is as follows. At the end of each month, I sort stocks into five equal-weighted quintile portfolios according to the value of the return asymmetry measure. For each of the asymmetry quintile portfolios, I further construct three equal-weighted stock portfolios based on the value of the skewness measure. I use the values at the 30<sup>th</sup> and the 70<sup>th</sup> percentiles as the breakpoints. For each of the skewness measures under consideration, this procedure results in a total of 15 portfolios. For each portfolio, I calculate monthly risk-adjusted returns from observed monthly returns at the end of each month using the Fama-French three-factor model.<sup>13</sup>

According to the statistics reported in Table 4.9, the estimated risk-adjusted returns consistently decline as I move from asymmetry quintile portfolios 1 to 4. For some skewness portfolios, the value of alpha increases slightly as I move from asymmetry portfolios 4 to 5. Importantly, the returns for the difference portfolio, as shown in columns labelled 1–5, are statistically significant for all skewness-sorted portfolios. The results suggest that the strong and negative relation between return asymmetry and expected stock returns persists even after controlling for the effect of skewness.

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<sup>13</sup>The results are similar when I calculate the excess return, the CAPM, the Carhart four-factor and the Fama-French five-factor alphas.

Table 4.9: Two-way portfolio sorts by return asymmetry and skewness

At the end of each month, I calculate the skewness variables for each stock: Total skewness ( $Tskew$ ), co-skewness ( $Coskew$ ) and idiosyncratic skewness ( $Iskew$ ). Then I independently sort stocks into five portfolios based on their return asymmetry and sort stocks into three portfolios based on their variables. The breakpoints for skewness variables are the 30th and 70th percentiles for CRSP stocks. I calculate the equal-weighted return for each portfolio. Note that the subscript 1 denotes the portfolio comprising stocks with low variables. The subscript 3 represents the portfolio containing stocks with high variables. This table presents post-ranking Fama-French three factor alpha. The t-statistics based on Newey and West (1987) are reported in the parentheses. Statistical significance at 10%, 5% and 1% levels is indicated by \*, \*\*, \*\*\* respectively. The sample periods are from January 1963 to December 2014.

|           | Quintile           |                   |                   |                   |                   |
|-----------|--------------------|-------------------|-------------------|-------------------|-------------------|
|           | 1                  | 2                 | 3                 | 4                 | 5                 |
| $Tskew_1$ | 1.59<br>(10.60)*** | 0.95<br>(9.20)*** | 0.58<br>(6.58)*** | 0.53<br>(9.08)*** | 0.61<br>(8.06)*** |
| $Tskew_2$ | 2.48<br>(10.28)*** | 1.34<br>(8.13)*** | 0.80<br>(8.47)*** | 0.68<br>(8.20)*** | 0.67<br>(6.61)*** |
| $Tskew_3$ | 2.96<br>(11.64)*** | 2.01<br>(7.65)*** | 1.55<br>(8.11)*** | 1.24<br>(8.05)*** | 1.56<br>(9.32)*** |

(Continued)

(Continued)

|                            |                    | Quintile           |                   |                   |                   |                   |
|----------------------------|--------------------|--------------------|-------------------|-------------------|-------------------|-------------------|
|                            |                    | 1                  | 2                 | 3                 | 4                 | 5                 |
|                            |                    |                    |                   |                   |                   | 1-5               |
| <i>Coskew</i> <sub>1</sub> | 2.29<br>(11.62)*** | 1.49<br>(10.28)*** | 1.06<br>(9.77)*** | 0.87<br>(8.54)*** | 0.90<br>(7.69)*** | 1.39<br>(7.00)*** |
| <i>Coskew</i> <sub>2</sub> | 2.48<br>(11.67)*** | 1.45<br>(8.95)***  | 0.92<br>(8.07)*** | 0.69<br>(9.41)*** | 0.90<br>(9.45)*** | 1.58<br>(7.59)*** |
| <i>Coskew</i> <sub>3</sub> | 2.32<br>(10.22)*** | 1.23<br>(7.17)***  | 0.58<br>(6.82)*** | 0.53<br>(8.42)*** | 0.59<br>(5.88)*** | 1.73<br>(7.38)*** |
| <i>Iskew</i> <sub>1</sub>  | 1.63<br>(11.12)*** | 1.01<br>(9.17)***  | 0.61<br>(6.90)*** | 0.57<br>(9.81)*** | 0.60<br>(8.03)*** | 1.03<br>(6.28)*** |
| <i>Iskew</i> <sub>2</sub>  | 2.56<br>(10.46)*** | 1.38<br>(8.35)***  | 0.82<br>(8.80)*** | 0.68<br>(8.60)*** | 0.67<br>(7.16)*** | 1.89<br>(8.04)*** |
| <i>Iskew</i> <sub>3</sub>  | 2.85<br>(10.86)*** | 1.87<br>(7.43)***  | 1.41<br>(8.38)*** | 1.07<br>(7.68)*** | 1.38<br>(8.36)*** | 1.47<br>(6.65)*** |

#### 4.3.7.2 Cross-sectional regressions with skewness factors

I analyse the effect of return asymmetry on expected return at the stock level by employing the two-step Fama and MacBeth (1973) cross-sectional regression technique. I simultaneously control for the size, book-to-market, momentum, short-term reversal, liquidity factors along with idiosyncratic volatility and skewness in my regressions. Specifically, I run the following regressions:

$$R_{i,t+1} - R_{f,t+1} = \lambda_0 + \lambda_1 Asym_{i,t} + \boldsymbol{\lambda}'_2 \mathbf{X}_{i,t} + \lambda_3 Tskew_{i,t} + \varepsilon_{i,t+1} \quad (4.13)$$

$$R_{i,t+1} - R_{f,t+1} = \lambda_0 + \lambda_1 Asym_{i,t} + \boldsymbol{\lambda}'_2 \mathbf{X}_{i,t} + \lambda_3 Coskew_{i,t} + \varepsilon_{i,t+1} \quad (4.14)$$

$$R_{i,t+1} - R_{f,t+1} = \lambda_0 + \lambda_1 Asym_{i,t} + \boldsymbol{\lambda}'_2 \mathbf{X}_{i,t} + \lambda_3 Iskew_{i,t} + \varepsilon_{i,t+1} \quad (4.15)$$

where

$$\mathbf{X}_{i,t} = \left[ \ln(MV_{i,t}) \quad \ln(B/M_{i,t}) \quad Mom_{i,t} \quad Rev_{i,t} \quad Liq_{i,t} \right]'$$

is a vector containing the well-known pricing factors. The estimation results are reported in Table 4.10.

Table 4.10: Fama-MacBeth (1973) regressions with skewness factors

At the end of each month, I estimate the average coefficient from Fama and MacBeth cross-sectional regressions of monthly excess returns on a set of lagged predicted variables: return asymmetry (*Asym*) market capitalization ( $\ln(MV)$ ), book-to-market ratio ( $\ln(B/M)$ ), momentum (*Mom*), short-term return reversal (*Rev*), liquidity (*Liq*), idiosyncratic volatility (*Ivol*), total skewness (*Tskew*), co-skewness (*Coskew*) and idiosyncratic skewness (*Iskew*). The t-statistics based on Newey and West (1987) are reported in the parentheses. Statistical significance at 10%, 5% and 1% levels is indicated in the bold face and by \*, \*\*, \*\*\* respectively. The sample includes all common stocks on the NYSE, AMEX, and NASDAQ for the period from January 1963 to December 2014.

|      | Constant  | <i>Asym</i>       | $\ln(MV)$           | $\ln(B/M)$        | <i>Mom</i>     | <i>Rev</i>           | <i>Liq</i>      | <i>Ivol</i>       | <i>Tskew</i>    | <i>Coskew</i>  | <i>Iskew</i>     |
|------|-----------|-------------------|---------------------|-------------------|----------------|----------------------|-----------------|-------------------|-----------------|----------------|------------------|
| 2.40 | (3.33)*** | -1.28<br>(-1.74)* | -0.13<br>(-2.76)*** | 0.26<br>(4.04)*** | 0.09<br>(0.42) | -6.33<br>(-12.99)*** | 0.09<br>(1.65)* | 0.06<br>(3.38)*** | 0.03<br>(1.93)* |                |                  |
| 2.47 | (3.48)*** | -1.33<br>(-1.82)* | -0.13<br>(-2.90)*** | 0.26<br>(3.98)*** | 0.10<br>(0.48) | -6.27<br>(-12.84)*** | 0.08<br>(1.47)  | 0.06<br>(3.44)*** |                 | 0.23<br>(1.51) |                  |
| 2.39 | (3.33)*** | -1.29<br>(-1.76)* | -0.13<br>(-2.76)*** | 0.26<br>(4.04)*** | 0.09<br>(0.41) | -6.33<br>(-12.98)*** | 0.09<br>(1.66)* | 0.06<br>(3.38)*** |                 |                | 0.03<br>(2.15)** |

My findings show that, even after controlling for well-documented pricing factors, the return asymmetry measure is found to be an important explanatory variable in the predictive pricing models. The coefficient on the measure is negatively signed and statistically significant. Moreover, the size effect appears to be negative while the value effect is found to be positive and statistically significant. The parameters on the momentum, the short-term return reversal and the liquidity factors as well as the idiosyncratic volatility are all correctly signed and statistically significant.

Although the coefficient on the co-skewness is not statistically significant at the 10% significance level, the parameters on the total skewness and the idiosyncratic skewness measures are both positive and statistically significant. My results may seem surprising at first glance as theories suggest that the impact of skewness on stock returns should be negative. However, as Jiang et al. (2014) conclude in their paper, the evidence on the ability of skewness to consistently explain expected stock returns is mixed. They too find that the effect of skewness on returns is positive during periods when the sentiment is low. My results point to the limitation of skewness in quantifying the degree of asymmetry of a distribution.

## 4.4 Conclusions

In this chapter, I investigate the pricing implications of the return asymmetry measure, calculated following Patil et al. (2012), for the cross section of stock returns. The measure exploits the relation between the probability density function and the cumulative probability density function of a distribution to quantify the degree of asymmetry of the distribution of a random variable.

#### 4.4. CONCLUSIONS

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My findings reveal that return asymmetry can be employed to predict future stock returns. The relation between return asymmetry and stock returns is found to be negative and statistically significant. The results strongly support the skewness preference theory proposed by Brunnermeier et al. (2007) and Barberis and Huang (2008) who show that investors are attracted to assets with positive skewness and willing to pay more for them thereby driving down the assets' returns.

My univariate portfolio-level analysis indicates that the return on a portfolio containing stocks with low return asymmetry is on average greater than the return on a portfolio containing stocks with high return asymmetry. The difference between the returns of the low and the high asymmetry-sorted portfolios are large and statistically significant. After controlling for well-documented pricing factors, such as size, book-to-market, momentum, short-term return reversal, liquidity, idiosyncratic volatility, total skewness, co-skewness and idiosyncratic skewness, results of the bivariate portfolio sort suggest that the effect of return asymmetry on future stock returns remains strong in the presence of these factors. Employing the two-step Fama-MacBeth method to examine the effect of return asymmetry at the individual stock level, controlling for the aforementioned factors, I find that return asymmetry possesses explanatory power and can be used to predict future stock returns. Moreover, my findings hold for different time periods.

Interestingly, when each of the skewness measures is included in the Fama-MacBeth regressions along with my asymmetry measure, the co-skewness measure loses its predictability while the coefficients on total and idiosyncratic skewness turn positive. The findings shed light on the mixed evidence on the ability of skewness to consistently predict asset returns.

## Chapter 5

# Default Risk and the Market Skewness Risk Effect

### 5.1 Introduction

It has been long accepted that market-wide volatility is an important pricing factor<sup>1</sup>. Recent evidence, however, has emerged showing that market-wide volatility, measured by higher moments of the return distribution, is also priced in the cross-section of expected returns. For example, Harvey and Siddique (2000a) find that conditional coskewness can explain idiosyncratic components in cross-section of expected returns. Boyer et al. (2009) use lagged volatility, lagged skewness and a number of firm characteristics to predict idiosyncratic skewness. They document that expected idiosyncratic skewness also has an impact on asset prices. Conrad et al. (2013) and Bali and Murray (2013) calculate implied skewness by using individual option data and show that risk-neutral skewness is negatively related to

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<sup>1</sup>I would like to thank Ning Gao from Manchester Business School for his invaluable input into this chapter. This chapter is based on research article which has been submitted to a peer-reviewed journal. The co-authors are Xiafei Li, Thanaset Chevapatrakul and Ning Gao. The research ideas for the paper and empirical results are discussed by my supervisors and Ning Gao.

expected returns or the skewness asset returns. More interestingly, Chang et al. (2013) prefer to focus on the option implied market skewness and they report that stocks with low market skewness risk outperform stocks with high market skewness risk significantly, even after adjusting for the Fama and French's (1993) three factors.

From the rational expectations perspective, Kraus and Litzenberger (1976) and Harvey and Siddique (2000a) develop the three-moment models to incorporate the effect of skewness in the return distribution. Their models are based on the assumption that investors have preference for stocks with positive skewness and require lower returns for holding those stocks. A model introduced by Mitton and Vorkink (2007) assumes that investors have heterogeneous preference for skewness and predicts that idiosyncratic skewness is a priced component of stock returns. From a behavioural point of view, Barberis and Huang (2008) and Brunnermeier et al. (2007) offer the explanations based on the cumulative prospect theory and optimal beliefs. The negative relation, they argue, stems from the fact that investors overinvest in stocks with positive skewness and underinvest in stocks with negative skewness.

Understanding the economic mechanism of the underlying market skewness risk effect is important for investors who seek to hedge the risk exposure. Over the past forty years, extensive studies have developed hundreds of factors to explain the cross-section of expected returns. Those factors might be highly correlated with each other. Harvey et al. (2015) evaluate the statistical significance of one factor in the previous tests on other factors from 317 papers and find the explanatory power of the pricing factors in those studies are likely to be spurious. Clearly, ignoring the interaction

effect between asset pricing factors on stock returns may lead to misleading conclusions for investors.

In this chapter, I examine the impact of default risk and financial crisis on the market skewness risk effect documented by Chang et al. (2013). My work is motivated by two strands of literature. First, skewness is highly related to default risk according to several important studies. Berd et al. (2007) and Engle (2011) further document that long-term negative skewness could cause massive defaults and high default correlations would increase the possibility of another negative return shock on asymmetric volatility. More recently, Campbell et al. (2008) point out that the low returns in distressed stocks may be on account of investors' preference of positive skewness of returns, and Conrad et al. (2014) develop a model on the prediction of extremely large returns and find that firms with a high default probability have high positive individual skewness. Engle and Mistry (2014) also provide evidence that firms with high default probability and poor credit ratings have high average skewness of stock returns.

On the other hand, an indirect relationship between skewness and default risk can be found from a number of studies. Engle (2011) and Engle and Mistry (2014) document that long-term negative skewness of return distribution is associated with asymmetric volatility. Black (1976) and Christie (1982) put "leverage effect" forward to explain the asymmetric volatility property of individual stock returns. The leverage hypothesis argues that return shocks raise operating and financial leverage, which is the reason for the changes in conditional volatility. Merton (1974) extends the Modigliani-Miller theorem and shows that leverage is highly related to default risk.

Second, Yuan (2005) develops a rational expectations equilibrium model that predicts an asymmetric market return distribution after negative shocks. These shocks, which are common during financial crises, often lead to negative skewness and massive default. After the financial crisis of 2007-2008, the average default risk of stocks increases. I expect that the strong market skewness risk effect disappears after the crisis. Schwert (1989), Hamilton and Lin (1996), and Perez-Quiros and Timmermann (2001) find that stock market volatility and conditional skewness are highly correlated with business cycle. I then further test whether the market skewness risk is priced differently between the periods of economic growth and economic downturn.

In this chapter, I first confirm the market skewness risk effect documented by Chang et al. (2013). Following the positive skewness preference theory of Kraus and Litzenberger (1976), I hypothesize that other things being equal, risk averse investors prefer to hold stocks with positive market skewness risk and require lower expected returns on these stocks. As a result, I expect a negative relation between market skewness risk and expected stock returns. Second, Engle (2011) shows a significant negative link between long-term skewness and default risk. According to Bates (2000), Pan (2002), Engle (2011), and Chang et al. (2013), holding stocks with low exposures to innovations in market skewness would allow to hedge against downside risk. I then hypothesize that the market skewness risk effect is more pronounced when investors are not worry about default risk. When default risk is high, investors have greater demand for hedging against downside risk and require higher returns for stocks with high market skewness risk because these stocks lack hedging ability. The higher expected returns on stocks with high

default risk offset the significant market skewness risk effect. Therefore, I expect a strong market skewness risk effect for stocks with low default risk and a weaker effect for stocks with high default risk.

To achieve my research objectives, I estimate the innovations in the implied market skewness using information from Standard and Poor's (S&P) 500 index option prices following Bakshi and Madan (2000), Carr and Madan (2001), Bakshi et al. (2003), and Chang et al. (2013). The advantage of utilizing option prices is that the prices contain forward-looking information and can capture the expectations of market participants. I also compute the default likelihood indicator of Vassalou and Xing (2004) and the O-score of Ohlson (1980) for each firm as the proxies for default risk. In order to investigate the predictive ability of market skewness risk on expected stock returns under the different economic climates, I use the bank loan spread and the expected market risk premium to identify good and bad economic times following Campello and Chen (2010) and Petkova and Zhang (2005), respectively.

To make this empirical study comparable to the study of Chang et al. (2013), my first dataset consists of all common stocks traded on the New York Stock Exchange (NYSE), American Stock Exchange (Amex), and NASDAQ from 1996 through 2007. In line with Chang et al. (2013), I find that stocks with the lowest sensitivity to innovations in implied market skewness earn the highest returns; while stocks with the highest sensitivity to innovations in implied market skewness yield the lowest returns across market skewness risk quintile portfolios. Interestingly, stocks with the lowest and the highest market skewness risk tend to be financially distressed stocks that have small market size, high book-to-market ratios, and high default risk. These firms

generate negative returns on their assets and produce negative cash flows from their operations.

More importantly, using two-way portfolio sorts, I find that market skewness risk is highly related to firm size, book-to-market ratio, and default risk. Specifically, the significant market skewness risk effect is concentrated on stocks with large market capitalizations, low book-to-market ratios, low default likelihood indicators, and low O-scores. On the other hand, the size effect, the value and default risk premiums are stronger among stocks with high market skewness risk. The results from Fama and MacBeth's (1973) cross-sectional regressions confirm that the impact of market skewness risk on stock returns significantly interacts with market value, book-to-market ratio, and default risk.

I next use out-of-sample data from 2008 to 2013 and investigate the market skewness risk effect after the financial crisis of 2007-2008. My results show that the significant return differences between stocks with lowest and highest sensitivity to innovations in implied market skewness disappear after the crisis. This is consistent with the prediction of the rational expectations equilibrium model of Yuan (2005). Moreover, the strong size effect, the value and default risk premiums cannot be observed in stocks with high market skewness risk. Then, I use the methods by Campello and Chen (2010) and Petkova and Zhang (2005) to define good times and bad times for the monthly market data and run cross-sectional regressions in each period of time. The results from the cross-sectional regressions indicate that market skewness risk is only priced during good economic periods, but is not priced during bad economic periods.

This study is the first in the literature to explore the default risk and financial crisis explanations for the market skewness risk effect. Empirical research provides little understanding of the effect. I highlight a significant interaction effect of market skewness risk with market size, book-to-market ratio, and default risk on expected stock returns. This allows a deeper understanding of the source of the effect. In addition, my results suggest that the positive skewness preference theory of Kraus and Litzenberger (1976) might only hold for stocks with large market value, high growth, low default risk, and during good economic conditions. This provides new insight into the market skewness risk effect and the positive skewness preference theory.

The rest of the chapter is organized as follows. Section 5.2 develops the hypotheses on the relationship between market skewness, default risk, and negative shocks. Section 5.3 describes data used in this study and explains the measures of market skewness risk and default risk. Section 5.4 presents the empirical results and Section 5.5 concludes the chapter.

## 5.2 Hypotheses Development

Kraus and Litzenberger (1976) and Harvey and Siddique (2000a) develop the three-moment CAPM by including coskewness as a risk measure in addition to variance. Following their studies, I assume that investors are averse to variance in their portfolio and the return distribution of investors' portfolio is non-symmetric. My model is given by:

$$\bar{r}_i = \lambda_0 + \lambda_1 \beta_{mkt} + \lambda_2 \beta_{\Delta SKEW} + \varepsilon_i \quad (5.1)$$

where

$$\bar{r}_i = \frac{R_i - R_f}{R_f}, \beta_{mkt} = \frac{\sum_t (r_{i,t} - \bar{r}_i) (r_{m,t} - \bar{r}_m)}{\sum_t (r_{m,t} - \bar{r}_m)^2} \quad (5.2)$$

$R_i$  is the expected rate of return for risk asset  $i$ ,  $R_m$  is the return for market portfolio,  $R_f$  is the rate of return for riskless asset,  $\beta_{\Delta SKEW}$  is the market skewness risk measure estimated from the innovations in implied skewness from S&P 500 index option prices,  $\lambda_1$  denotes the market price of  $\beta_{mkt}$ ,  $\lambda_2$  denotes the market price of  $\beta_{\Delta SKEW}$  with the opposite sign to the market skewness. According to the positive skewness preference theory of Kraus and Litzenberger (1976), Equation (5.1) implies a negative relationship between asset returns and market skewness risk for empirical tests. That is, investors are willing to pay a premium for possessing stocks with increased or positive market skewness risk and demand a premium for holding stocks with decreased or negative market skewness risk.

Skewness of the return distribution is a systematic deviation from symmetry (Engle, 2011). Engle (2011) and Neuberger (2012) show that the market returns are negatively skewed. A number of studies find that negative skewness is a source of systematic risk. For example, Adrian and Rosenberg (2008) report that market skewness risk is associated with the short-run component of market volatility. Engle (2011) documents that long-term negative skewness increases long-term systemic risk because negative skewness leads to a rise in default risk. Kozhan et al. (2013) demonstrate that

skewness risk is closely related to variance risk and both risks are driven by a common factor. Engle and Mistry (2014) find a link between aggregate risk and individual stock skewness.<sup>2</sup>

Default risk has also been extensively studied in the literature. In the seminal structural-default model, Merton (1974) uses the probability of default to capture default risk. Vassalou and Xing (2004) argue that the measure of default probability does not correspond to the true probability of default in large samples. They term it as default likelihood indicator and find that default risk is a systematic pricing factor in the cross-section of equity returns. Other studies use accounting information to calculate default risk. Ohlson's (1980) O-score and Altman's (1968b) Z-score are the most popular accounting-based measures of financial distress.<sup>3</sup>

According to Engle (2011), skewness is highly related to default risk and default correlation. He extends Merton's (1974) default model and assumes that all firms face the same market risk, idiosyncratic volatility, probability of default and default threshold. Therefore, the probability of default,  $P_{i,def}$ , depends only on market returns and idiosyncratic returns, as follows:

$$\begin{aligned}
 P_{i,def} &= P(R_{i,t} < k_t) = E[P(R_{i,t} < k_t \mid R_{m,t})] \\
 &= E[P(\varepsilon_i < (k_t - R_{m,t})/\sigma_i \mid R_{m,t})] \\
 &= E[\Phi((k_t - R_{m,t})/\sigma_i)]
 \end{aligned} \tag{5.3}$$

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<sup>2</sup>Hong and Stein (2003), however, argue that the degree of negative skewness of the distribution of short-horizon returns is related to trading volume.

<sup>3</sup>Dichev (1998) shows that O-score is superior to Z-score in predicting bankruptcy among the CRSP delisted firms. Griffin and Lemmon (2002) suggest that O-score as an overall measure of economic strength is better than any single measure of economic stability.

where  $\sigma_i$  is the idiosyncratic volatility of stock  $i$ ,  $k$  is the default threshold. Engle (2011) calculate the skewness of log returns from a set of simulations. Equation (5.3) indicates that large market declines are likely to lead to more defaults because market returns and idiosyncratic returns dominate the distribution of defaults. When the market returns are positive, only firms with large negative idiosyncratic returns are likely to default. When the market returns largely decline with high negative skewness, more firms are likely to default with the exceptions of firms that have extreme positive idiosyncratic returns.

Default correlation is the correlation between default risk of a pair of companies defined by Engle (2011). It can be measured as the covariance between default indicators divided by the variance from the following model:

$$\begin{aligned}
 Corr_{i,def} &= \left( P(R_{i,t} < k_t \& R_{j,t} < k_t) - P_{def}^2 \right) / \left( P_{def} - P_{def}^2 \right) \\
 &= \left( E \left[ \Phi \left( (k_t - R_{m,t}) / \sigma \right)^2 \mid R_{m,t} \right] - P_{def}^2 \right) / \left( P_{def} - P_{def}^2 \right) \\
 &= \left( V \left[ \Phi \left( (k_t - R_{m,t}) / \sigma \right) \right] \right) / \left( P_{def} - P_{def}^2 \right)
 \end{aligned} \tag{5.4}$$

Equation (5.4) suggests that a large decline of the market return is associated with negative skewness and increases the default correlation between two companies. Engle (2011) further shows that high default correlation enhances the opportunity of future negative skewness. According to the literature related to option-implied skewness (See for example, Bates (2000), Pan (2002), Engle (2011), and Chang et al. (2013)), a positive innovation in market skewness implies a decrease in downside risk, while a negative

innovation in market skewness indicates an increase in downside risk. When default risk is low, downside risk would be low, stocks with positive market skewness risk are more desirable for risk averse investors. A strong market skewness risk effect for low default risk stocks would be expected. When default risk is high, investors increase their requirement for hedging against high downside risk. Stocks with high market skewness risk become less desirable for investors because of their weaker hedging ability for downside risk. Investors demand higher returns on these stocks, which offsets the market skewness risk effect. I then expect that the strong effect disappears for stocks with high default risk.

Yuan (2005) predicts that a financial crisis could increase the skewness of price distribution. He shows that the sensitivity of asset price to negative shocks increases when information asymmetry becomes severe and borrowing constraints are more binding. Calomiris et al. (2012) provide empirical evidence that stock returns are sensitive to financial constraints during the financial crisis of 2007-2008. I then postulate that the market skewness risk effect might be significantly affected by the financial crisis of 2007-2008. On the other hand, Perez-Quiros and Timmermann (2001) find a cyclical pattern for small firms, in which the negative conditional skewness is concentrated in the stages of late expansion and early recession of the economic cycle. Weinstein (1981), Denis and Denis (1995), and Chen (2010) point out that defaults are likely to happen in bad economic conditions because the shortage of available funds causes more failures of corporates in meeting their debt obligations. I then expect that the impact of market skewness risk on stock returns would change over the economic cycle.

## 5.3 Data and the Measures

The dataset of this empirical chapter contains all stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (Amex), and NASDAQ. The stock return series are downloaded from the Center for Research in Securities Price (CRSP) daily stock return files. The accounting data are obtained from the CRSP/Compustat Merged Database. Data on Fama and French's five factors includes size, book-to-market equity, profitability, investment, and market excess returns; the daily momentum factor, and the risk-free rates are obtained from Kenneth French's website.<sup>4</sup> All the variables required in the calculations of the bank loan spread and the expected market premium are extracted from the Federal Reserve Board Statistics.<sup>5</sup> S&P 500 index option data including strike prices, bid and ask prices, implied volatilities, and expiration dates are collected from OptionMetrics. The advantage for utilizing option prices is that the prices contain forward-looking information and can capture the expectations of market participants. Since OptionMetrics does not provide data prior to 1996, my sample covers the period starting from January 1996 until December 2013.

Following Chang et al. (2013), I first calculate the average value of the bid and ask quotes for each option contract. In the calculations, I exclude options with zero bid prices and those with average quotes that are less than \$3/8. Second, I eliminate all the quotes that do not meet the standard no-arbitrage conditions. Third, I remove in-the-money call options whose strike prices are less than 97% of the underlying asset prices, and in-the-

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<sup>4</sup><http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/>

<sup>5</sup><http://www.federalreserve.gov/econresdata/statisticsdata.htm>

money put options whose strike prices are more than 103% of the underlying asset prices from my dataset. I eliminate in-the-month options because in-the-money options are less liquid than out-of-the-money and at-the-money options. Finally, as pointed out by Jiang and Tian (2005), I exclude in-the-money options with maturity less than one week from my sample to avoid potential issues concerning liquidity and market microstructure. In order to calculate the skewness measure for the day, I need at least two out-of-the-money calls and two out-of-the-money puts so I have at least four options over an available moneyness range.<sup>6</sup>

#### 5.3.1 Estimation of implied market skewness

I employ a model-free approach following Bakshi and Madan (2000), Carr and Madan (2001), Bakshi et al. (2003), and Chang et al. (2013) to extract the skewness of market returns implied by S&P 500 index option prices over a 30-day horizon on options with one-month maturity as follows:

$$SKEW(t, \tau) = \frac{E_t^* \left\{ [R(t, \tau) - E_t^* [R(t, \tau)]]^3 \right\}}{\left\{ E_t^* \left[ (R(t, \tau) - E_t^* [R(t, \tau)])^2 \right] \right\}^{3/2}} \quad (5.5)$$

where the  $\tau$ -period return,  $R(t, \tau)$ , is defined as  $R(t, \tau) = \ln S(t + \tau) - \ln S(t)$ ,  $S(t)$  is the stock price at time  $t$ , and  $E_t^*[\bullet]$  is the expected value operator under the risk-neutral assumption.

Appendix B explains the calculation of the implied market skewness in more detail. To mitigate the impact of outliers in my analysis, I winsorize the

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<sup>6</sup>I adjust the returns on delisted stocks following a widely used approach suggested by Shumway (1997).

implied market skewness at the 1<sup>st</sup> and the 99<sup>th</sup> quantiles. Figure 5.1 shows the time series of the daily implied market skewness between 1996–2013. It can be seen from the plot that the implied market skewness values are all negative, ranging from the lowest value of  $-3.5$  to the highest value of  $-0.5$ .

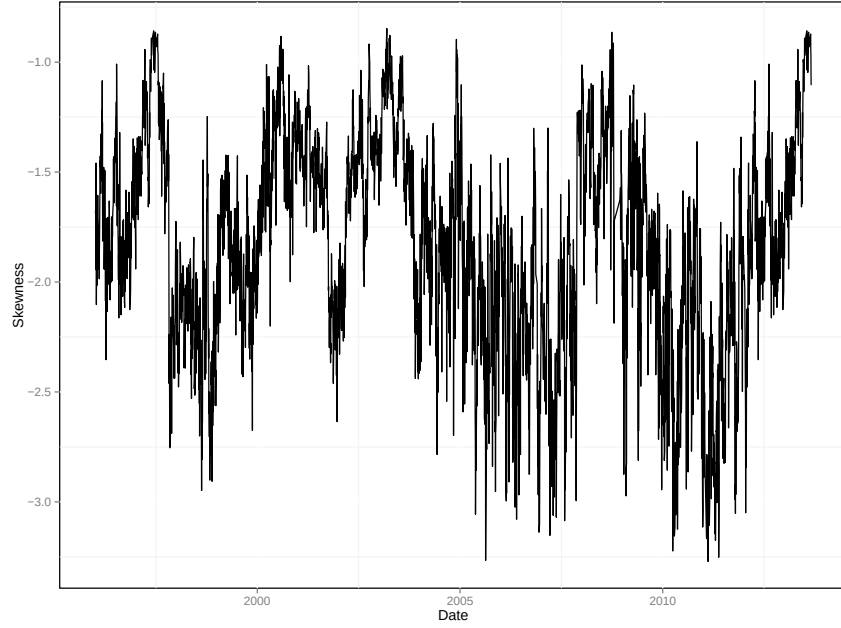


Figure 5.1: The daily option implied skewness of S&P 500 index  
I extract the implied skewness from S&P 500 index option prices and plot the daily option implied skewness from 1996 to 2013. Appendix A provides detailed explanations for the calculation of implied market skewness.

#### 5.3.2 Calculation of innovations in implied market skewness

Following Chang et al. (2013), the innovations in the implied market skewness are obtained from the residuals estimated by fitting an autoregressive moving average (hereafter ARMA)(1,1) model to the time series of the implied market skewness. The method allows us to remove most of the

autocorrelation from the data. I use the entire time series of the skewness to estimate the ARMA parameters, and then use those parameters to calculate the innovation of the implied market skewness. The resulting model has the following functional form:

$$\begin{aligned}\Delta SKEW_t = & 100 \times (SKEW_t - 0.9615 \times SKEW_{t-1} \\ & + 0.3540 \times \Delta SKEW_{t-1} + 0.0730)\end{aligned}\quad (5.6)$$

where  $\Delta SKEW_t$  and  $SKEW_t$  are the innovation of the implied market skewness and the implied market skewness at time  $t$ , respectively. It is worth noting that my estimated parameters are comparable to those reported in Chang et al. (2013). Figure 5.2 illustrates the daily innovations in the implied skewness from S&P 500 index option prices. Consistent with Chang et al. (2013), the innovations are mean reversion, fluctuating within a range of  $-0.01$  and  $0.01$ . Moreover, I also employ ARIMA(0,1,1) instead of the ARMA(1,1) model to estimate the innovations in market skewness. I find similar results on the relationship between skewness risk and stocks returns.

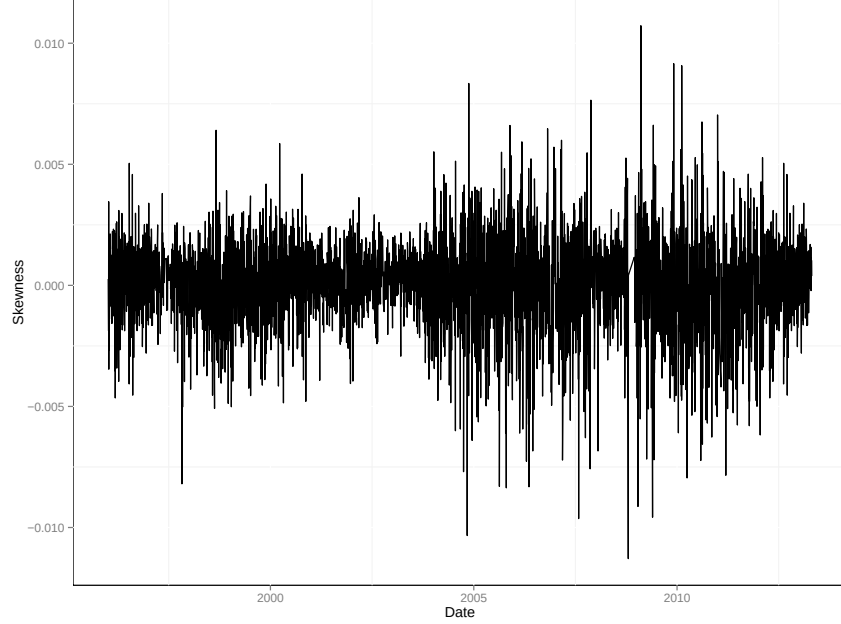


Figure 5.2: The daily innovations in option implied skewness of S&P 500 index

I estimate the innovations in option implied skewness of S&P 500 index and plot the daily innovations in option implied skewness from 1996 to 2013. The innovations in option implied market skewness are obtained from the residuals estimated by fitting an autoregressive moving average (ARMA)(1,1) model using the entire time series of the skewness.

In the next step, I follow Chang et al. (2013) and use the within-month daily data to estimate the market skewness beta for each stock. I require at least 17 observations in the month to be estimated. Moreover, I vary the number of observations required in the calculation of the skewness betas from 15 to 22. The results are similar and I can still find the same relationship between skewness risk and stock returns. The model has the following functional form:

$$R_{i,t} - R_{f,t} = \beta_0 + \beta_{mkt} (R_{m,t} - R_{f,t}) + \beta_{\Delta SKEW} \Delta SKEW_t + \epsilon_{i,t} \quad (5.7)$$

where  $R_{i,t}$  is the daily return on stock  $i$  at time  $t$ ,  $R_{f,t}$  is the daily risk-free rate, and  $R_{m,t}$  is the daily market return on all stocks listed on the NYSE, AMEX, and NASDAQ. The parameter  $\beta_{\Delta SKEW}$  is the measure of risk loading of stock excess returns on the innovations in implied market skewness. I will use  $\beta_{\Delta SKEW}$  to form portfolios and test the relationship between the skewness beta and expected stock returns.

#### 5.3.3 Default risk measures

Numerous measures of default risk have been proposed in the literature over the past decades. In this empirical chapter, I adopt two popular measures which have been employed in earlier studies: the default likelihood indicator (*DLI* henceforth) of Vassalou and Xing (2004) and the O-score of Ohlson (1980). The *DLI* measure has forward looking property because it uses the market value of equity that reflects the expectations of investors about the future performance of the company.

##### 5.3.3.1 Calculation of the default likelihood indicator (*DLI*)

Default likelihood indicator discussed by Vassalou and Xing (2004) is based on probability of default from Merton's (1974) model. Let  $V_t$  denote the value of the firm's assets at time  $t$  and  $V_t$  is assumed to follow a geometric Brownian motion process. Using the formula for pricing a call option as explained in Black and Scholes (1973), the value of the firm's equity at time  $t$  is given by:

$$S_t(V_t, \sigma_V) = N(d_1)V_t - N(d_2)Fe^{-r(T-t)} \quad (5.8)$$

where  $\sigma_V$  is the volatility of the firm's assets,  $F_t$  is the book value of the firm's debt with a maturity date of  $T$ ,  $r$  is the risk-free interest rate, and  $N(\bullet)$  denotes the cumulative density function of the standard normal distribution.

The values of  $d_1$  and  $d_2$  can be obtained as follows:

$$d_1 = \frac{1}{\sigma_V \sqrt{T-t}} \left[ \ln \left( \frac{V_t}{F} \right) + \left( r + \frac{\sigma_V^2}{2} \right) (T-t) \right], \quad (5.9)$$

$$d_2 = d_1 - \sigma_V \sqrt{T-t}. \quad (5.10)$$

The *DLI* of the firm at time  $t$ , denoted by  $P_{def}$ , can be computed from the following model:

$$P_{def} = P(V_T < F) = N(-d_2) = N \left[ -\frac{\ln \left( \frac{V_t}{F} \right) + \left( \mu - \frac{\sigma_V^2}{2} \right) (T-t)}{\sigma_V \sqrt{T-t}} \right] \quad (5.11)$$

where  $\mu$  is the drift rate of the firm's assets.

Following Vassalou and Xing (2004), I employ the recursive procedure to estimate the *DLI*. First, for each stock in the dataset, I estimate the volatility of the firm's equity, denoted  $\sigma_E$ , by calculating the standard deviation of the daily returns on the stock over the past 12 months. I then

treat  $\sigma_E$  as an initial value in an iterative procedure in order to estimate  $\sigma_V$ . Specifically, I use the Black-Scholes formula to extract the daily value,  $V_t$ , for each trading day during the past 12 months by using  $S(V_t, \sigma)$  as the market value of equity of that day. This procedure allows us to extract daily values of  $V_t$ . Moreover, I define an interval based on the market value and the book value of the company's debt in order to extract the root from the equations. The standard deviation of daily value,  $\sigma_V$ , is then calculated, which is subsequently used as the value of  $\sigma_V$  in the next iteration. This procedure is repeated until the adjacent values of  $\sigma_V$  from the two iterations converge which is when the two values differ from each other by less than 0.0001. Although I restrict the maximum number of iterations to 1,000, it takes only a few iterations to reach convergence for most firms. After I get the daily value of  $V_t$ , the drift  $\mu$  is computed as the mean of the log returns of  $V_t$ . Finally, I calculate the monthly *DLI* for each stock using the estimated values of  $\mu$  and  $\sigma_V$  together with the values of the firm's debt and assets.<sup>7</sup>

#### 5.3.3.2 Calculation of O-score

I use nine accounting ratios to construct the O-score of a firm based on the following model:

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<sup>7</sup>Following Vassalou and Xing (2004), the book value of debt is calculated by using "Debt in One Year" plus half of the "Long Term Debt" collected from the Compustat annual files.

$$\begin{aligned}
O - score = & -1.32 - 0.407SIZE + 6.03TLTA - 1.43WCTA \\
& + 0.76CLCA - 1.72OENEG - 2.37NITA - 1.83FUTL \\
& + 0.285INTWO - 0.521CHIN
\end{aligned} \tag{5.12}$$

where *SIZE* is the log total assets (item *AT*), *TLTA* is the ratio of total liabilities (item *LT*) to total assets, *WCTA* is the ratio of working capital (item *WCAP*) to total assets, *CLCA* is the ratio of current liabilities (item *LCT*) to current assets (item *ACT*), *OENEG* is a dummy variable which takes the value of one if the firm's total liabilities exceed its total assets and zero otherwise, *NITA* is the ratio of net income (item *NI*) to total assets, *FUTL* is the ratio of funds from operations (item *FOPT*) to total liabilities, *INTWO* is a dummy variable taking the value of one if the firm experienced net loss in the last two years and zero otherwise, and *CHIN* is the ratio of change in net income. I use annual data to compute O-score for each stock in my dataset.

## 5.4 Empirical Results and Analysis

Table 5.1 presents the descriptive statistics and the correlation coefficients for the market skewness beta ( $\beta_{\Delta SKEW}$ ), default likelihood indicator (*DLI*), O-score, the market value (*MV*), and the book-to-market ratio (*B/M*) for the period starting from January 1996 to December 2013. The mean value of  $\beta_{\Delta SKEW}$  is  $-0.05$ , indicating that on average the innovations in

#### 5.4. EMPIRICAL RESULTS AND ANALYSIS

the implied market skewness has a negative impact on the individual stock returns.

Table 5.1: Descriptive statistics

The table reports the mean, standard deviation ( $SD$ ), minimum ( $Min$ ), maximum ( $Max$ ) and correlation coefficients of market skewness risk ( $\beta_{SKEW}$ ), default likelihood indicator ( $DLI$ ), O-score, market capitalization ( $MV$ ), and book-to-market ratio ( $B/M$ ). The implied market skewness is extracted from S&P 500 index option prices. The  $DLI$  is calculated using Merton's (1974) structure model of default. O-score is calculated following the method of Ohlson (1980).  $MV$  (in thousands of dollar) is the firm's market capitalization.  $B/M$  is the book-to-market ratio. The mean, standard deviation and Spearman rank correlation coefficient are computed by averaging the time-series values of the cross-sectional estimates. The sample includes all common stocks traded on the NYSE, AMEX, and NASDAQ for the period beginning in January 1996 and ending in December 2013.

|                                           | $\beta_{\Delta SKEW}$ | $DLI$ | $O\text{-score}$ | $MV$    | $B/M$ |
|-------------------------------------------|-----------------------|-------|------------------|---------|-------|
| <i>Panel A: Descriptive statistics</i>    |                       |       |                  |         |       |
| Mean                                      | -0.05                 | 0.03  | -0.98            | 3182746 | 0.84  |
| $SD$                                      | 0.90                  | 0.02  | 0.32             | 1260260 | 0.28  |
| $Min$                                     | -5.06                 | 0.00  | -1.59            | 1087405 | 0.55  |
| $Max$                                     | 3.08                  | 0.10  | -0.52            | 5706715 | 1.72  |
| <i>Panel B: Spearman rank correlation</i> |                       |       |                  |         |       |
| $DLI$                                     | -0.03                 | 1.00  |                  |         |       |
| $O\text{-score}$                          | -0.02                 | 0.62  | 1.00             |         |       |
| $MV$                                      | -0.04                 | -0.46 | -0.90            | 1.00    |       |
| $B/M$                                     | -0.02                 | 0.35  | 0.15             | 0.00    | 1.00  |

Regarding the correlation, when two variables exhibit high correlation in magnitude, this means that the two variables contain very similar information content or are likely to capture the same characteristics. It is worth noting that  $DLI$  is positively correlated with O-score and the correlation coefficient is 0.62, suggesting that the two measures largely agree on the classification of default risk. The correlation coefficient between O-score and  $MV$  is  $-0.90$ , indicating that small firms are likely to be financially distressed. These preliminary findings are consistent with the arguments

put forward by Vassalou and Xing (2004) who suggest that the size effect can be viewed as the default risk effect. I can also find that skewness beta is not highly correlated with default likelihood indicator ( $DLI$ ), O-score, the market value ( $MV$ ), and the book-to-market ratio ( $B/M$ ).

### 5.4.1 Default risk and the market skewness risk effect

#### 5.4.1.1 One-way portfolio sorts

In this section, I first examine the return performance of market skewness risk portfolios. At the end of each month, I sort stocks based on their lagged market skewness risk, captured by  $\beta_{\Delta SKEW}$ , and form five quintile portfolios. I hold the portfolios for the subsequent month and rebalance the portfolios monthly. Table 5.2 reports the average monthly raw returns along with the abnormal returns across five market skewness risk portfolios. I calculate the value-weighted returns by weighting the market value of each stock in a quintile portfolio to the total market value of all the stocks in the same quintile portfolio at the end of the beta estimation period. Quintile 1 contains stocks with the bottom  $\beta_{\Delta SKEW}$ s, while Quintile 5 contains stocks with the top  $\beta_{\Delta SKEW}$ s. The column labelled 1–5 represents the long-short portfolio that is long stocks in Quintile 1 and short stocks in Quintile 5.

The abnormal returns are the intercepts from the CAPM, the Fama and French (1993) three-factor model (hereafter FF3), the Carhart (1997) four-factor model (hereafter Carhart), and the Fama and French (2015) five-factor model (hereafter FF5). The functional forms of the models are shown below.

$$R_{p,t} - R_{f,t} = \alpha_{CAPM} + \beta_{p, mkt} (R_{m,t} - R_{f,t}) + \epsilon_{p,t} \quad (5.13)$$

$$R_{p,t} - R_{f,t} = \alpha_{FF3} + \beta_{p,mkt} (R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + \epsilon_{p,t} \quad (5.14)$$

$$\begin{aligned} R_{p,t} - R_{f,t} = & \alpha_{Carhart} + \beta_{p,mkt} (R_{m,t} - R_{f,t}) + s_p SMB_t \\ & + h_p HML_t + m_p UMD_t + \epsilon_{p,t} \end{aligned} \quad (5.15)$$

$$\begin{aligned} R_{p,t} - R_{f,t} = & \alpha_{FF5} + \beta_{p,mkt} (R_{m,t} - R_{f,t}) + s_p SMB_t \\ & + h_p HML_t + r_p RMW + c_p CMA_t + \epsilon_{p,t} \end{aligned} \quad (5.16)$$

where  $R_{p,t}$  is the return on portfolio  $p$  in month  $t$ .  $SMB_t$  (Small-Minus-Big),  $HML_t$  (High-Minus-Low),  $UMD_t$  (Up-Minus-Down),  $RMW_t$  (Robust-Minus-Weak) and  $CMA_t$  (Conservative-Minus-Aggressive) are the differences between the returns on diversified portfolios of stocks with small and big market value, high and low book-to-market ratio, high and low past returns, robust and weak profitability, and low and high investment, respectively. I compute the abnormal returns by regressing the post-average monthly returns on the selected factors. The intercepts from the regressions are the risk-adjusted returns.

Table 5.2: Equity returns across market skewness risk portfolios from 1996 to 2007

This table reports the value-weighted monthly average returns and the abnormal returns for market skewness risk portfolios. At the end of each month, the market skewness risk of each stock is estimated from the following regression using daily returns:

$$R_{i,t} - R_{f,t} = \beta_o^i + \beta_{MKT}^i(R_{m,t} - R_{f,t}) + \beta_{\Delta SKEW}^i \Delta SKEW_t + \varepsilon_{i,t}$$

where  $\beta_{\Delta SKEW}^i$  is the market skewness risk of stock  $i$ . All stocks are then sorted into five quintile portfolios based on their lagged market skewness risk measure,  $\beta_{\Delta SKEW}^i$ . I hold the portfolios for the subsequent month and rebalance the portfolios monthly. Quintile 1 contains stocks with the lowest  $\beta_{\Delta SKEW}^i$  and Quintile 5 contains stocks with the highest  $\beta_{\Delta SKEW}^i$ . The  $t$ -statistics are calculated using Newey and West's (1987) heteroskedasticity and autocorrelation consistent covariance standard errors and are reported in parentheses. Statistical significance at the 10%, 5% and 1% levels is indicated by \*, \*\*, \*\*\* respectively. The sample includes all common stocks traded on the NYSE, AMEX, and NASDAQ for the period from January 1996 to December 2007.

| Sorting statistic | Quintile portfolio |                   |                   |                  |                   |
|-------------------|--------------------|-------------------|-------------------|------------------|-------------------|
|                   | 1                  | 2                 | 3                 | 4                | 5                 |
| Average return    | 1.75<br>(3.02)***  | 1.18<br>(2.62)*** | 1.13<br>(3.20)*** | 0.83<br>(2.00)** | 0.53<br>(0.83)    |
| CAPM alpha        | 0.98<br>(2.17)**   | 0.57<br>(1.96)*   | 0.59<br>(3.27)*** | 0.23<br>(1.05)   | -0.22<br>(-0.68)  |
| FF3 alpha         | 1.38<br>(3.12)***  | 0.70<br>(2.21)**  | 0.65<br>(3.21)*** | 0.40<br>(1.70)*  | 0.15<br>(0.53)    |
| Carhart alpha     | 1.78<br>(3.29)***  | 0.89<br>(2.50)**  | 0.63<br>(3.13)*** | 0.27<br>(1.14)   | 0.12<br>(0.43)    |
| FF5 alpha         | 1.71<br>(3.39)***  | 0.75<br>(2.00)**  | 0.63<br>(2.96)*** | 0.42<br>(1.51)   | 0.57<br>(1.82)*   |
|                   |                    |                   |                   |                  | 1.14<br>(2.84)*** |

The empirical results in Table 5.2 show a negative relationship between the market skewness risk and the portfolio returns. Quintile 1 generates the highest returns, while Quintile 5 yields the lowest returns across portfolios. The negative relationship is consistently observed across the various measures of return. Moreover, portfolios show a not strictly decreasing pattern in average returns and abnormal returns. The abnormal returns are lower than the average returns. A trading strategy of buying stocks in Quintile 1 and short selling stocks in Quintile 5 earns the abnormal returns around 1.14%–1.65% per month. They are statistically significant at the 1% level. My results are in line with the findings of Chang et al. (2013) on the strong market skewness risk effect. They also find significant skewness risk premium by using the skewness beta calculated from one-month estimation period as well as six-month estimation period. Chang et al. (2013) use two models to calculate the skewness betas: univariate model and multivariate model. They find similar results. But the risk premiums are more significant when they use univariate model. On the other hand, they also find that volatility and kurtosis are not strong priced risk factors. In this chapter, I mainly focus on the impact of default risk on the skewness effect. Therefore, I only replicate the result by using univariate model without controlling for volatility and kurtosis.

Panel A of Table 5.3 presents firm characteristics for each of the quintile portfolios. They are calculated by averaging the time-series of the cross-section of means. The reported firms' characteristics include market value ( $MV$ ), book-to-market ratio ( $B/M$ ), book leverage ( $Leverage$ ), cash flow ratio ( $CF$ ), cash holding ratio ( $CH$ ), return on assets ( $Profitability$ ), net sales ( $Sales$ ), and R&D ratio ( $R\&D$ ). Appendix C provides detailed explanations

on the measures of firm characteristics. Although different in terms of the direction of market skewness risk, Panel A shows that stocks in Quintiles 1 and 5 have similar characteristics. That is, they tend to be small and value stocks (low  $MV$  and high  $B/M$ ), and generate negative profits and cash flows from their operations. They also have lower leverage and hold more cash. Opler and Titman (1994) argue that firms with high R&D ratios tend to have high financial distress costs due to their high sensitivity to sale loss. My results are consistent with their argument that stocks in both Quintiles 1 and 5 are likely to be financially distressed stocks with high R&D ratios and low sales. Panel B of Table 5.3 reports the mean values of the default risk measures for each portfolio. The results confirm that stocks in Quintiles 1 and 5 have higher default risk than stocks in the rest of the portfolios.

##### 5.4.1.2 Two-way portfolio sorts

To investigate whether the market skewness risk effect can be explained by default risk, I use a two-way sorts approach. Specifically, at the end of each month, I sort stocks into five quintile portfolios according to their lagged market skewness beta, and independently sort stocks into three portfolios based on their past  $MV$ ,  $B/M$ ,  $DLI$ , and  $O\text{-score}$  using 30th and 70th percentiles as the breakpoints, producing a total of 15 portfolios. I calculate the value-weighted returns in the subsequent month for each portfolio and rebalance the portfolios monthly. Table 5.4 reports the average monthly returns for the two-way sorted portfolios.

Table 5.3: Firm characteristics and default risk of market skewness risk portfolios

At the end of each month, I sort stocks into five quintile portfolios based on their lagged market skewness risk measure,  $\beta_{\Delta SKEW}^i$ . I hold the portfolios for the subsequent month and rebalance the portfolios monthly. Quintile 1 contains stocks with the lowest  $\beta_{\Delta SKEW}^i$  and Quintile 5 contains stocks with the highest  $\beta_{\Delta SKEW}^i$ . Panel A reports firm characteristics for each quintile. The reported characteristics are market capitalization ( $MV$ , in thousands of dollar), book-to-market ratio ( $B/M$ ), book leverage ( $Leverage$ ), cash flow ratio ( $CF$ ), cash holding ratio ( $CH$ ), return on assets ( $Profitability$ ), net sales ( $Sales$ , in millions of dollar) and R&D to sales ratio ( $R\&D$ ). Appendix C provides detailed explanations on the measures of firm characteristics. Panel B reports the average values of the default risk measures: default likelihood indicator ( $DLI$ ) and O-score. The sample includes all common stocks listed on the NYSE, AMEX, and NASDAQ for the period from January 1996 to December 2007.

|                                      | Quintile |         |         |         |         |
|--------------------------------------|----------|---------|---------|---------|---------|
|                                      | 1        | 2       | 3       | 4       | 5       |
| <i>Panel A: Firm characteristics</i> |          |         |         |         |         |
| $\beta_{\Delta SKEW}$                | -11.19   | -2.87   | -0.02   | 2.79    | 10.87   |
| $MV$                                 | 1246918  | 3261105 | 3796027 | 2938912 | 1175454 |
| $B/M$                                | 0.84     | 0.75    | 0.75    | 0.75    | 0.84    |
| $Leverage$                           | 0.20     | 0.22    | 0.22    | 0.22    | 0.20    |
| $CF$                                 | -0.06    | 0.02    | 0.04    | 0.02    | -0.06   |
| $CH$                                 | 0.24     | 0.19    | 0.17    | 0.19    | 0.24    |
| $Profitability$                      | -0.02    | 0.07    | 0.09    | 0.07    | -0.03   |
| $Sales$                              | 831.77   | 2084.56 | 2482.12 | 1894.12 | 770.47  |
| $R\&D$                               | 2.90     | 1.31    | 1.60    | 1.75    | 2.41    |
| <i>Panel B: Default risk</i>         |          |         |         |         |         |
| $DLI$                                | 0.06     | 0.02    | 0.02    | 0.02    | 0.06    |
| O-score                              | -0.32    | -1.09   | -1.21   | -1.10   | -0.35   |

#### 5.4. EMPIRICAL RESULTS AND ANALYSIS

Table 5.4: Portfolio returns based on two-way independent sorts

This table reports the value-weighted monthly average returns based on two-way independent sorts. At the end of each month, I sorted stocks into five quintile portfolios based on their lagged market skewness risk measure,  $\beta_{SKEW}$ , and independently sort stocks into three portfolios based on their past month's market capitalization ( $MV$ ), book-to-market ratios ( $B/M$ ), default likelihood indicators ( $DLI$ ), and O-scores using 30th and 70th percentiles as the breakpoints. The portfolios are held for the subsequent month and rebalanced monthly. Subscript 1 represents the bottom portfolios comprising stocks with the lowest values of the variables, while subscript 3 represents the top portfolios comprising stocks with the highest values of the corresponding variables. The rows labelled 3-1 denote the return differences between the top portfolio and the bottom portfolio. The  $t$ -statistics are calculated using Newey and West's (1987) heteroskedasticity and autocorrelation consistent covariance standard errors and are reported in the parentheses. Statistical significance at the 10%, 5% and 1% levels is indicated by \*, \*\*, \*\*\* respectively. The sample periods are from January 1996 to December 2007.

|         | Quintile portfolio |                   |                   |                    |                     | 1-5               |
|---------|--------------------|-------------------|-------------------|--------------------|---------------------|-------------------|
|         | 1                  | 2                 | 3                 | 4                  | 5                   |                   |
| $MV_1$  | 3.54<br>(4.71)***  | 2.34<br>(5.03)*** | 2.06<br>(4.97)*** | 2.34<br>(4.73)***  | 3.35<br>(4.41)***   | 0.20<br>(0.99)    |
| $MV_2$  | 1.52<br>(2.83)***  | 1.28<br>(4.49)*** | 1.29<br>(4.51)*** | 1.03<br>(2.93)***  | 1.03<br>(1.69)*     | 0.48<br>(2.01)**  |
| $MV_3$  | 1.74<br>(2.77)***  | 1.16<br>(2.34)**  | 1.11<br>(2.92)*** | 0.79<br>(1.75)*    | 0.21<br>(0.31)      | 1.53<br>(3.67)*** |
| 3-1     | -1.80<br>(-2.04)** | -1.18<br>(-1.72)* | -0.95<br>(-1.76)* | -1.55<br>(-2.37)** | -3.14<br>(-3.22)*** |                   |
| $B/M_1$ | 1.77<br>(2.39)**   | 1.20<br>(2.12)**  | 1.09<br>(2.20)**  | 0.73<br>(1.26)     | 0.38<br>(0.57)      | 1.39<br>(2.63)*** |
| $B/M_2$ | 1.66<br>(4.18)***  | 1.16<br>(3.61)*** | 1.10<br>(4.47)*** | 0.99<br>(3.76)***  | 0.84<br>(1.53)      | 0.83<br>(2.40)**  |
| $B/M_3$ | 2.16<br>(5.73)***  | 1.64<br>(4.99)*** | 1.30<br>(4.67)*** | 1.06<br>(3.11)***  | 2.15<br>(4.97)***   | 0.01<br>(0.02)    |
| 3-1     | 0.38<br>(0.55)     | 0.43<br>(0.83)    | 0.20<br>(0.42)    | 0.34<br>(0.62)     | 1.77<br>(2.77)***   |                   |

(Continued)

#### 5.4. EMPIRICAL RESULTS AND ANALYSIS

(Continued)

|         | Quintile portfolio |                   |                   |                   |                   | 1-5               |
|---------|--------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
|         | 1                  | 2                 | 3                 | 4                 | 5                 |                   |
| $DLI_1$ | 1.94<br>(3.81)***  | 0.92<br>(1.91)*   | 1.15<br>(3.27)*** | 0.85<br>(2.31)**  | 0.60<br>(1.18)    | 1.34<br>(2.95)*** |
| $DLI_2$ | 1.60<br>(3.07)***  | 1.36<br>(4.33)*** | 1.18<br>(3.60)*** | 0.86<br>(2.17)**  | 0.42<br>(0.66)    | 1.18<br>(2.69)*** |
| $DLI_3$ | 2.05<br>(2.75)***  | 1.81<br>(3.63)*** | 1.50<br>(2.89)*** | 2.00<br>(2.60)**  | 1.89<br>(2.41)**  | 0.16<br>(0.39)    |
| 3-1     | 0.11<br>(0.18)     | 0.90<br>(3.43)*** | 0.35<br>(0.75)    | 1.15<br>(2.13)**  | 1.29<br>(2.48)**  |                   |
| $O_1$   | 1.91<br>(2.94)***  | 1.20<br>(2.25)**  | 1.13<br>(2.46)**  | 0.87<br>(1.64)    | 0.18<br>(0.28)    | 1.73<br>(4.29)*** |
| $O_2$   | 1.80<br>(4.65)***  | 1.45<br>(4.89)*** | 1.22<br>(4.06)*** | 0.91<br>(3.43)*** | 0.90<br>(2.33)**  | 0.90<br>(2.06)**  |
| $O_3$   | 2.48<br>(4.32)***  | 1.37<br>(4.51)*** | 1.32<br>(4.27)*** | 0.94<br>(1.90)*   | 1.81<br>(2.46)**  | 0.68<br>(1.46)    |
| 3-1     | 0.58<br>(1.19)     | 0.17<br>(0.40)    | 0.19<br>(0.55)    | 0.07<br>(0.17)    | 1.63<br>(3.80)*** |                   |

With the same level of market skewness risk, small ( $MV_1$ ), value ( $BM_3$ ), and high default risk portfolios ( $DLI_3$  and  $O_3$ ) outperform their corresponding large ( $MV_3$ ), growth ( $BM_1$ ) and low default risk portfolios ( $DLI_1$  and  $O_1$ ). In particular, Quintile 5 generates the largest size effect, value premium, and default risk premium across market skewness risk portfolios. For instance, the size effect is  $-3.14\%$  ( $t = -3.22$ ) per month, the value premium is  $1.77\%$  ( $t = 2.77$ ) per month, the  $DLI$  premium is  $1.29\%$  ( $t = 2.48$ ) per month, and the O-score premium is  $1.63\%$  ( $t = 3.8$ ) per month in Quintile 5. Interestingly, the strong size effect, the value and default risk premiums in Quintile 5 are mainly driven by low returns of stocks with large size, high growth potential, and low default risk. The results are fully consistent with my hypothesis that investors prefer to hold positive-skewed stocks with large size, high growth, and low default risk due to their being risk averse,

and therefore, those stocks have very low returns.

Controlling for  $MV$ ,  $B/M$ ,  $DLI$ , and  $O$ -score ( $O$ ), the returns on long-short market skewness risk portfolios (1-5) increase monotonically from small, value, and high default risk portfolios to large, growth, and low default risk portfolios. In addition, they are statistically significant at the 1% level for  $MV_3$ ,  $BM_1$ ,  $DLI_1$ , and  $O_1$ , but they do not differ from zero for  $MV_1$ ,  $BM_3$ ,  $DLI_3$ , and  $O_3$ . For example, the market skewness effect is 1.53% ( $t = 3.67$ ) per month for  $MV_3$ , 1.39% ( $t = 2.63$ ) per month for  $BM_1$ , 1.34% ( $t = 2.95$ ) per month for  $DLI_1$ , and 1.73% ( $t = 4.29$ ) per month for  $O_1$ . Overall, my results indicate that the positive skewness preference theory only holds for safe stocks; the market skewness risk effect is stronger among stocks with large size, high growth potential, and low default risk.

#### 5.4.1.3 Cross-sectional regressions

Two-way portfolio sorts show that skewness effect can be affected by  $MV$ ,  $B/M$ ,  $DLI$ , and  $O$ -score. The results in Table 5.4 clearly indicate that the relationship between market skewness risk and stock returns is highly influenced by default risk. In this section, I will examine whether the skewness effect differs in different level of default risk with and without control variables by employing cross-sectional regressions. I run Fama and MacBeth (1973) cross-sectional regressions as follows:

$$\begin{aligned}
 R_{i,\tau+1} = & \lambda_0 + \lambda_1 \beta_{\Delta SKEW_{i,\tau}} + \lambda_2 Default_{i,\tau} \\
 & + \lambda_3 Interaction_{i,\tau} + \lambda_4 \mathbf{X}_{i,\tau} + \varepsilon_{i,\tau+1}
 \end{aligned} \tag{5.17}$$

where  $R_{i,\tau+1}$  denotes the monthly average return of stock  $i$  from July of year  $\tau$  to June of year  $\tau + 1$ ,  $\beta_{\Delta SKEW_{i,\tau}}$  is the lagged market skewness beta from June of year  $\tau$  to May of year  $\tau + 1$ ,  $Default_{i,\tau}$  denotes the default risk variables of  $DLI$  and O-score,  $Interaction_{i,\tau}$  denotes the interaction term between  $\beta_{\Delta SKEW_{i,\tau}}$  and the default risk variables,  $\mathbf{X}_{i,\tau}$  is the  $3 \times 1$  vector of the lagged control variables, including  $\ln(MV)$ ,  $\ln(B/M)$ , and  $MOM$ .  $\ln(MV)$  is the natural logarithm of firm's size calculated with information available at the end of June of year  $\tau$ ,  $\ln(B/M)$  is the natural logarithm of the ratio of the book value of equity for the fiscal year ending in year  $\tau - 1$  divided by market equity at the end of December of year  $\tau - 1$ ,  $MOM$  is the cumulative compounded stock returns over the last 6 months from June of year  $\tau$  to May of year  $\tau + 1$ . The models are estimated using the weighted least square (WLS) technique. Normal ordinary least square (OLS) gives the same weights to the errors from regressions, indicating that small size stocks and big size stocks have the same weights. I use WLS to remove size noise since large stocks are shown to have a stronger impact on the market skewness risk effect than small stocks. To overcome the potential issues of heteroskedasticity and autocorrelation in the regression residuals, the  $t$ -statistics are computed using Newey and West's (1987) robust standard errors. Specifically, I regress the time-series values of returns or coefficients on a unit constant and then apply the Newey and West (1987) adjustment to the estimated intercept coefficient of the regression. This helps produce a new standard error for the estimated mean. The number of lags to use when performing the adjustment is the only input required for Newey and West (1987). I use the default set lags from the economics software.

Table 5.5 reports the coefficients on the estimated variables. Panels A and B

#### 5.4. EMPIRICAL RESULTS AND ANALYSIS

Table 5.5: Fama-MacBeth (1973) cross-sectional regressions for the size, book-to-market, and default risk subgroups

For each month from July of year  $\tau$  to June of year  $\tau + 1$ , I estimate Fama and MacBeth (1973) cross-sectional regressions of monthly returns on a set of independent variables. These variables are the lagged market skewness beta ( $\Delta SKEW_t$ ), default risk (*Default risk*), the interaction terms (*Interaction*) between the lagged market skewness beta and default risk.  $\ln(MV)$  is the natural logarithm of firm's size calculated with information available at the end of June of year  $\tau$ .  $\ln(B/M)$  is the natural logarithm of the ratio of the book value of equity for the fiscal year ending in year  $\tau - 1$  divided by the market value of equity at the end of December of year  $\tau - 1$ . *Mom* is the cumulative compounded returns over the last 6 months from June of year  $\tau$  to May of year  $\tau + 1$ . I use default likelihood indicators (*DLI*) and O-score as the proxies for default risk. The *t*-statistics are calculated using Newey and West's (1987) heteroskedasticity and autocorrelation consistent covariance standard errors and are reported in the parentheses. Statistical significance at the 10%, 5% and 1% levels is indicated by \*, \*\*, \*\*\* respectively. The sample period is from January 1996 to December 2007.

| <i>Constant</i>                                   | $\beta_{\Delta SKEW}$ | <i>Default risk</i> | <i>Interaction</i> | $\ln(MV)$ | $\ln(BM)$ | <i>Mom</i> |
|---------------------------------------------------|-----------------------|---------------------|--------------------|-----------|-----------|------------|
| <i>Panel A: DLI as a default risk measure</i>     |                       |                     |                    |           |           |            |
| 1.76                                              | -0.06                 |                     |                    | -0.05     | 0.22      | 0.45       |
| (1.12)                                            | (-3.68)***            |                     |                    | (-0.49)   | (1.81)*   | (0.93)     |
| 1.78                                              |                       | -3.94               |                    | -0.05     | 0.23      | 0.49       |
| (1.13)                                            |                       | (-1.73)*            |                    | (-0.48)   | (1.99)**  | (1.01)     |
| 1.87                                              | -0.06                 | -3.72               |                    | -0.05     | 0.23      | 0.44       |
| (1.17)                                            | (-3.72)***            | (-1.65)             |                    | (-0.53)   | (1.84)*   | (0.93)     |
| 1.86                                              | -0.06                 | -3.65               | 0.64               | -0.05     | 0.23      | 0.44       |
| (1.16)                                            | (-3.85)***            | (-1.57)             | (3.66)***          | (-0.53)   | (1.83)*   | (0.93)     |
| <i>Panel B: O-score as a default risk measure</i> |                       |                     |                    |           |           |            |
| 1.76                                              | -0.06                 |                     |                    | -0.05     | 0.22      | 0.45       |
| (1.12)                                            | (-3.68)***            |                     |                    | (-0.49)   | (1.81)*   | (0.93)     |
| 1.92                                              |                       | -0.08               |                    | -0.07     | 0.16      | 0.52       |
| (1.05)                                            |                       | (-0.56)             |                    | (-0.57)   | (1.10)    | (1.15)     |
| 1.95                                              | -0.07                 | -0.09               |                    | -0.07     | 0.16      | 0.47       |
| (1.08)                                            | (-3.92)***            | (-0.69)             |                    | (-0.61)   | (1.06)    | (1.05)     |
| 2.02                                              | -0.03                 | -0.09               | 0.02               | -0.08     | 0.16      | 0.46       |
| (1.12)                                            | (-1.57)               | (-0.69)             | (2.42)**           | (-0.64)   | (1.04)    | (1.04)     |

present the results based on the default risk measures of *DLI* and O-score, respectively. After controlling for market size, book-to-market, and momentum, the coefficients on market skewness beta are significantly negative

in all regressions with only one exception (the insignificant coefficient on market skewness beta in model 4 based on the O-score measure), indicating that market skewness beta has strong explanatory power for stock returns. While the coefficients on default risk variables do not differ from zero.<sup>8</sup> More importantly, I find that the coefficients on the interaction term are statistically significant, with 0.64 ( $t = 3.66$ ) for the *DLI* measure and 0.02 ( $t = 2.42$ ) for the O-score measure. Thus, my results suggest that the market skewness risk effect increases significantly with default risk.

In order to explore whether market skewness risk has different impacts on expected returns between stocks with high and low market value, book-to-market, and default risk, I use dummy variables to replace the actual values of the default risk variables in Equation (5.17) and the interaction term is defined as that between the market skewness beta and dummy variables. I assign a value of one to the dummy variables when the *B/M*, *DLI* and O-score are above the mean and a value of zero otherwise. For the *MV* dummy variable, it takes the value of one if the *MV* of a firm is less than the mean and zero otherwise.

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<sup>8</sup>I find the insignificant coefficients on default risk variable, which are inconsistent with the findings of Vassalou and Xing (2004). This may be due to the fact that I use WLS approach and remove the size effect in my estimation.

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Table 5.6: Fama-MacBeth (1973) regressions with the interaction terms for the full sample

For each month from July of year  $\tau$  to June of year  $\tau + 1$ , I estimate Fama and MacBeth (1973) cross-sectional regressions of monthly excess returns on a set of independent variables for the full sample. These variables are the lagged market skewness beta, the dummy variables, the interaction terms between the lagged market skewness beta and the dummy variables. I assign the dummy variables equal to one if the book-to-market ratio ( $B/M$ ), the default risk measures are above the mean and zero otherwise. For the market size ( $MV$ ) dummy variable, I take the value of one if the  $MV$  of a firm is less than the mean and the value of zero otherwise. The control variables are  $\ln(MV)$ ,  $\ln(B/M)$  and momentum ( $Mom$ ).  $\ln(MV)$  is the natural logarithm of firm's size calculated with information available at the end of June of year  $\tau$ .  $\ln(B/M)$  is the natural logarithm of the ratio of the book value of equity for the fiscal year ending in year  $\tau - 1$  divided by market equity at the end of December of year  $\tau - 1$ .  $Mom$  is the cumulative compounded returns over the last 6 months from June of year  $\tau$  to May of year  $\tau + 1$ . I use default likelihood indicators ( $DLI$ ) and O-score as the proxies for default risk. The  $t$ -statistics are calculated using Newey and West's (1987) heteroskedasticity and autocorrelation consistent covariance standard errors and are reported in the parentheses. The sample period is from January 1996 to December 2007.

| <i>Constant</i>                           | $\beta_{\Delta SKEW}$ | <i>Dummy</i>   | <i>Interaction</i> | $\ln(MV)$        | $\ln(BM)$      | <i>Mom</i>     |
|-------------------------------------------|-----------------------|----------------|--------------------|------------------|----------------|----------------|
| <i>Panel A: MV as the dummy variable</i>  |                       |                |                    |                  |                |                |
| 0.95<br>(3.11)***                         | -0.06<br>(-2.84)***   |                |                    |                  | 0.23<br>(1.15) | 0.49<br>(1.20) |
| 0.94<br>(3.11)***                         |                       | 0.05<br>(0.14) |                    |                  | 0.22<br>(1.20) | 0.55<br>(1.29) |
| 0.93<br>(3.10)***                         | -0.06<br>(-2.94)***   | 0.06<br>(0.17) |                    |                  | 0.22<br>(1.19) | 0.49<br>(1.19) |
| 0.93<br>(3.08)***                         | -0.08<br>(-3.02)***   | 0.06<br>(0.19) | 0.08<br>(3.11)***  |                  | 0.22<br>(1.16) | 0.48<br>(1.17) |
| <i>Panel B: B/M as the dummy variable</i> |                       |                |                    |                  |                |                |
| 1.59<br>(0.91)                            | -0.06<br>(-3.01)***   |                |                    | -0.06<br>(-0.51) |                | 0.54<br>(1.25) |
| 1.43<br>(0.84)                            |                       | 0.17<br>(0.63) |                    | -0.05<br>(-0.43) |                | 0.58<br>(1.31) |
| 1.46<br>(0.84)                            | -0.06<br>(-3.12)***   | 0.13<br>(0.52) |                    | -0.05<br>(-0.45) |                | 0.54<br>(1.24) |
| 1.44<br>(0.83)                            | -0.06<br>(-3.12)***   | 0.18<br>(0.69) | 0.06<br>(2.79)***  | -0.05<br>(-0.44) |                | 0.54<br>(1.23) |
| <i>(Continued)</i>                        |                       |                |                    |                  |                |                |

#### 5.4. EMPIRICAL RESULTS AND ANALYSIS

(Continued)

| <i>Constant</i>                               | $\beta_{\Delta_{SKEW}}$ | <i>Dummy</i>     | <i>Interaction</i> | $\ln(MV)$        | $\ln(BM)$        | <i>Mom</i>     |
|-----------------------------------------------|-------------------------|------------------|--------------------|------------------|------------------|----------------|
| <i>Panel C: DLI as the dummy variable</i>     |                         |                  |                    |                  |                  |                |
| 1.76<br>(1.12)                                | -0.06<br>(-3.68)***     |                  |                    | -0.05<br>(-0.49) | 0.22<br>(1.81)*  | 0.45<br>(0.93) |
| 1.81<br>(1.14)                                |                         | -0.55<br>(-1.41) |                    | -0.05<br>(-0.49) | 0.24<br>(2.00)** | 0.49<br>(1.00) |
| 1.90<br>(1.18)                                | -0.06<br>(-3.74)***     | -0.53<br>(-1.37) |                    | -0.05<br>(-0.54) | 0.23<br>(1.84)*  | 0.44<br>(0.92) |
| 1.88<br>(1.17)                                | -0.06<br>(-3.89)***     | -0.45<br>(-1.12) | 0.13<br>(4.15)***  | -0.05<br>(-0.53) | 0.23<br>(1.83)*  | 0.44<br>(0.92) |
| <i>Panel D: O-score as the dummy variable</i> |                         |                  |                    |                  |                  |                |
| 1.71<br>(0.99)                                | -0.07<br>(-3.72)***     |                  |                    | -0.05<br>(-0.44) | 0.18<br>(1.16)   | 0.46<br>(1.03) |
| 1.97<br>(1.08)                                |                         | -0.16<br>(-0.57) |                    | -0.06<br>(-0.55) | 0.16<br>(1.00)   | 0.51<br>(1.14) |
| 1.99<br>(1.11)                                | -0.07<br>(-3.74)***     | -0.17<br>(-0.65) |                    | -0.06<br>(-0.56) | 0.16<br>(0.97)   | 0.45<br>(1.00) |
| 1.98<br>(1.11)                                | -0.08<br>(-3.86)***     | -0.15<br>(-0.55) | 0.05<br>(2.10)**   | -0.06<br>(-0.57) | 0.15<br>(0.96)   | 0.44<br>(1.00) |

The results are reported in Table 5.6. Panels A to D present the coefficients on the dummy variables based on market value, book-to-market, *DLI*, and *O-score*, respectively. The results in Table 5.6 show that the slopes of skewness beta are all negatively significant, while the slopes of dummy variables are all insignificant. These results are similar with and without control variables. Interestingly, I find that the coefficients on interaction term are significantly positive across the market value, book-to-market, *DLI*, and *O-score* dummy variables, indicating that the market skewness risk effect is significantly different between stocks with large and small market size, low and high book-to-market, and low and high default risk. Specifically, for example, in panel A, dummy equals 1 means the size of stock is less than the mean value, which are regarded as small size stocks.

Positive and significant interaction means the small stocks have an impact on the skewness risk. The positive effect can be offset by the negative slopes of the skewness beta. Overall, market skewness beta is strongly priced in the cross-section of expected returns only for stocks with large market value, high growth, and low default risk.

##### **5.4.2 The financial crisis of 2007-2008 and the market skewness risk effect**

The financial crisis of 2007-2008 led to a large number of defaults and a global economic downturn. The impact of the crisis lingered on for several years while the global economy went through a rebalancing period. In this section, I shift my focus to the period after the financial crisis. My objective is to examine whether the market skewness risk effect persists in the aftermath of the sharp slump where high default rates were common. I adopt the same approach in Section 5.4.1.1 using the sample period from January 2008 to December 2013.

Table 5.7 reports the results of the one-way portfolio sorts. It can be seen that Quintiles 1 and 5 generate the highest and the second highest average raw returns of 1.65% and 1.46% per month, respectively. Instead of the return pattern of monotonic decline, which I observe in the sample period between January 1996 and December 2007, there is a U-shape return pattern from Quintile 1 to Quintile 5 after the crisis. Across the various performance measures, the returns of the long-short portfolios do not differ from zero, suggesting that the strong market skewness risk effect is not persistent after the crisis. I can find that the risk premium for average return is positive but insignificant and risk premiums for abnormal returns

are negative but insignificant, meaning that the return difference is equal to zero and there is no relationship between skewness risk and expected stocks returns. A plausible explanation is that the global financial crisis of 2007-2008 increases the default risk of stocks across the board, including the risk of stocks with positive market skewness risk. Since risk averse investors only prefer to hold positive-skewed stocks with low default risk, they require the risk premiums for holding stocks with high default risk even though these stocks have positive skewness. As a result, the strong market skewness risk effect disappears after the financial crisis. The findings further confirm that the positive skewness theory does not hold consistently.

##### **5.4.3 Cross-sectional regressions during good times and bad times**

As a check for robustness of my results in the previous section, I investigate the impact of market skewness risk on stock returns under different economic conditions using the whole sample period between January 1996 and December 2013. This time, however, I divide my full sample into two subsamples based on the economic conditions. I use the bank loan spread of Campello and Chen (2010) and the expected market risk premium of Petkova and Zhang (2005) to identify good time and bad time. The bank loan spread is calculated as the difference between the bank prime loan rate and the 3-month Treasury bill rate. A deterioration in the economic or credit condition (bad time) is associated with a positive change in the bank loan spread whereas a negative change signals an economic growth (good time).

Table 5.7: Equity returns across market skewness risk portfolios after the financial crisis of 2007-2008

This table reports the value-weighted monthly average returns and the abnormal returns for market skewness risk portfolios for the period from January 2008 to December 2013. At the end of each month, the market skewness risk of each stock is estimated from the following regression using daily returns:

$$R_{i,t} - R_{f,t} = \beta_o^i + \beta_{MKT}^i(R_{m,t} - R_{f,t}) + \beta_{\Delta SKEW}^i \Delta SKEW_t + \varepsilon_{i,t}$$

where  $\beta_{\Delta SKEW}^i$  is the market skewness risk of stock  $i$ . All stocks are then sorted into five quintile portfolios based on their lagged market skewness risk measure,  $\beta_{\Delta SKEW}^i$ . I hold the portfolios for the subsequent month and rebalance the portfolios monthly. Quintile 1 contains stocks with the lowest  $\beta_{\Delta SKEW}^i$  and Quintile 5 contains stocks with the highest  $\beta_{\Delta SKEW}^i$ . The  $t$ -statistics are calculated using Newey and West's (1987) heteroskedasticity and autocorrelation consistent covariance standard errors and are reported in parentheses. Statistical significance at the 10%, 5% and 1% levels is indicated by \*, \*\*, \*\*\* respectively.

| Sorting statistic | Quintile portfolio |                  |                   |                  |                  |
|-------------------|--------------------|------------------|-------------------|------------------|------------------|
|                   | 1                  | 2                | 3                 | 4                | 5                |
| Average return    | 1.65<br>(3.47)***  | 0.96<br>(2.61)** | 1.06<br>(3.32)*** | 1.01<br>(2.01)** | 1.46<br>(2.59)** |
| CAPM alpha        | 0.73<br>(1.20)     | 0.24<br>(0.60)   | 0.39<br>(0.85)    | 0.21<br>(0.55)   | 0.50<br>(0.71)   |
| FF3 alpha         | 0.60<br>(1.22)     | 0.23<br>(0.59)   | 0.39<br>(0.84)    | 0.19<br>(0.52)   | 0.44<br>(0.66)   |
| Carhart alpha     | 0.60<br>(1.25)     | 0.24<br>(0.58)   | 0.39<br>(0.79)    | 0.19<br>(0.51)   | 0.44<br>(0.67)   |
| FF5 alpha         | 0.49<br>(0.92)     | -0.02<br>(-0.05) | -0.11<br>(-0.24)  | -0.41<br>(-1.42) | -0.09<br>(-0.14) |
|                   |                    |                  |                   |                  | 0.58<br>(1.53)   |

To compute the expected market risk premium, I follow Petkova and Zhang (2005) and run the following regression:

$$R_{m,t+1} = \beta_0 + \beta_1 DIV_t + \beta_2 DEF_t + \beta_3 TERM_t + \beta_4 TB_t + \varepsilon_{m,t+1} \quad (5.18)$$

where  $R_{m,t+1}$  is the realized market excess return between  $t$  and  $t + 1$ ,  $DIV_t$  is the dividend yield,  $DEF_t$  is the default spread,  $TERM_t$  is the term spread, and  $TB_t$  is the one-month Treasury bill rate. The variable  $DIV_t$  is calculated as the sum of the dividends of the CRSP value-weighted market portfolio over the past 12 months divided by the value of the CRSP market index. The default spread,  $DEF_t$ , is the difference between the yields on Moody's BAA- and AAA-rated corporate bonds. The variable,  $TERM_t$ , is computed by subtracting the yield on the one-month Treasury bill from the yield on the ten-year Treasury bond.

I use the OLS technique to estimate the coefficients in Equation (5.18). The expected market risk premium, denoted  $\hat{\gamma}_t$ , is the fitted values calculated from Equation (5.19) below.

$$\hat{\gamma}_t = \hat{\beta}_0 + \hat{\beta}_1 DIV_t + \hat{\beta}_2 DEF_t + \hat{\beta}_3 TERM_t + \hat{\beta}_4 TB_t \quad (5.19)$$

A time period is identified as “good” when the expected market risk premium is lower than the mean value, while a “bad” time is identified when the expected market risk premium is higher than its mean value.

For each month from July of year  $\tau$  to June of year  $\tau + 1$ , I run Fama and MacBeth (1973) cross-sectional regressions of monthly excess returns on the

#### 5.4. EMPIRICAL RESULTS AND ANALYSIS

Table 5.8: Fama-MacBeth (1973) regressions during good times and bad times

Following Campello and Chen (2010) and Petkova and Zhang (2005), I define “good” and “bad” time periods based on the bank loan spread and the expected market risk premium. A positive change in the bank loan spread and the expected market risk premium above the mean are defined as “bad” time, while a negative change in the bank loan spread and the expected market risk premium below the mean are defined as “good” time. I split the full sample into the good and bad times subgroups. For each month from July of year  $\tau$  to June of year  $\tau + 1$ , I estimate Fama and MacBeth (1973) cross-sectional regressions of monthly excess returns on the lagged market skewness beta and the lagged control variables of the size ( $\ln(MV)$ ), book-to-market ratio ( $\ln(B/M)$ ) and momentum ( $Mom$ ) for the subgroups.  $\ln(MV)$  the natural logarithm of firm’s size calculated with information available at the end of June of year  $\tau$ .  $\ln(B/M)$  is the natural logarithm of the ratio of the book value of equity for the fiscal year ending in year  $\tau - 1$  divided by market equity at the end of December of year  $\tau - 1$ .  $Mom$  is the cumulative compounded returns over the last 6 months from June of year  $\tau$  to May of year  $\tau + 1$ . I use default likelihood indicators ( $DLI$ ) and O-score as the proxies for default risk. The  $t$ -statistics are calculated using Newey and West’s (1987) heteroskedasticity and autocorrelation consistent covariance standard errors and are reported in the parentheses. The sample period is from January 1996 to December 2013.

|                                              | <i>Constant</i> | $\beta_{\Delta SKEW}$ | $\ln(MV)$ | $\ln(B/M)$ | <i>Mom</i> |
|----------------------------------------------|-----------------|-----------------------|-----------|------------|------------|
| <i>Panel A: Bank loan spread</i>             |                 |                       |           |            |            |
| Good                                         | 0.77            | -0.05                 |           |            |            |
|                                              | (1.84)*         | (-1.66)*              |           |            |            |
|                                              | 1.64            | -0.05                 | -0.06     | 0.02       | -0.07      |
|                                              | (1.53)          | (-2.55)**             | (-0.89)   | (0.10)     | (-0.10)    |
| Bad                                          | 0.83            | -0.03                 |           |            |            |
|                                              | (1.71)*         | (-0.92)               |           |            |            |
|                                              | 1.24            | -0.04                 | -0.02     | 0.13       | 0.44       |
|                                              | (0.50)          | (-1.63)               | (-0.13)   | (0.69)     | (0.99)     |
| <i>Panel B: Expected market risk premium</i> |                 |                       |           |            |            |
| Good                                         | 0.51            | -0.09                 |           |            |            |
|                                              | (0.97)          | (-2.85)***            |           |            |            |
|                                              | 2.81            | -0.08                 | -0.14     | 0.12       | -0.26      |
|                                              | (2.26)**        | (-3.45)***            | (-2.10)** | (0.52)     | (-0.30)    |
| Bad                                          | 1.31            | 0.01                  |           |            |            |
|                                              | (4.01)***       | (0.31)                |           |            |            |
|                                              | 0.52            | -0.01                 | 0.05      | 0.08       | 0.28       |
|                                              | (0.31)          | (-0.37)               | (0.48)    | (0.79)     | (0.90)     |

lagged independent variables separately for the “good” and the “bad” time subgroups. My independent variables include the market skewness beta

plus the control variables of  $\ln(MV)$ ,  $\ln(B/M)$ , and  $MOM$ . The estimated coefficients from the regressions are presented in Table 5.8. Panels A and B report the results based on the economic condition that is determined by the bank loan spread and the expected market risk premium, respectively. Without the control variables, the coefficient on  $\beta_{\Delta SKEW}$  is significantly negative during good times in Panel B and marginal significant in Panel A; while it is insignificant during bad times under the two measures of economic conditions. The findings remain unchanged when the control variables are included in the models. These results imply that market skewness risk has strong explanatory power for stock returns during good economic times, but has no explanatory power during bad economic times.

## 5.5 Conclusions

The impact of the market skewness risk on stock returns is well documented in literature although why the relationship is observed is not well understood. Using data prior to the global financial crisis of 2007–2008, I find that the market skewness risk and stock returns are negatively related. In addition, stocks with low market skewness risk generate significantly higher returns than stocks with high market skewness risk. My results are consistent with recent findings documented by Chang et al. (2013).

In the chapter, I examine the default risk explanation for the market skewness risk effect and find that the effect is stronger among stocks with large size, high growth, and low default risk. In addition, the effect of market skewness risk on expected returns significantly interacts with default risk. The results from Fama and MacBeth (1973) cross-sectional regression

## 5.5. CONCLUSIONS

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confirm that market skewness risk is important for the pricing of stocks with large size, high growth, low default risk, and during good economic conditions. Ang et al. (2006) and Engle (2011) argue that investors would seek to hedge against downside risk and require higher returns for holding stocks with high downside risk. Holding stocks with low default risk allows investors to hedge against downside risk. Investors require extreme low returns for the stocks with high market skewness risk, while demand higher returns for the stocks with low market skewness risk due to the negative price of market skewness risk (Chabi-Yo (2012b)). Therefore, the market skewness risk effect is more pronounced for stocks with low default risk. When default risk of stocks is high, investors have greater demand for hedging against downside risk and require higher returns for the stocks with both high and low market skewness risk. This offsets the market skewness risk effect and the strong effect disappears among stocks with high default risk.

I also show that the financial crisis has strong impact on the market skewness risk effect. Using data for the period after the financial crisis of 2007–2008, the significant market skewness risk effect disappears. This might be due to the fact that risk averse investors demand higher returns for compensation of holding stocks with increasing default risk caused by the financial crisis although those stock have positive skewness. The results of this empirical chapter suggest that the positive skewness preference theory of Kraus and Litzenberger (1976) only holds for safe stocks with large size, high growth and low default risk, and during good economic conditions.

# Chapter 6

## Tail risk, Default risk and the Financial Crisis

### 6.1 Introduction

A large number of studies have investigated the time-varying extreme event risk in the financial markets during past two decades. Moreover, heavy-tailed shocks can help understand much asset pricing behaviour. More recently, Kelly and Jiang (2014) find that tail risk is prices in the cross-section of stock returns. In this chapter, I examine the impact of default risk on the tail risk effect.

In early years, Mandelbrot (1963) and Fama (1965) find that stock returns are not normal distributed and have heavy tails. This can be described by a power law. Other studies also find disasters matter in the financial markets. For example, Rietz (1988) finds that the equity premium puzzle can be solved when they take the large, unlikely market crashes into consideration. Barro (2006) extends Rietz's (1988) model by incorporating stochastic, persisting fluctuations in the rare event probability and argue that the disasters during twentieth century are frequent and large.

However, Rietz-Barro hypothesis is usually accompany by constant intensity of disasters. Gabaix (2012) applies a variable-intensity version of the disaster hypothesis and examines the effect of time-varying disaster intensity on stock and bond returns. This extended model helps resolve many finance puzzles and can be regarded as a simple benchmark for various problems in macroeconomics and finance. Following previous studies, Gourio (2012) incorporates time-varying risk premia in a business cycle model and considers the feedback from the this premia to macroeconomic activities. Wachter (2013) also introduces a model with a time-varying disaster. All these studies provide a better understanding on the equity premium puzzle. Wachter (2013) also finds that the time-variation on the probability of a disaster is the reason for high market volatility and excess return predictability.

More recently, three approaches are widely used to measure tail risk of stock returns. The first method is related to skewness risk. According to the model-free approach by Carr and Madan (2001) and Bakshi and Madan (2000), Bakshi et al. (2003) extract model free implied moments from option data. Chang et al. (2013) compute risk-neutral skewness at the market level by using S&P 500 index option data. Then they calculate the sensitivities for each stock to the market skewness and the results show that stocks with the highest sensitivity to market skewness risk tend to have the lowest returns in the next month. Conrad et al. (2013) calculate risk-neutral skewness for each stock and find that stocks with high implied skewness will generate lower returns in the future. however, this negative relation is challenged by Bali et al. (2014), they choose the price target-based expected return as their ex-ante expected return measure and find that implied skewness risk is positively related to expected returns.

The second approach is based on high frequency return data. Bollerslev and Todorov (2011) extract the expected jump tails by using high-frequency intraday returns and out-of-the-money options with short maturity. Their results show that the compensation for jump tail risk may lead to the historically large equity and variance risk premium. Bollerslev et al. (2013) find that jump tail risk deduced from high frequency data combined with variation in the diffusive volatility lead to the "extreme" joint dependence. They also insist that the distribution of jumps are close to symmetric with heavy tails. By using this method, Bollerslev and Todorov (2014) suggest that there exists strongly significant temporal variation in both tails. This is more pronounced for left tail, which is associated with market distress and financial crisis.

These two methods are sometimes limited by dataset. Option implied skewness is calculated based on option data which is normally available from 1996. On the other hand, some variables fail to have high-frequency data. Therefore, there comes another method based on Hill et al.'s (1975) estimator. Kelly and Jiang (2014) estimate the tail risk from a large cross section of stock returns. This method helps capture the common process of the tail behaviour experienced by all the individual stocks. They argue that stocks with high sensitivities to tail risk will be discounted more steeply. Therefore, these stocks will generate higher returns in the future. Stocks with low sensitivities to tail risk are always used as effective hedges and thus lower expected returns required.

In this chapter, I extend Kelly and Jiang's (2014) investigation by interoperate default risk into analysis and try to find whether the tail risk can be affected by default risk. This empirical work is motivated by two strands of

studies. First, investors evaluate risk in the financial market according to cumulative prospect theory documented by Tversky and Kahneman (1992). Under probability weighting, investors tend to overweight the tail event in their decision making. Barberis (2013) argues that the probability weighting also works for understanding the aggregate stock market. As a result of occasional large crashes, the aggregate stock market is negatively skewed. Kelly and Jiang (2014) use Hill et al.'s (1975) estimator from a large cross section of stock returns to capture the large crashes. When the tail risk increases, investors prefer to hold stocks with low sensitivity to tail risk in order to hedge the large crashes. Then the stocks with high sensitivity to tail risk will be discounted more steeply. Therefore, probability weighting leads to a new prediction.

However, from the view of behaviour finance, Hertwig et al. (2004) point out that people are more likely to underweight tail events when they make decisions according to their experience. Barberis (2013) states that the reason for Hertwig et al.'s (2004) findings might be because people use simple reasoning rather than experience. They argue that the prices of stocks with high default risk have been beaten down. Therefore, these stocks have limited downside. Under their hypothesis, when investors hold stocks with high default risk, they tend to underweight the tail event. This indicates that even when the market will experience a large crash, investors believe the distressed stocks have limited downside and they are not expected to buy stocks with low sensitivity to tail risk to hedge the tail risk. Barberis (2013) also discusses that if an investor believes that a tail event is not likely to occur, he may ignore the tail event in his decision making. My empirical analysis tries to figure out whether the default risk has an impact on the

effect of tail risk.

Second, Werner and Upper (2004) argue that the tail index of bond future is not stable over time and the changes of tail index may be on account of the Russia and LTCM crises. Gourio (2012) also points out that the variation in the probability of disaster has some connections with a significant fraction of business cycle dynamics. Therefore, I would like to find out whether the tail risk is affected during different economic conditions.

To achieve my goals, I estimate tail risk from a large cross section of daily stock returns at the end of each month by using Hill et al.'s (1975) estimator. Then I calculate the tail loadings for each stock by regressing the monthly returns on the tail risk with predictive regressions. The default risk factors used in this chapter are default likelihood indicator proposed by Vassalou and Xing (2004) and the O-score presented by Ohlson (1980). Moreover, I expected market risk premium to identify good times and bad times according to Petkova and Zhang (2005).<sup>1</sup>

In order to compare with the studies by Kelly and Jiang (2014), I use the same sample period of all common stocks listed on the NYSE, AMEX, and NASDAQ from January 1963 to December 2010. I find that the relationship between tail risk and stock returns is positive and this is consistent with the results from Kelly and Jiang (2014). Moreover, I also use two-way portfolio sorts to control for size, book-to-market ratio and default risk. The results show that the tail risk premium are highly significant in stocks with large market capitalizations, low book-to-market ratios, low default likelihood indicators, and low O-scores. However, the effect of tail risk disappears in

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<sup>1</sup>The expected market risk premium is computed based on dividend yield, default spread, term spread, and one-month Treasury bill rate.

the the stocks with small market capitalizations, high book-to-market ratios and high default risk. I also use Fama and MacBeth (1973) cross-sectional regressions to test the tail risk effect in different default risk groups. Cross-sectional regressions enable us to test the effect of tail risk with several control variables at the same time. The results are consistent with the portfolio sorts. Tail risk effect disappears in the stocks with small market capitalizations, high book-to-market ratios and high default risk, indicating that the price of high distressed stocks is usually beaten down, and the investors who hold these stocks expect a huge increase in the future. The investors tend to ignore the tail risk and are not willing to hold stocks with low sensitivities to tail risk in order to hedge the tail risk.

I then use the sample period after the financial crisis of 2007-2008, which is from January 2008 to December 2014. I sort portfolios into quintile portfolio by the loadings to the tails, then I also compute post equal-weighted and value-weighted returns for each portfolio. My results show that the positive relationship between tail risk and stocks returns disappears. The average returns and risk-adjusted returns are nearly all insignificant for equal-weighted and value-weighted portfolios. The financial crisis does have an impact on the tail risk effect. I also use expected market risk premium to define good times and bad times. The results from Fama and MacBeth (1973) cross-sectional regressions in different economic conditions show that the tail risk premium is insignificant during the bad times.

This empirical chapter contributes to the literature that default risk has a significant impact on the effect of tail risk. There are few empirical studies examining this effect. I highlight that when investors hold stocks with small size, high book-to-market ratios and high default risk, the tail risk

tends to be insignificant. The empirical findings are consistent with the behavioural explanation by Barberis (2013). In addition, the strategy that long the stocks with lowest tail loadings and short the stocks with highest tail loadings does not always work when the default risk and economy conditions are taken into consideration.

The rest of the chapter is organized as follows. Section 6.2 presents the data and measures. I illustrate the details of the calculation of tail risk and tail loadings. Section 6.3 describes the empirical analysis, including portfolio sorts, Fama and MacBeth's (1973) cross-sectional regressions and the effect of tail risk during different time period. Section 6.4 concludes the chapter.

## 6.2 Data and the Measures

This empirical chapter uses daily Center for Research in Securities Price (CRSP) data from January 1963 until December 2014 for all stocks listed on the NYSE, AMEX, and NASDAQ. The variables are holding period returns, share code, exchange code, share outstanding, prices and delisted returns. I choose the period starting from 1963 because of the cross-section expansion of CRSP data beginning in August 1962. Moreover, I will use the same sample period used by Kelly and Jiang (2014) and test whether my results are consistent with theirs. The annual accounting data are collected from the CRSP/Compustat Merged Database. Data on Fama and French's five factors, including size, book-to-market equity, profitability, investment, and market excess returns; the Carhart's (1997) daily momentum factor, and the risk-free rates are obtained from Kenneth French's website.<sup>2</sup> All

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<sup>2</sup><http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/>

the variables required in the calculations of the expected market premium are extracted from the Federal Reserve Board Statistics.<sup>3</sup> These variables include the 1-month Treasury bill rate, the 3-month Treasury bill rate, the default spread and the term spread.

### 6.2.1 Estimation of tail risk

Following Kelly and Jiang (2014), the lower tail distribution is asset returns exceeding some extreme lower threshold. The returns obey a power law:

$$P(R_{i,t+1} < r \mid R_{i,t+1} < u_t \text{ and } \mathcal{F}_t) = \left(\frac{r}{u_t}\right)^{-a_i/\lambda_t} \quad (6.1)$$

where  $\mathcal{F}_t$  is information set.  $u_t$  is the extreme negative threshold.  $r < u_t < 0$ .  $a_i/\lambda_t$  is the tail exponent, which is only determined by  $\lambda_t$ . Kelly and Jiang (2014) point out that  $\lambda_t$  varies according to the conditioning information set  $\mathcal{F}_t$ . Moreover,  $a_i$  also varies across assets because different assets have different levels of tail risk. However, different assets are driven by the common process  $\lambda_t$ , therefore, dynamics are the same for different assets.

According to Kelly and Jiang (2014), I also estimate the tail risk from a large cross section in order to gather enough information about the tail for each month according to Equation (6.1). Tail exponent estimates are computed based on only a small fraction of data exceeding some extreme lower threshold. Pooling all daily stock returns within the month, I estimate the tail risk for each month by using Hill et al.'s (1975) power law estimator:

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<sup>3</sup><http://www.federalreserve.gov/econresdata/statisticsdata.htm>

$$\lambda_t = \frac{1}{K_t} \sum_{k=1}^{K_t} \ln \frac{R_{k,t}}{u_t} \quad (6.2)$$

where  $R_{k,t}$  is the stock returns exceeding the tail threshold on day  $k$  during month  $t$ .  $u_t$  is extreme value threshold. Therefore, the daily stock returns used in the calculation fulfil  $R_{k,t}/u_t > 1$ .  $K_t$  is the number of daily stock returns exceeding the threshold during month  $t$ . Kelly and Jiang (2014) point out that the tail exponent estimates will be contaminated by using the data from the centre of a distribution. Therefore, a mild threshold is not appropriate. However, a very extreme threshold is also not appropriate because this may lead to noisy estimates from limited data exceeding the threshold. Gabaix et al. (2006) use a simple rule to define the threshold, using a fixed value at 5% for unconditional power law estimation. Kelly and Jiang (2014) use various thresholds from the first to the fifth percentile and find that the results are similar. In order to replicate the results by Kelly and Jiang (2014), I also choose the fifth percentile of the cross-section each period for the threshold.

Kelly and Jiang (2014) point out that the correlation between upper tail risk and lower tail risk is 81%, indicating that tail risk dynamics are highly symmetric. They also find that lower tail risk dominates upper tail risk in the predictive regressions. I also compute the upper tail risk using 95th percentile of cross-sectional daily returns in a month, I find that lower tail risk has a correlation of 78% with upper tail risk in my sample. I also compute the tail loadings on the upper tail risk and sorts all the stocks into portfolios based on their tail loadings. I find less significant risk premium. Adrian and Rosenberg (2008) state that the skewness of individual stocks

are always positive and market skewness is always negative. Chang et al. (2013) provide evidence for a negative market skewness risk. Negative skewness means the left tail of a distribution is longer than the right tail of the distribution. The tail risk calculated is at the market level. Therefore, the lower tail effect is more pronounced than the upper tail. In the following empirical sections, I only focus on the test using lower tail risk.

Figure 6.1 plots the monthly tail estimates from 1963 to 2014. The result is consistent with the tail exponent estimates by Kelly and Jiang (2014). My estimates are not scaled. I can find that the tail estimates range from 0.35% to 0.55%. The average value of tail estimates is 0.43%. The monthly AR(1) coefficient is 0.96, proving that tail estimates is highly persistent. This result is similar with the findings by Kelly and Jiang (2014). Therefore,  $\lambda_t$  can be used to predict extreme returns of individual returns in the future.

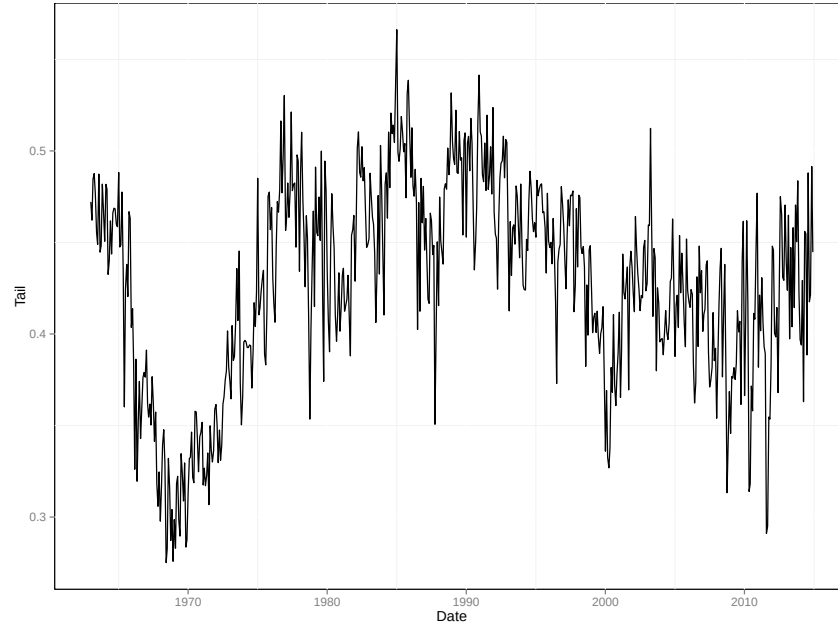


Figure 6.1: Tail exponent estimates

Tail exponent estimates are computed based on only a small fraction of data exceeding some extreme lower threshold. Pooling all daily returns of NYSE/AMEX/NASDAQ stocks, I compute monthly tail estimates from January 1963 to December 2014.

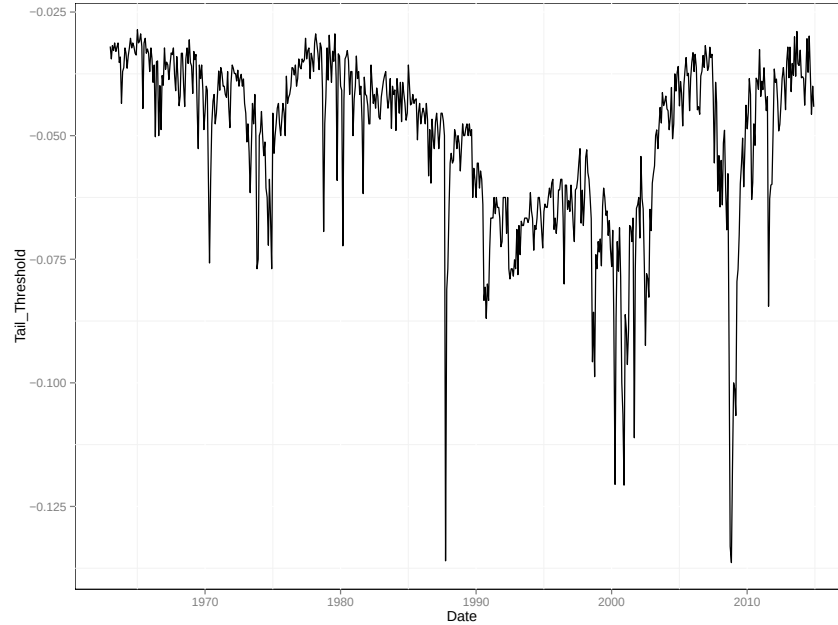


Figure 6.2: Threshold

Tail threshold estimates are defined as the fifth percentile of all the daily returns at the end of each month. Pooling all daily returns of NYSE/AMEX/NASDAQ stocks, I compute monthly threshold from January 1963 to December 2014.

Figure 6.2 plots the monthly threshold. It is clear that all thresholds are negative and the average value of threshold is -5.1%. The threshold decreases dramatically during the crisis. The pattern is consistent with the pattern in Kelly and Jiang's (2014) paper. In each month, the number of stocks exceeding the threshold varies from 778 to 4150. The average number of stocks used to calculate the tail risk is 2158. Regarding the number of the observations used, the number varies from 1782 to 8562. The average number of observations is 4998.

### 6.2.2 Calculation of tail loadings

In order to test the explanation of the tail risk on the cross-sectional stock returns, I have to compute the loadings on the tail risk for each stock. In this section, I use modified predictive regressions by Cai and Wang (2014) to estimate the tail sensitivities of individual stocks at the end of each month with the following regressions:<sup>4</sup>

$$r_{i,t} = \beta_0^i + \beta_1^i u_t + \beta_{Tail}^i \lambda_{t-1} + v_{i,t} \quad (6.3)$$

where

$$\lambda_t = \rho \lambda_{t-1} + u_t \quad (6.4)$$

$r_{i,t}$  is the return of stock  $i$  at the end of month  $t$ .  $u_t$  is the residual of autoregressive model (Equation 6.4). At the end of each month, I use the previous 120 months' data to estimate the tail loadings for each stock. For each estimation window, I require at least 36 months' nonmissing returns. The parameter  $\beta_{Tail}$  is the measure of the sensitivity of stock returns to tail risk. Kelly and Jiang (2014) state that stocks with high predictive sensitivities to the tail risk will be discounted more steeply. Therefore, these stocks tend to have higher returns in the future. Stocks with low sensitivities to the tail risk can be used as effective hedges, resulting in comparatively

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<sup>4</sup>Kelly and Jiang (2014) use the predicted regressions of the form  $r_{i,t+1} = \beta_0^i + \beta_{Tail}^i \lambda_t + \varepsilon_{i,t+1}$ . Cai and Wang (2014) point out that the coefficient calculated without considering the autocorrelation of the independent variables will be biased because of the embedded endogeneity. I also use the same regression as Kelly and Jiang (2014) and find similar results.

higher prices. Therefore, these stocks will generate lower returns in the future. Consistent with intuition from the predictive regression (6.3), stocks with high values of  $\beta_{Tail}$  are the stocks with high loadings on the tail risk and they will have high returns in the future. On the other hand, stocks with low values of  $\beta_{Tail}$  are the stocks with low loadings on the tail risk and they will have low expected returns.

### 6.2.3 Default risk measures

The default risk has been studied for decades and there are various measures. In this empirical chapter, I adopt the default likelihood indicator (*DLI* henceforth) of Vassalou and Xing (2004) and the *O*-score of Ohlson (1980) as the measures of default risk. These two measures are widely used. The *DLI* measure incorporates the volatility of the firm's asset and market value of equity into the calculation. Campbell et al. (2001) state that volatility is an important determinant of default risk. The *O*-score measure is based on accounting model and fails to capture the volatility of a firm's assets. Vassalou and Xing (2004) argue that *O*-score has backward looking problems and *DLI* has an advantage of forward looking property.

Details of calculating the default likelihood indication and *O*-score are illustrated in section 5.3.3. In order to investigate the effect of tail risk after I control for default risk, I use the same period of sample, which is from January 1963 to December 2014, to compute default risk measures. I will test the effect of tail risk after controlling for default risk by applying two-way portfolio sorts.

## 6.3 Empirical Results and Analysis

Table 6.1 reports the descriptive statistics and the Spearman rank correlation for the tail risk loading ( $\beta_{Tail}$ ), default likelihood indicator ( $DLI$ ),  $O$ -score, market capitalization ( $MV$ ), and book-to-market ratio ( $B/M$ ) for the period starting from January 1963 to December 2014. I choose Spearman rank correlation rather than Pearson correlation. This is because Pearson correlation assesses linear relationships between two variables, while Spearman rank correlation assesses monotonic relationships no matter whether the relationship is linear or not. Spearman rank correlation will be higher than Pearson correlation when two variables have a similar rank. In this section, I expect to test the correlation between tail risk loadings with other factors. However, the relationships between tail risk loadings with other variables are unknown and may not be linear. Therefore, I prefer to choose Spearman rank correlation. It does not make any big difference to the results when I use Pearson correlation.

From Panel A of Table 6.1, I can find that the mean value of  $\beta_{Tail}$  is 0.34. Moreover, all the tail loadings are positive, and tail exponent estimates are positive as well, indicating that the tail risk has a positive effect on the individual stock returns. The mean value of  $DLI$  is 0.02, which is consistent with the results by Vassalou and Xing (2004). Stocks with large value of  $DLI$  have large probability to default. The mean value of  $O$ -score is  $-1.47$ . Stocks with large value of  $O$ -score are those stocks with high default risk.

Panel B shows the Spearman rank correlation. The correlation coefficients are computed from the time-series values of the corss-sectional estimates. Specifically, at the end of each month, I calculate the mean value of tail risk

Table 6.1: Descriptive statistics

The table reports the mean, standard deviation ( $SD$ ), minimum ( $Min$ ), maximum ( $Max$ ) and correlation coefficients of tail risk ( $\beta_{Tail}$ ), default likelihood indicator ( $DLI$ ),  $O$ -score, market capitalization ( $MV$ ), and book-to-market ratio ( $B/M$ ). The tail risk is estimated by using Hill's (1975) power law estimator. The  $DLI$  is calculated using Merton's (1974) structure model of default.  $O$ -score is calculated following the method of Ohlson (1980).  $MV$  (in thousands of dollar) is the firm's market capitalization.  $B/M$  is the book-to-market ratio. The mean, standard deviation and Spearman rank correlation coefficient are computed by averaging the time-series values of the cross-sectional estimates. The sample includes all common stocks traded on the NYSE, AMEX, and NASDAQ for the period beginning in January 1963 and ending in December 2014.

|                                           | $\beta_{Tail}$ | $DLI$ | $O$ -score | $MV$     | $B/M$ |
|-------------------------------------------|----------------|-------|------------|----------|-------|
| <i>Panel A: Descriptive statistics</i>    |                |       |            |          |       |
| <i>Mean</i>                               | 0.34           | 0.02  | -1.05      | 2633547  | 0.97  |
| <i>SD</i>                                 | 0.16           | 0.01  | 0.27       | 2285898  | 0.32  |
| <i>Min</i>                                | 0.06           | 0.00  | -1.47      | 401858   | 0.56  |
| <i>Max</i>                                | 0.70           | 0.09  | -0.52      | 10261025 | 2.21  |
| <i>Panel B: Spearman rank correlation</i> |                |       |            |          |       |
| <i>DLI</i>                                | -0.12          | 1.00  |            |          |       |
| <i>O</i> -score                           | 0.20           | 0.49  | 1.00       |          |       |
| <i>MV</i>                                 | 0.37           | -0.16 | 0.21       | 1.00     |       |
| <i>B/M</i>                                | -0.26          | 0.18  | -0.23      | -0.58    | 1.00  |

( $\beta_{Tail}$ ), default likelihood indicator ( $DLI$ ),  $O$ -score, market capitalization ( $MV$ ), and book-to-market ratio ( $B/M$ ) for all the stocks. Then I calculate the correlation by using the time series data. The correlation between  $\beta_{Tail}$  and  $MV$  is 0.37, which is slightly higher than other correlation coefficients. The correlation between  $DLI$  and  $O$ -score is 0.49, which is not very high but still suggesting that the two measures largely agree on the classification of default risk.<sup>5</sup>

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<sup>5</sup>The correlations between some variables are different from the corresponding correlations in Chapter 4 and Chapter 5. This is because different sample used.

### 6.3.1 Default risk and the tail risk effect

#### 6.3.1.1 One-way portfolio sorts

In this section, I use one-way portfolio sort to investigate the return performance of tail risk portfolios. At the end of each month, I sort all the stocks into quintile portfolios based on their tail loadings,  $\beta_{Tail}$ . I hold the portfolios for the subsequent month and calculate the equal-weighted and value-weighted returns for each portfolio. The portfolios are rebalanced monthly. Panel A of Table 6.2 presents the equal-weighted returns and Panel B of Table 6.2 reports the value-weighted returns. The weights for value-weighted portfolios are calculated based on the market value of each stock at the beta estimation period. Quintile 1 contains stocks with the lowest  $\beta_{Tail}$ s and Quintile 5 contains stocks with the highest  $\beta_{Tail}$ s. Portfolio 5-1 represents the long-short strategy that is at the end of each month, I long stocks in Quintile 5 and short stocks in Quintile 1.

The risk adjusted returns are the intercepts from capital asset pricing model (hereafter CAPM) of Sharpe (1964) and Lintner (1965), the Fama and French (1993) three-factor model (hereafter FF3), the Carhart (1997) four-factor model (hereafter Carhart), and the Fama and French (2015) five-factor model (hereafter FF5). In order to get monthly abnormal returns for each portfolio, I regress the raw returns on the factors for the whole period. The intercepts from the regressions for each portfolio are the risk-adjusted returns.

Table 6.2: Equity returns across tail risk portfolios from 1963 to 2010

This table reports the equal-weighted (Panel A) and value-weighted (Panel B) monthly average returns and the abnormal returns for tail risk portfolios. At the end of each month, the tail risk of each stock is estimated from the previous 12-month daily returns. All stocks are then sorted into five quintile portfolios based on their exposures to the tail risk,  $\beta_{Tail}$ . I hold the portfolios for the subsequent month and rebalance the portfolios monthly. Quintile 1 contains stocks with the lowest  $\beta_{Tail}$  and Quintile 5 contains stocks with the highest  $\beta_{Tail}$ . The  $t$ -statistics are calculated using Newey and West's (1987) heteroskedasticity and autocorrelation consistent covariance standard errors and are reported in parentheses. Statistical significance at the 10%, 5% and 1% levels is indicated by \*, \*\*, \*\*\* respectively. The sample includes all common stocks traded on the NYSE, AMEX, and NASDAQ for the period from January 1963 to December 2010.

| Sorting statistic              | Quintile portfolio |                    |                    |                    |                    |
|--------------------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
|                                | 1                  | 2                  | 3                  | 4                  | 5                  |
| <i>Panel A: Equal-weighted</i> |                    |                    |                    |                    |                    |
| Average return                 | 1.13<br>(4.78) *** | 1.29<br>(6.03) *** | 1.37<br>(5.87) *** | 1.50<br>(5.82) *** | 1.62<br>(5.64) *** |
| CAPM alpha                     | 0.24<br>(2.37) **  | 0.45<br>(4.18) *** | 0.49<br>(3.43) *** | 0.57<br>(3.42) *** | 0.63<br>(3.30) *** |
| FF3 alpha                      | 0.03<br>(0.46)     | 0.19<br>(2.97) *** | 0.21<br>(2.69) *** | 0.25<br>(3.16) *** | 0.34<br>(3.42) *** |
| Carhart alpha                  | 0.07<br>(1.07)     | 0.21<br>(3.79) *** | 0.26<br>(3.97) *** | 0.32<br>(3.91) *** | 0.43<br>(4.11) *** |
| FF5 alpha                      | 0.10<br>(1.12)     | 0.10<br>(1.68) *   | 0.08<br>(1.28)     | 0.12<br>(1.79) *   | 0.22<br>(2.21) **  |
| <i>(Continued)</i>             |                    |                    |                    |                    |                    |
|                                |                    |                    |                    |                    | 0.49<br>(2.91) *** |
|                                |                    |                    |                    |                    | 0.38<br>(2.19) **  |
|                                |                    |                    |                    |                    | 0.31<br>(2.22) **  |
|                                |                    |                    |                    |                    | 0.36<br>(2.40) **  |
|                                |                    |                    |                    |                    | 0.11<br>(0.76)     |

(Continued)

| Sorting statistic              | Quintile portfolio |                   |                   |                   |                   |
|--------------------------------|--------------------|-------------------|-------------------|-------------------|-------------------|
|                                | 1                  | 2                 | 3                 | 4                 | 5-1               |
| <i>Panel B: Value-weighted</i> |                    |                   |                   |                   |                   |
| Average return                 | 1.06<br>(4.62)***  | 1.19<br>(5.57)*** | 1.28<br>(5.33)*** | 1.50<br>(5.87)*** | 1.52<br>(5.25)*** |
| CAPM alpha                     | 0.16<br>(1.40)     | 0.33<br>(2.63)*** | 0.37<br>(2.41)**  | 0.54<br>(3.04)*** | 0.50<br>(2.40)**  |
| Fama three-factor alpha        | -0.07<br>(-0.88)   | 0.08<br>(0.94)    | 0.09<br>(1.00)    | 0.26<br>(2.46)**  | 0.27<br>(2.15)**  |
| Carhart four-factor alpha      | -0.03<br>(-0.40)   | 0.10<br>(1.39)    | 0.14<br>(1.60)    | 0.33<br>(3.10)*** | 0.36<br>(2.69)*** |
| Fama five-factor alpha         | -0.01<br>(-0.06)   | -0.02<br>(-0.33)  | -0.01<br>(-0.11)  | 0.13<br>(1.32)    | 0.12<br>(1.03)    |
|                                |                    |                   |                   |                   | 0.34<br>(1.95)*   |
|                                |                    |                   |                   |                   | 0.39<br>(2.34)**  |
|                                |                    |                   |                   |                   | 0.13<br>(0.84)    |

The results in Panel A of Table 6.2 show that Quintile portfolio 1 generates the lowest average return and Quintile portfolio 5 has the highest average return. When tail risk is increasing, the average return is also increasing from Quintile portfolio 1 to Quintile portfolio 5. The results are consistent when I use risk adjusted returns except Fama five-factor alpha. I find that the pattern of FF5 alpha is not monotonously increasing across tail risk portfolios. 5-1 portfolio strategy shows that tail risk premium is highly positively significant, which will earn 0.31%-0.49% per month. They are statistically significant at the 5% level. The risk premium disappears when I use FF5 alpha. This finding shows that the tail risk is not always significant. In the Fama-French five factor model, the new factors added compared with other factor models are profitability factor and investment factor. Profitability factor might be the reason for the insignificant FF5 alpha difference. Profitability is related to default risk, indicating that default risk might have an impact on the tail risk effect.

I can also find similar results in Panel B of Table 6.2 when I calculate value-weighted returns for the five portfolios. The average return and risk adjusted returns are increasing across tail risk portfolios, which means stocks with high tail risk loadings will have higher returns in the future. The risk premium are all positively significant except Fama five-factor alpha, which will earn 0.34%-0.46% per month. They are statistically significant at the 10% level. My results are consistent with the results by Kelly and Jiang (2014). Kelly and Jiang (2014) report the equal-weighted and value-weighted portfolio returns in a one-month as well as 12-month postformation window. The results show that tail risk is positively related to expected stock returns. In addition to their findings, I find that the tail risk premium

is not significant by using abnormal return from Fama and French (2015) five-factor model.

Table 6.3 reports firm characteristics and default risk of tail risk portfolios. At the end of each month, I sort all the stocks into Quintile portfolios and then I compute the firm characteristics and default risk for each portfolio. The reported characteristics are market capitalization ( $MV$ , in thousands of dollars), book-to-market ratio ( $B/M$ ), book leverage ( $Leverage$ ), cash flow ratio ( $CF$ ), cash holding ratio ( $CH$ ), return on assets ( $Profitability$ ), net sales ( $Sales$ , in millions of dollar) and R&D to sales ratio ( $R\&D$ ). Appendix C provides detailed explanations on the measures of firm characteristics. The results show that stocks in Quintile portfolio 5 with the highest tail risk loadings tend to be small size stocks and these stocks generate lower profit and low sales. Stocks in Quintile portfolio 1 and portfolio 5 are likely to be likely to be financial distressed stocks as they have high  $R\&D$ . Opler and Titman (1994) state that firms with high  $R\&D$  ratio are associated with high financial distress costs as a result of their high sensitivity to sale loss. Panel B of Table 6.3 shows that Quintile portfolio 5 tend to have stocks with high default likelihood indication and O-score, indicating that stocks with high tail risk loadings tend to have high default risk.

#### 6.3.1.2 Two-way portfolio sorts

In this section, I will investigate whether the tail risk effect can be explained by default risk by using two-way independent portfolio sorts. Vassalou and Xing (2004) find that size effect and book-to-market effect are related to the default risk. Therefore, I use market capitalization ( $MV$ ), book-to-market

### 6.3. EMPIRICAL RESULTS AND ANALYSIS

Table 6.3: Firm characteristics and default risk of tail risk portfolios

At the end of each month, I sort stocks into five quintile portfolios based on their tail risk measure,  $\beta_{Tail}$ . I hold the portfolios for the subsequent month and rebalance the portfolios monthly. Quintile 1 contains stocks with the lowest  $\beta_{Tail}$  and Quintile 5 contains stocks with the highest  $\beta_{Tail}$ . Panel A reports firm characteristics for each quintile. The reported characteristics are market capitalization ( $MV$ , in thousands of dollar), book-to-market ratio ( $B/M$ ), book leverage ( $Leverage$ ), cash flow ratio ( $CF$ ), cash holding ratio ( $CH$ ), return on assets ( $Profitability$ ), net sales ( $Sales$ , in millions of dollar) and R&D to sales ratio ( $R\&D$ ). Appendix C provides detailed explanations on the measures of firm characteristics. Panel B reports the average values of the default risk measures: default likelihood indicator ( $DLI$ ) and  $O$ -score. The sample includes all common stocks listed on the NYSE, AMEX, and NASDAQ for the period from January 1963 to December 2010.

|                                      | Quintile |         |         |         |        |
|--------------------------------------|----------|---------|---------|---------|--------|
|                                      | 1        | 2       | 3       | 4       | 5      |
| <i>Panel A: Firm characteristics</i> |          |         |         |         |        |
| $\beta_{Tail}$                       | -0.10    | 0.17    | 0.31    | 0.48    | 0.87   |
| $MV$                                 | 3874363  | 3801522 | 2836537 | 1675557 | 757802 |
| $B/M$                                | 0.76     | 0.78    | 0.78    | 0.84    | 0.69   |
| $Leverage$                           | 0.28     | 0.27    | 0.25    | 0.26    | 0.29   |
| $CF$                                 | 0.04     | 0.06    | 0.06    | 0.06    | 0.03   |
| $CH$                                 | 0.10     | 0.09    | 0.09    | 0.10    | 0.12   |
| $Profitability$                      | 0.11     | 0.13    | 0.13    | 0.12    | 0.08   |
| $Sales$                              | 3130.85  | 3200.97 | 2600.10 | 1733.50 | 926.08 |
| $R\&S$                               | 0.81     | 0.38    | 0.10    | 0.17    | 0.54   |
| <i>Panel B: Default risk</i>         |          |         |         |         |        |
| $DLI$                                | 0.03     | 0.02    | 0.02    | 0.03    | 0.05   |
| $O$ -score                           | -0.92    | -1.14   | -1.16   | -0.96   | -0.37  |

ratios ( $B/M$ ), default likelihood indicators ( $DLI$ ), and O-scores as control variables. Specifically, at the end of each month, I sort all the stocks into Quintile portfolios based on their tail loadings,  $\beta_{Tail}$ . Then I independently sort all the stocks into three portfolios based on control variables using 30th and 70th percentiles as the breakpoints. Therefore, at the end of each month, I get 15 portfolios. The portfolios are held for one month and rebalanced monthly. I calculate equal-weighted return for each portfolio. Table 6.4 reports the portfolio returns based on two-way independent sorts.

Table 6.4: Portfolio returns based on two-way independent sorts

This table reports the equal-weighted monthly average returns based on two-way independent sorts. At the end of each month, I sorted stocks into five quintile portfolios based on their tail risk measure,  $\beta_{Tail}$ , and independently sort stocks into three portfolios based on their past month's market capitalization ( $MV$ ), book-to-market ratios ( $B/M$ ), default likelihood indicators ( $DLI$ ), and O-scores using 30th and 70th percentiles as the breakpoints. The portfolios are held for the subsequent month and rebalanced monthly. Subscript 1 represents the bottom portfolios comprising stocks with the lowest values of the variables, while subscript 3 represents the top portfolios comprising stocks with the highest values of the corresponding variables. The rows labelled 3-1 denote the return differences between the top portfolio and the bottom portfolio. The  $t$ -statistics are calculated using Newey and West's (1987) heteroskedasticity and autocorrelation consistent covariance standard errors and are reported in the parentheses. Statistical significance at the 10%, 5% and 1% levels is indicated by \*, \*\*, \*\*\* respectively. The sample periods are from January 1963 to December 2010.

|         | Quintile portfolio  |                     |                     |                    |                   | 5-1               |
|---------|---------------------|---------------------|---------------------|--------------------|-------------------|-------------------|
|         | 1                   | 2                   | 3                   | 4                  | 5                 |                   |
| $MV_1$  | 1.27<br>(4.59)***   | 1.54<br>(6.27)***   | 1.45<br>(6.71)***   | 1.57<br>(6.72)***  | 1.54<br>(5.59)*** | 0.27<br>(1.57)    |
| $MV_2$  | 1.09<br>(4.74)***   | 1.19<br>(5.30)***   | 1.35<br>(5.88)***   | 1.42<br>(5.39)***  | 1.56<br>(5.76)*** | 0.47<br>(2.88)*** |
| $MV_3$  | 0.78<br>(3.36)***   | 1.01<br>(5.02)***   | 1.08<br>(4.70)***   | 1.14<br>(4.28)***  | 1.38<br>(4.77)*** | 0.60<br>(3.03)*** |
| $3-1$   | -0.49<br>(-3.04)*** | -0.53<br>(-3.42)*** | -0.38<br>(-2.75)*** | -0.43<br>(-2.45)** | -0.16<br>(-1.00)  |                   |
| $B/M_1$ | 0.73<br>(2.90)***   | 1.00<br>(4.43)***   | 1.17<br>(5.39)***   | 1.18<br>(4.48)***  | 1.39<br>(4.61)*** | 0.66<br>(3.21)*** |
| $B/M_2$ | 1.14<br>(4.96)***   | 1.22<br>(5.87)***   | 1.32<br>(5.61)***   | 1.42<br>(5.75)***  | 1.59<br>(5.54)*** | 0.46<br>(2.60)*** |
| $B/M_3$ | 1.42<br>(5.65)***   | 1.51<br>(7.01)***   | 1.62<br>(7.17)***   | 1.55<br>(5.79)***  | 1.63<br>(5.76)*** | 0.21<br>(1.22)    |
| $3-1$   | 0.69<br>(4.33)***   | 0.52<br>(3.57)***   | 0.45<br>(3.27)***   | 0.38<br>(1.98)**   | 0.24<br>(1.34)    |                   |

(Continued)

### 6.3. EMPIRICAL RESULTS AND ANALYSIS

(Continued)

|           | Quintile portfolio |                   |                   |                   |                   | 5-1               |
|-----------|--------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
|           | 1                  | 2                 | 3                 | 4                 | 5                 |                   |
| $DLI_1$   | 0.92<br>(4.48)***  | 1.14<br>(5.65)*** | 1.13<br>(6.10)*** | 1.30<br>(6.23)*** | 1.60<br>(6.42)*** | 0.68<br>(4.04)*** |
| $DLI_2$   | 1.09<br>(4.82)***  | 1.26<br>(6.16)*** | 1.40<br>(6.49)*** | 1.35<br>(5.11)*** | 1.42<br>(5.19)*** | 0.33<br>(2.12)**  |
| $DLI_3$   | 1.23<br>(4.18)***  | 1.36<br>(4.94)*** | 1.46<br>(5.23)*** | 1.52<br>(5.14)*** | 1.52<br>(4.73)*** | 0.29<br>(1.45)    |
| $\beta-1$ | 0.31<br>(1.75)*    | 0.22<br>(1.28)    | 0.32<br>(2.23)**  | 0.22<br>(1.44)    | -0.08<br>(-0.43)  |                   |
| $O_1$     | 1.00<br>(3.64)***  | 1.10<br>(4.99)*** | 1.27<br>(5.92)*** | 1.33<br>(5.53)*** | 1.61<br>(6.07)*** | 0.62<br>(3.21)*** |
| $O_2$     | 1.07<br>(4.84)***  | 1.22<br>(5.86)*** | 1.32<br>(5.87)*** | 1.38<br>(5.67)*** | 1.59<br>(5.46)*** | 0.51<br>(2.78)*** |
| $O_3$     | 1.08<br>(4.26)***  | 1.32<br>(6.37)*** | 1.42<br>(5.65)*** | 1.41<br>(4.96)*** | 1.35<br>(4.63)*** | 0.27<br>(1.46)    |
| $\beta-1$ | 0.08<br>(0.58)     | 0.22<br>(1.72)*   | 0.15<br>(1.36)    | 0.08<br>(0.52)    | -0.27<br>(-1.58)  |                   |

The results show that across the tail risk portfolios, when size ( $MV$ ) and book-to-market ratios ( $B/M$ ) increase, the average returns decrease and increase, respectively. For default likelihood indicators ( $DLI$ ) and O-scores, I can find that high default risk is associated with high returns in all tail risk portfolios except the Quintile portfolio 5. More interestingly, after I control for the tail risk beta, the size effect, book-to-market effect and default risk effect are all insignificant in the Quintile portfolio 5.

At the end of each month, for each control variable portfolio, I also construct the portfolio strategy that long Quintile portfolio 5 and short Quintile portfolio 1 and then record the average returns for the subsequent month. I can find that the tail risk premium disappear in small size ( $MV_1$ ), high book-to-market ratios ( $B/M_3$ ), high default likelihood indicators ( $DLI_3$ ), and high O-scores ( $O_3$ ) portfolios. Obviously, the tail risk effect concentrates

on stocks with large size, high growth potential, and low default risk. For these stocks, when the tail risk loadings are increasing, the post average returns are increasing. However, sometimes the patterns are not strictly monotonically increasing. The tail risk premiums are significant when the stocks have large size, high growth potential, and low default risk. The significant risk premium range from 0.33%-0.68% per month. They are nearly all statistically significant at the 1% level.

#### 6.3.1.3 Cross-sectional regressions

In this section, I use Fama and MacBeth (1973) cross-sectional regressions to examine whether the tail risk has an effect on the stock returns. Portfolio-level analysis provides a clear picture of return patterns across different portfolios. Moreover, there is no need to impose a functional form on the relation between tail risk and stock returns. However, portfolio sorts have potential disadvantage stated by Fama and French (2008). They argue that the sorts are hard to interpret as to which risk factors have the unique effect on the average returns. Fama and MacBeth (1973) cross-sectional regressions provide us with another way to test the tail risk premium.

Fama and French (2008) point out that the cross-sectional regressions can produce potential bias because of some extreme stocks in the dataset. Moreover, I already find that the tail risk effect disappears when stocks have small size ( $MV_I$ ), high book-to-market ratios ( $B/M_3$ ), high default likelihood indicators ( $DLI_3$ ), and high O-scores ( $O_3$ ) portfolios. Therefore, I split my dataset into three subsamples according to market capitalization ( $MV$ ), book-to-market ratios ( $B/M$ ), default likelihood indicators ( $DLI$ ),

and O-scores. At the end of each month, I sort all the stocks into three portfolios based on control variables using 30th and 70th percentiles as the breakpoints. For the low and high subgroups with the corresponding control variables, I run the following cross-sectional regressions:

$$R_{i,\tau+1} - R_{f,\tau+1} = \lambda_0 + \lambda_1 \beta_{i,\tau}^{Tail} + \lambda_2' \mathbf{X}_{i,\tau} + \epsilon_{i,\tau+1} \quad (6.5)$$

where  $R_{i,\tau+1}$  denotes the monthly raw return of stock  $i$  from July of year  $\tau$  to June of year  $\tau + 1$ .  $\beta_{i,\tau}^{Tail}$  is the lagged tail loadings from June of year  $\tau$  to May of year  $\tau + 1$ .  $\mathbf{X}_{i,\tau}$  is the  $3 \times 1$  vector of the lagged control variables that are  $\ln(MV)$ ,  $\ln(B/M)$ , and  $MOM$ .  $\ln(MV)$  is the natural logarithm of firm's size calculated with information available at the end of June of year  $\tau$ .  $\ln(B/M)$  is the natural logarithm of the ratio of the book value of equity for the fiscal year ending in year  $\tau - 1$  divided by market equity at the end of December of year  $\tau - 1$ .  $MOM$  is the cumulative compounded stock returns over the last 6 months from June of year  $\tau$  to May of year  $\tau + 1$ . I compute  $t$ -statistics by employing Newey and West's (1987) robust standard errors in order to overcome potential issues of heteroskedasticity and autocorrelation in the regression residuals.

Table 6.5 reports the Fama and MacBeth (1973) regressions for the size, book-to-market, and default risk subgroups. I can find that the coefficients of tail risk loadings are insignificant in the small size ( $MV_1$ ), high book-to-market ratios ( $B/M_3$ ), high default likelihood indicators ( $DLI_3$ ), and high O-scores ( $O_3$ ) portfolios with or without control variables. These results are consistent with the results from portfolio sorts. However, the coefficients of tail risk loadings are all positively significant in the big size

( $MV_3$ ), low book-to-market ratios ( $B/M_1$ ), low default likelihood indicators ( $DLI_1$ ), and low O-scores ( $O_1$ ) portfolios with or without control variables, indicating that stocks with high tail loadings tend to generate high returns in the future. The positive relationship is consistent with the results from portfolio sorts. High-Low represents the difference between the slopes of tail risk loadings in high control variable portfolios and the slopes of tail risk loadings in low control variable portfolios. The differences are all statistically significant at the 10% level, proving that the tail risk effect differs when the stocks have different level of default risk.

From the results of portfolio sorts and cross-sectional regressions, I already find that the default risk has an impact on the relationship between tail risk and expected returns. Specifically, tail risk disappears in the portfolios of the stocks with high default risk. Barberis (2013) argues that the prices of stocks with high default risk have been beaten down. Therefore, these stocks have limited downside. This means even when the market experiences a large crash, investors believe the distressed stocks have limited downside and they are not expect to buy the stocks with low sensitivity to tail risk to hedge the tail risk. In the next section, I will test whether the prices of stocks with high default risk have been beaten down.

Table 6.5: Fama-MacBeth (1973) cross-sectional regressions for the size, book-to-market, and default risk subgroups

At the end of each month, I sort stocks into three subgroups based on their past month's market size ( $MV$ ), book-to-market ratio ( $B/M$ ), and the default risk measures using 30th and 70th percentiles as the breakpoints. "Low" denotes the bottom subgroup that consists of stocks with the lowest variables. "High" denotes the top subgroup that consists of stocks with the highest corresponding variables. "High-Low" denotes the difference between the top and the bottom subgroups. For each month from July of year  $\tau$  to June of year  $\tau + 1$ , I estimate Fama and MacBeth (1973) cross-sectional regressions of monthly excess returns on the lagged tail risk beta and the lagged control variables of the size ( $\ln(MV)$ ), book-to-market ( $\ln(B/M)$ ) and momentum ( $Mom$ ) for the subgroups.  $\ln(MV)$  is the natural logarithm of firm's size calculated with information available at the end of June of year  $\tau$ .  $\ln(B/M)$  is the natural logarithm of the ratio of the book value of equity for the fiscal year ending in year  $\tau - 1$  divided by market equity at the end of December of year  $\tau - 1$ .  $Mom$  is the cumulative compounded returns over the last 6 months from June of year  $\tau$  to May of year  $\tau + 1$ . I use default likelihood indicators ( $DLI$ ) and  $O$ -score as the proxies for default risk. The  $t$ -statistics are calculated using Newey and West's (1987) heteroskedasticity and autocorrelation consistent covariance standard errors and are reported in the parentheses. The sample period is from January 1963 to December 2010.

|                              | <i>Constant</i> | $\beta_{Tail}$ | $\ln(MV)$ | $\ln(B/M)$ | <i>Mom</i> |
|------------------------------|-----------------|----------------|-----------|------------|------------|
| <i>Panel A: Market value</i> |                 |                |           |            |            |
| Low                          | 1.26            | 0.28           |           |            |            |
|                              | (4.82)***       | (1.26)         |           |            |            |
| High                         | 1.24            | 0.12           |           | 0.18       | 0.85       |
|                              | (4.81)***       | (0.62)         |           | (2.28)**   | (4.56)***  |
| High-Low                     | 0.93            | 0.63           |           |            |            |
|                              | (4.63)***       | (2.50)**       |           |            |            |
|                              | 0.90            | 0.46           |           | 0.18       | 0.54       |
|                              | (4.30)***       | (2.10)**       |           | (2.64)***  | (2.19)**   |
|                              | -0.33           | 0.35           |           |            |            |
|                              | (-2.30)**       | (1.69)*        |           |            |            |
|                              | -0.34           | 0.34           |           | 0.00       | -0.31      |
|                              | (-2.43)**       | (1.81)*        |           | (-0.04)    | (-1.46)    |
| <i>(Continued)</i>           |                 |                |           |            |            |

### 6.3. EMPIRICAL RESULTS AND ANALYSIS

(Continued)

|                                                      | <i>Constant</i> | $\beta_{Tail}$ | $\ln(MV)$ | $\ln(B/M)$ | <i>Mom</i> |
|------------------------------------------------------|-----------------|----------------|-----------|------------|------------|
| <i>Panel B: Book-to-market ratio</i>                 |                 |                |           |            |            |
| Low                                                  | 0.80            | 0.80           |           |            |            |
|                                                      | (3.55)***       | (3.02)***      |           |            |            |
| High                                                 | 0.74            | 0.45           | -0.01     |            | 0.52       |
|                                                      | (1.12)          | (2.05)**       | (-0.15)   |            | (2.35)**   |
| High-Low                                             | 1.33            | 0.32           |           |            |            |
|                                                      | (5.63)***       | (1.48)         |           |            |            |
|                                                      | 1.83            | 0.08           | -0.05     |            | 0.62       |
|                                                      | (3.58)***       | (0.42)         | (-1.41)   |            | (3.47)***  |
|                                                      | 0.53            | -0.49          |           |            |            |
|                                                      | (4.01)***       | (-1.95)*       |           |            |            |
|                                                      | 1.09            | -0.37          | -0.04     |            | 0.10       |
|                                                      | (2.09)**        | (-1.71)*       | (-1.00)   |            | (0.57)     |
| <i>Panel C: DLI as a measure of default risk</i>     |                 |                |           |            |            |
| Low                                                  | 1.02            | 0.78           |           |            |            |
|                                                      | (5.24)***       | (3.19)***      |           |            |            |
| High                                                 | 1.72            | 0.37           | -0.05     | 0.21       | 0.62       |
|                                                      | (3.36)***       | (1.95)*        | (-1.67)*  | (2.74)***  | (2.89)***  |
| High-Low                                             | 1.16            | 0.25           |           |            |            |
|                                                      | (3.96)***       | (1.05)         |           |            |            |
|                                                      | 1.46            | -0.04          | -0.03     | 0.23       | 0.56       |
|                                                      | (2.41)**        | (-0.19)        | (-0.60)   | (3.08)***  | (2.30)**   |
|                                                      | 0.14            | -0.53          |           |            |            |
|                                                      | (0.86)          | (-2.17)**      |           |            |            |
|                                                      | -0.26           | -0.41          | 0.03      | 0.03       | -0.06      |
|                                                      | (-0.57)         | (-2.14)**      | (0.64)    | (0.34)     | (-0.34)    |
| <i>Panel D: O-score as a measure of default risk</i> |                 |                |           |            |            |
| Low                                                  | 1.02            | 0.76           |           |            |            |
|                                                      | (4.56)***       | (3.10)***      |           |            |            |
| High                                                 | 1.37            | 0.38           | -0.03     | 0.22       | 0.51       |
|                                                      | (2.49)**        | (1.77)*        | (-0.85)   | (2.56)**   | (2.47)**   |
| High-Low                                             | 1.12            | 0.32           |           |            |            |
|                                                      | (4.71)***       | (1.32)         |           |            |            |
|                                                      | 1.56            | 0.07           | -0.04     | 0.24       | 0.61       |
|                                                      | (2.69)***       | (0.32)         | (-1.07)   | (3.28)***  | (2.83)***  |
|                                                      | 0.09            | -0.44          |           |            |            |
|                                                      | (0.94)          | (-2.10)**      |           |            |            |
|                                                      | 0.19            | -0.31          | -0.01     | 0.02       | 0.10       |
|                                                      | (0.49)          | (-1.67)*       | (-0.34)   | (0.24)     | (0.52)     |

### 6.3.2 Have the prices of stocks with high default risk been beaten down?

In this section, I will sort all the stocks into portfolios by default risk and examine whether the prices of stocks with the highest default risk have been beaten down. In general, at the end of each month, I sort all the stocks into three portfolios by default risk by using 30th and 70th as the breakpoints. I use default likelihood indicators (*DLI*) and *O-score* as the proxies for default risk. Then I calculate the average prices and average market value for each portfolio at the end of each month. I report the mean value of the price and market value for each portfolio in Table 6.6. For the robustness test, I also sort all the stocks into five portfolios by default risk by using 20th, 40th, 60th and 80th as the breakpoints.

Panel A of Table 6.6 presents the average price and market value for each portfolio sorted by default likelihood indicator. When stocks are sorted into three portfolios, Portfolio 3 contains the stocks with the highest default risk. The average market value is 1298679 and average price is 15.15. However, the average price of Portfolio 1, which is the portfolio with the lowest default risk, is 94.18. The price of portfolio with the highest default risk is much lower than the price of portfolio with the lowest default risk, indicating the prices of stocks with high default risk have been beaten down. Moreover, the stocks with high default risk are usually tiny stocks, which are the stocks with small size. When I sort stocks into five portfolios, the average price of portfolio with the highest default risk (Portfolio 5) is 13.92. The results support the conclusion that the prices of stocks with high default risk have been beaten down.

Table 6.6: Price and market value of default risk portfolios

At the end of each month, I sort stocks into portfolios by default risk. When stocks are sorted into three portfolios, Portfolio 1 contains stocks with the lowest default risk and Portfolio 3 contains stocks with the highest default risk. When stocks are sorted into five portfolios, Portfolio 1 contains stocks with the lowest default risk and Portfolio 5 contains stocks with the highest default risk. I report the average price and market value for each portfolio. I use default likelihood indicators (*DLI*) and *O-score* as the proxies for default risk. The sample period is from January 1963 to December 2010.

|                                                      | <i>Portfolios sorted by default risk</i> |         |         |         |         |
|------------------------------------------------------|------------------------------------------|---------|---------|---------|---------|
|                                                      | 1                                        | 2       | 3       | 4       | 5       |
| <i>Panel A: DLI as a measure of default risk</i>     |                                          |         |         |         |         |
| <i>MV</i>                                            | 5169722                                  | 2002247 | 1298679 |         |         |
| <i>PRC</i>                                           | 94.18                                    | 28.60   | 15.15   |         |         |
| <i>MV</i>                                            | 5915164                                  | 3176704 | 1966110 | 1354527 | 1294762 |
| <i>PRC</i>                                           | 110.48                                   | 48.63   | 29.50   | 18.67   | 13.92   |
| <i>Panel B: O-score as a measure of default risk</i> |                                          |         |         |         |         |
| <i>MV</i>                                            | 4764577                                  | 2148860 | 749349  |         |         |
| <i>PRC</i>                                           | 29.36                                    | 24.62   | 16.77   |         |         |
| <i>MV</i>                                            | 5382423                                  | 3245218 | 2047747 | 1323079 | 570863  |
| <i>PRC</i>                                           | 29.90                                    | 27.66   | 24.52   | 21.22   | 15.15   |

Panel B of Table 6.6 presents the average price and market value for each portfolio sorted by *O-score*. Despite the price of portfolio with the lowest *O-score* being much lower than price of portfolio with the lowest *DLI*, I can still find that the average prices of portfolio with the highest default risk have been beaten down. I can conclude that the prices of stocks with high default risk have been beaten down. Therefore, these stocks have limited downside. From the view of behaviour finance, when the market experiences a large crash, investors believe the distressed stocks have limited downside and they are not expected to buy the stocks with low sensitivity to tail event to hedge the tail risk.

On the other hand, following the method by Kelly and Jiang (2014), I exclude the prices below \$5 at the portfolio formation date. This is because these penny stocks are usually associated with high transaction costs and short selling constraints. They are normally illiquid assets. However, the penny stocks are usually have high default risk. Then I include the prices below \$5 at the portfolio formation date and sort all the stocks into five portfolios according to the methods illustrated in section 6.3.1.1. I find that the tail risk premiums are almost insignificant. The results are consistent with the findings that the positive relationship between tail risk and expected returns disappears when the stocks have high default risk.

#### **6.3.3 The financial crisis of 2007-2008 and the tail risk effect**

A large number of defaults and a global recession occurred as a result of the financial crisis of 2007-2008. This recession pushed the economy into a rebalancing period. In this section, I investigate whether the tail risk effect is still significant for the period January 2008 to December 2014, where high default rates were common.

Table 6.7 reports equity returns across tail risk portfolios after the financial crisis of 2007-2008. At the end of each month, I sort all the stocks into quintile portfolios based on their tail loadings,  $\beta_{Tail}$ . I hold the portfolios for the subsequent month and calculate the equal-weighted and value-weighted returns for each portfolio. The portfolios are rebalanced monthly. I find that average returns are both increasing from the Quintile portfolio 1 to Quintile 5 when I calculate equal-weighted and value-weighted returns. But the patterns are not monotonically increasing and the risk premium are

insignificant. While I use risk adjusted returns, the increasing pattern turns out to be decreasing pattern, the risk premium are negative but insignificant except the Carhart four-factor alpha for value-weighted returns. All the these results prove that the tail risk premium do not different from zero, indicating that the strong tail risk effect is not stable after the financial crisis. This result supports the findings by Werner and Upper (2004). They estimate the tail index of bond future and find that the tail index is not not stable over time. Specifically, there are several breaks in the degree of heaviness of the tail index. These breaks are pronounced during the period of 1998 and 2001, which may provides evidence that the the effect of tail risk is affected by Russia and LTCM crises. Therefore, the trading strategy of buying stocks with the highest tail risk loadings and selling stocks with the lowest tail risk loadings does not produce significant profits.

Table 6.7: Equity returns across tail risk portfolios after the financial crisis of 2007-2008

This table reports the equal-weighted (Panel A) and value-weighted (Panel B) monthly average returns and the abnormal returns for tail risk portfolios for the period from January 2008 to December 2014. At the end of each month, the tail risk of each stock is estimated from the previous 12-month daily returns. All stocks are then sorted into five quintile portfolios based on their exposures to the tail risk,  $\beta_{Tail}$ . I hold the portfolios for the subsequent month and rebalance the portfolios monthly. Quintile 1 contains stocks with the lowest  $\beta_{Tail}$  and Quintile 5 contains stocks with the highest  $\beta_{Tail}$ . The  $t$ -statistics are calculated using Newey and West's (1987) heteroskedasticity and autocorrelation consistent covariance standard errors and are reported in parentheses. Statistical significance at the 10%, 5% and 1% levels is indicated by \*, \*\*, \*\*\* respectively.

| Sorting statistic              | Quintile portfolio |                   |                   |                 |                  |
|--------------------------------|--------------------|-------------------|-------------------|-----------------|------------------|
|                                | 1                  | 2                 | 3                 | 4               | 5-1              |
| <i>Panel A: Equal-weighted</i> |                    |                   |                   |                 |                  |
| Average return                 | 0.89<br>(1.56)     | 1.05<br>(1.99)*   | 1.14<br>(1.86)*   | 1.19<br>(1.60)  | 1.26<br>(1.63)   |
| CAPM alpha                     | 0.22<br>(1.54)     | 0.36<br>(2.75)*** | 0.32<br>(2.00)**  | 0.23<br>(1.04)  | -0.02<br>(-0.03) |
| FF3 alpha                      | 0.18<br>(0.91)     | 0.34<br>(3.84)*** | 0.28<br>(3.32)*** | 0.18<br>(1.63)  | -0.07<br>(-0.18) |
| Carhart alpha                  | 0.19<br>(1.09)     | 0.34<br>(4.18)*** | 0.28<br>(2.98)*** | 0.17<br>(1.95)* | -0.10<br>(-0.44) |
| FF5 alpha                      | 0.23<br>(1.55)     | 0.32<br>(3.25)*** | 0.24<br>(2.83)*** | 0.21<br>(1.61)  | -0.02<br>(-0.05) |

(Continued)

(Continued)

| Sorting statistic              | Quintile portfolio |                   |                 |                  |                   |
|--------------------------------|--------------------|-------------------|-----------------|------------------|-------------------|
|                                | 1                  | 2                 | 3               | 4                | 5-1               |
| <i>Panel B: Value-weighted</i> |                    |                   |                 |                  |                   |
| Average return                 | 1.07<br>(1.95)*    | 1.05<br>(1.86)*   | 1.13<br>(1.79)* | 1.14<br>(1.46)   | 1.16<br>(1.45)    |
| CAPM alpha                     | 0.33<br>(2.41)**   | 0.21<br>(1.20)    | 0.13<br>(0.62)  | -0.04<br>(-0.16) | -0.10<br>(-0.25)  |
| Fama three-factor alpha        | 0.29<br>(1.83)*    | 0.18<br>(1.95)*   | 0.09<br>(1.10)  | -0.09<br>(-0.79) | -0.19<br>(-1.24)  |
| Carhart four-factor alpha      | 0.29<br>(2.22)**   | 0.18<br>(2.80)*** | 0.09<br>(1.19)  | -0.09<br>(-0.84) | -0.18<br>(-1.32)* |
| Fama five-factor alpha         | 0.32<br>(2.16)**   | 0.15<br>(1.19)    | 0.03<br>(0.47)  | -0.07<br>(-0.51) | -0.12<br>(-0.57)  |
|                                |                    |                   |                 |                  | -0.44<br>(-1.33)  |

### 6.3.4 Cross-sectional regressions during good times and bad times

In the previous section, I found that the tail risk effect disappears after the financial crisis of 2007-2008. In this section, I shift my focus to different economic conditions for the robust test by using the period of January 1963 to December 2014. Specifically, I divide my sample into two subsamples: good-time sample and bad-time sample. I use the expected market risk premium of Petkova and Zhang (2005) to identify good time and bad time by employing the following regression:

$$R_{m,t+1} = \beta_0 + \beta_1 DIV_t + \beta_2 DEF_t + \beta_3 TERM_t + \beta_4 TB_t + \epsilon_{m,t+1} \quad (6.6)$$

where  $R_{m,t+1}$  is the realized market excess return between  $t$  and  $t + 1$ ,  $DIV_t$  is the dividend yield,  $DEF_t$  is the default spread,  $TERM_t$  is the term spread, and  $TB_t$  is the one-month Treasury bill rate. The variable  $DIV_t$  is computed as the sum of the dividends of the CRSP value-weighted market portfolio over the past 12 months divided by the value of the CRSP market index. The default spread,  $DEF_t$ , is the difference between the yields on Moody's BAA- and AAA-rated corporate bonds. The variable,  $TERM_t$ , is calculated by subtracting the yield on the one-month Treasury bill from the yield on the ten-year Treasury bond.

OLS technique is applied to estimate the coefficients in Equation 6.6. The expected market risk premium, denoted  $\hat{\gamma}_t$ , is the fitted values calculated from Equation (6.7) below.

$$\hat{\gamma}_t = \hat{\beta}_0 + \hat{\beta}_1 DIV_t + \hat{\beta}_2 DEF_t + \hat{\beta}_3 TERM_t + \hat{\beta}_4 TB_t \quad (6.7)$$

When the expected market risk premium is lower than the mean value, I define this period of time as "good", while the expected market risk premium is higher than its mean value, then the period of time is identified as "bad".

At the end of each month for "good" and "bad" time subgroups from July of year  $\tau$  to June of year  $\tau + 1$ , I run Fama and MacBeth (1973) cross-sectional regressions of monthly excess returns on the lagged tail risk loadings with or without control variables, which are  $\ln(MV)$ ,  $\ln(B/M)$ , and  $MOM$ . Table 6.8 reports the regressions results during good times and bad times. The results show that during good times, the slopes of tail risk loadings are positively significant, which is 0.98% per month without control variables and 0.76% per month with control variables. They are statistically significant at the 5% level. However, the slopes turn out to be insignificant during the bad times. The results are consistent with the findings of effect after financial crisis of 2007-2008. Weinstein (1981), Denis and Denis (1995), and Chen (2010) point out that defaults are likely to happen in bad economic conditions because the shortage of available funds causes more failures of corporates in meeting their debt obligations. Barberis (2013) imply that investors tend to ignore tail risk when they hold high distress stocks. Therefore, I can conclude that the tail risk effect is only significant during good times with low default risk.

Table 6.8: Fama-MacBeth (1973) regressions during good times and bad times

Following Petkova and Zhang (2005), I define “good” and “bad” time periods based on the expected market risk premium. A positive change in the expected market risk premium above the mean are defined as “bad” time, while a negative change in the expected market risk premium below the mean are defined as “good” time. I split the full sample into the good and bad times subgroups. For each month from July of year  $\tau$  to June of year  $\tau + 1$ , I estimate Fama and MacBeth (1973) cross-sectional regressions of monthly excess returns on the lagged tail risk beta and the lagged control variables of the size ( $\ln(MV)$ ), book-to-market ratio ( $\ln(B/M)$ ) and momentum ( $Mom$ ) for the subgroups.  $\ln(MV)$  the natural logarithm of firm’s size calculated with information available at the end of June of year  $\tau$ .  $\ln(B/M)$  is the natural logarithm of the ratio of the book value of equity for the fiscal year ending in year  $\tau - 1$  divided by market equity at the end of December of year  $\tau - 1$ .  $Mom$  is the cumulative compounded returns over the last 6 months from June of year  $\tau$  to May of year  $\tau + 1$ . I use default likelihood indicators ( $DLI$ ) and  $O$ -score as the proxies for default risk. The  $t$ -statistics are calculated using Newey and West’s (1987) heteroskedasticity and autocorrelation consistent covariance standard errors and are reported in the parentheses. The sample period is from January 1963 to December 2014.

|      | <i>Constant</i>   | $\beta_{Tail}$   | $\ln(MV)$        | $\ln(B/M)$        | <i>Mom</i>       |
|------|-------------------|------------------|------------------|-------------------|------------------|
| Good | 0.60<br>(1.11)    | 0.98<br>(2.38)** |                  |                   |                  |
|      | 0.88<br>(0.91)    | 0.76<br>(2.18)** | -0.04<br>(-0.73) | 0.06<br>(0.35)    | -0.07<br>(-0.13) |
| Bad  | 1.41<br>(3.89)*** | -0.06<br>(-0.30) |                  |                   |                  |
|      | 1.61<br>(1.39)    | 0.01<br>(0.08)   | -0.01<br>(-0.14) | 0.29<br>(3.44)*** | 0.15<br>(0.73)   |

## 6.4 Conclusions

The relationship between tail risk and stock returns have been well documented in literature. Investors usually use stocks with low sensitivities to tail risk as hedges against large downsides in the market returns. From the view of behaviour finance, investors tend to underweight the tail event and they may ignore the tail event. This empirical chapter tries to figure out whether the default risk has an impact on the tail risk effect.

Using the data from January 1963 to December 2010, I find that stocks

with high tail loadings tend to have higher returns in the future. This result is consistent with findings documented by Kelly and Jiang (2014).

I examine the effect of default risk on tail risk and find that market size, book-to-market ratio, and default risk have large impact on the tail risk effect. When stocks with small size, low growth, and high default risk, the tail risk premium disappears. This result provides the evidence that in high distress stocks, tail risk turns out to be insignificant. I also use Fama and MacBeth (1973) cross-sectional regressions to test the effect of tail risk in different default risk groups. I find that the tail risk is only significant for the stocks with large size, high growth, low default risk. Moreover, I provide evidence that the prices of stocks with high default risk have been beaten down.

I also present the effects of tail risk after financial crisis as well as in different economic conditions. Using the sample period after the financial crisis of 2007-2008, the strong positive relationship between tail risk and stock returns turns out to be insignificant. Then I define good times and bad times according to the method by Petkova and Zhang (2005) and I find tail risk disappears in bad times. According to Barberis's (2013) study, my research implies that when investors hold high distress stocks, they pay little attention to the tail risk. Even when tail risk increases, they believe that the stocks have limited downside. Therefore, they will not require stocks with low sensitivity to tail risk in order to hedge tail risk. I would like to conclude that tail risk tends to be insignificant when investors hold stocks with small size, low growth, high default risk, and during bad times.

# Chapter 7

## Conclusion

### 7.1 Conclusion

In this thesis, I mainly focus on three predictive patterns of return distributions: skewness risk, tail risk and return asymmetry. In Chapter 4, I proposed a new measure of asymmetry in the stock returns instead of skewness risk. I called this new predictive variable "return asymmetry". I examined the relationship between return asymmetry and stock returns. I further investigated the effect of return asymmetry after controlling for other commonly used predictive factors. In Chapter 5, I examined the impact of default risk on the relationship between skewness risk and expected stock returns. I investigated whether the skewness risk effect would be affected by default risk. Moreover, I examined the performance of skewness risk effect after the financial crisis of 2007-2008, as well as good times and bad times. In Chapter 6, I followed the same methodology as in Chapter 5. I examined whether the tail risk would be affected when stocks have high default risk. I also investigated the performance of tail risk after the financial crisis of 2007-2008 and whether the tail risk would also be affected during bad times.

This thesis is motivated by three strands of literature. Motivated by the mixed results on the relationship between skewness risk and stock returns, I question whether skewness is a proper measure of asymmetry. Then, I propose a new measure of asymmetry in the stock market and examine the relationship between return asymmetry and stock returns. I apply Patil et al.'s (2012) method to the daily stock returns and construct a new factor called return asymmetry. I find that return asymmetry is negatively related to expected stock returns. The average raw and abnormal returns for portfolios with the highest values of return asymmetry are significantly lower than the average and abnormal returns for portfolios with the lower values of return asymmetry. I also find that this new factor cannot be explained by other well-known pricing factors like firm's size, the book-to-market ratio, the momentum factor, the liquidity risk factor and the idiosyncratic volatility. My study provides a new measure of asymmetry in the stock returns and this new predictive variable performs better than skewness. This study provides a new insight into the relationship between predictive variable and stock returns.

Motivated by Berd et al. (2007) and Engle (2011), skewness risk might have some connections with default risk. Campello and Chen (2010); Campello et al. (2011) and Calomiris et al. (2012) also document that financial constraints are sensitive to the financial crisis of 2007-2008. I examine the importance of default risk in the relationship between skewness risk stock returns. In the second empirical chapter, I incorporated the default risk, which is measured by default likelihood indicator and O-score, into the investigation of the skewness risk effect. I found that market skewness risk is highly related to firm size, book-to-market ratio, and default risk.

## 7.1. CONCLUSION

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Specifically, the significant market skewness risk effect is concentrated on stocks with large market capitalizations, low book-to-market ratios, low default likelihood indicators, and low O-scores. On the other hand, the size effect, the value and default risk premiums are stronger among stocks with high market skewness risk. The results from Fama and MacBeth (1973)'s cross-sectional regressions confirm that the impact of market skewness risk on stock returns significantly interact with market value, book-to-market ratio, and default risk. I also used out-of-sample data from 2008 to 2013 and investigate the market skewness risk effect after the financial crisis of 2007-2008. My results show that the significant return differences between stocks with lowest and highest sensitivity to innovations in implied market skewness disappear after the crisis. Moreover, the skewness risk disappears during the bad times.

I highlighted the strong interaction effect between market skewness risk and default risk on expected stock returns. This can help to understand the relationship between skewness risk and stock returns. My study provides additional empirical evidence in support of the rational expectations equilibrium model developed by Yuan (2005).

Motivated by Tversky and Kahneman (1992), Hertwig et al. (2004) and Barberis (2013), the prices of stocks with high default risk have been beaten down. Therefore, these stocks have limited downside. Under their hypothesis, when investors hold stocks with high default risk, they tend to underweight the tail event. This means even when the market experiences a large crash, investors believe the distressed stocks have limited downside and thus the tail event does not matter. I start from this behavioural explanation of tail event and try to find that whether there is also a connection between

tail risk and default risk from the rational way.

I examine the impact of default risk on the relationship between tail risk and stock returns in the third empirical chapter. The empirical results show that the tail risk premium are highly significant in the stocks with large market capitalizations, low book-to-market ratios, low default likelihood indicators, and low O-scores. However, the effect of tail risk disappears in the the stocks with small market capitalizations, high book-to-market ratios and high default risk. This is because prices of stocks with high default risk have been beaten down. The stocks with high default risk have limited downside risk. I provide evidence that stocks with high default risk tend to be the stocks with low prices. The findings in the third empirical chapter contribute to the literature that default risk have a large interaction with the effect of tail risk. This can help in understanding the tail risk effect in the stock market.

## 7.2 Limitations of the study

There are some limitations of this study. In the first empirical chapter, I only tested the effect of return asymmetry after controlling firm's size, the book-to-market ratio, the momentum factor, the liquidity risk factor, the idiosyncratic volatility and various skewness factors. Whether this new factor can be explained by other pricing factors needs to be explored. In Chapter 5, I used the sample period from 1996 to 2013 because the sample is constrained by the availability of index option data collected from OptionMetrics. Going further back in time would be much better.

In Chapter 6, I found the empirical results varied when I defined dummy variables based on market value, book-to-market, *DLI*, and *O-score*. When I chose mean value and median value as the standard of dummy variable, the interactions were insignificant. Only when we chose 30th or 70th breakpoints to define the dummy variables, did the interactions turn out to be significant. Thus, I excluded the test on the dummy variables in Chapter 6. Moreover, I found that tail risk does not differ when I define good times and bad times using the method by Campello and Chen (2010). The results in Chapter 5 provide the evidence that the skewness risk is less significant during good times using the method by Campello and Chen (2010). The definition of good times and bad times following Campello and Chen (2010) may not be a good method. Therefore, I also excluded the test on the good times and bad times according to Campello and Chen (2010) in Chapter 6.

## 7.3 Future work

This thesis is based on the test on three predictive variables. There is some future work according to each of the empirical chapters.

In Chapter 4, I defined the return asymmetry for each stock and found a negative relationship with stock returns. Chen et al. (2001) document that aggregate stock market returns are asymmetrically distributed. I could have applied Patil et al. (2012)'s method to the cross-sectional daily stock returns and compute the return asymmetry at the market level. Then I could have tested whether this new measure can be used to predict returns. Finally, the new asymmetry measure could also be applied to other markets instead of

### 7.3. *FUTURE WORK*

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the stock market. In Chapter 5, collecting option data from other databases to get a longer period of sample seems worthwhile. I examine the skewness risk at market level and find that the skewness effect can be affected by default risk. For further studies, I could have focused on the option implied skewness of individual stocks and whether the default risk still has an impact on the relationship between implied skewness and expected stock returns. In Chapter 6, using high frequency data to calculate tail risk for each stocks, I could have tested whether the tail risk is underweighted by investors when they hold stocks with high default risk and during bad times. I found similar results on the skewness risk and tail risk. They both disappeared in the group of stocks with high default risk. Exploring the relationship between skewness risk and tail risk could also be interesting.

# Appendix A

## Plug-in Bandwidth Selection

According to Altman and Léger (1995), the mean integrated squared error can be transformed to the following equations under Sarda's (1993) conditions:

$$MISE(h) = V_1 n^{-1} - V_2 h n^{-1} + B_3 h^4 + C h^2/n + \text{smaller order terms} \quad (\text{A.1})$$

where  $V_1$  and  $V_2$  are the variance terms and  $B_3$  is the squared bias term, defined as follows:

$$V_1 = \int F(r) [1 - F(r)] f(r) W(r) dr \quad (\text{A.2})$$

$$V_2 = 2 \int r k(r) K(r) dr \times \int [f(r)]^2 W(r) dr \quad (\text{A.3})$$

$$B_3 = \frac{1}{4} \left[ \int r^2 k(r) dr \right]^2 \times \int [f'(r)]^2 f(r) W(r) dr \quad (\text{A.4})$$

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and  $C > 0$ . Therefore, the asymptotically optimal bandwidth is

$$h_{opt} = (0.25V_2/B_3)^{1/3}n^{-1/3}. \quad (\text{A.5})$$

Following Hall and Marron (1987), I use the following kernel estimator to estimate  $V_2$ :

$$\hat{V}_2 = 2 \int r k(r) K(r) dr \times \frac{1}{n(n-1)} \sum_{p \neq q} \alpha_v^{-1} k_v \left( \frac{R_p - R_q}{\alpha_v} \right) W(R_p) \quad (\text{A.6})$$

where  $k_v$  is a kernel and  $\alpha_v$  is its bandwidth. Altman and Léger (1995) also introduce the following kernel estimator to estimate  $B_3$ :

$$\begin{aligned} \hat{B}_3 &= \frac{1}{4} \left[ \int r^2 k(r) dr \right]^2 \\ &\times \frac{1}{n^3 \alpha_b^4} \sum_{p=1}^n \sum_{q=1}^n \sum_{k=1}^n k'_b \left( \frac{R_p - R_q}{\alpha_b} \right) k'_b \left( \frac{R_p - R_k}{\alpha_b} \right) W(R_p) \end{aligned} \quad (\text{A.7})$$

where  $k'_b$  is the derivative of a kernel  $k_b$  and  $\alpha_b$  is the associated bandwidth. Then, the optimum bandwidth  $\hat{h}_{opt}$  is estimated as follows:

$$\hat{h}_{opt} = (0.25\hat{V}_2/\hat{B}_3)^{1/3}n^{-1/3}. \quad (\text{A.8})$$

The pilot bandwidths  $\alpha_v$  and  $\alpha_b$  are calculated using the cross-validation approach. Finally, I obtain the result  $\hat{h}_{opt}$  as the plug-in estimator.

# Appendix B

## Implied Market Skewness

I follow Bakshi et al. (2003), Carr and Madan (2001) and Chang et al. (2013) and extract the skewness measure from the option prices as follows:

$$SKEW(t, \tau) = \frac{E_t^* \left\{ [R(t, \tau) - E_t^* [R(t, \tau)]]^3 \right\}}{\left\{ E_t^* \left[ (R(t, \tau) - E_t^* [R(t, \tau)])^2 \right] \right\}^{3/2}} \quad (\text{B.1})$$

The payoff  $H[S]$  is defined as follows

$$H[S] = \begin{cases} R(t, \tau) \\ R^2(t, \tau) \\ R^3(t, \tau) \\ R^4(t, \tau) \end{cases} \quad (\text{B.2})$$

Following Bakshi and Madan (2000), the payoff function can be spanned by out-of-the-money (OTM) European calls and puts.

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$$\begin{aligned}
H[S] &= H[\bar{S}] + (S - \bar{S}) H_S[\bar{S}] + \int_{\bar{S}}^{\infty} H_{SS}[K] (S - K)^+ dK \\
&\quad + \int_0^{\bar{S}} H_{SS}[K] (K - S)^+ dK
\end{aligned} \tag{B.3}$$

where  $H_S[\bullet]$  and  $H_{SS}[\bullet]$  represent the first order and the second order derivative, respectively. The prices of the contracts are obtained by valuing both sides of Equation (B.3) using the risk-neutral measure:

$$\begin{aligned}
E_t^* \{e^{-r\tau} H[S]\} &= \left( H[\bar{S}] + \bar{S} H_S[\bar{S}] \right) e^{-r\tau} + H_S[\bar{S}] S(t) \\
&\quad + \int_{\bar{S}}^{\infty} H_{SS}[K] C(t, \tau; K) dK \\
&\quad + \int_0^{\bar{S}} H_{SS}[K] P(t, \tau; K) dK
\end{aligned} \tag{B.4}$$

where  $C(t, \tau; K)$ ,  $P(t, \tau; K)$ ,  $\tau$  and  $K$  are the price of the European call options, the price of the European put options, the maturity of the options and the exercise price of the options, respectively.

Replacing  $\bar{S}$  in Equation (B.4) with  $S(t)$ , I obtain

$$\begin{aligned}
E_t^* \{e^{-r\tau} H[S]\} &= \int_{S(t)}^{\infty} H_{SS}[K] C(t, \tau; K) dK \\
&\quad + \int_0^{S(t)} H_{SS}[K] P(t, \tau; K) dK
\end{aligned} \tag{B.5}$$

Then, the skewness can be specified as follows:

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$$\begin{aligned}
SKEW(t, \tau) &= \frac{E_t^* \left\{ [R(t, \tau) - E_t^* [R(t, \tau)]]^3 \right\}}{\left\{ E_t^* \left[ (R(t, \tau) - E_t^* [R(t, \tau)])^2 \right] \right\}^{3/2}} \\
&= \frac{e^{r\tau} W(t, \tau) - 3\mu(t, \tau) e^{r\tau} V(t, \tau) + 2\mu(t, \tau)^3}{\left[ e^{r\tau} V(t, \tau) - \mu(t, \tau)^2 \right]^{3/2}} \quad (B.6)
\end{aligned}$$

where  $V(t, \tau)$ ,  $W(t, \tau)$ ,  $X(t, \tau)$ , and  $\mu(t, \tau)$  are defined as follows

$$\begin{aligned}
V(t, \tau) &= \int_{S(t)}^{\infty} \frac{2 \left( 1 - \ln \left[ \frac{K}{S(t)} \right] \right)}{K^2} C(t, \tau; K) dK \\
&\quad + \int_0^{S(t)} \frac{2 \left( 1 + \ln \left[ \frac{S(t)}{K} \right] \right)}{K^2} P(t, \tau; K) dK \quad (B.7)
\end{aligned}$$

$$\begin{aligned}
W(t, \tau) &= \int_{S(t)}^{\infty} \frac{6 \ln \left[ \frac{K}{S(t)} \right] - 3 \left( \ln \left[ \frac{K}{S(t)} \right] \right)^2}{K^2} C(t, \tau; K) dK \\
&\quad - \int_0^{S(t)} \frac{6 \ln \left[ \frac{S(t)}{K} \right] + 3 \left( \ln \left[ \frac{S(t)}{K} \right] \right)^2}{K^2} P(t, \tau; K) dK \quad (B.8)
\end{aligned}$$

$$\begin{aligned}
X(t, \tau) &= \int_{S(t)}^{\infty} \frac{12 \left( \ln \left[ \frac{K}{S(t)} \right] \right)^2 - 4 \left( \ln \left[ \frac{K}{S(t)} \right] \right)^3}{K^2} C(t, \tau; K) dK \\
&\quad + \int_0^{S(t)} \frac{12 \left( \ln \left[ \frac{S(t)}{K} \right] \right)^2 + 4 \left( \ln \left[ \frac{S(t)}{K} \right] \right)^3}{K^2} P(t, \tau; K) dK \quad (B.9)
\end{aligned}$$

$$\mu(t, \tau) \approx e^{r\tau} - 1 - \frac{e^{r\tau}}{2} V(t, \tau) - \frac{e^{r\tau}}{6} W(t, \tau) - \frac{e^{r\tau}}{24} X(t, \tau) \quad (B.10)$$

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where  $r$  is risk free rate.

For a given maturity on each trading day, I employ the cubic spline interpolation to interpolate the implied volatilities between the lowest and the highest available moneyness levels in order to obtain the continuous values of implied volatilities. I use the values of the implied volatility at the boundaries as the implied volatilities that lie outside the range of moneyness. Furthermore, the implied volatilities for the moneyness levels which are between 0.01% and 300% are eliminated. I then use the Black-Scholes options pricing model to calculate the options prices using the available data on implied volatilities. Using Equation (B.6), (B.7), (B.8), (B.9) and (B.10), I calculate the implied skewness for each of the maturity dates based on the call and the put prices. Finally, I employ the linear interpolation to interpolate between maturities to obtain the implied skewness for S&P 500 index options with one month maturity.

# Appendix C

## Firm Characteristics

*MV*: market value, calculated by price per share times shares outstanding at the end of each month.

*B/M*: book-to-market equity, the ratio of the book value of equity to the market equity. According to Davis et al. (2000), the book equity (item *BE*) is the stockholders' equity (item *SHE*), plus balance sheet deferred taxes and investment tax credit (item *TXDITC*), less book value of preferred stock (in the following order: item *PSTKRV* or item *PSTKL* or item *PSTK*). The *B/M* ratio of year  $t$  is the book value of equity for the fiscal year ending in year  $t-1$ , divided by market value at the end of December in year  $t-1$  from CRSP.

*Leverage*: financial leverage using book values, measured as long-term debt (item *DLTT*) plus debt in current liabilities (item *DLC*) divided by book value of total assets (item *AT*).

*CF*: cash flow to assets, calculated as earnings after interest, dividends, and

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taxes but before depreciation divided by book value of total assets ((item *OIBDP* - item *XINT* - item *TXT* - item *DVP* - item *DVC*) / item *AT*).

*CH*: cash holding ratio, calculated by cash and short-term investments (item *CHE*) divided by book value of total assets.

*Profitability*: return on assets, calculated as the ratio of the operating income before depreciation (item *OIBDP*) to the book value of the total assets.

*Sales*: net sales (*SALE* in millions of dollar).

*R&D*: R&D to sales, computed as the ratio of research and development expense (*XRD*) to sales (*SALE*). The ratio is equal to zero when R&D is missing.

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