Option-Implied Betas, Moment Risk Premia and Stock Returns

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I certify that all material in this thesis which is not my own work has been identified and that no material has previously been submitted and approved for the award of a degree by this or any other University.

Signature ....

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Abstract

This thesis examines how stock returns are determined by different *ex ante* risk factors implied from options; these *ex ante* risk factors include option-implied betas, the variance, skew and kurtosis risk premia.

I first compare different option-implied beta measures in future stock return prediction on the basis of Buss and Vilkov (2012). The option-implied beta proposed by Buss and Vilkov (2012) (BV) is found to outperform other beta approaches included in the research. I also propose the implied downside betas and find that the BV implied downside beta performs best and offers an improvement over the BV implied beta. However, the relationship between option-implied or implied downside betas and stock returns is not robust to firm-level variables such as firm size, book-to-market ratio or option-implied moments. These variables are correlated with option-implied betas and implied downside betas, which may obscure the beta-return relationship.

Next, I investigate comprehensively whether the moment risk premia are able to predict the cross-section of stock returns. Cross-sectionally, I find that the variance, skew and kurtosis risk premia are determined differently by firm-level and risk factors. I also find that the moment risk premia have different effects on stock returns. For *ex post* realised stock returns, there is a negative relationship with both the variance and skew risk premia. However, the kurtosis risk premium has a noisy and insignificant relationship with realised stock returns. The price target expected return (PTER) and the implied cost of capital (ICC) are adopted as proxies for *ex ante* expected stock returns. I demonstrate that there is a significantly negative relationship between the variance and skew risk premia and expected stock returns, while there is a significantly positive relationship between the kurtosis risk premium and expected stock returns. The results are robust to firm-level and risk factors, sub-periods and different maturities.

Finally, I investigate whether the moment risk premia are able to explain future index returns at the aggregate stock market level; they are found to have different impacts on index returns depending on the return measure. Both the variance and skew risk premia are inversely related to subsequent realised S&P 500 index returns; however, the variance risk premium has a stronger relationship than the skew risk premium. The kurtosis risk premium has no effect on realised index returns. For the index price target expected return (PTER), neither the variance risk premium nor the skew risk premium has explanatory power with the PTER, while the kurtosis risk premium has a robust and positive relationship with the PTER. For the index implied cost of capital (ICC), both the variance and skew risk premia are significantly and positively related to the ICC, while the kurtosis risk premium has a significantly negative relationship with the ICC. However, the relationships between the moment risk premia and the ICC are not robust to macroeconomic variables. I also find that both the PTER and the ICC can be explained by macroeconomic factors.

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Abbreviations

ATM	At-The-Money
CAPM	Capital Asset Pricing Model
EKurt	Expected Realised Kurtosis
ESkew	Expected Realised Skewness
EVar	Expected Realised Variance
FM regression	Fama-MacBeth (1973) Regression
ICC	Implied Cost of Capital
KRP	Kurtosis Risk Premium
ln(BE/ME)	Log of Book to Market Ratio
ln(ME)	Log of Market Capitalisation
LPM	Lower Partial Moment
MFIK	Model-Free Implied Kurtosis
MFIS	Model-Free Implied Skewness
MFIV	Model-Free Implied Variance
MR	Monotonicity Relation
OTM	Out-Of-The-Money
PTER	Price Target Expected Return
RK	Realised Kurtosis
RN	Risk Neutral
RR	Realised Return
RS	Realised Skewness
RV	Realised Variance
SRP	Skew Risk Premium
VRP	Variance Risk Premium

Chapter 1

Introduction

1.1 Background

Return predictability has long been at the heart of modern finance and the cornerstone of modern empirical asset pricing. Asset pricing models describe relations between the *ex ante* risk of a security and the expectation of the security's future return. Historically, researchers usually focus on the relationship between historical risk and future realised return. The most famous model of asset pricing is the Capital Asset Pricing Model (CAPM), introduced independently by Sharpe (1964), Lintner (1965) and Mossin (1966). According to the CAPM, the expected rate of stock return on a security depends primarily on its systematic risk, known as the market beta, and the risk-return relationship is linear and positive. Since its proposition, the CAPM has been the dominating capital equilibrium model and it has been used widely in practical portfolio management and in academic research.

The CAPM is used widely to estimate the cost of capital of firms and to evaluate their performance. Because of its importance, the CAPM has been tested heavily in empirical studies. Unfortunately, researchers generally reject the validity of the CAPM model (e.g. the famous study by Fama and French, 1992). According to the study of Fama and French (1992), beta has hardly any explanatory power for the expected rate of return on a security. Actually, the expected rate of return depends much more on the size of a company and the book-to-market ratio. Berk (1995) points out that these effects can be traced back to a flawed measurement of beta.

The failure of the CAPM might be caused by the estimate of betas using a regression analysis of historical data. This introduces substantial statistical error into estimates of beta that cannot reflect fully the current market conditions. These methods use past data to estimate betas and thus assume that the future will repeat the patterns of the past in order to justify a simple extrapolation of current or lagged betas. There is a widespread consensus that market beta is time-varying. Historical betas can easily capture this by using a rolling window of historical returns. Even more complicated models are built to capture the time-variation in the betas. However, no matter how complicated models are employed, the historical beta method cannot perform well if future patterns are different from past ones or if past patterns are unstable. Thus, accurate measurement of market beta becomes increasingly important in return predictability. Researchers begin to think how to estimate the *ex ante* risk of a security by employing options.

Options, as forward-looking instruments, attract researchers interest and have been recently used for asset pricing. An option contract is defined as an asset whose future payoff depends on the uncertain realisation of the price of an underlying asset. Black (1975) claims that options trading is growing and that informed investors prefer to transact in option markets directly because of lower brokerage charges and the ability to make leveraged bets. The likely result is that information is reflected in option prices before it is reflected in stock prices.

Because of useful information in options, researchers use options to forecast future volatility of the underlying assets before beta estimation; this is done by means of implied volatility. The concept of implicit volatility is proposed by Latane and Rendleman (1976). Implied volatility is defined as the volatility of the underlying asset that equates the market option price to the corresponding Black and Scholes (1973) option price. Since option prices are expected to incorporate the views of market participants regarding potential future outcomes of the underlying asset price, option-implied volatility is demonstrated to be a strong predictor of future volatility in equity markets (see Poon and Granger, 2003 for a review of option-implied volatility). Option-implied volatility is based on the current market price of an option instead of past observations. All option models require a volatility forecast while the estimation of a standard deviation from a sample of data does not require that. In this respect, options are more informative than historical stock data.

Although standard approaches focus mainly on option-implied volatility, modelling the third moment and even the fourth moment using options is becoming increasingly important for asset pricing. Existing literature shows that investors prefer positive skewness in return distributions (e.g. Arditti, 1967; Kraus and Litzenberger, 1976; Kane, 1982; Harvey and Siddique, 2000). The literature, going back to Kraus and Litzenberger (1976) and including the more recent study of Xing et al. (2010), demonstrates that the asymmetry of the return distribution is important for asset pricing. Furthermore, Conrad et al. (2013) find that option-implied skewness and kurtosis are strongly related to future returns.

Based on option-implied moments, options could be applied to improve market betas. For example, French et al. (1983) (FGK) first introduce the concept of improving historical betas by using option-implied volatility. Chang et al. (2012) (CCJV) use both option-implied volatility and skewness to estimate market betas. They find that the CCJV beta estimates perform relatively well and can explain a sizeable amount of cross-sectional variation in expected returns. Buss and Vilkov (2012) (BV) model option-implied betas using option-implied correlation and volatility. They report that the BV beta confirms a monotonically increasing risk-return relation consistent with the indication of the CAPM.

Besides option-implied betas, downside betas are considered in the literature to be an efficient approach to improve historical betas. For example, Roy (1952) argues that investors usually care for more downside risk than upside gains. Markowitz (1959) advocates replacing variance by semi-variance as a measure of risk, because semi-variance measures downside losses rather than upside gains. Downside betas are indeed found to perform better than the beta from the CAPM (Hogan and Warren, 1972; Ang et al., 2006a). The combination of downside measures and option-implied moments introduces a potential new method to model market betas, implied downside betas, which will be presented in this thesis.

Contrary to the CAPM, the literature regarding asset pricing shows that many risk factors related to option-implied moments, e.g. the variance risk premium can help explain stock returns. Variance swaps have been traded in the market. It allows investors to speculate on or hedge risks associated with the uncertainty about the return variance. A variance swap pays the difference between a standard estimate of the realised variance and the fixed variance swap rate. Since a variance swap costs zero to enter, the variance swap rate represents the risk-neutral expected value of the realised variance. As in Carr and Wu (2009), a direct estimate of the variance risk premium is the difference between the realised variance and the variance swap rate, which measures the terminal profit and loss from a long variance swap contract and holding it to maturity. The expected sign of the average variance risk premium should be negative. Writing variance swaps, receiving fixed and paying floating, is on average profitable. The variance risk premium has been found to have predictive ability in stock returns at the aggregate market level (see Bollerslev et al., 2009) as well as at the individual firm level (see Bali and Hovakimian, 2009 and Han and Zhou, 2012). Although the third and fourth moments (skewness and kurtosis) occupy a prominent role in stock return predictability, skew and kurtosis swaps are not traded in the market and research on the higher moment risk premia is very limited in the asset pricing framework. Kozhan et al. (2013) propose the concept of 'the skew risk premium'; they provide strong empirical evidence for the co-existence of both skew and variance risk premia in the equity market. Bali et al. (2014) investigate the cross-sectional relation between the market's *ex ante* view of a stock's risk and the stock *ex ante* return, and they present that the moment risk premia have a significantly positive relationship with *ex ante* expected returns. There is no published literature at the time of writing on the relationship between the skew and kurtosis risk premia and the cross-sectional realised stock returns, as well as the relationship between the moment risk premia and index returns; the work presented in this thesis fills this gap.

1.2 Research Questions

There are two main research aspects to improve the risk-return relation indicated in asset pricing theories. The first aspect is to investigate whether option-implied moments and their combination with downside risk measures can provide an improvement over historical betas. It is documented in the literature that options contain forward-looking information and that downside measures can improve traditional betas. The second aspect is to construct the moment risk premia as the *ex ante* risk contrary to the CAPM, using the difference between expected realised moments and option-implied moments with the objective of improving the risk-return relation. The research focuses separately on the aggregate stock market and the individual firm level.

The research presented in this thesis addresses the following questions:

1. I compare different option-implied beta methods, named the Historical, FGK, CCJV and BV betas. Which option-implied beta method performs best? I construct implied downside betas. Will they outperform option-implied betas? Are they robust to firm-level factors?
2. Can the moment risk premia help explain the cross-section of stock returns? If they can, are their effects on realised returns and expected return proxies different?
3. Can the moment risk premia predict subsequent stock returns at the aggregate market level? If they can, will they have different effects on realised and expected index returns? Are they robust to macroeconomic factors?

In order to carry out a thorough investigation of the determinants of stock returns in Questions 1 and 2, this research adopts a portfolio analysis, which can be used to detect a linear or nonlinear relationship. In addition, I conduct the Fama and

MacBeth (1973) (FM) regression to examine whether option-implied betas and the moment risk premia can still predict the cross-section of stock returns, even when controlling for different firm-level and risk variables. In order to answer Question 3, this research uses a simple linear regression and a multiple linear regression with macroeconomic variables.

1.3 Contributions of the Thesis

The contributions of this thesis are threefold. First, this thesis compares the Historical, FGK, CCJV and BV beta methods and reports that the BV beta measure works best. Specifically, a portfolio trading strategy that sells the stocks ranked in the bottom quintile by the BV implied beta and buys the stocks in the top quintile by the BV implied beta earns positive profit. Only the BV beta has a monotonically increasing relationship with the equally-weighted return without dividend. This is consistent with the findings of Buss and Vilkov (2012), who show that the BV beta has a monotonically increasing relationship with the value-weighted returns. Additionally, I am the first to propose the implied downside betas based on the downside correlation of Ang et al. (2006a) and option-implied moments. The implied downside betas are modified on the basis of the FGK and BV betas. The thesis shows that the BV implied downside beta performs best and offers an improvement over the BV implied beta. In the portfolio analysis, the BV implied downside beta gives the biggest return difference between the extreme portfolios. Only the BV implied downside beta has a monotonically increasing relationship with the equally-weighted return without dividend. The positive beta-return relation becomes more pronounced when using the BV downside beta. However, the beta-return relation for the BV implied beta and the BV implied downside beta is not robust to firm-level factors. Once firm-level control variables are included in the FM regression, the explanatory power of the BV implied beta and the BV downside beta disappears. This means that option-implied betas and implied downside betas are correlated with these firm-level control variables and this obscures the beta-return relation.

Secondly, this thesis first comprehensively presents that the moment risk premia can be used to explain the cross-section of stock returns with the realised return measure and the expected return measure. Cross-sectionally, the variance, skew and kurtosis risk premia are determined differently by firm-level and risk factors. This thesis first studies the determinants of the skew and kurtosis risk premia. Most importantly, the effects of the variance, skew and kurtosis premia on stock returns are different. To be more specific, for realised stock returns, both the variance and skew risk premia are negatively related to subsequent realised stock returns. The skew risk premium is as important as the variance risk premium in subsequent stock return prediction. However, the kurtosis risk premium has a noisy and insignificant relationship with realised stock returns; the result depends on whether the portfolio is value-weighted or equally-weighted. The negative relation between the skew risk premium and stock returns is robust to firm-level and risk variables, while the variance risk premium is not robust to firm-level and risk control variables. The results are robust to subperiods and different maturities. The thesis is the first work to investigate the relationship between the skew and kurtosis risk premia and realised stock returns. Moreover, I adopt the price target expected return (PTER) and the implied cost of capital (ICC) as proxies for *ex ante* expected stock returns. The variance and skew risk premia are found to be inversely related to expected stock returns. However, the kurtosis risk premium is found to be positively related to expected stock returns. The FM regression shows that the relationship between the moment risk premia and expected stock returns is robust to firm-level and risk control variables, subperiods and different maturities.

Thirdly, this thesis investigates the explanatory power of the moment risk premia in the aggregate market with realised and expected stock returns. For realised index returns, the thesis documents that both the variance and skew risk premia have an inverse relationship with subsequent realised returns in the aggregate stock market. However, the variance risk premium is found to have a stronger relationship than the skew risk premium. The negative relation between the variance and skew risk premia and index returns is robust to macroeconomic factors. For the kurtosis risk premium, I find that it cannot describe realised index returns. This is the first study to investigate the explanatory power of the skew and kurtosis risk premia in aggregate stock market returns. For the *ex ante* expected return proxy, this thesis is the first work to construct two types of index expected returns using the price target expected return (PTER) and the implied cost of capital (IC-C) of all constituents in the S&P 500 Index, respectively. The thesis examines the relationship between the variance, skew and kurtosis risk premia and *ex ante* expected returns in the aggregate stock market. Neither the variance risk premium nor the skew risk premium have a robust and significant relationship with the PTER, but the kurtosis risk premium is positively related to the PTER. For another *ex ante* return measure, both the variance and skew risk premia are significantly and positively related to the ICC, while the kurtosis risk premium has a significantly negative relationship with the ICC. However, the relations between the moment risk premia and the ICC are not robust to macroeconomic variables. Finally, the work of this thesis tests the explanatory power of macroeconomic factors in the aggregate stock market with the *ex ante* and *ex post* return measures. Both the PTER and the ICC can be explained satisfactorily by macroeconomic factors, while realised index returns cannot be described by macroeconomic factors.

1.4 Structure of the Thesis

The remainder of this thesis is organised as follows. In Chapter 2, I provide the comprehensive literature on different risk measures and its application to stock return prediction. Section 2.1 gives a thorough literature review on market betas, including the traditional beta indicated from the CAPM, option-implied betas and downside betas. Section 2.2 presents realised and risk-neutral variance, skewness and kurtosis, and their relationship with stock returns. Section 2.3 describes the literature on the variance, skew and kurtosis risk premia, and their predictability in stock returns.

Chapter 3 describes the data and models of option-implied variance, skewness and kurtosis that are used in this thesis. Section 3.1 presents the data sources and how option and equity data on the S&P 500 Index and its constituents are collected and merged. Section 3.2 presents the formulas of risk-neutral variance, skewness and kurtosis following the model-free method of Bakshi et al. (2003)[1].

Chapter 4 reports an investigation of the relationship between option-implied betas or implied downside betas and stock returns. I adopt a portfolio analysis to study the beta-return relation and the Fama and MacBeth (1973) (FM) regression to further study whether the beta-return relation is robust to firm-level control variables.

Chapter 5 provides a test of the variance, skew and kurtosis risk premia in stock return prediction for individual firms. I employ both the realised return measure and the expected return measure. The methodologies employed in the research are a univariate portfolio analysis, a double portfolio analysis and the FM regression. This chapter also provides a robustness test for firm-level and risk factors, subperiods and moments with different maturities.

Chapter 6 examines the variance, skew and kurtosis risk premia in stock return prediction at the aggregate stock market level. Both the realised return measure and the expected return measure are constructed in the thesis. This chapter employs both a simple linear regression and a multiple linear regression to test the relationship between the variance, skew and kurtosis risk premia and index returns. Macroeconomic variables are included in the multiple regression for the robustness test.

In the last chapter, Chapter 7, I conclude my findings. I also describe the limitations of the presented work and make suggestions for future work.

[1] The model-free risk-neutral volatility has been earlier modelled by Britten-Jones and Neuberger (2000) and Dupire et al. (1994).

Chapter 2

Literature Review

In this chapter, I review the literature on the risk-return relation within the asset pricing framework. Understanding how stock returns are determined has been at the centre of finance. The CAPM is the first and most famous asset pricing model in the literature. The market betas in the CAPM are usually modelled by using historical returns, which are essentially historical risk. However, asset pricing theories actually describe that different *ex ante* risks of the security are able to cause different future stock returns. Since options are forward-looking instruments, the *ex ante* risks are normally evaluated by option-implied information.

The following review will start with the systematic risk, known as the market betas, indicated in the CAPM. When the CAPM was first tested, they did not have any other means to estimate betas other than with historical data. The CAPM indicates that market beta is the only variable describing the cross-section of stock return. However, the famous paper by Fama and French (1992) rejects the CAPM. Fama and French (1992) state that the beta-return relationship disappears and they support the size effect and the book to market effect. Due to the failure of the CAPM, two main approaches are proposed by asset pricing researchers. This first approach is to develop different betas by using options or using downside measures in order to improve traditional betas. In this thesis, I will review traditional market betas, downside betas and option-implied betas. The second approach is to model the *ex ante* risk instead of market betas, like the moment risk premia. Return moments, especially high moments, have become popular in asset pricing recently. I will provide a comprehensive review of the measures of realised and option-implied moments; both of these measures contain more useful information than the measures from historical data. They are found to be able to describe stock returns. Since there exists a difference between realised and option-implied moments, the difference between these two measures represents the moment risk premia. The thesis finally provides a review of the development of the moment risk premia and their importance in asset pricing.

2.1 Market Betas

2.1.1 Traditional Market Betas

The CAPM of Sharpe (1964), Lintner (1965) and Mossin (1966) has long shaped the way academics and practitioners think about average returns and risk. The CAPM is built on the mean-variance framework of Markowitz (1952) whereby the market portfolio of invested wealth is mean-variance efficient. The efficiency of the market portfolio indicates that the relationship between beta and return is positive and linear, and that market betas are the only factor describing the cross-section of expected returns. The CAPM is the first co-moment model. For individual assets, the CAPM implies the following relationship:

$$E(R_i) = R_f + \beta_i(E(R_M) - R_f) \tag{2.1}$$

where R_i denotes the return on stock i, R_f is the risk-free interest rate and R_M is the market return. The market beta β_i for stock i is estimated by:

$$\beta_i = \rho_{i,M}\frac{\sigma_{i,t}}{\sigma_{M,t}} = \frac{Cov(R_i,R_M)}{Var(R_M)} \tag{2.2}$$

According to the CAPM, expected asset returns are decided only by their systematic risk, the market betas. In this way, the CAPM can be rejected by providing evidence that the beta-return relation disappears or other factors can be used to describe stock returns.

2.1.2 Empirical Studies of Traditional Market Betas

The famous and established study of Fama and MacBeth (1973) proposes a cross-sectional regression running period by period to test the risk-return relationship.

$$R_{i,t} = \alpha_t + \lambda_t \hat{\beta}_{i,t} + \varepsilon_{i,t} \tag{2.3}$$

In the regression, the coefficients α and λ have a subscript t in equation (2.3) because they are estimated for each period. After running regressions for each period, I obtain a series of estimated coefficients. I then calculate the time-series average of these coefficients. More recently, the Fama-MacBeth regression has become the accepted standard method used in the literature. The empirical results of Fama and MacBeth (1973) support the positive risk-return relationship during the pre-1969 period, as predicted by the CAPM in the US stock market.

The CAPM has been tested extensively throughout the world equity markets and its validity has often been questioned. The early study of Jensen et al. (1972) puts the CAPM in doubt by finding that the expected return on an asset is not strictly proportional to its beta. The positive and linear risk-return relationship is put in doubt by some later studies (see Reinganum, 1981; Lakonishok and Shapiro, 1986; Fama and French, 1992). Among these, the most influential study was conducted by Fama and French (1992), who provide strong evidence that the relation between market beta and average return disappears during the more recent 1963-1990 period of US stock return data even when beta is the only explanatory variable to average returns. The recent study by Wurgler et al. (2010) shows that high beta stocks have performed substantially worse than low beta stocks in the US markets. Apart from the US markets, the failure of the CAPM has been observed in the UK stock market by Strong and Xu (1997) and Fletcher (1997), and in the German market by Schlag and Wohlschieß (1997).

Since the late 1970s and early 1980s, empirical tests of the CAPM have shifted to firm-level or alternative risk variables other than market betas. The CAMP implies that only market beta can describe the expected rate of returns. If firm-level or other risk variables can explain the cross-section of stock returns then the CAPM is rejected.

There is mounting evidence in the literature to support that firm-level variables describe the cross-section of stock returns. Banz (1981) presents evidence of a size effect in US stock returns; that is, the negative relation between firm size and stock returns. The size effect is also found by Levis (1985) in the UK market and Ho et al. (2000) in the Hong Kong market. Basu (1983) finds the book-to-market effect; the book-to-market ratio has a positive relation with stock returns. Studies by Chan et al. (1991), Chan and Chui (1996) and Ho et al. (2000) provide strong evidence of the book-to-market effect in the Japanese, UK and Hong Kong markets, respectively. The most famous study by Fama and French (1992) confirms the existence of the size effect and the book-to-market effect. The current 'industry standards' are the Fama and French (1993) three-factor model (market risk premium, size, and book-to-market) and the Carhart (1997) four-factor model (the three factors listed above augmented by return momentum). In addition, Amihud (2002) finds that expected market illiquidity has a positive and significant effect on *ex ante* stock excess return and that unexpected illiquidity has a negative and significant effect on contemporaneous stock return.

However, not all literature supports the size and book-to-market effect. Studies by Chan and Chui (1996), Fletcher (1997), Levis and Liodakis (2001) and Morelli (2007) in the UK market, Lilti and Montagner (1998) in the French market, and Artmann et al. (2012) in the German stock market fail to find any size effect. Patton and Timmermann (2010) also suggest that the size effect in expected returns is absent from growth firms and among loser stocks in the US market. Artmann et al. (2012) do not find evidence for the book-to-market effect in the German market.

2.1.3 Downside Betas

Since the failure of the CAPM, researchers have sought a downside risk method to improve market betas. If an asset tends to drop more in a bear market than its increase in a bull market, this asset is to be considered unattractive by investors. Investors who are sensitive to downside losses relative to upside gains require a premium for holding assets that covary strongly with the market when the market declines. When agents place greater emphasis on downside risk than upside gains, assets with high sensitivities to downside market movements have high average returns.

The early study of Roy (1952) argues that investors care for more downside risk than upside gains, or simply, safety from disaster as a foremost goal. Markowitz (1959) advocates replacing variance by semi-variance as a measure of risk, because semi-variance measures downside losses rather than upside gains. Hence, in equilibrium, investors who are averse to downside losses demand greater compensation, in the form of higher expected returns, for holding stocks with high downside risk.

Empirical tests of the mean-variance CAPM show that the average returns from low-beta (high-beta) stocks are too high (low) relative to the prediction of the CAPM (see, for example, Jensen et al.,1972; Fama and MacBeth,1973 and Fama and French, 1992). Price et al. (1982) show that the historical downside betas of US stocks differ systematically from the regular betas.

Hogan and Warren (1972) propose the semi-variance beta by employing Roy (1952)'s Safety First rule to replace variance with semi-variance.

$$\beta_i = \frac{E(R_i R_M | R_M \leq \theta)}{E(R_M^2 | R_M \leq \theta)} \tag{2.4}$$

where θ is the threshold to define the downside market.

Ang et al. (2006a) estimate downside betas based on the conditional downside covariance.

$$\beta_i = \frac{Cov(R_i, R_M | R_M \leq \theta)}{Var(R_M | R_M \leq \theta)} \tag{2.5}$$

where θ is the threshold to define the downside market.

Bawa (1975) also develops a proxy for downside beta as the Lower Partial Moment (LPM). Bawa and Lindenberg (1977) develop a market equilibrium model based on the LPM. In their model, the general beta in the CAPM is replaced with the mean-lower partial moment as a measure of systematic downside risk. Harlow and Rao (1989) examine a generalisation of the mean-semi-variance equilibrium model, based on general LPM. Post et al. (2012) find that the mean-semi-variance equilibrium model outperforms the other two downside models. When comparing downside betas with traditional betas, some researchers, e.g. Post and van Vliet (2005), Ang et al. (2006a), Tahir et al. (2013), report that downside risk based CAPM outperforms variance based CAPM.

2.1.4 Option-Implied Betas

Market betas are usually estimated by relying solely on historical stock returns. However, serious problems arise when using historical returns to model market betas, such as sensitivity to the realised premium in the time period used (see Mc-Nulty et al., 2002). Instead of using only historical stock returns, researchers have begun recently to focus on using information extracted from current option prices to measure betas. Such forward-looking betas reflect the most recent market information and impound traders' expectations. They have the potential to improve the performance of historical betas.

Options, as forward-looking instruments, contain predictive information about the future stock market. For example, many studies have demonstrated that option-implied volatility is a strong predictor of future volatility in equity markets (see Poon and Granger, 2003 for a review). Researchers have also found recently that option-implied high moments (skewness and kurtosis) and correlation contain predictive information about the stock market (see Christoffersen et al., 2011).

Based on option-implied moments, French et al. (1983) (FGK) first introduce a hybrid estimation method to compute market betas using correlations from historical return data and the ratio of stock-to-market implied volatilities. Chang et al. (2012) (CCJV) use both option-implied skewness and volatilities to estimate market betas. They find that the CCJV beta estimates perform relatively well and can explain a sizeable amount of cross-sectional variation in expected returns. Buss and Vilkov (2012) (BV) construct the option-implied beta using option-implied correlation and volatilities. They also find that the BV beta confirms a monotonically increasing risk-return relation consistent with the indication of the CAPM.

Besides the option-implied beta measures described above, some other researchers, e.g. McNulty et al. (2002), Husmann and Stephan (2007), Fouque and Kollman (2011), seek other ways to improve market betas using options and find that option-implied betas outperform historical betas. For example, Siegel (1995) proposes a method whereby betas can be estimated from current option prices without recourse to historical capital market data. Fouque and Kollman (2011) use a calibration technique for the beta parameter and it is calibrated from skews of implied volatilities. These studies exploring option markets to improve traditional beta methods find that options can improve the performance of historical betas in the determinants of the cross-sectional return.

2.2 Realised and Risk-Neutral Moments

2.2.1 Realised and Risk-Neutral Moment Measures

The second moment of returns, known as volatility, has played an important role in asset pricing, risk management and academic research. There are two new model-free variance measures commonly used in the recent academic and financial market practitioner literature. The first measure is that of model-free realised variances. As demonstrated in the literature, these types of measure afford much more accurate *ex post* observations of actual variance than the more traditional sample variances based on daily or high-frequency data (see Andersen et al., 2001; Barndorff-Nielsen, 2002; Andersen et al., 2003). Realised variances are computed by summing squared returns from high-frequency data over short time intervals during the trading day.

$$RV_t = \sum_{i=1}^{N} R_{t,i}^2 \tag{2.6}$$

where RV_t denotes the realised variance on day t, $R_{t,i}$ represents the intraday high-frequency return on day t, N is the total number of observations on day t.

The second variance measure is that of model-free implied variances, which are computed from option prices without the use of any particular option-pricing model. These measures provide the *ex ante* risk-neutral expectations of future variances and they do not rely on the Black-Scholes pricing formula. The most famous implied volatility is the VIX index, introduced by the Chicago Board Options Exchange (CBOE) in 1993. VIX has become the premier benchmark for US stock market volatility. Britten-Jones and Neuberger (2000) derive a model-free implied volatility under the diffusion assumption. Jiang and Tian (2005) extend the model-free implied volatility of Britten-Jones and Neuberger (2000) to asset price processes with jumps and they develop a simple method for implementing it using observed option prices. Over time, the CBOE adopts this method to calculate the VIX.

Although standard approaches to asset pricing concentrate largely on the first and second return moments, the third and fourth return moments have recently become increasingly important for asset pricing and risk management. There is mounting evidence in the literature to suggest the importance of co-skewness for both individual stocks and for the market as whole (e.g. Kraus and Litzenberger, 1976; Kane, 1982; Harvey and Siddique, 2000). Additionally, investors hold concave preferences and like positive skewness. Kraus and Litzenberger (1976), Kane (1982) and Harvey and Siddique (2000) extend the mean-variance portfolio theory of Markowitz (1952) to incorporate the effect of skewness on valuation. They present a three-moment asset pricing model in which investors prefer positive skewness.

Skewness is estimated using a model-free approach in two ways, similar to variances. For the 'model-free realised skewness', Amaya and Vasquez (2010), Amaya et al. (2011) and Choi and Lee (2014) compute realised skewness by using intraday high-frequency returns similar to the realised variance measure of Andersen et al. (2003), which is shown in equation (2.6). Neuberger (2012) proposes modelling realised skewness at long horizons that is computed from high-frequency data and from option returns.

For the 'model-free implied skewness', the most commonly used method is that proposed by Bakshi et al. (2003), whose method relies on a continuum of strikes and does not incorporate specific assumptions on an underlying model. The three moments (variance, skewness and kurtosis) can be expressed as functions of payoffs on a quadratic, a cubic and a quartic contract. Besides the model-free risk-neutral approach of Bakshi et al. (2003), there are also other related risk-neutral skew proxies. For instance, Xing et al. (2010) and Atılgan et al. (2010) use the difference between the implied volatilities of out-of-the-money (OTM) put options and the implied volatilities of at-the-money (ATM) call options as a proxy for skewness. Cremers and Weinbaum (2010) use the difference in implied volatilities between pairs of call and put options to measure deviations from the put-call parity.

There is limited literature on modelling kurtosis. Amaya et al. (2011) and Choi and Lee (2014) estimate realised kurtosis similar to the realised variance measure of Andersen et al. (2003). Bakshi et al. (2003) provide a model-free approach to model risk-neutral kurtosis.

2.2.2 Volatility and Stock Returns

The second return moment plays an important role in asset pricing and it has been researched extensively in the literature. The relationship between implied volatility and stock returns is mixed. Giot (2005) shows that there is negative relationship between implied volatility (VIX and VXN) and stock index returns for the S&P 100 and NASDAQ 100 indices. Conrad et al. (2013) document a negative relation between implied volatility and subsequent returns in the cross-section. Dennis et al. (2006) find that individual stock returns have only a modestly negative relation with innovations in their expected volatility. However, Guo and Whitelaw (2006), and Banerjee et al. (2007) find that market returns are positively related to implied volatilities. Bali et al. (2014) show that option-implied volatility is positively related to *ex ante* expected stock returns. Amaya et al. (2011) do not find a strong relationship between realised volatility and next week's stock returns.

Researchers have found recently the importance of idiosyncratic volatility in stock return determinants. If idiosyncratic risk drives returns, then the CAPM does not hold. Results for the cross-sectional relation between idiosyncratic risk and expected stock returns are mixed. Ang et al. (2006b) measure idiosyncratic volatility of individual stocks based on the three-factor Fama and French (1993) model and show that stocks with low idiosyncratic risk earn high average returns. Ang et al. (2009) show that stocks with high idiosyncratic volatility have abnormally low average returns around the world. However, Fu (2009) shows that idiosyncratic risk varies substantially over time and indicates that the existing literature cannot identify a positive relation because the conditional idiosyncratic volatility in earlier studies does not capture the time-varying property. Fu (2009) documents a positive relation between idiosyncratic risk and expected return when investors do not diversify their portfolio. Bali and Cakici (2008) document that data frequency (daily versus monthly) used to estimate idiosyncratic volatility, weighting schemes used to compute average portfolio returns, breakpoints utilised to sort stocks into quintile portfolios and exclusion of the smallest, lowest priced and least liquid stocks from the sample all play a crucial role in determining the existence and significance of a cross-sectional relation between idiosyncratic risk and expected returns.

2.2.3 Skewness and Stock Returns

Empirical studies have tested the ability of skewness or related measures to predict the cross-sectional variation in stock returns. Evidence for a relationship between risk-neutral skewness and stock returns is mixed. Atılgan et al. (2010), Bali et al. (2011), Yan (2011) and Conrad et al. (2013) find that there exists a theoretically consistent negative relation between risk-neutral skewness and stock returns. On the contrary, Xing et al. (2010), Cremers and Weinbaum (2010), Rehman and Vilkov (2012) and Stilger et al. (2014) favour that risk-neutral skewness is positively related to future stock returns. Additionally, Chang et al. (2013) find that stocks with high exposure to innovations in implied market skewness exhibit low returns on average. Diavatopoulos et al. (2012) show that changes in skewness have strong predictive power for future stock returns, even after controlling for implied volatility. Boyer et al. (2010) document that historical-based estimates of skewness provide poor forecasts of future skewness.

For the realised third moment, Amaya and Vasquez (2010) confirm a negative relation between realised skewness and stock returns in the cross section. Amaya et al. (2011) find a strong negative relationship between realised skewness and next week's stock returns. Choi and Lee (2014) find that there exists a negative relationship between realised daily skewness and subsequent stock returns when there is no high-impact information release, but that the relationship becomes positive if realised skewness is associated with such releases.

Co-skewness measures how much two random variables change together. It is the third standardised cross central moment, related to skewness as covariance is related to variance. Co-skewness may help explain the cross-section of stock returns across assets (e.g. Harvey and Siddique, 2000). Besides systematic risk, idiosyncratic skewness is also very important to stock return prediction. Historical and risk-neutral idiosyncratic skewness is able to explain stock returns. Boyer et al. (2010) investigate the relation between expected idiosyncratic skewness calculated from the Fama and French (1993) three-factor model and stock returns. They find that expected idiosyncratic skewness and stock returns are negatively related. Conrad et al. (2013) find that risk-neutral idiosyncratic skewness (the constant of regression of the risk-neutral total skewness by Bakshi et al. (2003) on the risk-neutral co-skewness by Harvey and Siddique (2000)) is negatively related to stock returns.

2.2.4 Kurtosis and Stock Returns

Published research on kurtosis in the asset pricing framework is very limited with only a few studies. Specifically, Conrad et al. (2013) find a positive relation between option-implied kurtosis and subsequent returns in the cross-section. Bali et al. (2014) show that option-implied kurtosis is positively related to *ex ante* expected returns. Amaya et al. (2011) find a very strong positive relationship between realised kurtosis and next week's stock returns.

2.3 The Variance, Skew and Kurtosis Risk Premia

2.3.1 Presence of the Variance, Skew and Kurtosis Risk Premia

Realised and risk-neutral variance, skewness and kurtosis are evaluated with different methods and using different types of data. Hence, there exist differences between these two moment measures and the difference is called the moment risk premia.

The presence of the variance risk premium at the aggregate market level and at the individual stock level has already been documented extensively in the literature. Bakshi and Kapadia (2003a) present the variance risk premium in a non-parametric way by analysing the profits and losses from the Black-Scholes delta-hedged positions in the S&P 500 and S&P 100 Index options. They find that the market volatility premium is negative. Bakshi and Kapadia (2003b) show the existence of a negative market volatility risk premium in index options and individual equity options, which is that implied volatilities exceed realised volatilities[1]. Bakshi et al. (2003) show that the skew and variance risk premia can be explained by higher moments of the distribution of log returns. Bakshi and Madan (2006) link the variance risk premium, the departure between the risk-neutral and physical index volatility, with higher order moments of the return distribution and investor risk aversion. They also find that the variance risk premium is positive when investors are risk averse and when the physical index distribution is negatively skewed and leptokurtic. The findings of Bakshi and Madan (2006) are in line with the results of Jiang and Tian (2005) and Bollerslev et al. (2011), who find that the risk-neutral index volatility generally exceeds the physical return volatility. Carr and Wu (2009) propose a direct and robust method to quantify the variance risk premium by using the difference between the realised variance and the synthetic variance swap rate. $VRP = (RV_{t,T} - SW_{t,T}) * 100$, where RV is the realised variance and SW is the variance swap rate. They show that this measure is, on average, negative for a range of stock market indices, which indicates that market variance risk is indeed priced. Todorov (2010) identifies and investigates the temporal variation in the market variance risk premium using 5-minute high frequency data on the S&P 500 Index. The variance risk is manifest in two salient features of financial returns: stochastic volatility and jumps. Konstantinidi and Skiadopoulos (2014) find that a deterioration of the economy and of the trading activity increases the variance risk premium.

Additional evidence for the presence of the variance risk premium is also avail-

[1] Jackwerth and Rubinstein (1996) provide an explanation of why implied volatilities exceed realised volatilities. Market volatility tends to increase when stock market falls. When options are added to a market portfolio, this will help hedge market risk. Hence, this is consistent with a negative volatility risk premium.

able from a fully parametric estimation of the pricing kernel[2]. For example, Bates (2000), Pan (2002) and Eraker (2004) analyse the variance risk premium in conjunction with the return risk premium by estimating various parametric option pricing models with either Bayesian methods or efficient methods of moments. Most recently, Kimmel et al. (2007) propose a maximum likelihood method for estimating stochastic volatility dynamics and the volatility risk premium based on closed-form approximations to the true likelihood function of the joint observations on the underlying asset and option prices.

Based on the definition of the variance risk premium by Carr and Wu (2009), Kozhan et al. (2013) propose the skew risk premium, which is defined as the excess return from a skew swap. $xs_t = rskew_t / skew_t - 1$, where xs_t is the excess return from a skew swap, $rskew_t$ is realised skewness and $skew_t$ is the skew swap rate. Kozhan et al. (2013) provide strong empirical evidence for the co-existence of both skew and variance risk premia in the equity market. They find that average realised skew is substantially smaller (in absolute terms) than average implied skew, pointing to the existence of a skew risk premium. Implied skew is negative throughout the sample period, and realised skew is on average negative. So the writer of a skew swap who receives fixed and pays floating generally receives and pays negative amounts and on average loses money. The average excess return from a skew swap is -42.1%.

2.3.2 The Variance Risk Premium and Stock Returns

The variance risk premium exists and has predictive power for returns in the aggregate market and among individual firms.

The variance risk premium is found to be able to predict stock returns at the aggregate market level. Specifically, Bollerslev et al. (2009) find that the variance risk premium, defined as the difference between risk-neutral and realised vari-

[2]The pricing kernel is estimated as the ratio of risk-neutral distributions and physical distributions.

ance, has explanatory power to the post-1990 aggregate stock market returns. They support that high values of the variance risk premium can predict high future index returns. Drechsler and Yaron (2011) demonstrate that the variance risk premium, defined as the difference between the squared VIX index and the expected realised variance, is useful for measuring agents' perceptions of uncertainty and the risk of influential shocks to the economic state vector. They show conditions under which the variance risk premium displays significant time variation and future return prediction. Bollerslev et al. (2011) detect significant evidence for the temporal variation in the volatility risk premium, which is directly linked to macro-finance state variables by applying a small-scale Monte Carlo experiment. They find that the volatility risk premium could predict future stock market returns for the S&P 500 Index. Bekaert and Hoerova (2014) decompose the squared VIX into two components, which are the conditional variance and the variance risk premium. They find that the variance risk premium predicts stock returns while conditional stock market variance predicts economic activity and has a relatively high predictive power for financial instability.

The variance risk premium also has predictive power for stock returns at the individual stock level. Bali and Hovakimian (2009) propose the volatility spread (similar to the variance risk premium) as the realised-implied volatility spread. They find a significantly negative relation between the volatility spread and the cross-section of stock returns. However, Han and Zhou (2012) estimate the variance risk premium as the difference between risk-neutral variance and realised variance and they show that the variance risk premium is positively related to the cross-section of stock returns. Bali et al. (2014) show that the variance, skew and kurtosis risk premia are positively related to *ex ante* expected stock returns.

The variance risk premium is able to explain stock returns in the global market. Bollerslev et al. (2014) define a 'global' variance risk premium and find stronger stock return predictability. Londono (2014) provide empirical evidence that the US variance risk premium has predictive power for international stock returns.

Chapter 3

Data and Option-Implied Moments

3.1 Data

I use the daily data of the S&P 500 Index and its constituents for a sample period from January 4, 1996 to December 31, 2012; a total of 4,278 trading days. The S&P 500 Index serves as a proxy for the US market.

The constituents of the S&P 500 Index are obtained from COMPUSTAT year by year. The total number of companies (including additions and deletions) in the index from 1996 to 2012 is reported in the second column of Table 3.1. The financial statement data, such as book value of common equity and balance-sheet deferred taxes, that are used in this thesis are also from COMPUSTAT. They are quarterly data, so I fill in the other months for each quarter. The daily S&P 500 Index and stock prices on its constituents are obtained from the Center for Research in Security Prices (CRSP). Holding period return, return without dividends, number of shares outstanding and share volume are also taken from CRSP. Holding period period is calculated on the basis of total returns from the asset or portfolio, i.e. income plus changes in value. The index weights for each day are computed using closing market capitalisation of all current index components from the previous day. It is the percentage of the market value of all securities used, which is downloaded from index data. For stocks, firm size is measured by market capitalisation, which is equal to equity price multiplying by shares outstanding. Daily option data on the S&P 500 Index and its constituents with all maturities are obtained from OptionMetrics. This database contains data for all US exchange-listed equities and market indices, as well as for all listed US index and equity options. I extract secid, date, exdate, last date, call or put flag, strike price$\times$1000, best bid, best offer, volume, open interest rate, implied volatility and delta. For European options, implied volatilities are calculated using mid-quotes and the Black-Scholes formula. For American options, a binomial tree approach that takes into account the early exercise premium is employed. Treasury bills, as a proxy for risk-free interest rates, are obtained from CRSP Treasuries Database.

After obtaining the constituents of the S&P 500 Index from COMPUSTAT, stock data from CRSP and option data from OptionMetrics, I merge these three databases. First, I merge stock data with index constituents (COMPUSTAT) and delete stock data which are not in the index period. Second, I merge the combined stock data with option data. After merging these three databases, I obtain the number of companies in the index with both option and stock data, which is reported in the fourth column of Table 3.1. The percentage of companies with both option and stock data is provided in the last column of Table 3.1.

Sorted by secid or PERMNO, I obtain a total number of 922 companies with both option and stock data in the data sample from 1996 to 2012. From Table 3.1, it can be seen that the companies in the S&P 500 Index with both option and stock data compose above 90% of all constituents. This percentage generally increases from 92.68% in 1996 to 100% in 2012. At each time point, there are exactly 500 firms. Over a period of time (one year), the number of companies in the S&P 500 Index exceeds 500 because of additions and deletions of firms in the index. From the difference between Column 2 and Column 3 in Table 3.1, I find that some firms are added to and removed from the S&P 500 Index in the same year.

I delete the data that do not meet some standards. As in Bakshi et al. (1997), Bakshi et al. (2003), Jiang and Tian (2005) and Chang et al. (2012), I use the average of the bid and ask quotes for each option contract. I filter out average quotes less than $3/8. These prices may not reflect true option value due to proximity to tick size. I also filter out quotes that do not satisfy standard no-arbitrage conditions. For calls, I require the bid price to be less than the spot price and the offer price to be at least as large as the spot price minus the strike price. For puts, I require the bid price to be less than the strike price and the offer price to be at least as large as the strike price minus the spot price. I eliminate in-the-money options because they are less liquid and more expensive than out-of-the-money (OTM) and at-the-money (ATM) options. Following Jiang and Tian (2005), in-the-money options are defined as put options with $K/S \geq 1.03$ and call options with $K/S \leq 0.97$. Around 60% of original option data that do not meet the standards are dropped for the S&P 500 index.

3.2 BKM Option-Implied Moments

Option-implied moments (including variance, skewness and kurtosis) are extracted from option data with the model-free approach. I follow the formulas presented in Bakshi and Madan (2000) and Bakshi et al. (2003). Bakshi and Madan (2000) show that the continuum of characteristic functions of risk-neutral return density[1] and the continuum of options are equivalent classes of spanning securities. Any payoff function with bounded expectation can be spanned by OTM European calls and puts. Based on this insight, Bakshi et al. (2003) formalise a mechanism to extract the variance, skewness and kurtosis of the risk-neutral return density from a contemporaneous collection of OTM calls and puts. Their method relies on a continuum of strikes and does not incorporate specific assumptions on an underlying model. The three moments can be expressed as functions of payoffs on a quadratic, a cubic and a quartic contract.

Let the $\tau-$period return be given by the log price relative:

$$R(t,\tau) = ln[S(t+\tau)] - ln[S(t)]. \tag{3.1}$$

[1] A theoretical risk-neutral density is defined as the density for which theoretical European option prices are the discounted expectations of final payoffs. According to Breeden and Litzenberger (1978), the risk-neutral density is the second derivative of the call function C with respect to the strike price K, $f(x) = e^{rT}\frac{\partial^2 C}{\partial K^2}$.

Define the quadratic, cubic and quartic contracts with the following payoffs:

$$H[S] = \begin{cases} R(t,\tau)^2, & \text{quadratic contract} \\ R(t,\tau)^3, & \text{cubic contract} \\ R(t,\tau)^4, & \text{quartic contract} \end{cases} \tag{3.2}$$

Let E^Q denote the expected value operator under the risk-neutral measure. The variance, skewness and kurtosis under the risk-neutral measure are defined as

$$\begin{aligned} VAR =& E^Q[(R - E^Q[R])^2], \\ SKEW =& \frac{E^Q[(R - E^Q[R])^3]}{VAR^{3/2}}, \\ KURTOSIS =& \frac{E^Q[(R - E^Q[R])^4]}{VAR^2}, \end{aligned} \tag{3.3}$$

Following BKM, I define the 'Quad', 'Cubic' and 'Quartic' contracts as having a payoff function equal to the squared, cubic and quartic returns, respectively, for a give maturity τ. The fair values of these contracts are given by:

$$\begin{aligned} Quad =& e^{-r\tau} E^Q[R^2], \\ Cubic =& e^{-r\tau} E^Q[R^3], \\ Quartic =& e^{-r\tau} E^Q[R^4] \end{aligned} \tag{3.4}$$

The prices of the Quadratic, Cubic and Quartic contracts are given by:

$$\begin{aligned} Quad =& \int_S^\infty \frac{2(1 - ln(K/S))}{K^2} C(\tau,K)dK + \int_0^S \frac{2(1 + ln(S/K))}{K^2} P(\tau,K)dK \\ Cubic =& \int_S^\infty \frac{6ln(K/S) - 3(ln(K/S))^2}{K^2} C(\tau,K)dK - \int_0^S \frac{6ln(S/K) + 3(ln(S/K))^2}{K^2} P(\tau,K)dK \\ Quartic =& \int_S^\infty \frac{12(ln(K/S))^2 - 4(ln(K/S))^3}{K^2} C(\tau,K)dK \\ &+ \int_0^S \frac{12(ln(K/S))^2 + 4(ln(K/S))^3}{K^2} P(\tau,K)dK \end{aligned} \tag{3.5}$$

where $C(\tau,K)$ and $P(\tau,K)$ are call and put prices with the underlying strike price K which expire in the τ period. S and K are the underlying stock price and strike price, respectively .

Substituting these expressions into the variance, skewness and kurtosis formulas, I then calculate the risk-neutral three moments:

$$\begin{aligned} VAR =& e^{r\tau}Quad - \mu^2 \\ SKEW =& \frac{e^{r\tau}Cubic - 3\mu e^{r\tau}Quad + 2\mu^3}{VAR^{3/2}} \\ KURTOSIS =& \frac{e^{r\tau}Quartic - 4\mu e^{r\tau}Cubic + 6\mu e^{r\tau}Quad - 3\mu^3}{VAR^2} \end{aligned} \tag{3.6}$$

where

$$\mu = e^{r\tau} - 1 - \frac{e^{r\tau}Quad}{2} - \frac{e^{r\tau}Cubic}{6} - \frac{e^{r\tau}Quartic}{24} \tag{3.7}$$

In order to calculate the integrals in the formulas precisely, I need a continuum of option prices. In practice, I do not have a continuum of option prices across moneyness and I therefore have to make a number of choices regarding implementations. I approximate them from available option data; as in Carr and Wu (2009) and Jiang and Tian (2005), for each maturity, I interpolate implied volatilities using a cubic interpolation across moneyness levels (K/S) to obtain a continuum of implied volatilities. The cubic interpolation is only effective for interpolating between the maximum and minimum available strike price. For moneyness levels below or above the available moneyness level in the market, I simply extrapolate the implied volatility of the lowest or highest available strike price. In other words, the volatility function is assumed to be constant beyond the maximum and minimum strike prices. Jiang and Tian (2005) point out that extrapolation may be necessary in empirical applications as the range of available strike prices may not be sufficiently large on all trading days. This extrapolation procedure introduces an approximation error that is different from the truncation error[2]. The approximate error is positively related to maturity and negatively related to truncation interval. For the risk-free interest rate, I also interpolate to obtain interest rates with different maturities.

After implementing the interpolation-extrapolation technique, I extract a fine grid of 1000 implied volatilities for moneyness levels (K/S) between 1/3 and 3[3]. Then

[2]Truncation errors are present when the tails of the distribution are ignored.
[3]This moneyness range covers about 98% of the risk-neutral probability.

I convert these implied volatilities into call and put option prices based on the following rule: moneyness levels less than 100% ($K/S \leq 1$) are used to generate put prices and moneyness levels greater than 100% ($K/S \geq 1$) are used to generate call prices. This fine grid of option prices is then used to compute the option-implied moments by approximating the Quad, Cubic and Quartic contracts using numerical integration. It is important to note that this procedure does not assume that the Black-Scholes model prices options correctly; it merely provides a translation between option prices and implied volatilities.

Table 3.1. Number of Companies in the S&P 500 Index

The table presents descriptive statistics for the number of companies in the S&P 500 Index year by year from 1996 to 2012. Column 2 reports the number of firms in the S&P 500 Index, obtained from Compustat for each year. For each year, some companies appear in the S&P 500 Index more than once. Sorted by 'gvkey', the number of unique firms in the S&P 500 Index is shown in Column 3. The number of firms with both option and equity data available sorted by PERMNO or secid is reported in Column 4. The percentage of firms with both option and equity data available is shown in Column 5. The percentage in Column 5 is obtained by using the data in Column 4 divided by the data in Column 3.

Year	No. of firms	No. of unique firms	No. of firms with both option and stock prices	Percentage of firms with both option and stock prices
1996	539	519	481	92.68%
1997	531	526	495	94.11%
1998	537	533	512	96.06%
1999	545	540	515	95.37%
2000	555	552	524	94.93%
2001	532	529	505	95.46%
2002	526	522	507	97.13%
2003	520	508	497	97.83%
2004	526	519	508	97.88%
2005	536	516	505	98.45%
2006	530	529	519	98.11%
2007	536	536	528	98.51%
2008	534	534	529	99.06%
2009	525	523	522	99.81%
2010	523	516	514	99.61%
2011	521	518	517	99.81%
2012	517	516	516	100.00%

Chapter 4

Option-Implied Betas and the Cross-Section of Stock Returns

4.1 Introduction

The CAPM, introduced independently by Sharpe (1964), Lintner (1965) and Mossin (1966), indicates that the relationship between market beta and stock return is positive and linear, and that market betas are the only factor describing the cross-section of expected returns. It has been tested extensively throughout the world equity markets and its validity has often been questioned. For example, the famous study of Fama and French (1992) proves that the relation between market beta and average return disappears during the more recent 1963-1990 period of US stock return data even when beta is the only explanatory variable to average returns. Since there exist serious problems when historical stock return is used to model market betas, such as sensitivity to the realised premium in the time period used (see McNulty et al., 2002), two commonly used methods arise to improve the measures of traditional market betas: using option-implied moments and introducing market downside measures.

The first method is to consider option-implied moments to improve traditional betas. Many studies have demonstrated that option-implied volatility is a strong predictor of future volatility in equity markets (see Poon and Granger, 2003). Recent research also finds that option-implied high moments (skewness and kurtosis) and correlation contain predictive information about the stock market (see Christoffersen et al., 2011). Based on option-implied moments, French et al. (1983) (FGK) first introduce a hybrid estimation method to compute market betas using correlations from historical return and the ratio of stock-to-market implied volatilities.

Chang et al. (2012) (CCJV) use both option-implied skewness and volatility to estimate market betas. They find that the CCJV beta estimates perform relatively well and could explain a sizeable amount of cross-sectional variation in expected returns. Buss and Vilkov (2012) (BV) construct the option-implied beta using option-implied correlation and volatility. They report that the BV beta confirms a monotonically increasing risk-return relation consistent with the indication of the CAPM. Besides the option-implied beta measures described above, other researchers, e.g. McNulty et al. (2002), Husmann and Stephan (2007), Fouque and Kollman (2011), find alternative methods to improve market betas using options and they find that options can indeed improve the performance of historical betas.

The second common and efficient way to improve the general market betas is modelling downside market betas. An early study by Roy (1952) argues that investors care more for downside risk than upside gains or, put more simply, safety from disaster as foremost goal. Markowitz (1959) advocates replacing variance by semi-variance as a measure of risk, because semi-variance measures downside losses rather than upside gains. Empirical tests of the mean-variance CAPM show that the average returns from low-beta (high-beta) stocks are too high (low) relative to the prediction of the CAPM (see, for example, Jensen et al.,1972; Fama and MacBeth,1973 and Fama and French, 1992). Price et al. (1982) show that the historical downside betas of US stocks differ systematically from the regular betas. Researchers propose different ways to measure downside betas. For example, Hogan and Warren (1972) propose the semi-variance beta by replacing variance with semi-variance. Bawa (1975) and Bawa and Lindenberg (1977) develop and extend a proxy for downside beta as the LPM. Ang et al. (2006a) estimate downside betas based on the conditional downside covariance.

In this study, I use options on the S&P 500 Index and its constituents to construct option-implied moments and then option-implied betas. I try to test whether option prices contain important information for the underlying equities to improve traditional betas. A portfolio sorting exercise is performed in order to compare the four beta methods: the Historical beta, the FGK beta by French et al. (1983), the C-CJV beta by Chang et al. (2012) and the BV beta by Buss and Vilkov (2012). I sort the stocks into quintiles on the basis of ranked betas for each beta method at the end of each month and then calculate both the value-weighted and equally-weighted portfolio returns in the next month. Based on the implied beta methods and the downside correlation of Ang et al. (2002), this is the first study to propose implied downside betas, including the FGK and BV implied downside betas. I investigate whether the combination of option-implied moments and downside measures can improve the general implied beta methods. I also test whether the beta-return relation is affected by firm-level factors using a portfolio analysis and the Fama and MacBeth (1973) (FM) regression. These factors include firm size, book-to-market ratio, momentum, option-implied volatility, skewness, kurtosis, the variance risk premium and illiquidity. To my knowledge, this is the first research to study whether option-implied betas or implied downside betas can be affected systematically by firm-level variables.

The reason for exploring whether firm-level factors can help option-implied betas explain the cross-section of stock returns is twofold. First, previous research has found that firm-level factors can help predict stock returns. It is well known that there exist the firm size effect of Banz (1981), the book-to-market effect of Basu (1983), the momentum effect of Jegadeesh and Titman (1993), the predictive ability of option-implied moments (see, e.g. Bali and Murray, 2010; Conrad et al., 2013) and the variance risk premium effect of Bali and Hovakimian (2009) and Bollerslev et al. (2009). Second, these firm characteristics may explain option-implied betas because option-implied betas are constructed by option-implied moments and recent research in risk-neutral moments demonstrates that some firm characteristics are related to option-implied moments. For example, Dennis and Mayhew (2002) investigate the relative importance of various firm characteristics (e.g. implied volatility, firm size, trading volume, leverage and beta) in explaining risk-neutral skewness implied from option prices. Hansis et al. (2010) find that risk-neutral moments (variance, skewness, and kurtosis) are well explained cross-sectionally by a number of firm characteristics. Buss and Vilkov (2012) just provide evidence that the relation between option-implied betas, especially the BV beta and returns, is robust to the variance risk premium and option-implied skewness, but they do not study the impact of other firm characteristics, e.g. firm size or book-to-market ratio.

The main contributions of this chapter are summarised as follows. First, I compare the Historical, FGK, CCJV and BV beta methods and find that the BV beta measure works best. A portfolio trading strategy that sells the stocks ranked in the bottom quintile by the BV implied beta and buys the stocks in the top quintile by the BV implied beta earns positive profit. This is consistent with the findings of Buss and Vilkov (2012), who find that the BV beta has a monotonically increasing relation with the value-weighted returns. Second, I first develop implied downside betas and show that the BV implied downside beta performs best, offering an improvement over the BV implied beta. The return difference between the extreme portfolios for the BV downside beta is greater than other implied downside betas and the BV beta. However, the beta-return relation for the BV implied beta and the BV implied downside beta is not robust to firm-level factors. Once firm-level control variables are included in the FM regression, the explanatory power of the BV beta and the BV downside beta disappears. This means that option-implied betas and implied downside betas are correlated with these firm-level control variables and this, in turn, obscures the beta-return relation.

This study contributes to the literature that examines the relation between market betas and stock returns. First, the research complements the paper of Buss and Vilkov (2012), who compared these four beta methods using a portfolio analysis based on options on the S&P 500 Index and its constituents from January 1996 to December 2009. Second, this research contributes to the literature on downside betas. Some studies, e.g. Post and van Vliet (2005), Ang et al. (2006a) and Tahir et al. (2013), report that downside risk based CAPM outperforms variance based CAPM. For instance, Post and van Vliet (2005) support that the mean-semivariance CAPM strongly outperforms the traditional mean-variance CAPM in terms of its ability to explain the cross-section of US stock returns. Tahir et al. (2013) test the beta and the downside based CAPM empirically and find that the downside based CAPM is a strong contender compared to the CAPM for the risk-return relationship.

The rest of this chapter is organised as follows. In Section 4.2, I present the calculation of four different beta methods, which are the Historical, FGK, CCJV and BV betas, as well as the downside beta methods, including the Historical, FGK and BV implied downside betas. Section 4.3 provides an overview of the data and a summary of option-implied moments and betas. Section 4.4 discusses the empirical result for testing the risk-return relation with different implied beta methods. Section 4.5 presents the empirical result for the relation between different implied downside beta methods and returns. Section 4.6 summarises the main findings of this chapter.

4.2 Models of Market Betas

4.2.1 Option-Implied Betas

There are four beta models used in this study: Historical, FGK, CCJV and BV betas. The calculation of the four different beta methods is described as follows.

Historical Beta

Sharpe (1964), Lintner (1965) and Mossin (1966) independently propose the CAP-M, which asserts that the expected return for any individual asset is a positive function of only three variables: beta (the covariance of asset return and market return), the risk-free rate and the expected market return. The relationship is shown below:

$$E(R_i) = R_f + \beta_i (E(R_M) - R_f) \tag{4.1}$$

where R_i denotes the return on stock i, R_f is the risk-free interest rate and R_M is market return.

Let P denote the probability distribution function under the physical measure. The Historical beta is usually calculated using the following formula:

$$\beta_{iM}^{His} = \rho_{i,M} \frac{\sigma_{i,t}^P}{\sigma_{M,t}^P} \tag{4.2}$$

where $\sigma_{i,t}^P$ and $\sigma_{M,t}^P$ are the stock and index return standard deviations from historical data, respectively, and $\rho_{i,M}$ is the correlation between stock and index returns. Traditionally, the Historical beta is calculated using the historical rolling-window method. The window length is 180 days or 126 trading days.

FGK Beta

French et al. (1983) (FGK) first introduce a hybrid estimation method using option-implied volatility to improve the performance of beta forecasts. Let Q denote the probability function under the risk-neutral measure.

$$\beta_{iM}^{FGK} = \rho_{i,M} \frac{\sigma_{i,t}^Q}{\sigma_{M,t}^Q} \tag{4.3}$$

where $\sigma_{i,t}^Q$ and $\sigma_{M,t}^Q$ are the option-implied volatility for stock *i* and index, respectively, and $\rho_{i,M}$ is the correlation between historical stock and index returns.

CCJV Beta

Chang et al. (2012) (CCJV) suppose a one-factor model and assume zero skewness of the market return residual to propose a new market beta method by using both option-implied volatility and option-implied skewness.

$$\beta_{iM}^{CCJV} = \left(\frac{SKEW_{i,t}^Q}{SKEW_{M,t}^Q}\right)^{1/3} \frac{\sigma_{i,t}^Q}{\sigma_{M,t}^Q} \tag{4.4}$$

where $\sigma_{i,t}^Q$ and $\sigma_{M,t}^Q$ are the option-implied volatility for stock *i* and index, respectively. $SKEW_{i,t}^Q$ and $SKEW_{M,t}^Q$ are the option-implied skewness on stock *i* and index, respectively. $(\frac{SKEW_{i,t}^Q}{SKEW_{M,t}^Q})^{1/3}$ serves as a proxy for the risk neutral correlation.

BV Beta

Buss and Vilkov (2012) (BV) propose a new way to model the option-implied beta by combining option-implied correlation with option-implied volatility.

First, I have one identifying restriction: the observed implied variance of the market index $(\sigma_{M,t}^{Q})^2$ equals the implied variance of a portfolio of all market index constituents $i = 1, ..., N$:

$$(\sigma_{M,t}^{Q})^2 = \sum_{i=1}^{N}\sum_{j=1}^{N} \omega_i \omega_j \sigma_{i,t}^{Q} \sigma_{j,t}^{Q} \rho_{ij,t}^{Q}, \tag{4.5}$$

where $\sigma_{i,t}^{Q}$ denotes the implied volatility of stock i in the index and ω_i represents the index weights.

Empirically, I use stock returns in the market index constituents to identify $N \times (N-1)/2$ physical correlations $\rho_{ij,t}^{P}$ and then transfer these into implied correlations $\rho_{ij,t}^{Q}$ [1].

$$\rho_{ij,t}^{Q} = \rho_{ij,t}^{P} - \alpha_t (1 - \rho_{ij,t}^{P}), \tag{4.6}$$

where $\rho_{ij,t}^{P}$ is the expected correlation under the physical measure and α_t denotes the parameter to be identified.

Substituting the option-implied correlation in equation (4.6) into restriction (4.5), I obtain the following formula to compute α_t:

$$\alpha_t = -\frac{(\sigma_{M,t}^{Q})^2 - \sum_{i=1}^{N}\sum_{j=1}^{N} \omega_i \omega_j \sigma_{i,t}^{Q} \sigma_{j,t}^{Q} \rho_{ij,t}^{P}}{\sum_{i=1}^{N}\sum_{j=1}^{N} \omega_i \omega_j \sigma_{i,t}^{Q} \sigma_{j,t}^{Q} (1 - \rho_{ij,t}^{P})}, \tag{4.7}$$

After estimating option-implied volatility and correlation, I then compute the BV

[1] Buss and Vilkov (2012) identify that the transfer must satisfy two technical conditions and two empirical observations. The two technical conditions are that (i) all correlations $\rho_{ij,t}^{Q}$ do not exceed one, and (ii) the correlation matrix is positive definite. Furthermore, the implied correlations are consistent with two empirical observations: (i) the implied correlation $\rho_{ij,t}^{Q}$ is higher than the correlation under the physical measure $\rho_{ij,t}^{P}$, (ii) the correlation risk premium is larger in magnitude for pairs of stocks that provide higher diversification benefits (i.e., low or negatively correlated s-tocks), and hence are exposed to a higher risk of losing diversification in bad times characterised by increasing correlations. The second empirical observation is supported by the negative correlation between the correlation under the objective measure and the correlation risk premium in Stathopoulos et al. (2012)

beta as:

$$\beta^{BV}_{iM,t} = \frac{\sigma^{Q}_{i,t} \sum_{j=1}^{N} \omega_j \sigma^{Q}_{j,t} \rho^{Q}_{ij,t}}{(\sigma^{Q}_{M,t})^2}, \tag{4.8}$$

4.2.2 Implied Downside Betas

In this subsection, I show how to model implied downside betas. I find three ways to model implied downside betas (Historical, FGK and BV downside betas). I do not find an approach to construct the CCJV downside beta. The CCJV beta is constructed from option-implied volatility and skewness (see equation (4.4)). Modelling option-implied volatility or skewness does not require the use of historical stock returns. However, historical stock returns are needed to model downside betas or correlations. Therefore, it is impossible to construct a downside analogue of the CCJV beta due to its estimated nature.

For the Historical downside beta, I follow the semi-variance beta approach of Hogan and Warren (1972). The computation of historical downside betas is as follows:

$$\beta^{D-His}_{\theta} = \frac{E(R_i R_M | R_M \leq \theta)}{E(R_M^2 | R_M \leq \theta)} \tag{4.9}$$

where the numerator is the second lower partial co-movement between the stock excess return R_i and the market excess return R_M; it measures the co-movements with the market during market downturns. The threshold, θ is used to define the downside market.

The principle for modelling implied downside betas is based mainly on modelling downside correlations. Ang et al. (2002) decompose downside betas into a conditional correlation term and a ratio of conditional total volatility to conditional market volatility. The downside correlation is given by:

$$\rho^{-}_{\theta} = corr\{R_i, R_M | R_M \leq \theta\} = \frac{E(R_i R_M | R_M \leq \theta)}{\sqrt{E(R_i^2 | R_M \leq \theta) E(R_M^2 | R_M \leq \theta)}} \tag{4.10}$$

Following Ang et al. (2002), I combine downside correlations and option-implied volatility to obtain implied downside betas. I substitute the historical correlation of the FGK beta in equation (4.3) by the downside correlation in equation (4.10) to obtain the FGK implied downside betas.

$$\beta_{\theta}^{D-FGK} = \rho_{\theta}^{-} \frac{\sigma_{i,t}^{Q}}{\sigma_{M,t}^{Q}} \tag{4.11}$$

For the BV beta method, I use individual stock returns satisfying $(R_i | R_{M,t} \leq \theta)$ to calculate the physical downside correlations ρ_{θ}^{-} and then obtain the BV implied downside beta following equations (4.5)-(4.8) in Section 4.2.1.

4.3 Data

I employ daily options on the S&P 500 Index and its constituents from January 1996 to December 2012; a total of 4,278 trading days. The S&P 500 Index serves as a proxy for the US market. The option data are taken from OptionMetrics. The daily S&P 500 Index and stock prices on its constituents are obtained from the Center for Research in Security Prices (CRSP). The financial statement data that are used in this thesis, such as book value of common equity and balance-sheet deferred taxes, are also from COMPUSTAT; they are quarterly data, so I fill in the missing months for each quarter.

4.3.1 Summary Statistics on Option-Implied Moments

Option-implied moments are calculated following the formulas in Bakshi et al. (2003). The detail of the BKM method is described in Section 3.2.

I choose the 180-day VAR and SKEW contracts to construct option-implied betas. For each day, I calculate the risk-neutral moments using options with different maturities for each stock. In each calculation, I require that a minimum of two OTM calls and two OTM puts with different strikes have valid prices. If insufficient data are available, the observation is discarded. When using daily options with all maturities, I can in principle obtain daily option-implied volatility, skewness and kurtosis with various maturities for each stock. I then interpolate linearly to get the 180-day VAR, SKEW and KURTOSIS, using both contracts with maturity in more than 180 days and contracts with maturity in less than 180 days. If there is only one maturity in a particular day then I do not interpolate and I use this to represent the 180-day VAR, SKEW and KURTOSIS on that day. The choice of a 180-day horizon is, to some extent, based on a trade-off between option liquidity that is largest for options with 30-90 days to maturity and the relevant horizon for firm risk, which is arguably considerably longer (see Chang et al., 2012).

Table 4.1 presents summary statistics for option-implied volatility, skewness and kurtosis for the sample period January 1996 to December 2012. It reports the number of observations, average, standard deviation and median as well as 25th and 75th percentiles of option-implied moments for both the S&P 500 Index and its constituents. The average S&P 500 Index volatility is 0.2422 and the average stock volatility is 0.3934. It is obvious that the average S&P 500 Index volatility is less than the average stock volatility. This is because stocks in the S&P 500 Index are not correlated perfectly. The average S&P 500 Index skewness is -1.5342; more negative than the average stock skewness (-0.4417). This shows that the distribution of both index and stock returns is negatively skewed. The average S&P 500 Index kurtosis is 7.1139 and the average stock kurtosis is 3.5738. The average S&P 500 Index kurtosis is much greater than the average stock kurtosis. The average kurtosis for both index and stock is greater than 3, which indicates that the distribution of both index and stock returns has high peaks. Overall, the risk-neutral distribution of index return is more skewed and fat-tailed than the stock risk-neutral distribution.

Figure 4.1 displays some properties of the S&P 500 implied moments from January 1996 to December 2012. It is obvious that the S&P 500 Index option-implied volatility fluctuates between 0 and 0.6. The market becomes more volatile in recent years. Volatility peaks at 0.6 around the year 2008. The S&P 500 Index option-implied skewness is always negative from 1996 to 2012; it becomes more negative after 2008. The S&P 500 Index option-implied kurtosis always fluctuates above 3. The index kurtosis becomes even higher in recent years, since 2008. From the shapes and outliers of the figures, I see that these three risk-neutral moments are correlated. This means that the risks associated with risk-neutral moments may be correlated with each other.

4.3.2 Summary Statistics on Option-Implied Betas and Downside Betas

In this subsection, I compute option-implied betas and implied downside betas discussed in Section 4.2 by applying daily data on the S&P 500 Index and its constituents from January 1996 to December 2012.

Traditionally, historical betas are calculated using historical rolling windows. In this test, the Historical beta is calculated using daily stock and index returns with a respective rolling-window length of 180 days (previous 126 trading days). For the FGK beta, the historical correlation is calculated using stock and index returns with the rolling-window length of 180 days (previous 126 trading days). Option-implied volatility is calculated following the BKM method. I put the historical correlations and the option-implied stock-to-market volatility ratio into equation (4.3) to calculate the FGK beta for each stock. For the CCJV beta, I compute option-implied volatility and skewness by the BKM method and put them into equation (4.4) to calculate the CCJV beta. For the BV beta, I first estimate option-implied volatility following the BKM method. I then compute correlations under the physical measure using daily returns with a respective rolling-window length of 180 days. The correlations under the risk-neutral measure are computed following equation (4.6) after calibrating the only unknown parameter α_t from equation (4.7). The BV beta is then computed from equation (4.8). The calculation of downside betas is very similar to general betas; the only difference is that when measuring downside betas, I use stock or index returns in market downturns. Following the computation procedure of different beta methods, I obtain the daily Historical, FGK and BV betas, as well as the downside betas for most stocks from the first trading day of July 1996 to the last trading day of December 2012. I obtain the daily CCJV beta from the first trading day of January 1996 to the last trading day of December 2012.

Table 4.2 reports descriptive statistics for different beta methods. Panel A presents summary statistics for general beta methods. I find that, for all these four beta methods, the average and the value-weighted average of betas are around unity. Both the mean and the value-weighted mean of the Historical beta are about 0.5% higher than 1. Both the mean and the value-weighted mean of the FGK beta are about 15% less than 1. For the CCJV beta, the mean and the value-weighted mean are about 3% greater than 1. The mean and the value-weighted mean of the BV beta are about 7% greater than 1. The Historical, FGK and CCJV betas have median less than 1 and the BV beta has median around 1. Panel B reports summary statistics for downside betas. The average of the Historical and BV downside betas is slightly greater than unity. The mean of the Historical downside betas is 1.0081 and the mean of the BV downside beta is 1.0976. For the FGK downside beta, the average is less than 1 (0.6506). For option-implied betas and downside betas, the market value-weighted average of all betas is not one, because risk-neutral volatility is used to estimate betas.

Panel C of Table 4.2 provides the correlation coefficients of different beta methods. The general betas are highly correlated with the downside betas. The correlation between the Historical beta and the Historical downside beta is 0.9229. The correlation between the FGK (BV) beta and the FGK (BV) downside beta is 0.7378 (0.8759). The Historical beta has a high correlation with the FGK beta, with the correlation of 0.7271. The FGK beta is highly correlated with the BV beta with the correlation of 0.7458. Similarly, for the downside measures the Historical downside beta is highly correlated with the FGK downside beta, as is the FGK downside beta with the BV downside beta. The correlations are around 0.63.

4.4 Option-Implied Betas and Stock Returns

As discussed in Section 4.3.2, the calculation of the four beta methods is different and summary statistics confirm that there is a variety among these four beta methods. I investigate whether different beta methods could cause differences in the risk-return relationship. Alternatively, I find out which beta method gives better performance in terms of the positive and linear beta-return relationship. In order to investigate this, I sort the stocks into quintile portfolios based on the values of market betas discussed in Section 4.4.1. To see whether betas are related to firm-level variables, I adopt a portfolio analysis shown in Section 4.4.2. In Section 4.4.3, I conduct the Fama and MacBeth (1973) regression to examine further whether market betas can still predict stock returns, when controlling for different firm-level variables.

4.4.1 Portfolio Analysis of the Beta-Return Relation

Before doing the analysis, I replicate the paper of Buss and Vilkov (2012) using the same sample and sample period; the result is shown in the appendix to this chapter. The replication result is very close to the result shown in BV's original paper and it demonstrates that the results of this research are valid.

In order to study the risk-return relation, I perform the portfolio sorting methodology similar to the early study of Jensen et al. (1972) and the recent study of Buss and Vilkov (2012). I sort the individual securities in the S&P 500 Index into five groups at the end of each month, and separately for each beta method, according to their pre-ranked betas. The pre-ranked betas are estimated using previous 180-day (126-trading day) daily returns at the end of month *t*. Jensen et al. (1972) and Fama and French (1992) use at least 24 months of 5-year monthly returns to calculate pre-ranked betas. Similar to them, I use 180-day rolling-window returns to calculate the Historical, FGK and BV betas. For example, I begin by estimating the coefficient beta for a half-year period from January 1996 to June 1996 for all equities listed on the S&P 500 Index at the beginning of July 1996. These stocks are then ranked from low to high on the basis of the values of estimated pre-ranked betas and are assigned to five portfolios with equal number of securities; the 20% of the stocks with the smallest betas are assigned to the first portfolio, the 20% of the stocks with the biggest betas are assigned to the fifth portfolio and so on. For the CCJV beta, the pre-ranked beta is the implied beta calculated at the end of the month. After constructing the portfolios based on the pre-ranked betas, I calculate the value-weighted and equally-weighted averages of betas, the annualised value-weighted and equally-weighted average of return without dividend, holding period return[2], for each beta methodology, for each portfolio in the next month *t+1*. The entire process is repeated for each month after July 1996 until December 2012. Finally, I calculate the time-series means of betas and realised returns.

The CAPM implies a monotonically increasing pattern in the stock return ranked by their market beta. In order to test the monotonically increasing beta-return relation, I adopt the monotonicity relation (MR) test method proposed by Patton and Timmermann (2010). The null hypothesis is based on the sign of the return spread between the fifth portfolio (highest beta) and the first portfolio (lowest beta), termed the 5-1 return spread. If the 5-1 return spread is negative, I test whether the beta-return relation is monotonically decreasing. If the 5-1 return spread is positive, I test whether the beta-return relation is monotonically increasing. The MR test result is decided by p-values. If the MR p-value is less than 5% and 5-1 return spread is positive (negative), it means that there is a monotonically increasing (decreasing) risk-return relation.

Table 4.3 provides a summary of the mean expected betas and the mean realised return for the beta-sorted quintile portfolios from January 1996 to December 2012. Panel A reports the time-series average of portfolio betas and returns sorted on

[2] I include return without dividend and holding period return in the analysis. They are downloaded from CRSP directly. Return without dividend has excluded dividends, while holding period return is a total return, which includes dividends.

the Historical beta. For the value-weighted portfolios, the 5-1 return spread is 3.545% for return without dividend and 2.174% for holding period return. For the equally-weighted portfolios, the 5-1 return spread is 6.014% for return without dividend, 4.574% for holding period return. This is consistent with Fama and MacBeth (1973) and Jensen et al. (1972), who find evidence to support the positive risk-return relationship as predicted by the CAPM. However, the t-statistics of the 5-1 return spread do not exceed the 10% level threshold, which means that the positive beta-return relation is not significant.

Panel B presents quintile portfolio performance sorted on the FGK beta measure. For both the value-weighted and equally-weighted portfolios, a long-short portfolio buying the stocks in the highest beta quintile and shorting the stocks in the lowest beta quintile produces positive average returns. For the value-weighted portfolios, the average is 2.376% per year for return without dividend and 1.097% per year for holding period return. For the equally-weighted portfolios, the average return is 5.577% for return without dividend and 4.422% for holding period return. The t-statistics of the return difference between the fifth and first portfolio are in the range of 0.15 to 0.65 for both the value-weighted and equally-weighted portfolios, which are less than the 10% significance level.

Panel C reports quintile portfolios sorted on the CCJV beta method. I find that the 5-1 return spread is negative for both the value-weighted and equally-weighted portfolios. The most negative return spread is -3.012% for the equally-weighted holding period return and the least negative return spread is -0.518% for the value-weighted return without dividend. The t-statistics of the 5-1 return spread for the CCJV beta indicate that the negative return difference is not significant. Chang et al. (2012) run a cross-section regression of stock returns on the CCJV betas year by year and find that for some years the slopes of the CCJV beta are negative.

The results for the portfolio analysis sorted on the basis of the BV beta are shown in Panel D. On a value-weighted basis, the portfolio return without dividend increases by 6.241% per year from 4.644% in the first portfolio to 10.884% in the fifth portfolio and the portfolio holding period return increases by 4.470% per year. On a equally-weighted basis, the portfolio return spread is 6.669% for return without dividend and 5.014% for holding period return. The t-statistics vary between 0.6 and 1, less than the 10% significance level.

I perform a formal monotonicity test of the risk-return relation, applying the non-parametric technique of Patton and Timmermann (2010). The result for the MR test with p-values obtained from time-series block bootstrapping[3] is shown in the last column of Table 4.3. From the MR test, I find that all MR p-values are greater than 10% except for the equally-weighted return without dividend for the BV beta method, whose MR p-value is 0.093. There is no significant evidence to support the existence of a monotonically increasing relation between all betas and returns. Buss and Vilkov (2012) find that there is a monotonically increasing relation between the BV beta and the value-weighted returns. Here, I find a monotonically increasing relation between the BV beta and the equally-weighted returns without dividend at the 10% significance level. Although the finding is slightly different from Buss and Vilkov (2012) in the weighting scheme, it still confirms the result of Buss and Vilkov (2012) that the BV implied beta performs best.

To summarise, Table 4.3 shows that the relationship between the Historical, FGK, BV betas and returns is positive, but it is not significant as indicated from the p-values of the 5-1 spread, which are greater than 10%. More importantly, the BV beta method gives the biggest value-weighted and equally-weighted return spread between the extreme portfolios (including return without dividend and holding period return). For example, the return spread of the BV beta is about 2.7% greater than that of the Historical beta and 3.9% greater than that of the FGK beta for the value-weighed return without dividend. The findings are consistent with Buss and Vilkov (2012), who find that the BV beta has the biggest 5-1 return spread.

[3]Block bootstrapping actually means resampling the sample data.

Figure 4.2 shows that all beta methods display a noisy beta-return relation across different quintiles for the value-weighted return without dividend. For the value-weighted portfolios, the return difference between the extreme quintile portfolios is more pronounced for the BV and Historical betas rather than for the FGK and C-CJV beta methods. The 5-1 return spread for the FGK and CCJV betas is 2.376% and -0.518%, respectively. For the Historical and BV betas, the average 5-1 return difference is 3.545% and 6.241%, respectively. The return spread of the BV beta is more pronounced than that of the Historical beta. The return difference of the BV beta is about 2.70% greater than that of the Historical beta. The plot of the BV beta and the value-weighted returns shows that the pattern is closest to linear compared with the Historical, FGK and CCJV betas. The equally-weighted return for both the Historical and BV beta methods displays a monotonically increasing risk-return relation, but the MR test in the last column of Table 4.3 proves that only the BV beta has a monotonically increasing risk-return relation at the 10% significance level.

Overall, the results in Table 4.3 and Figure 4.2 indicate that the positive relation between market beta risk and returns is much more pronounced for the BV beta, consistent with the findings of Buss and Vilkov (2012).

4.4.2 Firm-Level Factors Affecting the Beta-Return Relation

In Section 4.4.1, I use the portfolio analysis to examine the risk-return relation for the historical and option-implied betas. In this subsection, I perform a robustness test to see whether the beta-return relationship is affected by other factors related to firm characteristics or option-implied moments. If there is a difference in the distribution of these characteristics across beta-sorted portfolios for the different beta methods, then the risk-return relation may be not robust[4]. Buss and Vilkov (2012) show that the risk-return relation for the BV beta cannot be explained by the variance risk premium and option-implied skewness. In this subsection, I use the portfolio analysis to test whether betas have a clear pattern with firm size, book-to-market ratio, option-implied volatility, skewness and kurtosis, and the variance risk premium.

Banz (1981) may be the first empirical paper to present evidence of a size effect in US stock returns; that there is a negative relation between firm size and stock returns to be specific. Basu (1983) documents the book-to-market effect that book-to-market ratio has a positive relation with returns. Fama and French (1992) confirm that the size effect and the book-to-market effect do indeed exist. The reason for including volatility is that Ang et al. (2006b) show that high historical volatility strongly predicts low subsequent returns. The evidence for the explanatory power of implied skewness to stock return is provided by recent studies (Xing et al., 2010; Cremers and Weinbaum, 2010; Rehman and Vilkov, 2012; Conrad et al., 2013). Some researchers also find the effect of implied kurtosis on returns (Diavatopoulos et al., 2012; Bali et al., 2014). In terms of the variance risk premium, Bali and Hovakimian (2009) find a significantly negative relation between expected returns and the realised-implied volatility spread.

The calculation of firm size and book-to-market ratio follows Fama and French (1992). *Firm size*, ln(ME) is the log of the market capitalisation from the previous day. Market capitalisation, ME is equal to stock price multiplying shares outstanding. *Book-to-market ratio* is equal to ln(BE/ME), where BE is the book value of common equity plus balance-sheet deferred taxes. *Implied volatility*, *skewness* and *kurtosis* are calculated following the BKM method. As in Carr and Wu (2009),

[4] Buss and Vilkov (2012) identify three conditions to determine whether the beta-return relation is robust to these factors. The three conditions are shown as follows: (i) there must be a sizeable difference and clear pattern in the average characteristic value of the beta-sorted portfolios, (ii) there must be strong differences in the average characteristic value of the portfolios across beta methodologies, and (iii) the return pattern arising from the predictive power of a given characteristic and the beta-return relation for each beta must work in the same direction. Importantly, all three conditions must be satisfied to give rise to a spurious risk-return relation

the *variance risk premium* (VRP) is defined as the difference between the realised variance and the variance swap rate, which measures the terminal profit and loss from a long variance swap contract and holding it to maturity. The expected sign of the average variance risk premium should be negative. Writing variance swaps, receiving fixed and paying floating, is on average profitable. The variance risk premium is defined as the difference between realised and implied variance.

$$VRP(t) = \sigma_P^2(t) - \sigma_Q^2(t) \tag{4.12}$$

where $\sigma_P^2(t)$ and $\sigma_Q^2(t)$ denote the realised and implied variances on day t, respectively.

As in Merton (1980) and Andersen et al. (2003), the realised physical (annualised) variance is computed in a model-free manner, using daily stock returns.

$$\sigma_P^2(t) = \frac{252}{21}\sum_{i=0}^{20}(R(t-i) - \overline{R})^2 \tag{4.13}$$

Table 4.4 shows the average firm characteristics and option-implied moments from 1996 to 2012 for portfolios formed on different beta methods. Panel A presents the portfolio result based on the Historical beta. The 5-1 spread for option-implied volatility, skewness and the variance risk premium is positive and significant at the 5% level. However, the relation between the Historical beta and option-implied skewness is significantly negative. I also find that the Historical beta has a monotonically increasing relationship with option-implied volatility and a monotonically decreasing relationship with option-implied kurtosis. From the results in Panel B, I find that the FGK beta is negatively correlated with firm size, option-implied kurtosis. The relationships are monotonic. The FGK beta has a positive relationship with book-to-market ratio, option-implied volatility, skewness and the variance risk premium. The findings in Panel C report that the CCJV beta is significantly and negatively related to firm size and option-implied skewness. It has a monotonically decreasing relation with option-implied skewness. However, the CCJV beta has a monotonically increasing relation with option-implied volatility. Panel D presents that there is a significantly positive relationship between the BV beta and book-to-market ratio, option-implied volatility and skewness, while there is a negative relationship between the BV beta and firm size, and option-implied kurtosis. The relationship between the BV beta and firm size, book-to-market ratio, option-implied volatility and kurtosis is monotonic. Overall, I see clear patterns of betas with some of these factors. Thus, the beta-return relationship may be blurred by these factors.

Since I can see clear patterns between betas and some of these factors when portfolios are sorted by the different beta methods in Table 4.4, next I check whether these factors have a significant relationship with returns. The procedure is similar to the portfolio analysis for the beta-return relation in Section 4.4.1. At the end of each month, I calculate firm-level variables, including firm size, book-to-market ratio, option-implied volatility, skewness, kurtosis and the variance risk premium. I sort the individual securities in the S&P 500 Index into five groups at the end of each month and separately for each variable, according to the value of these factors. After constructing the portfolios based on these variables, I calculate the annualised value-weighted and equally-weighted return without dividend, holding period return for each variable, for each portfolio in the next month *t+1*. The entire process is repeated for each month in the whole sample period. Finally, I calculate the time-series average of realised returns.

Table 4.5 reports quintile portfolios formed on firm-level factors from January 1996 to December 2012. Panel A reports that the relation between firm size and returns is negative and significant at the 10% level. The MR p-value shows that the size-return relation decreases monotonically at the 10% significance level. This is consistent with the size effect by Banz (1981) and Fama and French (1992). However, the negative relationship between firm size and return is only significant at the 10% level. This is because the firms in the sample are the constituents of the S&P 500 Index, which are relatively big companies. Panel B presents the results for the portfolio analysis based on book-to-market ratio. The relation between book-to-market ratio and returns is positive. For both the value-weighted and equally-weighted returns, the 5-1 return spread is not significant at the 10% level. The MR p-value shows that the relationship between book-to-market ratio and return is not monotonically increasing. The spread t-statistics and MR p-value in Panel C show that option-implied volatility has no significant and positive relationship with returns. In Panel D, I find that there exists a significant and positive relation between option-implied skewness and stock returns, consistent with Xing et al. (2010), Cremers and Weinbaum (2010) and Rehman and Vilkov (2012). However, the findings are in contrast to Conrad et al. (2013) and Bali and Murray (2010), who find that option-implied skewness is negatively related to future stock returns. Panel E shows that option-implied kurtosis is negatively related to both the value-weighted and equally-weighted returns, but the 5-1 return spread is not significant at the 10% level. The MR p-value shows that the kurtosis-return relation is not monotonic. For portfolios sorted by the variance risk premium, shown in Panel F, the 5-1 return spread is negative and significant for both the value-weighted and equally-weighted returns at the 10% significance level. The MR test shows that there is a monotonically decreasing pattern between the variance risk premium and the value-weighted returns at the 1% significance level. The findings are in line with the result of Bali and Hovakimian (2009), who find a significantly negative relation between expected returns and the realised-implied volatility spread.

I have a close look at the explanation of the negative relationship between the CCJV beta and stock returns shown in Table 4.3. The CCJV beta is composed by option-implied skewness and volatility. From Table 4.4, I find a monotonically decreasing relationship between the CCJV beta and option-implied skewness. From Panel C of Table 4.5, I find that there exists a positive relationship between option-implied skewness and stock returns. When skewness is more negative, the CCJV beta becomes bigger; the portfolio returns become smaller. Therefore, the negative beta-return relationship can be explained by the skewness-return relationship.

Overall, the portfolio analysis in Table 4.5 shows that firm size, option-implied skewness and the variance risk premium have a significant relationship with returns. Firm size and the variance risk premium are negatively related to returns, while option-implied skewness is positively related to returns. From Table 4.4, I find that all beta methods are linked to some of the firm factors.

4.4.3 Fama-MacBeth Regressions

Through the portfolio analysis, I can see a simple picture of how average portfolio returns vary across the spectrum of betas and other variables. However, the portfolio analysis has its own potential pitfalls to test the risk-return relation (see Fama and French, 2008). For example, portfolio sorts are clumsy for examining the functional form of the relationship between average returns and the variables. Therefore, I adopt the Fama and MacBeth (1973) (FM) regression to test further whether the risk-return relationship is robust to firm-level variables. I perform a cross-sectional regression of the value-weighted returns on one or more explanatory variables monthly. I then calculate the time-series average of the cross-sectional regression coefficients. In addition to enabling control of multicollinearity among the explanatory variables, the slope coefficients from the regression analysis can also be interpreted as the risk premia associated with taking one unit of risk associated with each of the risk variables.

I include additional control variables, except betas, in the month-by-month FM regression. The reason for including firm size, book-to-market ratio, option-implied volatility, skewness and kurtosis, and the variance risk premium in the FM regression is shown in Section 4.4.2. Besides these, I also include momentum and illiquidity in the regression. *Momentum* is the cumulative daily return over the previous six months. *Illiquidity* is defined as the average ratio of the daily absolute return to the (dollar) trading volume on that day, $|R_{iyd}| / VOLD_{iyd}$, where R_{iyd} is the return on stock *i* on day *d* of year *y* and $VOLD_{iyd}$ is the respective daily volume in dollars. This follows Amihud (2002), who finds that expected market illiquidity has a positive and significant effect on *ex ante* stock excess return and that unexpected illiquidity has a negative and significant effect on contemporaneous stock return.

The standard FM regression has two stages. Before the two stages, I first sort the stocks into quintile portfolios according to the pre-ranked betas at the end of month t, for each beta methodology. I then calculate the annualised value-weighted average of stock returns in the next month $t+1$. I also calculate the average beta, firm size, book-to-market ratio, option-implied volatility, skewness, kurtosis, the variance risk premium, momentum and illiquidity at the end of month t. In the first stage, I estimate the following regression in the cross section for each month t:

$$r_{p,t+1} = \gamma_{0,t} + \gamma_{1,t}\beta_{p,t} + \phi_t' Z_{p,t} + \varepsilon_{p,t} \quad (4.14)$$

where $r_{p,t+1}$ is the portfolio return for portfolio p in month $t+1$, $\beta_{p,t}$ is the portfolio betas for portfolio p in month t and $Z_{p,t}$ are other explanatory variables for portfolio p in month t.

After obtaining a time series of slope coefficients, the second stage of the standard FM regression is to calculate the time-series average of these coefficients. With the FM regression, I can easily examine the significance of the predictability of betas; I can also control for several firm characteristics at the same time.

Table 4.6 presents the results for the FM regressions of the value-weighted portfolio returns on different betas and firm-level variables. In the first regression of each panel, betas are the only explanatory variable. I find that the coefficients of all beta methods are positive but not always significant. The coefficient of the FGK beta in Regression 1 of Panel B is 0.1256 with a t-statistic of 1.73. The coefficient of the BV beta in Regression 1 of Panel D is 0.1826 with a t-statistic of 2.28. The coefficients of the FGK, BV betas are significant at the 10% and 5% levels, respectively.

In order to separate the predictive power of betas from other control variables, I consider these control variables in the FM regression. Panel A shows that when the Historical beta is the only independent variable in Regression 1, the coefficient of the Historical beta is 0.0826, which is not significant. When adding all other control variables in the FM regression (Regressions 2-4), the Historical beta still has no explanatory power to returns. The coefficients of the Historical beta even become negative (see Regression 2), but they are insignificant. This result is consistent with Fama and French (1992), who find that the beta-return relation is very flat even when beta is the only explanatory variable. In Panel B, the FGK beta coefficient is 0.1256 in Regression 1 and significant at the 10% level. I find that the significant coefficient of the FGK beta disappears when other control variables are included in the FM regression (Regressions 2-4). In Regression 1 of Panel C, I find that the coefficient of the CCJV beta is 0.1009 (but insignificant) when only beta is included in the FM regression. However, when other control variables are added in Regressions 2-4, the coefficient of the CCJV beta becomes significantly negative. From Regression 1 of Panel D, I find that when the BV beta is the only explanatory variable in the FM regression it gives a positive coefficient of 0.1826, which is significant at the 5% level. The BV beta outperforms other beta methods. This is consistent with the portfolio analysis result in Table 4.3, which gives the biggest 5-1 spread. However, this positive relation for the BV beta does not persist when other explanatory variables are allowed in the FM regression indicated from Regressions 2-4 in Panel D. When including option-implied volatility, skewness, kurtosis and the variance risk premium, the coefficient of the BV beta becomes significantly negative (see Regression 3 of Panel D). When including all control variables, the coefficient of the BV beta becomes insignificantly negative (see Regression 4 of Panel D).

I now interpret the FM regression result in Table 4.6. When beta is the only explanatory variable to returns, the relation between the BV beta and returns is significantly positive and it outperforms other beta methods. However, the positive BV beta and return relation disappears when other control variables are included in the FM regression. From Table 4.4, I find that all beta methods have clear patterns with some of the control variables included in the FM regression in Table 4.6. For the BV beta in particular, there is a relationship with firm size, book-to-market ratio, option-implied volatility and kurtosis. When I add option-implied moments and the variance risk premium in Regression 3 of Panel D, the coefficient of option-implied volatility becomes significant. The only possible explanation for this is that betas are correlated with other explanatory variables and this obscures the relation between betas and stock return. This can also be demonstrated by previous research in the cross-sectional analysis of option-implied moments, which finds option-implied moments can be explained by firm characteristics (Dennis and Mayhew, 2002; Hansis et al., 2010; Taylor et al., 2009).

4.5 Implied Downside Betas and Stock Returns

In this section, I examine whether the risk-return relation is improved when using implied downside betas. I include the Historical, FGK and BV downside beta methods in this section. The construction of implied downside betas follows Ang et al. (2002), who decompose downside betas into a conditional correlation term and a ratio of conditional total volatility to conditional market volatility. The computation of downside betas follows the formulas given in Section 4.2.2. In order to demonstrate the predictability of downside betas, I conduct a portfolio analysis in Section 4.5.1 and the FM regression in Section 4.5.2.

4.5.1 Portfolio Analysis

In order to study the downside risk-return relation, I perform a portfolio sorting methodology similar to the procedure described in Section 4.4.1. I sort the individual securities in the S&P 500 Index into five groups at the end of each month and separately for each downside beta method, according to their pre-ranked downside betas. Portfolio 1 includes firms with the lowest downside betas and portfolio 5 contains firms with the highest downside betas. I then calculate the value-weighted and equally-weighted downside betas, the annualised value-weighted and equally-weighted return without dividend and holding period return[5] for each beta methods, for each portfolio in the next month. The procedure is repeated for all months. Finally, I calculate the time-series average of implied downside betas and realised returns.

Table 4.7 provides a summary of the mean downside betas and the mean realised returns for the downside beta sorted quintile portfolios. The table shows that the 5-1 return spread is positive for the Historical, FGK and BV downside beta methods in most cases. Taking the value-weighted return without dividend as an example, the 5-1 return spread is 3.401% for the Historical downside beta in Panel A, 0.443% for the FGK downside beta in Panel B and 7.260% for the BV downside beta in Panel C. The portfolio sorting method shows that there is a positive relationship between the Historical, FGK, BV downside betas and returns. From the t-statistics of these 5-1 return spreads, I find that none of them exceeds the 10% significance level. More importantly, I find that the BV implied downside beta gives the biggest value-weighted and equally-weighted return spread between the extreme portfolios, which is consistent with the result for general beta methods presented in Table 4.3.

From the MR test in the last column of Table 4.7, I find that all MR p-values are greater than 10% for the value-weighted returns, which means that there is no monotonically increasing relation between all downside betas and the value-weighted returns. However, there exist some monotonically increasing relations for the equally-weighted portfolios. For example, the Historical downside beta gives an MR p-value of 0.085 (less than 10%) for returns without dividend in Panel A; this means that there exists a monotonically increasing relation between the Historical downside beta and the equally-weighted return without dividend at the 10% significance level. The BV downside beta gives an MR p-value of 0.042 (less than 5%) for return without dividend and 0.066 (less than 10%) for holding

[5] I include return without dividend and holding period return in the analysis. They are downloaded from CRSP directly. Return without dividend has excluded dividends, while holding period return is a total return, which includes dividends.

period returns. There exists a monotonically increasing relation between the BV downside beta and the equally-weighted return without dividend at the 5% significance level and a monotonically increasing relation between the BV downside beta and the equally-weighted holding period return at the 10% significance level. Compared with the Historical and FGK downside beta methods, the monotonically increasing relation between the BV downside beta and return is more pronounced.

I now have a close look at the comparison of the BV implied downside beta with the BV implied beta. The BV implied downside beta performs better than the BV beta in terms of the positive, significant and linear beta-return relation. More specifically, the BV downside beta gives an average 5-1 return spread of 7.260% for the value-weighted return without dividend in Panel C of Table 4.7, which is 1.02% greater than that of the BV implied beta (6.241%) shown in Panel D of Table 4.3. The MR test for the BV implied beta gives an MR p-value of 0.093 for the equally-weighted return without dividend in Panel D of Table 4.3. Panel C of Table 4.7 gives an MR p-value of 0.042 for the BV implied downside beta. The monotonically increasing relation between the BV downside beta and the equally-weighted returns becomes more significant. The result that the BV downside beta outperforms the BV beta is consistent with published research in downside stock markets (e.g. Ang et al.,2006a; Post and van Vliet,2005). For instance, Post and van Vliet (2005) find that the mean semivariance CAPM strongly outperforms the traditional mean variance CAPM in terms of its ability to explain the cross-section of US stock returns.

Figure 4.3 shows that all downside beta methods display a noisy beta-return relation across different quintile portfolios for the value-weighted returns. For the value-weighted portfolios, the return difference between the extreme quintile portfolios is more pronounced for the BV downside beta rather than for the Historical and FGK downside beta methods. The FGK downside beta method gives the flattest beta-return relation with 0.443% return spread, while the BV downside beta displays a relatively increasing risk-return relation to some extent with 7.260% return spread. The equally-weighted quintile portfolio returns for the historical and BV downside beta methods display a monotonically increasing risk-return relation and the MR test proves that the Historical and BV downside betas indeed have a monotonically increasing risk-return relation at the 10% significance level.

Overall, the results in Table 4.7 and Figure 4.3 indicate that the BV downside beta outperforms the Historical, FGK downside beta methods. Additionally, the BV downside beta offers an improvement over the BV beta. The positive relation between market beta risk and returns is much stronger and more pronounced for the BV downside beta than the general BV beta method.

4.5.2 Fama-MacBeth Regressions

After the portfolio analysis sorted on the basis of downside betas in Section 4.5.1, I run the month-by-month FM regression in this subsection. Except for different downside betas, it includes the control variables: firm size, book-to-market ratio, option-implied volatility, skewness, kurtosis, the variance risk premium, momentum and illiquidity.

Table 4.8 presents the results for the FM regression of the value-weighted returns on different downside betas and other control variables. The first regression in each panel shows the result for the FM regression on only downside betas. When doing regressions on only downside betas, I find that the coefficients of all downside beta methods are positive but they are not always significant. Only the coefficient of the BV downside beta in Regression 1 of Panel C (0.2187 with a t-statistic of 2.31) is significant at the 5% level. This is consistent with the portfolio analysis result in Table 4.7, which gives the biggest 5-1 spread of 7.260% per year. However, this positive relation for the BV downside beta is not robust when other explanatory variables are allowed in Regressions 2-4 in Panel C. When option-implied volatility, skewness, kurtosis and variance risk premium are also included, the coefficient of the BV downside beta becomes negative and insignificant (see

Regression 3 of Panel C). When all control variables are included, the slope of the BV downside beta becomes significantly negative (see Regression 4 of Panel C). The only possible explanation to this is that the BV downside beta is correlated with other explanatory variables and this obscures the relation between the BV downside beta and returns.

Therefore, the FM regression confirms that the BV downside beta outperforms the Historical and FGK downside beta methods in terms of the positive beta-return relation. However, this kind of positive relationship disappears when other control variables are included in the cross-sectional FM regression.

4.6 Conclusion

On the basis of previous research of Buss and Vilkov (2012), this research investigates further the relationship between option-implied betas and implied downside beta, and stock returns using the portfolio analysis and the FM regression.

Consistent with Buss and Vilkov (2012), I find that the BV beta outperforms other beta methods, giving the biggest positive 5-1 return spread through the portfolio analysis. A long-short portfolio buying the stocks in the highest BV beta quintile and shorting the stocks in the lowest BV beta quintile produces positive average returns. The BV beta has a monotonically increasing relationship with the equally-weighted return without dividend at the 10% significance level, while there is no monotonically increasing or decreasing relationship between other betas and s-tock returns for both the value-weighted and equally-weighted portfolios.

This thesis is the first to propose to combine the downside correlation of Ang et al. (2002) and the option-implied moments of Bakshi et al. (2003) to measure option-implied downside betas following the previous implied beta methods of FGK and BV. When sorting the stocks on downside betas, I find that the BV downside beta performs best, giving the biggest 5-1 return spread compared with the Historical and FGK downside betas. The MR test shows that the BV downside beta is more pronounced in terms of the monotonically increasing beta-return relationship than the Historical and FGK downside betas. The BV downside beta has a monotonically increasing relationship with the equally-weighted return without dividend and holding period returns at the 5% and 10% significance levels, respectively.

Additionally, the BV downside beta can improve the performance of the BV beta in terms of the beta-risk relation. The BV downside beta gives 1.02% bigger 5-1 return spread than that of the general BV beta for the value-weighted return without dividend. The MR test shows that the monotonically increasing beta-return relation becomes more significant when using downside measures. The BV downside beta has a monotonically increasing relationship with the equally-weighted return without dividend and holding period returns at the 5% and 10% significance levels, respectively. The BV beta only has a monotonically increasing relationship with the equally-weighted return without dividend at the 10% significance level.

I find, however, that the beta-return relation for option-implied betas and implied downside betas is not robust to firm characteristics. The positive beta-return relation for the BV beta and the BV downside beta disappears when other control variables are included in the FM regression. For example, when option-implied betas or implied downside betas are the only explanatory variables in the cross-sectional FM regression, the coefficients of the BV beta and the BV downside beta are significant and positive. When considering other control variables, I find that the coefficients of the BV beta and the BV downside beta become insignificant or even negative. Overall, I find that the BV beta and the BV downside beta are correlated with other explanatory variables and that this obscures the relationship between betas and returns.

Appendix: Results for Replicating Buss and Vilkov (2012)

Data Comparison

In order to compare the results of this study with Buss and Vilkov (2012), I provide the result for the replication of Buss and Vilkov (2012). It is necessary to point out the similarities and differences between this analysis and the original paper. The S&P 500 Index and its constituents are used in both studies. The sample period ranges from January 4, 1996 to December 31, 2009. I use the same data dealing standard. I select OTM options (puts with deltas strictly larger than -0.50 and calls with deltas smaller than 0.5). I estimate option-implied moments with the same time horizon of one year. Risk-neutral moments are computed following the same method of Bakshi et al. (2003).

There are some aspects that Buss and Vilkov (2012) do not describe in their paper. First, Buss and Vilkov (2012) do not identify the risk-free interest rate used to estimate option-implied moments. In this replication, I use treasury bills from CRSP as a proxy for the risk-free interest rate. Second, Buss and Vilkov (2012) do not clarify how to calculate option-implied volatility with one year to maturity. I compute the option-implied moments with various maturities on each day. I then use linear interpolation to get the 365-day VAR, SKEW and KURTOSIS, using both contracts with maturity more than 365 days and contracts with maturity less than 365 days. If there is just one maturity in one day, I do not interpolate and I use this to represent the 365-day VAR, SKEW and KURTOSIS for that day.

There exist some data differences between the replication and Buss and Vilkov (2012). The number of firms that have both stock and option data in the S&P 500 Index available to collect is different from the description by Buss and Vilkov (2012). Sorted by PERMNO, Buss and Vilkov (2012) have a total of 950 firms in their data, which exceeds 500 because of index additions and deletions. I obtain the constituents of the S&P 500 Index from COMPUSTAT. Sorted by gvkey, I get

908 companies from January 4, 1996 to December 31, 2009. I then use the firms from COMPUSTAT to collect stock data from CRSP and option data from Option-Metrics. For firms with stock data available, I have a total of 897 names sorted by PERMNO. When applying the same data filtering role as in Buss and Vilkov (2012), i.e. selecting OTM options (puts with deltas strictly larger than -0.5 and calls with deltas smaller than 0.5), Buss and Vilkov (2012) obtain 373 in 1996 to 483 in 2009 out of 500 stocks in the S&P 500 Index. I obtain more than 450 in 1996 and 496 stocks at the beginning of 2009. This may be because the database has updated in recent years.

Table 4.9 presents descriptive statistics for option-implied volatility and skewness for the sample period January 1996 to December 2009. It reports the number of observations, average, standard deviation and median as well as 25th and 75th percentiles of option-implied volatility and skewness for both the S&P 500 Index and stocks. I Winsorise the variables, stock implied volatility and skewness, at the 1% and 99% levels following Ang et al. (2006a). For example, if an observation for stock option-implied volatility is extremely large and above the 99th percentile of all the firms' implied volatility, I replace the firm's option-implied volatility with the implied volatility corresponding to the 99th percentile. The same procedure applies to option-implied skewness. From Table 4.9, I find that the average S&P 500 Index volatility is 0.2378 and the average stock volatility is 0.3708. It is clear that the average S&P 500 Index volatility is less than the average stock volatility. The average S&P 500 Index skewness is -0.9608; this is more negative than the average stock skewness (-0.3804). This shows that the distribution of both index and stock return is negatively skewed.

Portfolio Analysis

Table 4.10 provides a summary of the mean expected betas and the mean realised returns for the beta-sorted quintile portfolios from the paper of Buss and Vilkov (2012). From the 5-1 return spread and the monotonicity test, I confirm that there is a monotonically increasing relation between the BV beta and returns.

Based on the collected option data in this study from January 1996 to December 2009, I perform a portfolio analysis. I sort the individual securities in the S&P 500 Index into five groups at the end of each month and separately for each beta method, according to their pre-ranked betas. The pre-ranked betas are estimated using previous one-year daily stock returns at the end of month *t* (at least 40% of 365-day daily returns). For example, I begin by estimating the coefficient beta for the one-year period from January 1996 to December 1996 for all equities listed on the S&P 500 Index at the beginning of January 1997. These stocks are then ranked from low to high on the basis of the estimated pre-ranked betas and are assigned to five portfolios with equal number of securities: the 20% of the stocks with the smallest betas to the first portfolio, the 20% of the stocks with the biggest betas to the fifth portfolio and so on. After constructing the portfolios based on the pre-ranked betas, I calculate the value-weighted betas, the annualised value-weighted return without dividend for each beta method, for each portfolio in the next month *t+1*. The procedure is repeated for the whole sample. Then I calculate the time-series average of the value-weighted betas, the value-weighted return without dividend in the next month *t+1*.

For some trading days and firms, option and stock data are available but risk-neutral moments may not be available after a series of data dealing and calculation. I use risk-neutral moments to calculate option-implied betas. For the portfolio analysis, I just use the available implied betas at the end of the month or I fill in the missing implied betas (stock data available at this day) at the end of the month for maximum of ten times. The portfolio sorting result with beta filling and without beta filling is shown in 4.11.

Table 4.11 provides a summary of the mean expected betas and the mean realised returns for the beta-sorted quintile portfolios for the replication from 1996 to 2009. I find that, for all methods, the difference between replicated quintile betas and betas from Buss and Vilkov (2012) is very small. For the quintile portfolio returns, the biggest difference for the BV beta is 1.79%, the biggest difference for the Historical beta is 1% and the biggest difference for the FGK beta is 1.03%. I conclude that there are two main reasons for the difference of the quintile portfolio return. The first reason is data differences, which I have described above; the number of companies I collect data for is slightly different from Buss and Vilkov (2012) because of database updating. The interpolation method to calculate the one-year option-implied moments may exist difference. The risk-free rate proxy may be different. The second reason is the sensitivity of the portfolio sorting method; I use daily arithmetic return in the portfolio sort, while I report annualised return, which is equal to daily return multiplying by 252. Daily returns are very small and sensitive. Once annualised, a small difference has the potential to cause large changes.

Figure 4.4 compares the portfolio result for the replication with the result in Buss and Vilkov (2012). I find that the linear shapes for all beta methods in the replication are similar to the shapes from the original paper. This shows that the replication is very close to the paper and it indicates that the results of this study are reasonable and valid.

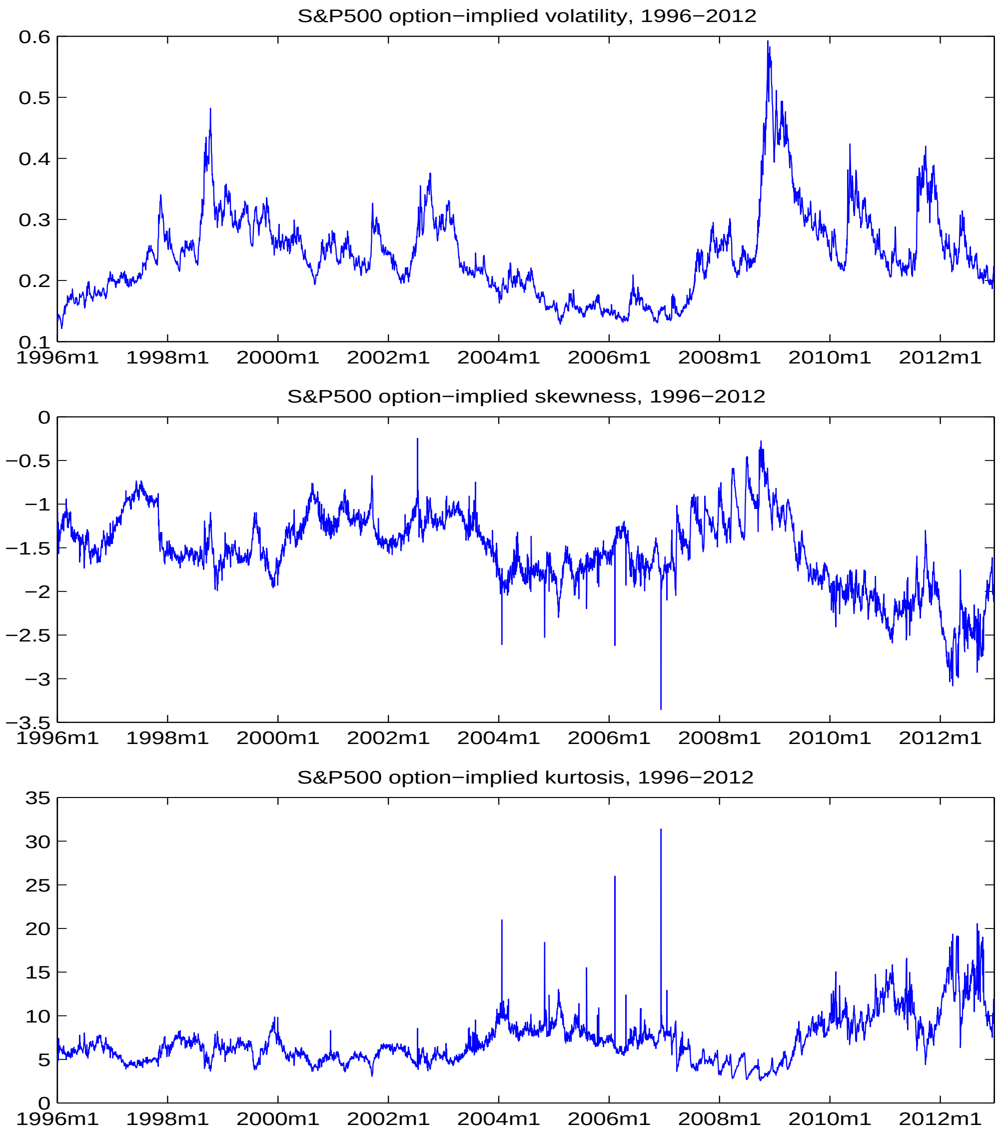
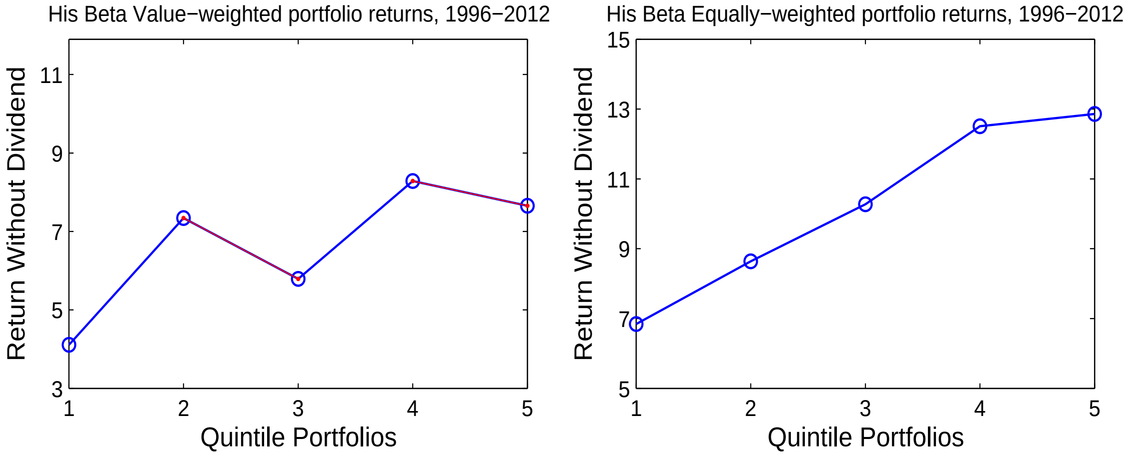
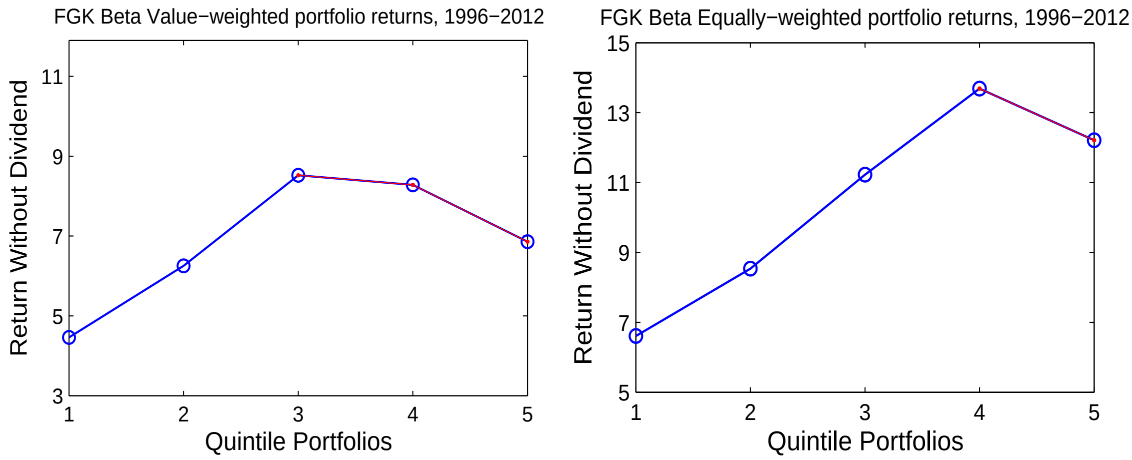


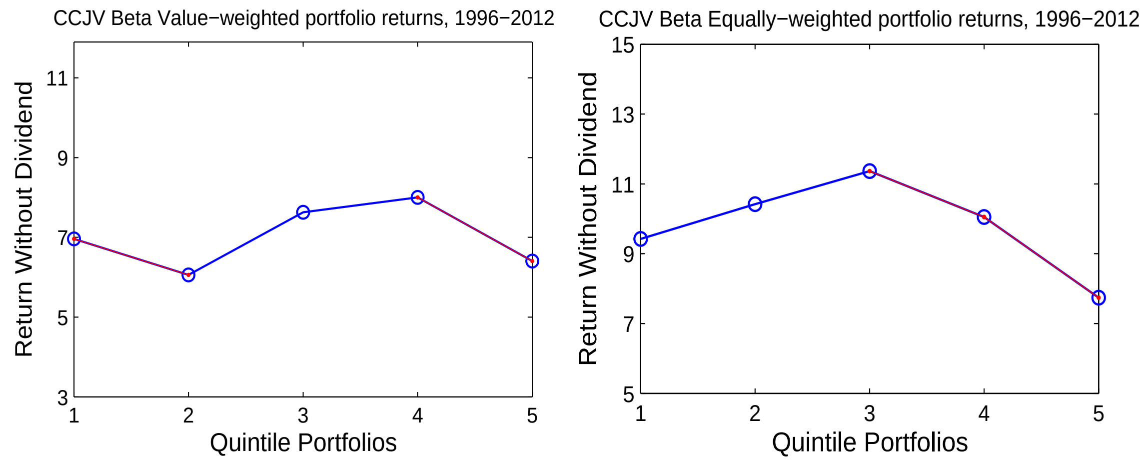
Figure 4.1. Plot of S&P 500 Option-Implied Moments This figure plots option-implied volatility, skewness and kurtosis for the S&P 500 Index from January 1996 to December 2012.



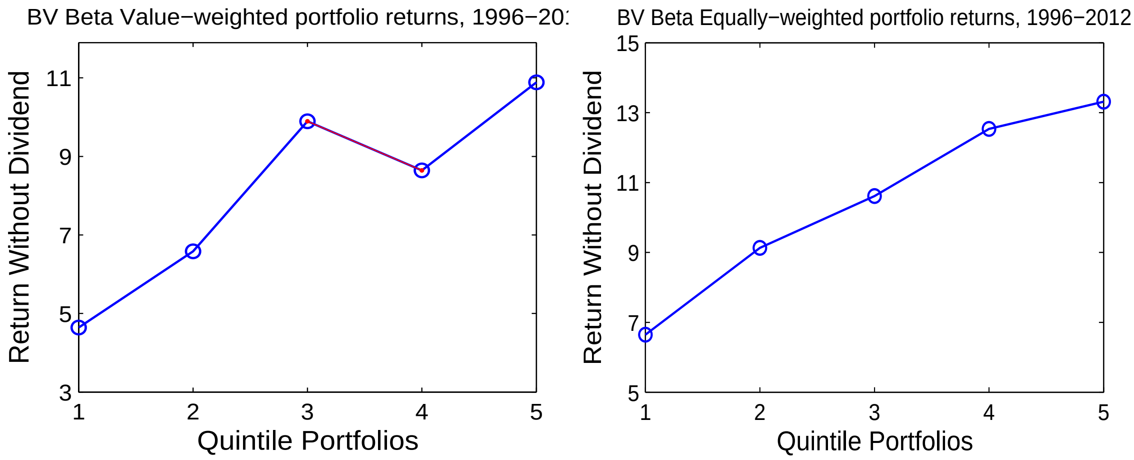
(a) Panel A: Historical Beta



(b) Panel B: FGK Beta

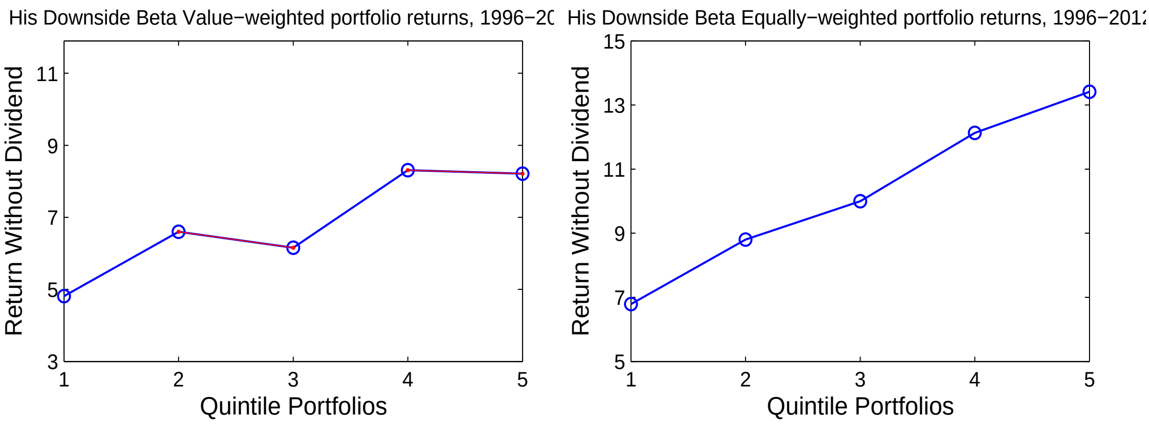


(c) Panel C: CCJV Beta

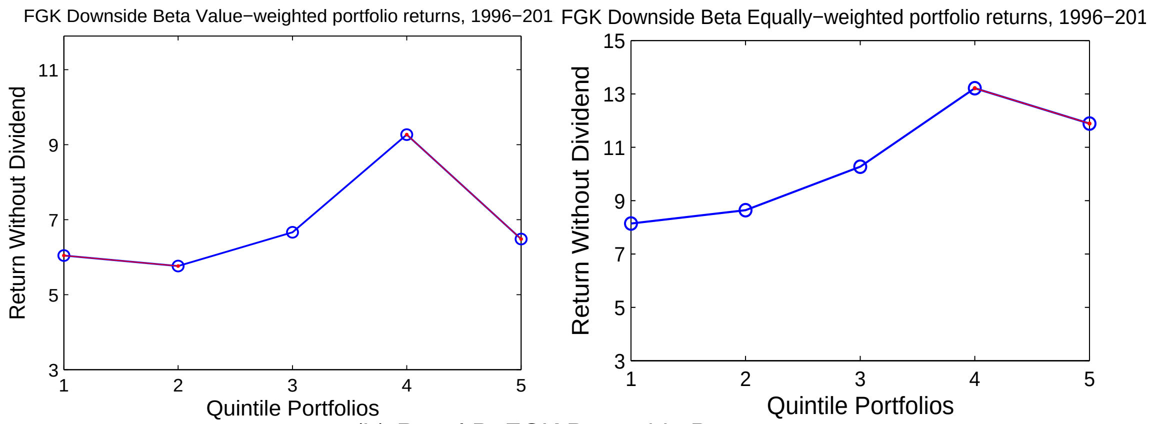


(d) Panel D: BV Beta

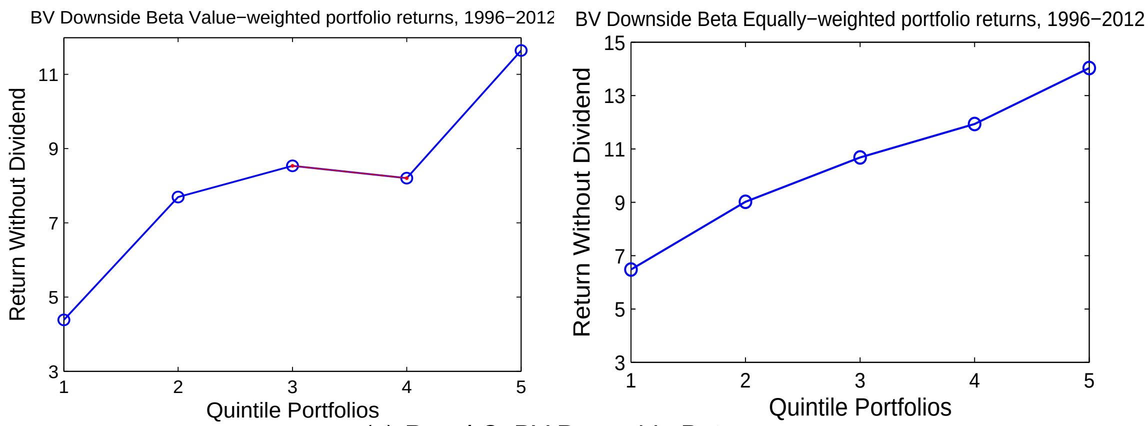
Figure 4.2. Plot of Betas and Returns The figure shows the annualised return without dividend of the five quintile portfolios sorted by pre-ranked betas over the sample period from January 1996 to December 2012. At the end of each month, I sort the stocks into quintiles based on their pre-ranked betas. The first portfolio then contains the stocks with the lowest beta, while the last portfolio contains the stocks with the highest beta. I then compute the annualised value-weighted and equally-weighted realised return without dividend over the next month for each quintile portfolio, month and beta methodology. Exact numerical values for the betas and returns of each portfolio are shown in Table 4.3. The four panels present the results for four different beta methods. The returns are expressed in percentages.



(a) Panel A: Historical Downside Beta

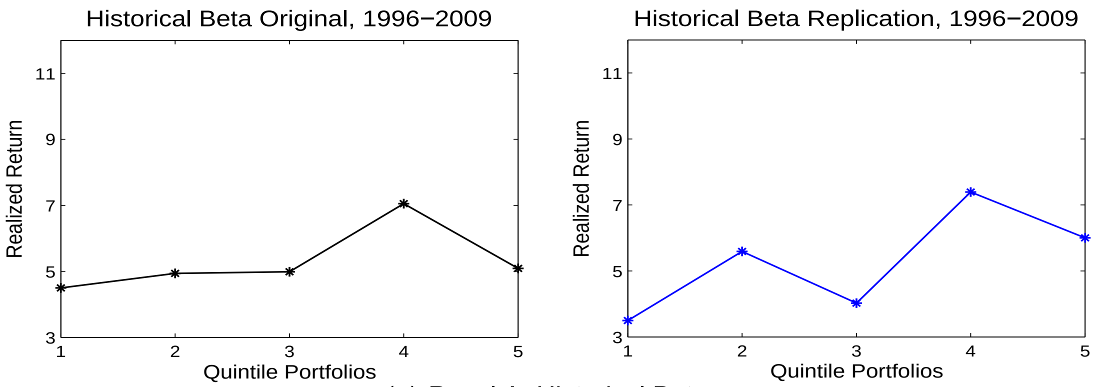


(b) Panel B: FGK Downside Beta

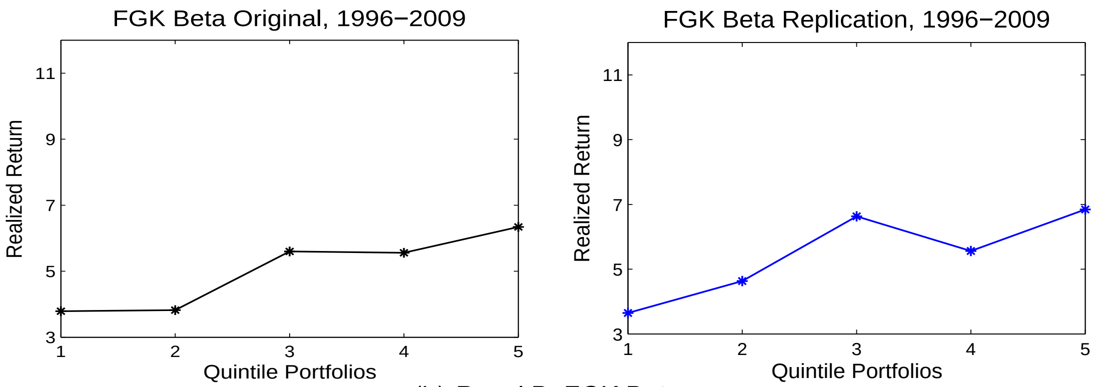


(c) Panel C: BV Downside Beta

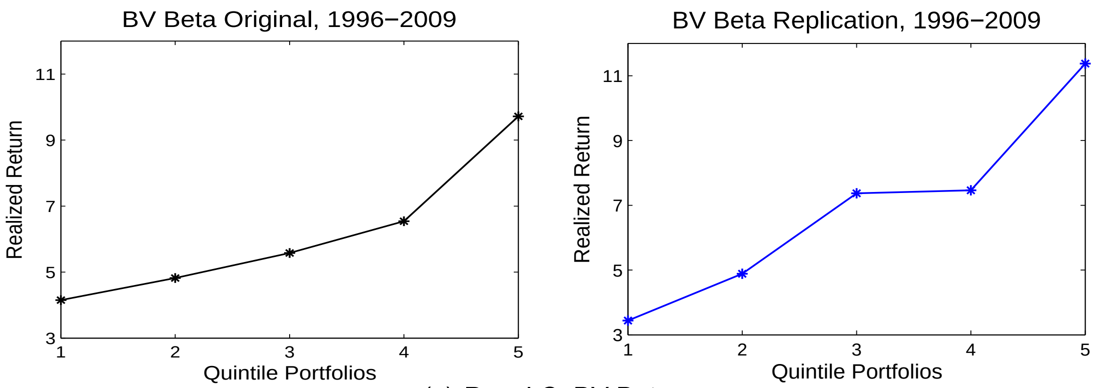
Figure 4.3. Plot of Downside Betas and Returns The figure shows the annualised return of the five quintile portfolios sorted by pre-ranked downside betas over the sample period from January 1996 to December 2012. At the end of each month, I sort the stocks into quintiles based on their pre-ranked downside betas. The first portfolio then contains the stocks with the lowest downside market beta, while the last portfolio contains the stocks with the highest downside market beta. I then compute the annualised value-weighted and equally-weighted realised returns without dividend over the next month for each quintile portfolio, month and downside beta methodology. Exact numerical values for the returns and betas of each portfolio are shown in Table 4.7. The three panels present the results for different downside beta methods. The returns are expressed in percentages.



(a) Panel A: Historical Beta



(b) Panel B: FGK Beta



(c) Panel C: BV Beta

Figure 4.4. Plot of Betas and Returns Comparing with the BV Paper The figure shows the annualised realised return of the five quintile portfolios sorted by pre-ranked betas over the sample period from January 1996 to December 2009. At the end of each month, I sort the stocks into quintiles based on their pre-ranked betas. The first portfolio then contains the stocks with the lowest beta, while the last portfolio contains the stocks with the highest beta. I then compute the annualised value-weighted returns over the next month for each quintile portfolio, month and beta methodology. Exact numerical values for the returns and betas of each portfolio could be found in Table 4.10 and Table 4.11. The three panels present the results for different beta methods. The returns are expressed in percentages. The figures on the left hand side are the original figures from Buss and Vilkov (2012) and the figures on the right hand side are the figures from the replication. Note: the figure plots the quintile portfolios with beta filling.

Table 4.1. Descriptive Statistics for Option-Implied Moments
The table reports descriptive statistics on risk-neutral moments: volatility, skewness and kurtosis for the S&P 500 Index and its constituents from January 1996 to December 2012. Risk-neutral moments are calculated following the model-free procedure of Bakshi et al. (2003). The table reports the number of observation, mean, median, standard deviation and 25th and 75th percentiles.

	Observation	Mean	StDev	25th Percentile	Median	75th Percentile
S&P 500 Volatility	4,278	0.2422	0.0713	0.1934	0.2338	0.2810
S&P 500 Skew	4,278	-1.5342	0.4333	-1.7882	-1.5165	-1.2222
S&P 500 Kurtosis	4,278	7.1139	2.7082	5.2367	6.5108	8.3001
Stock Volatility	1,683,646	0.3934	0.1760	0.2760	0.3526	0.4600
Stock Skew	1,683,646	-0.4417	0.4035	-0.6586	-0.4318	-0.1975
Stock Kurtosis	1,683,646	3.5738	1.1391	3.0026	3.2660	3.7450

Table 4.2. Descriptive Statistics for Different Beta Methods
The table provides summary statistics for the general beta methods and the downside beta methods. The sample period is from January 1996 to December 2012. For each day, I compute, for each methodology separately, the daily betas for all stocks in the S&P 500 Index. The table reports the number of observation, mean, value-weighted mean, standard deviation and the 25th, 50th and 75th percentiles. Panel A reports summary descriptives for the general beta methods. Panel B presents summary statistics for the downside beta methods. Panel C provides the correlations of different betas.

	Observation	Mean	Weighted Mean	StDev	25th Percentile	Median	75th Percentile
			Panel A: General Betas				
Historical	1,964,655	1.0046	1.0050	0.5029	0.6739	0.9373	1.2555
FGK	1,612,617	0.8476	0.8483	0.4082	0.5779	0.8045	1.0586
CCJV	1,531,197	1.0323	1.0329	0.4086	0.7643	0.9770	1.2314
BV	1,612,617	1.0732	1.0734	0.3891	0.8207	1.0162	1.2655
			Panel B: Downside Betas				
Historical	1,964,655	1.0081	1.0086	0.4990	0.6782	0.9425	1.2600
FGK	1,612,949	0.6506	0.6511	0.3566	0.4089	0.6224	0.8601
BV	1,612,949	1.0974	1.0976	0.3708	0.8456	1.0310	1.2800
			Panel C: Correlations of Betas				
	Historical	FGK	CCJV	BV	His D	FGK D	
FGK	0.7271						
CCJV	0.1934	0.4187					
BV	0.6887	0.7458	0.3762				
His D	0.9229	0.6714	0.1909	0.6460			
FGK D	0.5266	0.7378	0.2939	0.5348	0.6267		
BV D	0.5420	0.6057	0.4279	0.8759	0.5920	0.6299	

Table 4.3. Portfolios Sorted by Different Beta Methods and MR Test

The five quintile portfolios are sorted by pre-ranked betas over the sample period from January 1996 to December 2012. At the end of each month, I sort the stocks into quintiles based on their pre-ranked betas. The first portfolio then contains the stocks with the lowest beta, while the last portfolio contains the stocks with the highest beta. I then compute the annualised value-weighted and equally-weighted realised returns over the next month for each quintile portfolio, month and beta methodology. The table reports the time-series average of the value-weighted and equally-weighted betas and portfolio returns, as well as the 5-1 portfolio return spread, separately for each methodology. In addition, the table provides t-statistics and p-values for the 5-1 spread to test whether the spread is significant or not. It also provides p-values, obtained from time-series block bootstrapping, for the Patton and Timmermann (2010) MR test. In this table, v-beta, e-beta denotes the value-weighted, equally-weighted betas, respectively. v-rwd, v-hpr represents the value-weighted return without dividend and holding period return, respectively. e-rwd, e-hpr denotes the equally-weighted return without dividend and holding period return, respectively. The returns are expressed in percentages.

	1	2	3	4	5	5-1	t-stat	t-pval	MR-p
Panel A: Historical Beta									
v-beta	0.470	0.732	0.928	1.169	1.643	1.172	-	-	-
e-beta	0.464	0.732	0.929	1.165	1.713	1.249	-	-	-
v-rwd	4.110	7.342	5.792	8.284	7.656	3.545	0.567	0.285	0.490
v-hpr	6.680	9.598	7.664	9.913	8.854	2.174	0.349	0.363	0.608
e-rwd	6.844	8.639	10.273	12.510	12.858	6.014	0.895	0.185	0.131
e-hpr	9.403	10.711	12.042	14.113	13.978	4.574	0.682	0.248	0.170
Panel B: FGK Beta									
v-beta	0.411	0.624	0.783	0.967	1.283	0.872	-	-	-
e-beta	0.408	0.634	0.794	0.969	1.343	0.934	-	-	-
v-rwd	4.483	6.238	8.499	8.309	6.859	2.376	0.349	0.363	0.251
v-hpr	6.935	8.305	10.333	9.869	8.032	1.097	0.164	0.435	0.301
e-rwd	6.629	8.513	11.220	13.699	12.207	5.577	0.817	0.207	0.288
e-hpr	8.874	10.299	12.887	15.207	13.297	4.422	0.648	0.258	0.337
Panel C: CCJV Beta									
v-beta	0.617	0.787	0.919	1.090	1.419	0.801	-	-	-
e-beta	0.695	0.834	0.956	1.114	1.457	0.762	-	-	-
v-rwd	6.969	6.060	7.589	7.952	6.450	-0.518	0.089	0.465	0.498
v-hpr	9.576	8.067	9.295	9.259	7.502	-2.074	0.358	0.360	0.406
e-rwd	9.443	10.405	11.379	9.970	7.804	-1.640	0.301	0.382	0.424
e-hpr	11.824	12.229	12.972	11.288	8.811	-3.012	0.554	0.290	0.344
Panel D: BV Beta									
v-beta	0.644	0.848	1.000	1.189	1.537	0.893	-	-	-
e-beta	0.658	0.862	1.010	1.195	1.620	0.963	-	-	-
v-rwd	4.644	6.584	9.893	8.645	10.884	6.241	0.838	0.201	0.325
v-hpr	7.315	8.529	11.525	10.066	11.785	4.470	0.602	0.274	0.366
e-rwd	6.647	9.131	10.616	12.537	13.316	6.669	0.940	0.173	0.093
e-hpr	9.171	10.976	12.238	13.973	14.185	5.014	0.708	0.240	0.129

Table 4.4. Properties of Portfolios Formed on Different Betas

The table provides the average characteristics related to firms and option-implied moments for quintile portfolios sorted on the pre-ranked betas, over the sample period from January 1996 to December 2012. At the end of each month, the five portfolios are formed based on the pre-ranked betas. For each quintile portfolio, month and methodology, I compute the average of ln(ME), ln(BE/ME), option-implied moments and the variance risk premium for all stocks at the time when portfolios are sorted. The table reports the time-series means of these statistics for all quintile portfolios, as well as the 5-1 portfolio spread, separately for each methodology. In addition, the table provides t-statistics and p-values for the 5-1 spread to test whether the spread is significant or not. It also provides p-values, obtained from time-series block bootstrapping, for the Patton and Timmermann (2010) MR test.

	1	2	3	4	5	5-1	t-stat	t-pval	MR-pval
Panel A: Historical Beta									
ln(ME)	2.327	2.271	2.246	2.297	2.285	-0.042	0.337	0.368	0.594
ln(BE/ME)	-7.931	-7.924	-7.909	-7.885	-7.901	0.030	0.333	0.369	0.311
MFIV	0.305	0.328	0.354	0.397	0.517	0.212	11.300	0.000	0.000
MFIS	-0.410	-0.422	-0.430	-0.422	-0.359	0.051	1.912	0.028	0.566
MFIK	4.014	3.837	3.627	3.481	3.232	-0.781	9.842	0.000	0.000
VRP	-0.008	-0.007	-0.003	0.005	0.046	0.054	1.749	0.040	0.228
Panel B: FGK Beta									
ln(ME)	2.560	2.516	2.498	2.473	2.372	-0.188	1.795	0.036	0.063
ln(BE/ME)	-8.089	-8.006	-7.965	-7.924	-7.930	0.159	2.081	0.019	0.210
MFIV	0.301	0.327	0.357	0.405	0.536	0.234	11.926	0.000	0.000
MFIS	-0.402	-0.421	-0.427	-0.428	-0.372	0.030	1.283	0.100	0.946
MFIK	3.970	3.723	3.644	3.508	3.261	-0.709	9.419	0.000	0.000
VRP	-0.002	-0.002	0.004	0.004	0.035	0.038	1.316	0.094	0.237
Panel C: CCJV Beta									
ln(ME)	2.644	2.639	2.610	2.501	2.307	-0.338	4.776	0.000	0.153
ln(B/M)	-8.007	-8.037	-8.032	-8.021	-8.013	-0.005	0.109	0.457	0.403
MFIV	0.287	0.319	0.356	0.407	0.515	0.228	18.283	0.000	0.000
MFIS	-0.329	-0.433	-0.480	-0.520	-0.596	-0.267	17.947	0.000	0.000
MFIK	3.485	3.387	3.422	3.443	3.494	0.009	0.157	0.438	0.995
VRP	0.006	0.004	0.002	0.001	0.005	-0.001	0.080	0.468	0.306
Panel D: BV Beta									
ln(ME)	2.796	2.619	2.530	2.393	2.082	-0.714	12.268	0.000	0.000
ln(BE/ME)	-8.124	-8.009	-7.959	-7.921	-7.905	0.219	3.511	0.000	0.046
MFIV	0.269	0.317	0.357	0.416	0.568	0.298	20.423	0.000	0.000
MFIS	-0.429	-0.439	-0.434	-0.417	-0.330	0.100	4.886	0.000	0.423
MFIK	3.995	3.738	3.627	3.524	3.222	-0.773	8.231	0.000	0.000
VRP	0.001	-0.001	0.000	0.005	0.033	0.032	1.190	0.117	0.620

Table 4.5. Portfolio Returns Sorted by Firm Characteristics

The five quintile portfolios are sorted by firm-level factors over the sample period from January 1996 to December 2012. At the end of each month, I sort the stocks into quintiles based on these factors. I then compute the value-weighted and equally-weighted realised returns over the next month. The time-series average of the value-weighted and equally-weighted portfolio returns is reported in this table. In addition, the table provides t-statistics and p-values for the 5-1 spread to test whether the spread is significant or not. It also provides p-values, obtained from time-series block bootstrapping, for the Patton and Timmermann (2010) MR test. v-rwd, v-hpr represents the value-weighted return without dividend and holding period return, respectively. e-rwd, e-hpr denotes the equally-weighted return without dividend and holding period return, respectively. The returns are expressed in percentages.

	1	2	3	4	5	5-1	t-stat	t-pval	MR-p
Panel A: Firm Size									
v-rwd	13.016	9.751	8.999	7.188	6.007	-7.009	1.459	0.072	0.045
v-hpr	14.722	11.572	10.927	8.994	7.931	-6.791	1.413	0.079	0.056
e-rwd	14.839	10.412	9.881	8.324	7.701	-7.139	1.559	0.060	0.057
e-hpr	16.526	12.227	11.808	10.141	9.537	-6.988	1.526	0.064	0.068
Panel B: Book-to-Market Ratio									
v-rwd	6.449	5.713	6.837	8.145	6.777	0.328	0.067	0.473	0.279
v-hpr	7.945	7.401	8.958	10.563	9.322	1.377	0.286	0.388	0.251
e-rwd	8.863	7.639	8.661	10.893	13.608	4.745	1.095	0.137	0.300
e-hpr	10.286	9.071	10.392	12.853	16.092	5.806	1.336	0.091	0.301
Panel C: Option-Implied Volatility									
v-rwd	4.919	8.093	9.290	8.843	10.082	5.163	0.677	0.249	0.185
v-hpr	7.590	9.994	10.758	9.988	10.795	3.205	0.421	0.337	0.230
e-rwd	6.587	9.934	10.795	12.623	12.147	5.560	0.777	0.218	0.206
e-hpr	9.257	11.861	12.357	13.904	12.904	3.647	0.511	0.305	0.256
Panel D: Option-Implied Skewness									
v-rwd	4.584	7.644	7.820	9.219	10.213	5.630	1.462	0.072	0.046
v-hpr	6.385	9.473	9.690	10.846	12.104	5.720	1.494	0.068	0.042
e-rwd	5.434	9.046	10.035	13.295	14.257	8.823	2.196	0.014	0.018
e-hpr	7.246	10.776	11.683	14.743	15.818	8.573	2.138	0.016	0.015
Panel E: Option-Implied Kurtosis									
v-rwd	8.465	9.198	10.812	5.155	5.665	-2.800	0.547	0.292	0.379
v-hpr	9.714	10.730	12.507	7.176	7.701	-2.013	0.394	0.347	0.426
e-rwd	12.918	15.002	10.943	6.171	7.032	-5.886	1.233	0.109	0.301
e-hpr	14.056	16.417	12.575	8.171	9.043	-5.013	1.052	0.146	0.298
Panel F: Variance Risk Premium									
v-rwd	19.201	15.224	9.096	5.617	-9.573	-28.774	4.306	0.000	0.000
v-hpr	20.249	16.758	10.981	7.730	-7.527	-27.776	4.137	0.000	0.001
e-rwd	13.170	13.552	12.301	10.342	3.108	-10.062	1.646	0.050	0.149
e-hpr	14.234	15.085	14.094	12.324	4.871	-9.363	1.531	0.063	0.236

Table 4.6. Fama-MacBeth Regressions for General Betas

The table shows the results for the Fama and MacBeth (1973) regression of the annualised value-weighted returns on betas and firm characteristics. The sample period is from January 1996 to December 2012. I report the average of coefficients and the t-statistics of the independent variables. The t-statistics are shown in brackets. Note: *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

	Constant	β	ln(ME)	ln(BE/ME)	MFIV	MFIS	MFIK	VRP	Momentum	Illiquidity
					Panel A: Historical Beta					
1	-0.0088	0.0826								
	(-0.23)	(1.54)								
2	-0.8189	-0.0905	-0.0242	-0.1261						
	(-0.43)	(-0.72)	(-0.18)	(-0.58)						
3	-0.7490	-0.6688***			2.9220*	-1.7811	-0.0931	2.1495		
	(-0.47)	(-2.71)			(1.81)	(-1.39)	(-0.26)	(1.46)		
4	-1.9239	0.0238	-0.0704	-0.1835	-0.0023	-0.0882	0.2079	0.0356	0.1505	0.0000
	(-1.19)	(0.18)	(-0.50)	(-1.14)	(-0.06)	(-0.75)	(0.93)	(0.37)	(1.52)	(omitted)
					Panel B: FGK Beta					
1	-0.0196	0.1256*								
	(-0.44)	(1.73)								
2	0.6137	0.0305	0.0485	0.0717						
	(0.39)	(0.18)	(0.30)	(0.33)						
3	-2.6857**	-0.1532			-0.0648	0.8782	-0.8021**	2.9166**		
	(1.98)	(-0.49)			(-0.07)	(0.70)	(-2.39)	(2.41)		
4	-0.7008	-0.0825	0.1679	-0.1827	0.1369	-0.1580	-0.3269*	-0.0058	0.2074	0.0000
	(-0.39)	(-0.59)	(1.33)	(-0.91)	(1.42)	(-0.95)	(-1.79)	(-0.08)	(1.24)	(omitted)

Table 4.6---Continued

	Constant	β	ln(ME)	ln(BE/ME)	MFIV	MFIS	MFIK	VRP	Momentum	Illiquidity
					Panel C: CCJV Beta					
1	0.0090	0.1009								
	(0.17)	(1.42)								
2	-0.1864	0.029	-0.0830	-0.0565						
	(-0.10)	(0.23)	(-0.80)	(-0.24)						
3	1.1213	-1.6315***			5.0799***	-1.8917***	-0.6468	-0.0418		
	(0.91)	(-2.85)			(3.11)	(-2.58)	(-1.57)	(-0.05)		
4	-0.1284	-0.3364**	-0.1031	0.0572	0.3134	-0.2352**	0.2840*	0.0083	0.0784	0.0000
	(-0.08)	(-2.09)	(-0.90)	(0.32)	(1.54)	(-2.01)	(1.67)	(0.07)	(0.44)	(omitted)
					Panel D: BV Beta					
1	-0.1027	0.1826**								
	(-1.65)	(2.28)								
2	-0.1945	0.0193	-0.1192	-0.0698						
	(-0.15)	(0.14)	(-1.08)	(-0.42)						
3	1.7934	-1.1780**			3.5074**	0.3619	-0.4704	-0.5609		
	(1.62)	(-2.57)			(2.44)	(0.53)	(-1.59)	(-0.37)		
4	1.6936	-0.1287	-0.1465	-0.0172	0.1236	0.0137	-0.3901*	0.0051	-0.1083	0.0000
	(0.85)	(-0.61)	(-0.72)	(-0.07)	(1.48)	(0.09)	(-1.66)	(0.05)	(-1.24)	(omitted)

Table 4.7. Portfolio Sorts on Downside Betas and MR Test

The five quintile portfolios are sorted by pre-ranked downside betas over the sample period from January 1996 to December 2012. At the end of each month, I sort the stocks into quintiles based on their pre-ranked downside betas. The first portfolio then contains the stocks with the lowest downside beta, while the last portfolio contains the stocks with the highest downside beta. I then compute the value-weighted and equally-weighted realised returns over the next month. The time-series average of the value-weighted and equally-weighted portfolio returns is reported in this table. In addition, the table provides t-statistics and p-values for the 5-1 spread to test whether the spread is significant or not. It also provides p-values, obtained from time-series block bootstrapping, for the Patton and Timmermann (2010) MR test. Note: v-rwd, v-hpr represents the value-weighted return without dividend and holding period return, respectively. e-rwd, e-hpr denotes the equally-weighted return without dividend and holding period return, respectively. The returns are expressed in percentages.

	1	2	3	4	5	5-1	t-stat	t-pval	MR-p
Panel A: Historical Downside Beta									
v-beta	0.473	0.738	0.934	1.174	1.641	1.169	-	-	-
e-beta	0.468	0.739	0.936	1.167	1.712	1.244	-	-	-
v-rwd	4.812	6.601	6.158	8.310	8.213	3.401	0.549	0.291	0.232
v-hpr	7.383	8.809	8.057	9.940	9.407	2.025	0.328	0.371	0.333
e-rwd	6.788	8.801	9.996	12.132	13.410	6.622	0.979	0.164	0.085
e-hpr	9.325	10.897	11.777	13.767	14.485	5.160	0.763	0.223	0.118
Panel B: FGK Downside Beta									
v-beta	0.266	0.465	0.603	0.764	1.026	0.760	-	-	-
e-beta	0.258	0.472	0.610	0.766	1.066	0.807	-	-	-
v-rwd	6.043	5.762	6.665	9.268	6.485	0.443	0.076	0.470	0.448
v-hpr	8.322	7.757	8.506	10.909	7.786	-0.537	-0.092	0.537	0.513
e-rwd	8.139	8.636	10.268	13.210	11.886	3.747	0.622	0.267	0.259
e-hpr	10.125	10.452	11.973	14.831	13.051	2.926	0.486	0.314	0.323
Panel C: BV Downside Beta									
v-beta	0.692	0.878	1.016	1.200	1.540	0.848	-	-	-
e-beta	0.710	0.891	1.029	1.212	1.632	0.923	-	-	-
v-rwd	4.384	7.695	8.536	8.206	11.643	7.260	0.939	0.174	0.145
v-hpr	7.065	9.620	10.060	9.572	12.461	5.395	0.700	0.242	0.166
e-rwd	6.479	9.013	10.675	11.933	14.030	7.551	1.068	0.143	0.042
e-hpr	9.067	10.898	12.262	13.340	14.858	5.791	0.820	0.206	0.066

Table 4.8. Fama-MacBeth Regressions for Implied Downside Betas

The table shows the results for the Fama and MacBeth (1973) regression of the annualised value-weighted returns on downside betas and firm characteristics. The sample period is from January 1996 to December 2012. I report the coefficients and the t-statistics of the independent variables. The t-statistics are shown in brackets. Note: *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

	Constant	β	ln(ME)	ln(BE/ME)	MFIV	MFIS	MFIK	VRP	Momentum	Illiquidity
					Panel A: Historical Downside Beta					
1	-0.0061	0.0812								
	(-0.16)	(1.50)								
2	-1.1341	-0.1297	0.0140	-0.1611						
	(-0.77)	(-1.11)	(0.13)	(-0.88)						
3	-1.7829	-0.1732			1.7287	-0.8464	0.3498	-1.3202		
	(-1.38)	(-0.70)			(1.35)	(-1.09)	(1.03)	(-1.37)		
4	-2.1130*	-0.0288	-0.2583	-0.4030**	-0.0061	0.0480	-0.0886	0.1822**	0.0052	0.0002
	(-1.66)	(-0.17)	(-1.37)	(-2.49)	(0.13)	(0.41)	(-0.59)	(2.33)	(0.05)	(omitted)
					Panel B: FGK Downside Beta					
1	0.0230	0.0913								
	(0.63)	(1.26)								
2	0.0577	-0.0178	-0.3791	-0.1130						
	(0.04)	(-0.08)	(-1.37)	(-0.52)						
3	0.6866	-0.4863			0.4028	-1.5003	-0.5277*	-1.3675		
	(0.50)	(-1.25)			(0.35)	(-0.94)	(-1.74)	(-0.66)		
4	0.2407	-0.0641	-0.0289	0.0155	0.1316	-0.0450	-0.0091	-0.0398	0.0989	0.0000
	(0.16)	(-0.42)	(-0.22)	(0.09)	(0.50)	(-0.28)	(-0.06)	(-0.87)	(0.79)	(omitted)

Table 4.8---Continued

	Constant	β	ln(ME)	ln(BE/ME)	MFIV	MFIS	MFIK	VRP	Momentum	Illiquidity
					Panel C: BV Downside Beta					
1	-0.1402*	0.2187**								
	(-1.80)	(2.31)								
2	-1.3713	-0.0400	-0.1644	-0.2403						
	(-0.98)	(-0.19)	(-0.93)	(-1.32)						
3	-0.8048	-1.5393***			4.9366***	0.0964	-0.1770	-0.8048		
	(0.08)	(-3.86)			(4.11)	(0.13)	(-0.58)	(-0.46)		
4	2.8720*	-0.4116**	-0.1737	0.0977	0.0980	-0.0391	-0.3603**	-0.1128	0.0294	0.0000
	(1.88)	(-2.23)	(-1.03)	(0.56)	(1.40)	(-0.24)	(-2.00)	(-0.78)	(0.17)	(omitted)

Table 4.9. Descriptive Statistics for Option-Implied Volatility and Skewness (1996-2009)

This table reports the data descriptive statistics on risk-neutral moments: volatility and skewness for the S&P 500 Index and its constituents from January 1996 to December 2009. Risk-neutral moments are calculated using the model-free procedure in Bakshi et al. (2003). The table reports the number of observations, average, median, standard deviation and 25th and 75th percentiles.

	Observation	Mean	StDev	25th Percentile	Median	75th Percentile
S&P 500 Volatility	3,520	0.2378	0.0744	0.1812	0.2311	0.2691
S&P 500 Skew	3,520	-0.9608	0.3307	-1.1301	-0.9691	-0.8286
Stock Volatility	1,243,943	0.3708	0.1410	0.2691	0.3394	0.4369
Stock Skew	1,243,943	-0.3804	0.2736	-0.5587	-0.3784	-0.1854

Table 4.10. Quintile Portfolio Betas and Returns from BV(2012)
This table provides the mean expected beta and the annualised mean realised return for the five quintile portfolios sorted on the expected market betas, over the sample period from January 1996 to December 2009. At the end of each month, I sort, for each beta methodology, the stocks into quintiles based on their expected market beta. The first portfolio thereby contains the stocks with the lowest expected market betas, and the last portfolio contains the stocks with the highest expected market betas. For each quintile portfolio, month and methodology, I then compute the value-weighted expected portfolio market beta and the annualised value-weighted realised return over the next month. I only include a stock in the sorting procedure if its expected beta is available for all approaches within a certain group (Daily, Monthly, CCJV). The table reports the time-series means of the expected betas and the realised returns for each methodology. In addition, the table provides p-values, obtained from time-series block bootstrapping, for the Patton and Timmermann (2010) MR test of the hypotheses for monotonically increasing and monotonically decreasing relations between expected betas and returns.

	1	2	3	4	5	5-1	H_0: increasing	H_0: decreasing
				Panel A: Historical Daily				
Expected Beta	0.48	0.71	0.88	1.09	1.52	1.04	-	-
Realised Return	4.50	4.94	4.99	7.05	5.09	0.60	0.40	0.31
				Panel B: BV Option-Implied Daily				
Expected Beta	0.66	0.83	0.96	1.12	1.45	0.79	-	-
Realised Return	4.15	4.82	5.58	6.54	9.72	5.57	0.71	0.05
				Panel C: FGK Daily				
Expected Beta	0.40	0.59	0.72	0.88	1.19	0.78	-	-
Realised Return	3.79	3.82	5.60	5.56	6.34	2.55	0.40	0.07

Table 4.11. Quintile Portfolio Betas and Returns from Replication
The table provides the mean expected beta and the annualised mean realised return for the five quintile portfolios sorted on different beta measures, over the sample period from January 1996 to December 2009. At the end of each month, I sort, for each beta methodology, the stocks into quintiles based on their expected market beta. The first portfolio thereby contains the stocks with the lowest expected market betas, and the last portfolio contains the stocks with the highest expected market betas. For each quintile portfolio, month and methodology, I then compute the value-weighted expected portfolio market beta and the annualised value-weighted realised return over the next month. The table reports the time-series means of the expected betas and the realised returns for each methodology. In addition, the table provides p-values, obtained from time-series block bootstrapping, for the Patton and Timmermann (2010) MR test.

	1	2	3	4	5	5-1	MR p-val
Panel A: Historical Daily							
Expected Beta	0.49	0.72	0.89	1.13	1.59	1.11	-
Realised Return	3.50	5.59	4.03	7.39	6.00	2.50	0.43
Panel B: BV Option-Implied Daily							
(No data filling)							
Expected Beta	0.69	0.84	0.97	1.14	1.43	0.74	-
Realised Return	3.17	4.66	7.84	6.74	8.95	5.79	0.27
(Data filling)							
Expected Beta	0.70	0.86	0.99	1.16	1.47	0.78	-
Realised Return	3.44	4.88	7.37	7.46	11.37	7.94	0.12
Panel C: FGK Daily							
(No data filling)							
Expected Beta	0.41	0.59	0.73	0.89	1.16	0.75	-
Realised Return	3.18	5.02	6.02	4.81	5.46	2.28	0.30
(Dta filling)							
Expected Beta	0.42	0.60	0.74	0.90	1.18	0.77	-
Realised Return	3.65	4.63	6.63	5.56	6.85	3.20	0.32

Chapter 5

Moment Risk Premia and the Cross-Section of Stock Returns

5.1 Introduction

Variance swaps have been traded in the market. It allows investors to speculate on or hedge risks associated with the uncertainty about the return variance. A variance swap pays the difference between a standard estimate of the realised variance and the fixed variance swap rate. Since a variance swap costs zero to enter, the variance swap rate represents the risk-neutral expected value of the realised variance. As in Carr and Wu (2009), a direct estimate of the variance risk premium is the difference between the realised variance and the variance swap rate, which measures the terminal profit and loss from a long variance swap contract and holding it to maturity. The expected sign of the average variance risk premium should be negative. Writing variance swaps, receiving fixed and paying floating, is on average profitable.

The variance risk premium has become increasingly important for asset pricing; it has been demonstrated to be able to predict future stock returns by the existing literature. For example, Bali and Hovakimian (2009) find that the realised-implied volatility spread, named the volatility risk premium, has a significantly negative relationship with stock returns. However, Han and Zhou (2012) estimate a stock's variance risk premium as the difference between risk-neutral variance and expected realised variance, and they support that high values of the variance risk premium can predict high future stock returns.

Unlike the variance risk premium, skew and kurtosis swaps are not traded in the market. The skew and kurtosis risk premia in asset pricing have not been studied extensively. Kozhan et al. (2013) are the first to propose the skew risk premium and to provide strong empirical evidence for the co-existence of both skew and variance risk premia in the equity market. Kozhan et al. (2013) find that the skew risk premium accounts for the slope in the implied volatility curve in the S&P 500 market and that skew risk is tightly related to variance risk. In the existing literature, both the variance risk premium and the slope of the implied volatility curve are found to be able to predict future stock returns (e.g. Xing et al., 2010; Yan, 2011), but no literature provides evidence on a direct relation between the skew and kurtosis risk premia and individual realised stock returns. Additionally, Bali et al. (2014) find that the volatility, skewness and kurtosis risk premia are each positively related to expected returns. Except for these two studies, no previous research focuses on the predictive ability of the skew and kurtosis risk premia on stock returns.

The study of the moment risk premia presented in this thesis is motivated by several previous studies of the variance risk premium (see e.g. Bali and Hovakimian, 2009; Han and Zhou, 2012). I first study comprehensively a direct relation between the moment risk premia and the cross-section of stock returns. I define the moment risk premia as the difference between expected realised moments and risk-neutral moments. The calculation of realised moments follows Andersen and Bollerslev (1998), Andersen et al. (2003), Amaya et al. (2011) and Choi and Lee (2014). The computation of risk-neutral moments follows the model-free method of Bakshi et al. (2003).

The most relevant literature studies for this chapter are Han and Zhou (2012) and Bali et al. (2014). The research complements Han and Zhou (2012). I add another two risk premium measures, named the skew and kurtosis risk premia, as well as another return measure, named *ex ante* expected stock returns. The study also complements Bali et al. (2014), who investigate the cross-sectional relation between the market's *ex ante* view of a stock's risk and the stock *ex ante* return. I modify their methodology for the moment risk premia. I include two more return measures, *ex post* realised stock returns and the implied cost of capital in the study, neither of which are used by Bali et al. (2014).

I employ daily options on the S&P 500 Index constituents from 1996 to 2012 for the empirical analysis. I examine the relationship between the moment risk premia and individual stock returns. I perform the test procedures as follows: I adopt a portfolio analysis to examine the cross-sectional relation between the variance, skew and kurtosis risk premia and stock returns. I also use the cross-sectional Fama and MacBeth (1973) (FM) regression to see whether the relationship between the moment risk premia and stock returns is robust to firm-level and risk variables. Finally, I perform a robustness test in subperiods, using moments with different maturities.

The main contributions of this chapter are now summarised. Firstly, the variance, skew and kurtosis risk premia are found to be determined differently by firm-level and risk factors. The study complements Han and Zhou (2012), who investigate only the determinant of the variance risk premium. This is the first work to study the determinants of the skew and kurtosis risk premia.

Secondly, I find that both the variance and skew risk premia are related negatively to subsequent realised stock returns. The skew risk premium is as important as the variance risk premium in subsequent stock return prediction. However, the kurtosis risk premium has a noisy and insignificant relationship with realised stock returns; the result depends on whether the portfolio is value-weighted or equally-weighted. The FM regression shows that the negative relation between the skew risk premium and stock returns is robust to firm-level and risk variables, while the variance risk premium is not robust to firm-level and risk control variables. The results are robust to subperiods and different maturities.

The results for the negative cross-sectional relation between the variance risk premium and *ex post* realised stock returns are consistent with Bali and Hovakimian (2009), who indicate a negative and significant relationship between stock returns and the realised-implied volatility spread. These results are also in line with empirical evidence presented by Han and Zhou (2012), who define the variance risk premium as the difference between risk-neutral variance and realised variance, and who support the positive relation between the variance risk premium and stock returns. I define the variance risk premium as the difference between realised and risk-neutral variance, which is opposite to Han and Zhou (2012). Therefore, the result of a negative relation between the variance risk premium and realised stock returns that is found in this research is consistent with Bali and Hovakimian (2009) and Han and Zhou (2012). To the best of my knowledge, I am the first to perform such an investigation for the relationship between the skew and kurtosis risk premia and realised stock returns.

Thirdly, I adopt the price target expected return (PTER) and the impled cost of capital (ICC) as measures of *ex ante* expected stock returns. The variance and skew risk premia are found to have a negative and significant relationship with *ex ante* expected stock returns. However, the kurtosis risk premium is found to be positively related to expected stock returns. The FM regression shows that the negative relation between the moment risk premia and expected stock returns is robust to firm-level and risk control variables. It is also robust to subperiods and different maturities.

For *ex ante* expected stock returns, the results for the variance and skew risk premia are consistent with Bali et al. (2014), who show that the PTER is positively related to both the volatility and skew risk premia. Their volatility and skew risk premia are calculated in a different way to the measure used in this study. Bali et al. (2014) use the difference between risk-neutral measures and realised measures, while I use the difference between realised measures and risk-neutral measures. The result for the relation between the kurtosis risk premium and expected stock returns is inconsistent with the result of Bali et al. (2014). In order to test the relationship between the volatility, skew and kurtosis risk premia and expected stock returns, Bali et al. (2014) run the FM regression of stock returns on the volatility, skew and kurtosis risk premia and on the control variables. In this study, I employ a univariate portfolio analysis for each moment risk premium. I also perform the FM regression separately for each risk premium. Different from Bali et al. (2014), I also add the ICC. The focuses of Bali et al. (2014) and this study are different. Bali et al. (2014) concentrate mainly on the relation between option-implied moments and expected stock returns, while I study the relation between the moment risk premia and stock returns.

The remainder of the chapter is organised as follows. Section 5.2 shows the calculation of realised and risk-neutral moments, as well as the moment risk premia. It also describes two *ex ante* expected return measures: the PTER and the ICC. Section 5.3 discusses the data and summary statistics used in this study. Section 5.4 investigates how the moment risk premia are determined by firm-level and risk factors. Section 5.5 analyses the cross-sectional relation between the variance, skew and kurtosis risk premia and *ex post* realised stock returns. Section 5.6 investigates the relationship between the variance, skew and kurtosis risk premia and *ex ante* expected stock returns. Section 5.7 reports the robustness test result with subperiods and different maturities. Section 5.8 concludes the main findings of this study.

5.2 Methodology

5.2.1 Moments and Moment Risk Premia

In this section, I calculate realised and risk-neutral moments (variance, skewness and kurtosis) using the model-free method. This section also describes the approaches to compute the variance, skew and kurtosis risk premia.

BKM Risk-Neutral Moments

Risk-neutral moments are calculated following the formulas given in Bakshi et al. (2003). The detail of the BKM method is described in Section 3.2.

I choose a maturity of 30 days for risk-neutral volatility, skewness and kurtosis. For each day, I calculate risk-neutral moments using options with different maturities for each stock. In each calculation, I require that a minimum of two OTM calls and two OTM puts have valid prices. If insufficient data are available, the observation is discarded. This may introduce a selection bias, but the interpolation for obtaining a continuum of strikes require a minimum of two OTM calls and two OTM puts. When using daily options with all maturities, I can in principle obtain daily option-implied volatility, skewness and kurtosis with various maturities for each stock. I then interpolate linearly to get the 30-day VAR, SKEW and KURTOSIS, using both contracts with maturity more than 30 days and contracts with maturity less than 30 days. If the risk-neutral moment is with only one maturity in a particular day, I do not interpolate and use this to represent the 30-day VAR, SKEW and KURTOSIS on that day. There are some outliers for risk-neutral moments for stocks. I Winsorise risk-neutral moments following Ang et al. (2006a). For example, if an observation for the risk-neutral variance of a stock is extremely large and above the 99th percentile of all the firms' risk-neutral variance, I replace the firm's risk-neutral variance with the risk-neutral variance corresponding to the 99th percentile. The same is done for firms with the risk-neutral variance below the 1%-tile of all the firms' risk-neutral variance. I take the same Winsorising procedure for risk-neutral skewness and kurtosis.

Realised Moments

The well-known daily realised variance (Andersen and Bollerslev, 1998; Andersen et al., 2003) is obtained by summing squares of intraday high-frequency returns. In this thesis, realised variance is calculated by summing squares of daily returns.

$$RV_t = \sum_{i=1}^{N} R_{t,i}^2 \tag{5.1}$$

where RV_t denotes the realised variance at time t.

An appealing characteristic of this variance measure compared with other estimation methods is its model-free nature (see Andersen et al., 2001; Barndorff-Nielsen, 2002 for details).

Following Amaya et al. (2011) and Choi and Lee (2014), I construct realised skewness as [1]

$$RS_t = \frac{\sqrt{N}\sum_{i=1}^{N} R_{t,i}^3}{RV_t^{\frac{3}{2}}} \tag{5.2}$$

where RS_t denotes the realised skewness at time t.

The measure of realised kurtosis is computed as

$$RK_t = \frac{N\sum_{i=1}^{N} R_{t,i}^4}{RV_t^2} \tag{5.3}$$

where RK_t denotes the realised kurtosis at time t.

Since the moment risk premia measure the terminal profit and loss from a long moment swap contract, the realised moments in equations (5.1), (5.2) and (5.3) are historical measures, which cannot represent future realised moments. Risk-neutral moments carry traders' expectations regarding the distribution of future returns, which are not contained in historical estimates. Following Drechsler and Yaron (2011) and Han and Zhou (2012), I calculate expected future realised moments using regression specifications that include risk-neutral moments in addition to historical realised moments. I adopt a multiple linear regression model to estimate the expected moments under the physical measure with lagged risk-neutral moments and historical realised moments. I run the following regressions

[1] Compared with the realised skewness by Neuberger (2012), the measure adopted in this thesis is easier. For modelling realised skewness with a short time horizon, this measure is effective. The realised skewness of Neuberger (2012) is better for modelling the long-horizon realised skewness.

with one-year of past data:

$$
\begin{aligned}
RV_t &= \alpha_1 + \beta_1 MFIV_{t-1} + \gamma_1 RV_{t-1} + \varepsilon_t^v \\
RS_t &= \alpha_2 + \beta_2 MFIS_{t-1} + \gamma_2 RS_{t-1} + \varepsilon_t^s \\
RK_t &= \alpha_3 + \beta_3 MFIK_{t-1} + \gamma_3 RK_{t-1} + \varepsilon_t^k
\end{aligned} \tag{5.4}
$$

where $MFIV$, $MFIS$ and $MFIK$ are the risk-neutral variance, skewness and kurtosis following the formula of Bakshi et al. (2003), respectively.

I take the physical expected variance $EVar_t$, the physical expected skewness $ESkew_t$ and the physical expected kurtosis, $EKurt_t$ for each firm as the fitted value from the regressions:

$$
\begin{aligned}
EVar_t &\equiv \widehat{RV}_{t+1} = \widehat{\alpha}_1 + \widehat{\beta}_1 MFIV_t + \widehat{\gamma}_1 RV_t \\
ESkew_t &\equiv \widehat{RS}_{t+1} = \widehat{\alpha}_2 + \widehat{\beta}_2 MFIS_t + \widehat{\gamma}_2 RS_t \\
EKurt_t &\equiv \widehat{RK}_{t+1} = \widehat{\alpha}_3 + \widehat{\beta}_3 MFIK_t + \widehat{\gamma}_3 RK_t
\end{aligned} \tag{5.5}
$$

In this chapter, I use daily data instead of high-frequency data to calculate realised moments. The 30-day realised physical (annualised) variance, skewness and kurtosis are computed using previous one-month daily stock returns. For example, RV_t is computed by summing squares of daily returns in the previous month and is then annualised by multiplying by 252/20 in my analysis. I obtain daily realised and risk-neutral variance, skewness and kurtosis.

Moment Risk Premia

After calculating expected realised moments and risk-neutral moments, I then compute the moment risk premia, which are the difference between these two measures.

$$
\begin{aligned}
VRP_t &= EVar_t - MFIV_t \\
SRP_t &= ESkew_t - MFIS_t \\
KRP_t &= EKurt_t - MFIK_t
\end{aligned} \tag{5.6}
$$

After obtaining the daily variance, skew and kurtosis risk premia, I select only the observations from the end of each month to represent the monthly variance, skew and kurtosis risk premia. I also select realised and risk-neutral moments observed at the end of each month.

The measure of the variance risk premium is similar to that in Carr and Wu (2009), who measure the variance risk premium as the difference between the realised variance and the variance swap rate. Their realised variance is estimated from daily stock returns. Since the variance swap rate is the risk-neutral expectation of realised variance, their measure of the variance risk premium is essentially the same as my measure. However, the measure used in this study has a different definition with that given in Bollerslev et al. (2009), Han and Zhou (2012) and Drechsler (2013), who model the variance risk premium as the difference between implied variance and realised variance. Their measure is essentially the measure used in this research multiplied by minus one. Using this directly observable proxy for the moment risk premia has the obvious advantage of being simple to implement and completely model-free.

5.2.2 Ex ante Expected Stock Return Measures

In this section, I present two methods to calculate $ex\ ante$ expected stock returns. The first method is to use the PTER and the second method is to use the ICC.

Price Target Expected Return

The first measure of $ex\ ante$ expected return is based on analyst price targets. For each analyst price target, the price target-based expected return ($PrcTgtER$) is calculated by dividing analyst price targets ($PrcTgt$) by the market price of stock at the end of the month during which the price target was announced ($MonthEndPrc$), minus 1.[2] To ensure good data quality, I remove observations where either the

[2]The end-of-month stock price is taken from CRSP. The analyst price target data are from I/B/E/S unadjusted Detail History database. They are matched by 'gvkey' and the end-of-month date. If the date of price target is in month t, then it is matched with the stock price at the end of month t.

announcement date or month-end stock price is missing or non-positive. In order to calculate the expected future return for stock i at the end of month t, I take the average of all price target implied expected returns from price targets announced during the given month. Therefore, the expected future return for stock i in month t is calculated as:

$$PTER_{i,t} = \frac{\sum_{j=1}^{n_{i,t}} PrcTgtER_j}{n_{i,t}} \tag{5.7}$$

where $n_{i,t}$ is the number of analyst price targets for stock i announced during month t and

$$PrcTgtER_j = \frac{PrcTgt_j}{MonthEndPrc} - 1. \tag{5.8}$$

The PTER measure may be up biased, because it is based on analysts' future forecasting of stock prices. Analysts are more likely to follow the stocks that have high investment potentials and report high price targets. In most cases, the reported price targets are normally higher than the current stock price.

As in Bali et al. (2014), the PTER measure displays several advantages. First, it is consistent with the definition of *ex ante* expected return as the expected future security value (analyst price target) divided by the current stock price (month-end stock price). The current stock price is easily observable, but the expected future stock price cannot be observed directly. Here, an analyst price target represents the estimate of the expected future security value. Second, compared with the ICC (described in the next subsection), the PTER measure is simple, easily calculated and largely free from assumptions that afflict alternative measures. The ICC relies on the assumptions of the future growth rate of the firm's earnings or the firm's future return on equity, while the PTER does not require such assumptions. Third, I use a time horizon of one year for the PTER. It is flexible enough to account for term structure variation in the risk and expected return profile of a stock, whereas the ICC measure requires that the expected rate of return on a stock should be constant for all future periods.

In addition to the conceptional appeal of the PTER, substantial previous literature indicates that price targets are the most informative component of analyst reports. Asquith et al. (2005) find that the market reaction to price target revisions is stronger than that of an equal percentage change in earnings forecasts. Price target revisions also contain new information even in the presence of earnings revisions and stock recommendations. Bradshaw (2002) shows that price targets reflect analysts' valuations of securities. Overall, these research results support the use of price targets over earnings and growth forecasts.

Implied Cost of Capital

The calculation of the implied cost of capital follows Gebhardt et al. (2001). Conceptually, the ICC is found by solving for the discount rate (r) that equates the current book value of equity plus the present value of expected future earnings to the current stock price. Algebraically, the ICC is the value r that solves:

$$P_t = B_t + \sum_{i=1}^{11} \frac{FROE_{t+i} - r}{(1+r)^i} B_{t+i-1} + \frac{FROE_{t+12} - r}{r(1+r)^{11}} B_{t+11} \tag{5.9}$$

where B_t is the book value of equity divided by the number of shares outstanding in the current month t and $FROE_{t+i}$ is the forecast return on equity (ROE) for the period $t+i$. The last term in equation (5.9) is the infinite summation of forecast earnings for year $t+12$ and after. The assumption in this term is that return on equity remains constant for year $t+12$ and after.

For each month and individual stock, I solve the ICC by finding the value of r that equates the stock price (P_t) on the date that I/B/E/S releases their earnings forecast summary data (the third Thursday of each month) to the right hand side of equation (5.9). I obtain I/B/E/S analysts' one-year-ahead ($FEPS_{t+1}$) and two-year-ahead ($FEPS_{t+2}$) EPS forecast, as well as an estimate of the long-term growth rate (Ltg). I use the mean one- and two-year-ahead EPS forecasts ($FEPS_{t+1}$ and $FEPS_{t+2}$). In addition, I use the long-term growth rate to compute a three-year-ahead earnings forecast: $FEPS_{t+3} = FEPS_{t+2}(1+Ltg)$. For the first three years, $FROE_{t+i}$ is computed as $FEPS_{t+i}/B_{t+i-1}$ for $i = 1,2,3$, where $FEPS_{t+i}$ is the I/B/E/S mean forecasted EPS for year $t+i$ and B_{t+i-1} is the book value per share for the last fiscal year for which earnings have been announced, taken from COMPUSTAT. Beyond the third year, I forecast $FROE$ using a linear interpolation to the industry median ROE. I categorise the firms in the S&P 500 Index into ten industries by the GICS sector. Thus, $FROE_{t+i} = FROE_{t+3} + \frac{i-3}{9}(ROE_{Median} - FROE_{t+3})$ for $i = 4, 5...12$. Industry median return on equity is taken to be the median return on equity for all firms in the same industry.

The book value per share at time t, B_t is taken from COMPUSTAT. As it is impossible to know the value of B_{t+1}, it is calculated as $B_{t+1} = B_t + FEPS_{t+1} - FDPS_{t+1}$, where $FDPS_{t+1}$ is the forecasted dividend per share for year $t+1$, estimated using the current dividend payout ratio (k). Alternatively, B_{t+1} can be expressed as $B_t + FEPS_{t+1}(1-k)$, where k is the proportion of earnings paid out as dividends, calculated as the ratio of actual dividends from the most recent fiscal year to earnings over the same time period. The dividends per share and earnings per share used for calculating the dividend payout ratio are taken from COMPUSTAT. I divide the dividends paid by 6% of total assets[3] for firms experiencing negative earnings as in Gebhardt et al. (2001). If the payout ratio value, k, is less than zero (greater than one), I assign the payout ratio a value of zero (one). If dividend information is missing from COMPUSTAT, I assign k a value of zero. B_{t+i} is calculated similarly for year $t+2$ through $t+11$, which is $B_{t+i} = B_{t+i-1}(1 + FROE_{t+i}(1-k))$ for $i = 2, 3...11$. The payout ratio k is held constant.

5.3 Data

5.3.1 Data

I employ options on the S&P 500 Index constituents for a total of 4,278 trading days in the sample period from January 1996 to December 2012.

[3]The long-run return-on-total assets in the US is approximately 6%, so I use 6% of total assets as a proxy for normal earnings levels when current earnings are negative.

The constituents of the S&P 500 Index are obtained from COMPUSTAT and the daily option data are obtained from OptionMetrics. I retain only options with expiration days of at least one week but no more than 700 days. In other words, I exclude options that mature within one week and more than 700 days. Daily equity data are taken from CRSP. After merging these three database, I have a total number of 922 companies with both option and stock data in the sample period sorted by PERMNO. Treasury bills, as a proxy for risk-free interest rates, are obtained from CRSP Treasuries database. The financial statement data that are used in this thesis, such as book value of common equity and balance-sheet deferred taxes, are also from COMPUSTAT; they are quarterly data, so I fill in the missing months for each quarter.

Analyst price target data are obtained from the Institutional Brokers Estimate System (I/B/E/S) unadjusted detail price target database. I take all price targets for the firms in the S&P 500 Index with a target horizon of twelve months where both the firm's base currency and the currency of the estimate are USD. The price target data cover the period from March 1999 through to December 2012.

I use data from the I/B/E/S summary history/summary statistics to obtain earnings forecasts for the next three years. I/B/E/S analysts supply a one-year-ahead ($FEPS_{t+1}$) and a two-year-ahead ($FEPS_{t+2}$) earnings per share (EPS) forecast, as well as an estimate of the long-term growth rate (Ltg). It also releases a one-year-ahead ($FBPS_{t+1}$) and a two-year-ahead ($FBPS_{t+2}$) book value per share (BPS) forecast. The data sample period is from January 1996 to December 2012. The I/B/E/S earnings forecast summary data are released on the third Thursday of each month.

5.3.2 Summary Statistics

Summary Statistics for Moments and Moment Risk Premia

Table 5.1 provides summary statistics on realised and risk-neutral moments and the moment risk premia and their correlations. In Panel A, its shows summary statistics on moments. The average expected realised variance is 0.1843 and the average risk-neutral variance is 0.1862. The average expected realised variance is less than the average risk-neutral variance, pointing to the existence of a negative variance risk premium for the S&P 500 Index constituents. The average of the variance risk premium is -0.0039. For the third moment, the average expected realised skewness is 0.1185, while the average risk-neutral skewness is negative with the value of -0.4555, indicating the existence of a positive skew risk premium. The mean of the skew risk premium is 0.5817. For the fourth moment, the average expected realised kurtosis is 3.3646 and the average risk-neutral kurtosis is 3.3564. It is obvious that the difference between the two kurtosis measures is small. The average of the kurtosis risk premium is 0.0038. Panel B shows the correlations of realised moments and the moment risk premia. Realised variance has a weak correlation with realised skewness, while the correlation between realised variance and realised kurtosis is relatively high, which is 0.2556. The correlation between realised skewness and kurtosis is 0.1392. The variance risk premium has a weak correlation with the skew risk premium and the correlation is 0.0302. The correlation between the variance risk premium and the kurtosis risk premium is 0.3044. The correlation between the skew risk premium and the kurtosis risk premium is 0.0157.

The result that realised variance is less than risk-neutral variance shown in Table 5.1 is in line with the results presented in the previous literature (see, e.g. Bakshi and Kapadia, 2003a; Carr and Wu, 2009; Egloff et al., 2010; Kozhan et al., 2013; Drechsler, 2013). The result that risk-neutral skewness is more negative than realised skewness is consistent with the findings of Bakshi et al. (2003) and Kozhan et al. (2013). Unlike the variance and skew risk premia, there is no existing literature that specifies the sign of the kurtosis risk premium.

Summary Statistics for Expected Stock Returns

Table 5.2 reports descriptive statistics for *ex ante* expected stock returns, including the PTER and the ICC. The PTER and the ICC are Winsorised at the 1% level. The mean value of the PTER is 16.90% with a time horizon of twelve months. The average of the ICC is 8.21%. The reason for the high PTER might be that analysts are more likely to follow the stocks that have high investment potentials, be positive about future markets and prefer to report high future stock price targets. In most cases, the reported price targets are normally higher than the current stock price. The standard deviation of the ICC is much smaller than the standard deviation of the PTER. This is because the ICC is smoothed, which is calculated by solving for the discount rate (r) that equates the current book value of equity plus the present value of expected future earnings to the current stock price.

5.4 Determinants of Moment Risk Premia

5.4.1 Control Variables

Stock returns are found to be affected by firm-level and risk factors. For example, some previous literature supports that there exist a firm size effect of Banz (1981), the book-to-market effect of Basu (1983), the momentum effect of Jegadeesh and Titman (1993), exposure to idiosyncratic volatility of Ang et al. (2006b), exposure to co-skewness of Friend and Westerfield (1980) and exposure to illiquidity risk of Amihud (2002). All of these factors imply different impacts on the cross-section of stock returns. Therefore, I adopt firm-level and risk factors in this study to see whether they are related to the moment risk premia.

The calculation of firm size and book-to-market ratio follows Fama and French

(1992). Firm size, $ln(ME)$ is the log of the market capitalisation from the previous day. Market capitalisation (ME) is equal to stock price multiplying shares outstanding. Book-to-market ratio is equal to $ln(BE/ME)$. BE is the book value of common equity plus balance-sheet deferred taxes. The market beta, β is estimated from the CAPM using previous one-year daily returns. Idiosyncratic Volatility, $IdioVol$ is the standard deviation of residuals from a regression of stock excess return on market excess return, the size (SMB) and book-to-market (HML) factors of Fama and French (1993).[4] Idiosyncratic Volatility is calculated using one year's worth of daily return data. The calculation of risk-neutral co-skewness, $CoSkew$ follows Harvey and Siddique (2000). *Momentum* is the cumulative daily stock returns over previous one month. *Illiquidity* is defined as the average ratio of the daily absolute return to the (dollar) trading volume on that day, $|R_{iyd}|$ /$VOLD_{iyd}$, where R_{iyd} is the return on stock *i* on day *d* of year *y* and $VOLD_{iyd}$ is the respective daily volume in dollars.

5.4.2 Fama-MacBeth Regressions

In order to better understand and compare the moment risk premia, I perform the cross-sectional Fama and MacBeth (1973) regressions of the moment risk premia on firm characteristics and risk factors. The firm characteristics and risk factors include firm size, book-to-market ratio, momentum, illiquidity, market beta, idiosyncratic volatility and co-skewness.

Table 5.3 shows the results for FM regressions with dependent variables of the variance risk premium (Panel A), the skew risk premium (Panel B) and the kurtosis risk premium (Panel C). Panel A examines the relationship between the variance risk premium and these firm-level control variables and risk factors. When I explore these independent variables , Models 1, 2, 5 and 6 demonstrate that the variance risk premium has significantly positive relations with β, $IdioVol$, $ln(BE/ME)$ and $Momentum$, while the variance risk premium is significantly and negatively re-

[4]Daily market excess return, SMB, HML and the risk free rate are taken from the website of Kenneth R. French. http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data library.html

lated to $Illiquidity$ detected in Model 7. When incorporating all of these variables in one regression in Model 8, I find that the variance risk premium is positively related to all of these variables. Panel B shows the relationship between the skew risk premium and these independent factors. I find that the skew risk premium can be explained by most of these variables. When regressing the skew risk premium with each of these variables separately, I see that the skew risk premium is positively and significantly correlated with firm size $ln(ME)$ (Model 4), $Momentum$ (Model 6) and $Illiquidity$ (Model 7), but negatively and significantly related to β (Model 1), $IdioVol$ (Model 2) and $ln(BE/ME)$ (Model 5). When all of these independent variables are included in the regression (Model 8), the skew risk premium is negatively related to risk factors and positively related to firm characteristics. In Panel C, when regressing the kurtosis risk premium on these variables, I find that all of the coefficients are significant at the 5% level. The kurtosis risk premium is significantly and positively related to β (Model 1), $IdioVol$ (Model 2) and $ln(BE/ME)$ (Model 5), while it has a significant and negative relation with $Coskew$ (Model 3), $ln(ME)$ (Model 4), $Momentum$ (Model 6) and $Illiquidity$ (Model 7). When including all of these variables in the FM regression in Model 8, I find that the kurtosis risk premium is still significantly correlated with these variables.

To summarise, the results show that firm-level variables and risk factors have different impacts on the variance, skew and kurtosis risk premia. The variance risk premium is positively related to most of these firm-level and risk factors. The skew risk premium has mixed determinants, being associated negatively with risk factors and associated positively with firm-level variables. The determinants of the kurtosis risk premium are also mixed. It is positively related to most of the risk factors, while it is inversely related to most of firm-level factors. Since the determinants of moment risk premia are different and these control variables are found to be able to predict stock returns, the moment risk premia might have different impacts on stock returns.

5.5 Moment Risk Premia and Realised Stock Returns

In Section 5.4 I found that the variance, skew and kurtosis risk premia are determined by firm-level variables and risk factors differently. Therefore, their effects on stock returns might be different. In this section, I test whether the variance, skew and kurtosis risk premia can predict subsequent realised stock returns. If they have predictive ability to stock returns, I study whether their effects on stock returns are different.

5.5.1 Univariate Portfolio Analysis

At the end of month t from January 1996 to December 2012, I rank all the stocks in the S&P 500 Index from low to high on the basis of the variance risk premium. I sort these pre-ranked stocks into quintile portfolios. The first quintile portfolio contains the stocks with the lowest variance risk premium, while the fifth quintile portfolio contains the stocks with the highest variance risk premium. After constructing the portfolios based on the variance risk premium, I then calculate the value-weighted and equally-weighted monthly returns for each day, for each portfolio in the next month *t+1*. The entire procedure is repeated for all securities listed, for each month in the sample, generating a series of the value-weighted and equally-weighted monthly returns. Finally, I calculate the time-series average of the value-weighted and equally-weighted portfolio returns.

Similarly, I take the same procedure for the univariate portfolio analysis based on expected realised moments, risk-neutral moments, the skew and kurtosis risk premia. The result for the portfolio analysis sorted by these variables is shown in Table 5.4.

In order to test whether the risk-return relations are monotonic, I adopt the monotonicity relation (MR) test method proposed by Patton and Timmermann (2010). The null hypothesis is based on the sign of the return spread between the fifth portfolio and the first portfolio, named the 5-1 return spread. For example, if the 5-1 return spread is negative, I test whether the relation is monotonically decreasing. If the 5-1 return spread is positive, I test whether the relation is monotonically increasing. The MR test result is decided by p-values. If the MR p-value is less than 5%, it means that there is a monotonically increasing or decreasing risk-return relation. The result for the MR test with p-values obtained from time-series block bootstrapping is shown in the last column of Table 5.4.

Table 5.4 provides a summary of the portfolio analysis from January 1996 to December 2012. Panel A shows the results from sorting portfolios on expected realised variance. The 5-1 return spread for the value-weighted portfolios is 0.078% per month with a t-statistic of 0.142, which is not statistically significant. For the equally-weighted portfolios, the 5-1 return spread is 0.266% per month with a t-statistic of 0.466, which is not statistically significant. The MR test shows that there is no monotonic relation between expected realised variance and returns. The results for the portfolio analysis sorted by risk-neutral variance are shown in Panel B. I find that the 5-1 return spreads for both the value-weighted and equally-weighted portfolios are positive, being 0.433% per month for the value-weighted returns and 0.455% per month for the equally-weighted returns. The t-statistics show that the 5-1 return spread is not statistically significant for both the value-weighted and equally-weighted portfolios. The MR test supports that there is no monotonically increasing or decreasing relation between risk-neutral variance and stock returns.

Panel C reports the portfolio returns sorted by the variance risk premium. For the value-weighted portfolios, I find that there is a negative and statistically significant average return difference between the extreme quintile portfolios. The average return difference between the fifth portfolio and the first portfolio is -0.807% per month. The t-statistic for the 5-1 return spread exceeds the threshold of the 1% significance level. For the equally-weighted portfolios, the relation between the variance risk premium and stock returns is negative and significant. The portfolio return decreases by -0.439% per month from 1.102% per month for the first portfolio to 0.662% per month for the fifth portfolio. The t-statistic of the 5-1 return spread is 1.664, which is significant at the 5% level. The MR test gives a p-value of 0.001 for the value-weighted returns and 0.176 for the equally-weighted returns, demonstrating that there is a monotonically decreasing relationship between the variance risk premium and the value-weighted returns. The negative relation between the variance risk premium and stock returns is in line with Bali and Hovakimian (2009), who provide strong evidence that there is a negative and significant relationship between stock returns and the realised-implied volatility spread.

In Panel D, portfolios are sorted by expected realised skewness. The 5-1 return spread is -0.234% per month for the value-weighted returns and -0.322% per month for the equally-weighted returns. The t-statistic shows that the value-weighted portfolio return spread is insignificant, while the equally-weighted portfolio return spread is significant at the 5% level. The MR test proves that the relation between expected realised skewness and stock returns is not monotonic for both the value-weighted and equally-weighted portfolios. The negative relation between realised skewness and stock returns is consistent with the findings of Amaya and Vasquez (2010), Amaya et al. (2011) and Choi and Lee (2014). Panel E reports portfolios sorted by risk-neutral skewness. Risk-neutral skewness has a positive relationship with stock returns. For the value-weighted portfolios, the 5-1 return spread is 0.545% per month with a t-statistic of 1.915, which is statistically significant at the 5% level. For the equally-weighted portfolios, the 5-1 return spread is 0.955% per month with a t-statistic of 3.170, which is statistically significant at the 1% level. The MR test shows that only the relation between risk-neutral skewness and the equally-weighted returns is monotonic at the 1% significance level. The positive relation between risk-neutral skewness and stock returns is consistent with Rehman and Vilkov (2012), Stilger et al. (2014) and Bali et al. (2014), who use the BKM risk-neutral skewness measure and find the same result. However, the result is different from Conrad et al. (2013); this might be because I use a different sample size and a longer sample period.

Panel F provides a summary of the portfolio returns sorted by the skew risk premium. For both the value-weighted and equally-weighted portfolios, a long-short portfolio buying the stocks in the highest SRP quintile and shorting the stocks in the lowest SRP quintile produces huge negative average returns, being -0.429% per month for the value-weighted portfolios with a t-statistic of 1.632. It means that the negative 5-1 return spread is significant the 10% level. For the equally-weighted portfolios, it is -0.649% per month with a t-statistic of 2.830, which is significant at the 1% level. From the MR test, I find that all MR p-values are greater than 5% for both the value-weighted and equally-weighted portfolio returns. This means that there is no monotonically decreasing relation between the skew risk premium and the value-/equally-weighted returns.

Panel G shows portfolios sorted by expected realised kurtosis. Expected realised kurtosis has a negative but insignificant relation with the value-weighted returns, while it has a positive but insignificant relationship with the equally-weighted return. The return difference between the extreme portfolios is -0.287% per month with a t-statistic of 1.272 for the value-weighted returns, and is 0.014% per month with a t-statistic of 0.096 for the equally-weighted returns. Amaya et al. (2011) document a positive relation between realised kurtosis and stock returns. For portfolios sorted by risk-neutral kurtosis (Panel H), I find that risk-neutral kurtosis is significantly and negatively related to both the value-weighted return and the equally-weighted return. The 5-1 return spread is -0.605% per month for the value-weighted portfolios and is -0.809% for the equally-weighted portfolios. The result for the negative relation between risk-neutral kurtosis and stock returns is consistent with Conrad et al. (2013).

Panel I shows the result for portfolios sorted by the kurtosis risk premium. The relation between the kurtosis risk premium and stock returns is mixed. The return spread between the extreme portfolio is -0.011% per month, negative but insignificant for the value-weighted returns, while the return spread is 0.402% per month, positive and significant for the equally-weighted returns.

To summarise, the relationship between realised/risk-neutral variance and stock returns is not significant. There is a negative relation between realised skewness and stock returns, while the relationship between risk-neutral skewness and stock returns is positive. There is a negative relationship between the variance risk premium and stock returns and the relationship is significant for both the value-weighted and equally-weighted portfolios. There is also a negative and significant relationship between the skew risk premium and subsequent stock returns. The relationship of the kurtosis risk premium with stock returns is mixed; it is negative for the value-weighted returns and positive for the equally-weighted returns.

Figure 5.1 plots the value-weighted and equally-weighted quintile portfolio returns sorted by the variance risk premium (Panel A), the skew risk premium (Panel B) and the kurtosis risk premium (Panel C). Panel A shows that the variance risk premium has a monotonically decreasing relationship with the value-weighted portfolio returns. The average monthly return decreases from around 1.002% per month for quintile 1 to 0.195% per month for quintile 5. For the equally-weighted portfolios there is a linearly decreasing relation between the variance risk premium and stock returns. Panel B shows that the skew risk premium has a decreasing relationship with both the value-weighted and equally-weighted portfolio returns. Specifically, the average value-weighted monthly return decreases from around 0.631% per month for quintile 1 to 0.202% per month for quintile 5. The average equally-weighted monthly return drops from 1.070% per month for quintile 1 to 0.421% per month for quintile 5. In Panel C, I see that the pattern between the kurtosis risk premium and stock return is mixed. For the value-weighted portfolio, the returns in the extreme portfolios are very close, being 0.385% in the first portfolio and 0.375% in the fifth portfolio. For the equally-weighted portfolio, the kurtosis risk premium has a monotonic increasing relationship with stock returns. The return increases from 0.507% for quintile 1 to 0.909% for quintile 5.

In summary, Table 5.4 and Figure 5.1 shed light on a significantly and monotonically negative relationship between the variance and skew risk premia and stock returns. The skew risk premium is as important as the variance risk premium in subsequent realised stock return prediction. The relationship between the kurtosis risk premium and stock returns is mixed, depending on whether the portfolio is value-weighted or equally-weighted. The kurtosis risk premium has a flat relationship with the value-weighted returns, while it has a significantly positive relationship with the equally-weighted returns.

5.5.2 Double Portfolio Sort

I investigate the relation between the moment risk premia and subsequent stock returns, while controlling for variation in firm characteristics and return moments, using two-way portfolio sorts. At the end of each month, I first sort the stocks into quintile portfolios based independently on firm size, book-to-market ratio, realised moments and risk-neutral moments. I then form portfolios based on the intersection of rankings of the moment risk premia. For each of the 25 portfolios formed, I calculate the average monthly returns in the next month. The procedure is repeated for each month. Finally, I calculate the time-series average of these portfolio returns.

Table 5.5 presents summary statistics on two-way sorted portfolios. Panel A reports results for the double portfolio sort on the variance risk premium. I observe that, holding firm size constant, the variance risk premium still remains a negative relation with subsequent stock returns for all levels of firm size and, holding book-to-market ratio constant, the return differential in the extreme VRP portfolios is negative for all five cases. In nine out of the ten cases, holding realised or risk-neutral variance constant gives a negative return differential in the extreme VRP portfolios.

In Panel B, portfolios are sorted by other factors first and then sorted by the skew risk premium. The skew risk premium continues to be negatively related to subsequent stock returns for all levels of firm size and book-to-market ratio, holding firm size and book-to-market ratio constant. The return differential across the extreme SRP portfolios is negative for all of the ten portfolios when holding realised and risk-neutral skewness constant.

Panel C presents the double portfolio sorts on other factors first and then on the kurtosis risk premium. When holding firm size, book-to-market ratio and realised kurtosis constant, the difference between the extreme portfolios remains positive for all cases. When sorting by risk-neutral kurtosis first, two out of the five cases are positive.

To summarise, the results for the two-way portfolio analysis in Table 5.5 are in line with the results in Table 5.4 for the univariate portfolio analysis. When controlling for firm size, book-to-market ratio and realised/risk-neutral moments, I find that the relation between the moment premia and subsequent stock returns remains.

5.5.3 Fama-MacBeth Regressions

The portfolio analysis described above demonstrates the relationship between the moment risk premia and realised stock returns. An alternative approach to examine the determinants of individual stock returns is the firm-level cross-sectional Fama and MacBeth (1973) (FM) regression. The purpose for using the FM regression is to test whether the significant relation between the moment risk premia and stock returns persists or not once I control for various cross-sectional effects. Besides the variance, skew and kurtosis risk premia, I include additional control variables in the month-by-month FM regression. These variables contain market beta (β), idiosyncratic volatility ($IdioVol$), coskewness ($CoSkew$), firm size ($ln(ME)$), book-to-market ratio ($ln(BE/ME)$), momentum and illiquidity. The reasons to include these variables and their calculation are described in Section 5.4.

For each month, I perform the cross-sectional regression of monthly realised stock returns on the moment risk premia, individual firm-level variables and risk factors. I then calculate the time-series average of the slope coefficients of the independent variables. With the FM regression, I can easily examine the significance of the predictability of the moment risk premia, as well as control for firm characteristics and risk factors. The FM regression model is given as follows:

$$r_{i,t+1} = \gamma_{0.t} + \gamma_{1,t}VRP_{i,t} + \gamma_{2,t}SRP_{i,t} + \gamma_{3,t}KRP_{i,t} + \phi_t'Z_{i,t} + \varepsilon_{i,t} \tag{5.10}$$

where $r_{i,t+1}$ is the individual realised stock return for stock i in month $t+1$. $VRP_{i,t}$, $SRP_{i,t}$ and $KRP_{i,t}$ are the variance, skew and kurtosis risk premia for stock i observed at the end of month t, respectively; $Z_{i,t}$ are other explanatory factors for individual stock i in month t, including firm-level and risk factors.

Table 5.6 provides the time-series averages of the slope coefficients from the monthly cross-sectional regressions and the t-statistics generated based on the time-series standard deviation of the coefficient estimates. When including only the variance risk premium in the regression of Model 1, I find that the slope of the variance risk premium is -0.0075 with a t-statistic of -0.73, which is not statistically significant. Model 2 specifies the result for performing a regression of subsequent realised stock returns on the skew risk premium only. The slope of the skew risk premium is -0.0024 with a t-statistic of -2.56, which is significant at the 5% level. In Model 3, I run a regression on the kurtosis risk premium and find that the coefficient is 0.0006, which is not statistically significant. When performing a regression on the variance, skew and kurtosis risk premia, I find that the coefficient of the variance risk premium in Model 4 remains negative but is statistically insignificant; the slope of the skew risk premium is -0.0017, which is significant at the 5% level and the coefficient of the kurtosis risk premium is 0.0012, which is significant at the 5% level. When risk factors (β, $IdioVol$, $CoSkew$) are added in the regression (Model 5), the coefficient of the skew risk premium becomes -0.0014, which is significant at the 10% level. The coefficient of the kurtosis risk premium is still significantly positive. I obtain a similar result when including firm-level variables in the regression (see Model 6). In Model 7, I include all firm-level variables and risk factors in the regression and find that the significantly positive coefficient of the kurtosis risk premium remains. The slope of the variance risk premium is negative and insignificant. The slope of the skew risk premium is -0.0014 and is significant at the 10% level.

Overall, the FM regression results in Table 5.6 show that the negative relation between the variance risk premium and stock returns is not robust to these firm-level variables and risk factors. However, the negative relation between the skew risk premium and stock returns is robust to firm characteristics and risk factors. The kurtosis risk premium exhibits a robust and positive relationship with stock returns when firm-level and risk factors are included.

5.6 Moment Risk Premia and Expected Stock Returns

I have explored the relationship between the moment risk premia and realised stock returns in Section 5.5. The variance and skew risk premia exhibit similar negative effects on realised stock returns, while the effect of the kurtosis risk premium on realised stock returns is mixed. In this section, I investigate whether the moment risk premia have explanatory power to *ex ante* expected stock returns.

5.6.1 Univariate Portfolio Analysis

I begin the analysis on the PTER and the ICC with the portfolio analysis to examine the relationship between the variance, skew and kurtosis risk premia and *ex ante* expected stock returns. At the end of each month from March of 1999 through to December of 2012, I sort all the stocks in the S&P 500 Index for which valid values of the PTER are available into five groups based on the ascending ordering of the variance, skew and kurtosis risk premia. I then calculate the equally-weighted average PTER for each of the five portfolios, as well as the expected return difference between the fifth and the first portfolios. Finally, I calculate the time-series average of the equally-weighted portfolio returns. I perform the same portfolio analysis for the ICC for each month from January of 1996 through to December of 2012.

The time series averages of the equally-weighted portfolio expected returns, using both the PTER and the ICC, are presented in Table 5.7. Panel A shows the result for the portfolio analysis on the variance risk premium. There is a negative relation between the variance risk premium and *ex ante* expected returns, including the PTER and the ICC. The 5-1 return spread for the PTER is -2.019% with a t-statistic of 2.646, which is significant at the 1% level . The 5-1 return spread for the ICC is -0.229%, with a t-statistic of 1.101. The MR test reports that the decreasing relation between the variance risk premium and *ex ante* expected stock returns is not monotonic for the PTER and the ICC.

The result for the portfolio analysis on the skew risk premium is presented in Panel B. I find that there is a monotonically decreasing relationship between the skew risk premium and *ex ante* expected returns. Specifically, the 5-1 return spread for the PTER is -5.766% with a t-statistic of 10.316, which is significant at the 1% level. The result for the ICC is remarkably similar. The 5-1 return spread for the ICC is -0.811% with a t-statistic of 5.472, which is significant at the 1% level. The MR test gives p-values of 0 for both the PTER and the ICC, which shows that there is a monotonically decreasing relation between the skew risk premium and *ex ante* expected returns.

Panel C reports the results of the portfolio analysis on the kurtosis risk premium. The kurtosis risk premium has a monotonically increasing relationship with *ex ante* expected returns. For the PTER, the 5-1 return spread is 4.372% with a t-statistic of 6.060. For the ICC, the 5-1 return spread is 1.215% with a t-statistic of 6.177. The p-values of the MR test are zero, which means that there is a monotonically decreasing relation between the kurtosis risk premium and *ex ante* expected returns.

Figure 5.2 plots the expected quintile portfolio returns sorted by the variance risk premium (Panel A), the skew risk premium (Panel B) and the kurtosis risk premium (Panel C). Panel A shows that, sorted by the variance risk premium, the portfolio returns drop from above 21% in quintile 1 to around 15% in quintile 4, and then increase to 19% in quintile 5 for the PTER. For the ICC, the average expected quintile portfolio returns decrease from around 8.4% for quintile 1 to 7.6% for quintile 4 and then ascend to 8% for quintile 5. Panel B displays a linearly decreasing relationship between the skew risk premium and expected returns. Specifically, the average quintile portfolio return for the PTER decreases from around 21% for quintile 1 to above 15% for quintile 5. The average quintile ICC drops from around 8.5% for quintile 1 to 7.6% for quintile 5. In Panel C, the patterns between the kurtosis risk premium and expected returns are monotonically increasing. For the PTER, the portfolio return increases from 15.2% in quintile 1 to 19.5% in quintile 5. For the ICC, the portfolio return increases from 7.3% in the first portfolio to 8.5% in the fifth portfolio.

In summary, Table 5.7 and Figure 5.2 shed light on the relation between the variance, skew and kurtosis risk premia and expected stock returns. The relation between the variance risk premium and expected stock returns is negative but noisy. There is a monotonically decreasing relation between the skew risk premium and expected stock returns. However, the kurtosis risk premium has a monotonically increasing relationship with expected stock returns.

5.6.2 Fama-MacBeth Regressions

The portfolio analysis has shown that the variance, skew and kurtosis risk premia have different relationships with expected stock returns. In order to test whether the relationships are robust to firm-level and risk factors, I employ the firm-level cross-sectional Fama and MacBeth (1973) (FM) regressions to control for these factors. In other words, the purpose for using the FM regression is to test whether the significant relationship between the moment risk premia and expected stock returns persists once I control for various cross-sectional effects. Besides the variance, skew and kurtosis risk premia, I include additional control variables in the month-by-month FM regressions. These variables contain market beta, idiosyncratic volatility, coskewness, firm size, book-to-market ratio, momentum and illiquidity.

Table 5.8 provides the time-series averages of the slope coefficients from the monthly cross-sectional regressions and the t-statistics generated based on the time-series standard deviation of the coefficient estimates. Panel A shows the result for the FM regression using the PTER. The results are highly consistent with the portfolio analysis presented in Table 5.7. From Model 1, I find that the slope of the variance risk premium is -0.0507 with a t-statistic of -2.80, which is statistically significant, when the variance risk premium is the only explanatory variable. When only the skew risk premium is included in the regression, the coefficient of the skew risk premium in Model 2 is -0.0299 with a t-statistic of -15.85, which is statistically significant at the 1% level. In Model 3, where I only perform the regression on the kurtosis risk premium, the coefficient is 0.0077 with a t-statistic of 8.46. When I test the effect of the combination of the variance, skew and kurtosis risk premia (Model 4), the coefficients of the variance and skew risk premia are still significantly negative and the coefficient of the kurtosis risk premium is still significantly positive. When risk factors and the moment risk premia are included in Model 5, the slopes of both the variance and skew risk premia remain negative and are statistically significant. The slope of the kurtosis risk premium is still significantly positive. Model 6 shows that the slopes of the variance and kurtosis risk premia are still significant when I include firm-level variables in the regression. In Model 7, I include all control variables in the regression. The variance and kurtosis risk premia still have significant coefficients, while the coefficient of the skew risk premium becomes insignificant.

Panel B shows the result for the FM regression of the ICC. When comparing the PTER with the ICC, I find that the FM regression result is very similar. When either the variance, skew or kurtosis risk premium is the only regressor, the coefficients of the variance and skew risk premia are negative and statistically significant and the coefficient of the kurtosis risk premium is significantly positive. When firm-level and risk variables are included in the regression (Models 5, 6 and 7), the coefficients of the variance and skew risk premia remain significantly negative and the slope of the kurtosis risk premium remains significantly positive.

Overall, the FM regression results in Table 5.8 show that the relationships between the variance, skew and kurtosis risk premia and *ex ante* expected stock returns are robust to these firm-level and risk factors.

5.7 Robustness Test

In order to confirm that the results presented in Section 5.5 and Section 5.6 are truly due to a cross-sectional relation between the moment risk premia and stock returns, I perform a robustness test. In other words, in this section, I explore further the relationship between the moment risk premia and stock returns by adopting several analyses that control for the effects of other potential determinants of these relations. First, I check for market downturns by analysing the relation between the moment risk premia and stock returns in different subperiods that contain different market conditions. Next, I compute the moment risk premia using realised and risk-neutral moments with different maturities in order to check whether the results are driven by different times to expiration.

5.7.1 Subperiods

The whole sample period is from January 1996 to December 2012. This sample period contains two financial crises. The first financial crisis is the stock market downturn of 2002, which began in 2000 and had a sharp drop in stock prices during 2002. The second financial crisis is the sub-prime crisis of 2008, which started in August of 2007. To verify that the results are not driven by the particular circumstances in this sample period, I repeat the portfolio analysis in four subperiods: 1996-1999, 2000-2002, 2003-2006, 2007-2012. The period of 2000-2002 contains the stock market downturn. The period of 2003-2006 is the recovery and economic boom period. The period of 2007-2012 experienced the sub-prime crisis. In each subperiod, I perform the portfolio analysis for each risk premium measure and for each return method.

Realised Stock Returns

In each subperiod, I sort the stocks into quintile portfolios on the basis of the moment risk premia at the end of each month. I then calculate both the value-weighted and equally-weighted monthly returns in the next month. Finally, I calculate the time-series average of the value-weighted and equally-weighted portfolio returns. The procedure is repeated for each subperiod.

Table 5.9 reports summary statistics on the portfolio analysis of realised stock returns in subperiods. Panel A presents the results for the quintile portfolios sorted by the variance risk premium. The 5-1 return spread between the extreme portfolios is negative for both the value-weighted and equally-weighted returns and for all subperiods. For the value-weighted portfolios, the 5-1 return spread varies from -0.231% per month in the subperiod of 2003-2006 to -1.992% per month in the subperiod of 1996-1999. The t-statistics show that the 5-1 return spread is significant at the 5% level for two out of the four subperiods. The MR test shows that the relationship between the variance risk premium and stock returns is not monotonic in most cases. For the equally-weighted portfolio returns, the 5-1 return spread is negative for all five cases, ranging from -0.079% per month in the subperiod of 2003-2006 to -0.929% per month in the subperiod of 1996-1999. The results for the MR test indicate that there is no monotonically decreasing relationship between the variance risk premium and the equally-weighted returns for all of the four subperiods at the 5% significance level.

Panel B reports the results for the quintile portfolios sorted on the skew risk premium. The 5-1 return spread between the extreme portfolios is negative for both the value-weighted and equally-weighted returns and for three out of the four subperiods. During the subperiod of 1996-1999, the 5-1 return spread is positive. It is 0.832% for the value-weighted portfolios and 0.172% for the equally-weighted portfolios. For the other three subperiods, the 5-1 return spread is negative, varying from -0.421% per month to -1.604% per month and the t-statistics range from 1.482 to 3, greater than the threshold of the 10% significance level. The biggest 5-1 return spread occurs in the subperiod 2000-2002 for both the value-weighted and equally-weighted portfolio returns.

In Panel C, portfolios are sorted by the kurtosis risk premium. During the subperiod of 1996-1999, the 5-1 return spread is negative for both the value-weighted and equally-weighted returns. In the subperiods of 2003-2006 and 2007-2012, the return differential between the extreme portfolios is positive and significant. The MR test shows that the relationship between the kurtosis risk premium and realised stock returns is linear in the subperiod of 2007-2012, while it is not monotonic in other subperiods.

Overall, Table 5.9 shows that there is a negative relationship between the variance and skew risk premia and subsequent stock returns for most subperiods. The kurtosis risk premium has a mixed relationship with realised stock returns. Therefore, the result is generally robust to subperiods.

Expected Stock Returns

In each subperiod, I sort the stocks into quintile portfolios on the basis of the moment risk premia at the end of each month. I then calculate expected returns for each portfolio. Finally, I calculate the time-series average of the equally-weighted portfolio returns. The procedure is repeated for each subperiod.

Table 5.10 reports summary statistics on the portfolio analysis of expected stock returns in subperiods. Panel A shows the results for the quintile portfolios sorted by the variance risk premium. The return difference between the fifth and the first portfolios is negative for both the PTER and the ICC in all subperiods. The return difference is statistically significant for the subperiods 2000-2002 and 2003-2006. The MR test shows that there is no monotonic relationship between the variance risk premium and expected stock returns for all subperiods. Panel B reports the results for quintile portfolios sorted by the skew risk premium. The 5-1 return spread between the extreme portfolios is negative and statistically significant for both the PTER and the ICC for all four subperiods. During the subperiod of 2000-2002, the 5-1 return spread is most negative (-7.886%) for the PTER. The biggest 5-1 return spread of the ICC occurs in the subperiod of 2007-2012, with a spread value of -1.113%. The MR test gives p-values of zero or close to zero for most of the subperiods. In Panel C, portfolios are sorted by the kurtosis risk premium. It is clear that the 5-1 return spread is significant and positive for all subperiods.

Overall, the result in Table 5.10 for the relationships between the moment risk premia and expected stock returns are robust to subperiods.

5.7.2 Different Maturities

The methodology of Bakshi et al. (2003) allows estimation of risk-neutral moments using different maturities. I have used a linear interpolation to obtain the 30-day risk-neutral moments in the previous analysis. Next, I choose three different longer horizons (60-day, 90-day and 180-day maturities) to estimate risk-neutral/realised moments in order to perform a robustness test. I investigate whether the relationship between the moment risk premia and realised/expected returns is robust to different time horizons.

Realised Stock Returns

Table 5.11 provides a summary of the portfolio returns sorted by the variance, skew and kurtosis risk premia with different time horizons. Panel A reports the results from sorting portfolios by the variance risk premium with different maturities. For both the value-weighted and equally-weighted portfolios, a long-short portfolio (buying the stocks in the highest variance risk premium quintile and shorting the stocks in the lowest variance risk premium quintile) produces negative average monthly returns in the range of -0.30% to -0.82% per month that are highly significant. The t-statistics range from 0.7 to 2.1 and the MR test shows that the negative relationship between the variance risk premium and stock returns is not monotonic for both the value-weighted and equally-weighted portfolios, for most of the maturities.

In Panel B, quintile portfolios are sorted on the basis of the skew risk premium with different maturities. For the 60-day maturity, the 5-1 return spread is -0.492% per month for the value-weighted portfolios and is -0.601% per month for the equally-weighted portfolios. When using the 90-day maturity, I find that the 5-1 return spread is -0.644% per month for the value-weighted portfolios and is -0.555% per month for the equally-weighted portfolios. For the 180-day maturity, there is -0.572% return differential among the extreme portfolios for the value-weighted portfolios and -0.511% 5-1 return spread for the equally-weighted portfolios. The t-statistics prove that the 5-1 return spreads for all of these three maturities are statistically significant at the 5% level. The MR test gives p-values greater than 10% for all maturities except the 180-day maturity with the equally-weighted return.

Panel C presents quintile portfolios sorted by the kurtosis risk premium with different maturities. For the 60-day maturity and the 180-day maturity, the 5-1 return spreads are -0.060% per month and -0.174% per month, respectively. For the 90-day maturity, the 5-1 return spread is 0.162% per month. The 5-1 return spread for the equally-weighted return is positive for all of the maturities, ranging from

0.185% to 0.367%.

Table 5.11 summarises that the negative relationship between the variance and skew risk premia and realised stock returns remains even when different maturities are selected to estimate risk-neutral/realised variance and skewness. The relationship between the kurtosis risk premium and realised stock returns is still mixed and insignificant even if I select different maturities.

Expected Stock Returns

Table 5.12 reports the result for the portfolio analysis sorted by the moment risk premia with different time horizons (60-day, 90-day and 180-day). The results of the portfolio analysis on the variance risk premium with different maturities are shown in Panel A. When sorted by the variance risk premium, the return difference between the extreme portfolios is negative for the PTER and the ICC for all cases. The return difference is statistically significant for the PTER, but it is not statistically significant for the ICC for all maturities. The MR test shows that the decreasing relationship between the variance risk premium and expected stock returns is not linear for all maturities. In Panel B, I sort portfolios on the basis of the skew risk premium with different maturities. For both the PTER and the ICC, the 5-1 return spreads are negative for all maturities. The t-statistics range from 5 to 9. The MR test shows that the negative relationship between the skew risk premium and expected stock returns is monotonic for all of the three maturities, because all of the MR p-values are zero. Panel C shows portfolios sorted on the kurtosis risk premium. The 5-1 return spread is positive and ranges from 1.1 to 4; it is also significant for all of the maturities. The t-statistics of the 5-1 spread range from 3 to 6.7. The MR test gives p-values around zero, which means that the positive relationship between the kurtosis risk premium and expected returns is monotonic.

In summary, Table 5.12 demonstrates that the result for the relationship between the moment risk premia and expected stock returns is robust to different maturities.

5.8 Conclusion

This study explores the direct relation between the moment risk premia and stock returns. I begin by comparing the explanatory power of the moment risk premia for *ex post* realised and *ex ante* expected return prediction. *Ex ante* expected return is proxied by the PTER and the ICC. The moment risk premia are defined as the difference between expected realised moments and risk-neutral moments. I find that the variance risk premium is negative, consistent with the previous literature (see, e.g. Bakshi and Kapadia, 2003a; Carr and Wu, 2009; Egloff et al., 2010; Kozhan et al., 2013). The skew risk premium is found to be positive, in line with Bakshi et al. (2003) and Kozhan et al. (2013), who find that realised skewness is greater than risk-neutral skewness. The kurtosis risk premium is slightly greater than zero. There is no existing literature providing the sign of the kurtosis risk premium.

I examine the determinants of the variance, skew and kurtosis risk premia cross-sectionally, and find that they are affected differently by firm-level characteristics (e.g. firm size, book-to-market ratio, momentum and illiquidity) and risk factors (e.g. market beta, idiosyncratic volatility and co-skewness). The variance risk premium is determined mainly by the positive effect of these firm-level and risk factors. The determinants of the skew risk premium are mixed; it is associated negatively with risk factors and associated positively with firm-level variables. The determinants of the kurtosis risk premium are also mixed; it is positively related to most of the risk factors, while it is inversely related to most of the firm-level factors. I provide the first research on the determinants of the skew and kurtosis risk premia.

For *ex post* realised stock returns, I find that both the variance and skew risk premia have a negative relation with subsequent realised stock returns, while the kurtosis risk premium has a mixed and insignificant relation with subsequent realised stock returns. The negative relation between the variance risk premium and subsequent stock returns is consistent with the results of Bali and Hovakimian (2009). The current findings for the skew and kurtosis risk premia have not been reported in earlier studies. I provide the first investigation for the cross-sectional relation between the skew and kurtosis risk premia and realised stock returns.

Expected stock returns are related negatively to both the variance and skew risk premia, which is consistent with the result of Bali et al. (2014). On the contrary, I find that the kurtosis risk premium has a robust and positive relation with expected stock returns, which is inconsistent with Bali et al. (2014).

The robustness test shows that the relation between the moment risk premia and stock returns is robust to firm characteristics and risk factors. It is also robust to subperiods and different maturities.

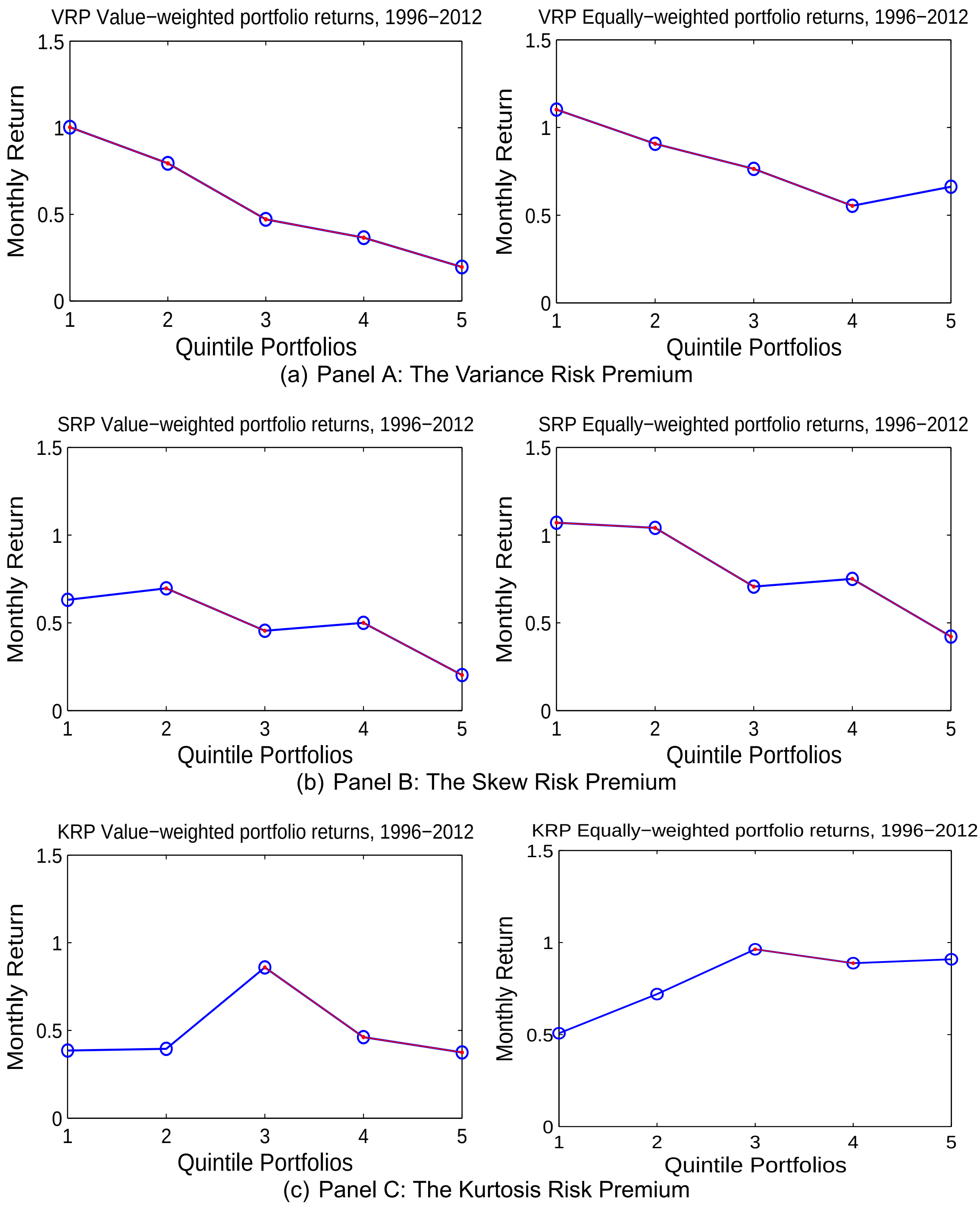
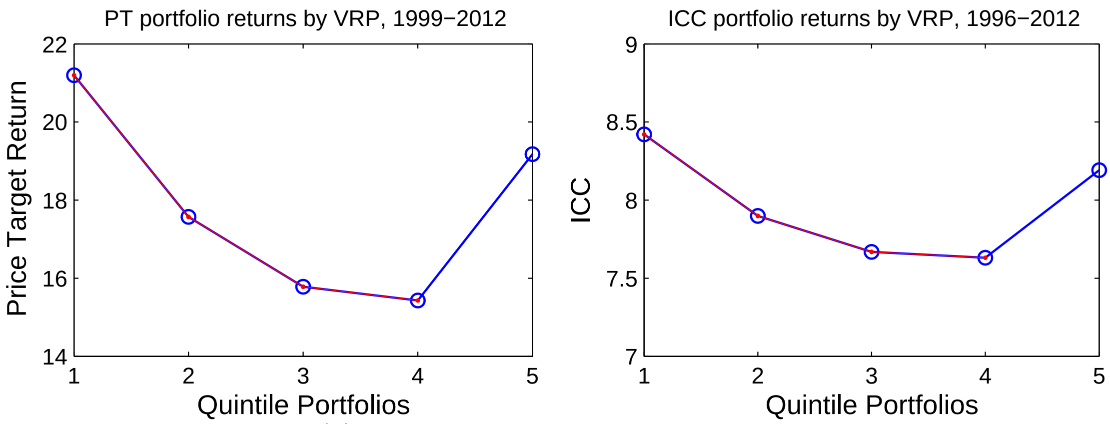
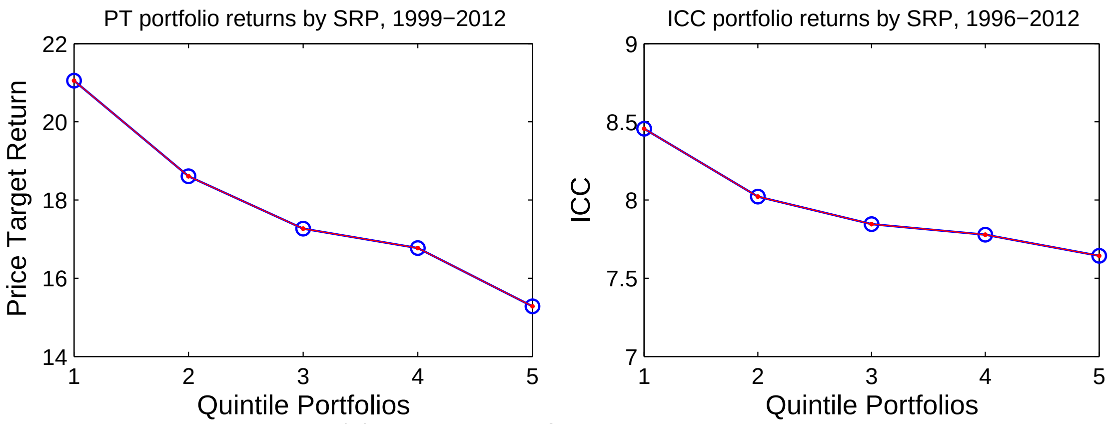


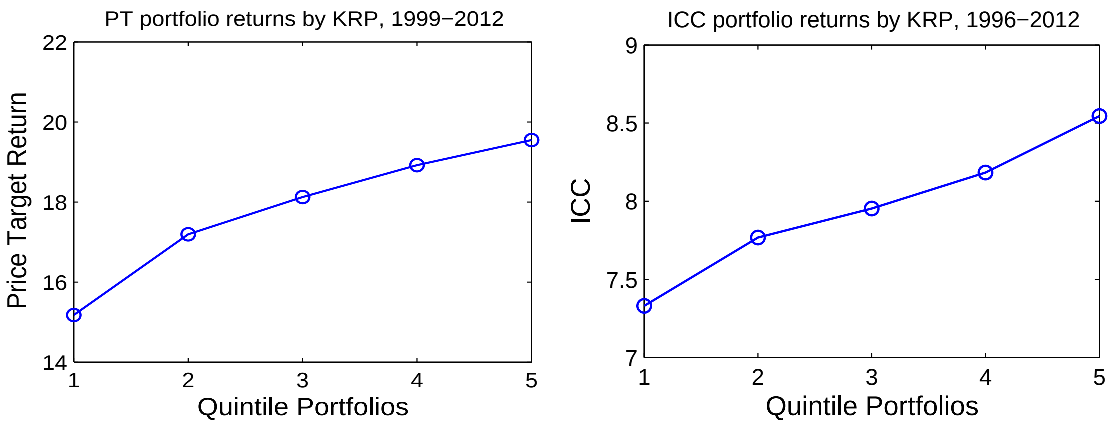
Figure 5.1. Plot of Realised Portfolio Returns Sorted by Risk Premia The figure shows the average monthly realised return of the five quintile portfolios sorted by the variance, skew and kurtosis risk premia over the period January 1996 to December 2012. At the end of each month, I sort the stocks into quintile portfolios based on their moment risk premia. The first portfolio then contains the stocks with the lowest risk premia, while the last portfolio contains the stocks with the highest risk premia. I then compute the value-weighted and equally-weighted monthly returns over the next month for each quintile portfolio and for each month. The exact numerical values of the portfolio returns could be found in Panel C, F and I of Table 5.4.



(a) Panel A: The Variance Risk Premium



(b) Panel B: The Skew Risk Premium



(c) Panel C: The Kurtosis Risk Premium

Figure 5.2. Plot of Expected Portfolio Returns Sorted by Risk Premia The figure shows the average expected returns of the five quintile portfolios sorted by the variance risk premium (Panel A), the skew risk premium (Panel B) and the kurtosis risk premium (Panel C). At the end of each month, I sort the stocks into quintile portfolios based on their variance, skew and kurtosis risk premia. The first portfolio then contains the stocks with the lowest risk premia, while the last portfolio contains the stocks with the highest risk premia. I then compute equally-weighted expected returns for each quintile portfolio and for each month. Table 5.7 shows the exact numerical values of the portfolio returns.

Table 5.1. Summary Statistics and Correlations for Moments and Moment Risk Premia

The table reports summary statistics and correlations for moments and moment risk premia. Panel A provides data descriptive statistics on risk-neutral and realised moments, as well as the variance, skew and kurtosis risk premia for the S&P 500 Index constituents from January 1996 to December 2012. The moment risk premia is defined as the difference between expected realised moments and risk-neutral moments. Risk-neutral moments are calculated following the model-free procedure in Bakshi et al. (2003) and are Winsorised at the 1% level. The table reports the number of observations, average, median, standard deviation and 25th and 75th percentiles. Panel B shows the correlations of realised moments and the moment risk premia. $Evar$ and $MFIV$ denote expected realised and risk-neutral variance, respectively. $Eskew$ and $MFIS$ represent expected realised and risk-neutral skewness, respectively. $EKurt$ and $MFIK$ denote expected realised and risk-neutral kurtosis, respectively.

Panel A: Summary Statistics

	Second Moment			Third Moment			Fourth Moment		
	$EVar$	$MFIV$	VRP	$ESkew$	$MFIS$	SRP	$EKurt$	$MFIK$	KRP
Observation	1,541,021	1,595,623	1,541,021	1,541,021	1,595,623	1,541,021	1,541,021	1,595,623	1,541,021
Mean	0.1843	0.1862	-0.0039	0.1185	-0.4555	0.5817	3.3646	3.3564	0.0038
StDev	0.7774	0.2014	0.7314	1.3093	0.3018	1.3452	11.7328	0.5658	11.7494
25th Percentile	0.0435	0.0726	-0.0597	-0.2506	-0.6248	0.1586	2.4326	3.0486	-0.9284
Median	0.0870	0.1204	-0.0275	0.1144	-0.4390	0.5797	2.8884	3.2329	-0.3841
75th Percentile	0.1820	0.2120	0.0001	0.4927	-0.2613	1.0139	3.6517	3.5208	0.4202

Panel B: Correlations

	Realised Moments				Moment Risk Premia		
	RV	RS	RK		VRP	SRP	KRP
RV	1	0.0731	0.2556	VRP	1	0.0302	0.3044
RS	0.0731	1	0.1392	SRP	0.0302	1	0.0157
RK	0.2556	0.1392	1	KRP	0.3044	0.0157	1

Table 5.2. Summary Statistics for Expected Stock Returns
The table provides summary statistics on *ex ante* expected stock returns, including the PTER and the ICC for the constituents in the S&P 500 Index. The sample period for the PTER is from March 1999 to December 2012. The sample period for the ICC is from January 1996 to December 2012. The PTER and the ICC are Winsorised at the 1% level. The table reports the number of observations, average, median, standard deviation and 25th and 75th percentiles.

	Observation	Mean	StDev	25th Percentile	Median	75th Percentile
PTER	64,001	0.1690	0.1913	0.0648	0.1387	0.2342
ICC	85,467	0.0821	0.0567	0.0620	0.0803	0.0986

Table 5.3. Moment Risk Premia and Firm Characteristics, Risk Factors

The table shows the results for the monthly Fama and MacBeth (1973) regressions of the variance risk premium (VRP, Panel A), the skew risk premium (SRP, Panel B) and the kurtosis risk premium (KRP, Panel C) on a set of risk factors (market beta (β), idiosyncratic volatility ($IdioVol$), coskewness ($CoSkew$)) and firm characteristic (log of market capitalisation ($ln(ME)$), log of book-to-market-ratio ($ln(BE/ME)$), return momentum ($Momentum$) and illiquidity). The table reports the time-series average of the cross-sectional regression coefficients and the t-statistics of the explanatory variables which are shown in brackets. Note: *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

Panel A: The Dependent Variable is the Variance Risk Premium								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
β	0.0651***							0.0613***
	(3.13)							(3.40)
$IdioVol$		0.0396***						0.0432***
		(3.70)						(5.08)
$CoSkew$			-0.0003					0.0009***
			(-1.63)					(5.18)
$ln(ME)$				-0.0042				0.0113***
				(1.46)				(5.39)
$ln(BE/ME)$					0.0169**			0.0046*
					(2.47)			(1.96)
$Momentum$						0.0793		0.0722**
						(1.63)		(2.02)
$Illiquidity$							-0.1994**	0.3812***
							(-1.91)	(4.25)
$Constant$	-0.0707***	-0.0912***	-0.0158	0.0051	0.1251**	-0.0166***	-0.0011	-0.1220***
	(-4.27)	(-5.04)	(-5.23)	(0.41)	(2.17)	(-2.41)	(-0.17)	(-7.34)
$Adj-R^2$	0.0520	0.0642	0.0564	0.0176	0.0155	0.0484	0.0039	0.1617

Table 5.3---Continued

Panel B: The Dependent Variable is The Skew Risk Premium								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
β	-0.0239**							-0.0517***
	(-2.04)							(-3.01)
$IdioVol$		-0.0595***						-0.0817***
		(-7.62)						(-9.26)
$CoSkew$			0.0001					-0.0013***
			(0.40)					(-8.25)
$ln(ME)$				0.0476***				0.0290***
				(10.51)				(5.91)
$ln(BE/ME)$					-0.0448***			0.0045
					(-9.04)			(0.96)
$Momentum$						3.5086***		3.8285***
						(24.23)		(25.91)
$Illiquidity$							2.0366****	2.2748***
							(4.04)	(4.30)
$Constant$	0.5870***	0.6567***	0.5578***	0.4400***	0.1982***	0.5170***	0.5511***	0.6127***
	(30.43)	(29.19)	(36.39)	(25.41)	(4.55)	(31.69)	(40.84)	(13.94)
$Adj-R^2$	0.0093	0.0120	0.0083	0.0139	0.0078	0.1364	0.0056	0.1885

Table 5.3---Continued

Panel C: The Dependent Variable is The Kurtosis Risk Premium								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
β	0.0535**							-0.1377***
	(1.91)							(-3.98)
$IdioVol$		0.4461***						0.5182***
		(20.92)						(19.53)
$CoSkew$			-0.0011***					0.0048***
			(-3.42)					(12.03)
$ln(ME)$				-0.2446***				-0.2081***
				(-32.69)				(-22.98)
$ln(BE/ME)$					0.0435***			-0.0560
					(3.08)			(-4.80)
$Momentum$						-0.8775***		-1.0021***
						(-4.09)		(-4.97)
$Illiquidity$							-8.4854****	-17.5560***
							(-6.47)	(-11.58)
$Constant$	-0.0321	-0.7399***	-0.0032	0.6509***	0.3831***	0.0042	0.0748***	-0.3389***
	(-0.72)	(-17.07)	(-0.11)	(19.39)	(3.60)	(0.15)	(2.83)	(-3.26)
$Adj-R^2$	0.0102	0.0404	0.0072	0.0295	0.0091	0.0219	0.0061	0.1064

Table 5.4. Portfolios Analysis by Moments and Risk Premia for Realised Returns

The five quintile portfolios are sorted by realised/ risk-neutral variance, skewness and kurtosis, as well as risk premia over the sample period from January 1996 to December 2012. At the end of each month, I sort the stocks into quintile portfolios based on risk premia. The first portfolio then contains the stocks with the lowest risk premia, while the last portfolio contains the stocks with the highest risk premia. I then compute the value-weighted and equally-weighted monthly returns over the next month for each quintile portfolio, month and risk premium. The table reports the time-series average of the value-weighted and equally-weighted portfolio returns. The row '5-1' refers to the average monthly return on an arbitrage portfolio with a long position in portfolio 5 and a short position in portfolio 1. In addition, the table provides t-statistics and p-values for the 5-1 return spread to test whether the spread is significant. It also provides p-values, obtained from time-series block bootstrapping, for the Patton and Timmermann (2010) MR test of the hypothesis for monotonically increasing or decreasing relationships between risk premia and stock returns. The parameters v-return and e-return represent the value-weighted and equally-weighted stock returns, respectively.

	1	2	3	4	5	5-1	t-stat	t-pval	MR-p
Panel A: Expected Realised Variance									
v-return	0.435	0.654	0.566	0.497	0.513	0.078	0.142	0.444	0.242
e-return	0.588	0.825	0.835	0.891	0.854	0.266	0.466	0.320	0.188
Panel B: Risk-Neutral Variance									
v-return	0.383	0.716	0.673	0.813	0.816	0.433	0.713	0.238	0.186
e-return	0.538	0.782	0.928	1.047	0.994	0.455	0.777	0.219	0.184
Panel C: The Variance Risk Premium									
v-return	1.002	0.794	0.470	0.365	0.195	-0.807	2.386	0.009	0.001
e-return	1.102	0.907	0.764	0.554	0.662	-0.439	1.664	0.048	0.176
Panel D: Expected Realised Skewness									
v-return	0.543	0.530	0.602	0.428	0.309	-0.234	1.035	0.150	0.139
e-return	0.985	0.765	0.811	0.765	0.664	-0.322	1.854	0.032	0.118
Panel E: Risk-Neutral Skewness									
v-return	0.258	0.608	0.698	0.914	0.802	0.545	1.915	0.028	0.293
e-return	0.296	0.688	0.977	1.076	1.251	0.955	3.170	0.001	0.001
Panel F: The Skew Risk Premium									
v-return	0.631	0.696	0.455	0.500	0.202	-0.429	1.632	0.051	0.091
e-return	1.070	1.042	0.707	0.750	0.421	-0.649	2.830	0.002	0.186
Panel G: Expected Realised Kurtosis									
v-return	0.501	0.470	0.659	0.570	0.213	-0.287	1.272	0.102	0.545
e-return	0.746	0.787	0.873	0.823	0.760	0.014	0.096	0.462	0.132
Panel H: Risk-Neutral Kurtosis									
v-return	0.932	0.951	0.625	0.491	0.327	-0.605	1.728	0.042	0.075
e-return	1.169	1.175	0.823	0.756	0.360	-0.809	2.339	0.010	0.050
Panel I: The Kurtosis Risk Premium									
v-return	0.385	0.395	0.859	0.461	0.375	-0.011	0.040	0.484	0.990
e-return	0.507	0.719	0.963	0.887	0.909	0.402	1.785	0.037	0.241

Table 5.5. Double-Sorted Portfolios

The table reports the results for two-way portfolio sorts on firm-level characteristics and risk premia. I independently first sort the stocks into quintile portfolios based on firm size, book-to-market ratio, expected realised and risk-neutral moments, and then on the moment risk premia. For each of the 25 portfolios, I calculate the average monthly returns in the subsequent period.

Panel A: The Variance Risk Premium													
	ln(ME)-VRP							ln(BE/ME)-VRP					
	VRP1	VRP2	VRP3	VRP4	VRP5	5-1		VRP1	VRP2	VRP3	VRP4	VRP5	5-1
S1	1.859	1.011	1.054	0.842	1.461	-0.398	BM1	1.185	0.948	0.442	0.267	0.472	-0.713
S2	0.678	1.142	1.139	0.785	0.704	0.026	BM2	0.771	0.710	0.659	0.365	0.829	0.058
S3	1.080	1.060	1.000	0.598	0.689	-0.391	BM3	1.059	0.783	0.712	0.483	0.304	-0.756
S4	1.031	0.666	0.719	0.438	0.364	-0.667	BM4	1.229	0.851	1.139	0.671	0.711	-0.518
S5	1.022	0.695	0.391	0.318	0.328	-0.695	BM5	1.418	1.468	1.127	0.660	0.919	-0.499
5-1	-0.836	-0.316	-0.663	-0.524	-1.133		5-1	0.233	0.520	0.684	0.393	0.447	
	EVar-VRP							MFIV-VRP					
	VRP1	VRP2	VRP3	VRP4	VRP5	5-1		VRP1	VRP2	VRP3	VRP4	VRP5	5-1
EVar1	10.984	0.669	0.576	0.377	0.330	-0.655	MFIV1	0.589	0.492	0.462	0.375	0.459	-0.130
EVar2	1.234	0.876	0.885	0.700	0.426	-0.807	MFIV2	0.803	0.882	0.679	0.497	0.786	-0.018
EVar3	1.288	0.934	0.669	0.552	0.740	-0.547	MFIV3	1.054	0.999	0.818	0.564	0.893	-0.161
EVar4	1.042	1.059	0.929	0.912	0.521	-0.521	MFIV4	0.947	1.290	0.739	1.210	0.894	-0.053
EVar5	0.766	0.987	0.819	0.801	0.892	0.126	MFIV5	1.140	0.844	0.808	0.935	0.863	-0.277
5-1	-0.218	0.318	0.243	0.425	0.563		5-1	0.551	0.352	0.346	0.560	0.404	

Table 5.5---Continued

Panel B: The Skew Risk Premium													
	In(ME)-SRP							In(BE/ME)-SRP					
	SRP1	SRP2	SRP3	SRP4	SRP5	5-1		SRP1	SRP2	SRP3	SRP4	SRP5	5-1
S1	1.470	1.378	1.119	1.348	0.871	-0.599	BM1	0.803	0.766	0.564	0.790	0.406	-0.397
S2	1.457	1.260	0.695	0.494	0.529	-0.928	BM2	0.946	0.758	0.791	0.344	0.531	-0.415
S3	1.432	1.003	0.850	0.447	0.659	-0.773	BM3	1.026	0.862	0.505	0.528	0.378	-0.649
S4	0.634	0.704	0.560	0.877	0.455	-0.179	BM4	1.164	1.179	1.189	0.652	0.453	-0.711
S5	0.905	0.711	0.450	0.516	0.174	-0.732	BM5	1.653	0.915	1.424	1.157	0.480	-1.173
5-1	-0.565	-0.667	-0.669	-0.831	-0.697		5-1	0.850	0.150	0.860	0.366	0.074	
	ESkew-SRP							MFIS-SRP					
	SRP1	SRP2	SRP3	SRP4	SRP5	5-1		SRP1	SRP2	SRP3	SRP4	SRP5	5-1
ESkew1	1.215	0.874	1.315	1.016	0.524	-0.691	MFIS1	0.471	0.044	0.189	0.006	0.357	-0.114
ESkew2	1.017	1.212	0.732	0.733	0.121	-0.896	MFIS2	0.827	0.661	0.785	0.564	0.383	-0.444
ESkew3	1.474	0.992	0.388	0.741	0.468	-1.005	MFIS3	0.919	0.782	1.007	1.073	0.600	-0.320
ESkew4	0.979	1.332	0.675	0.594	0.249	-0.730	MFIS4	1.377	1.260	0.792	0.785	0.866	-0.511
ESkew5	1.210	0.942	0.213	0.285	0.662	-0.548	MFIS5	1.455	0.963	1.399	1.312	1.056	-0.399
5-1	-0.005	0.068	-1.102	-0.732	0.139		5-1	0.984	0.919	1.210	1.306	0.698	

Table 5.5---Continued

Panel C: The Kurtosis Risk Premium													
	ln(ME)-KRP							ln(BE/ME)-KRP					
	KRP1	KRP2	KRP3	KRP4	KRP5	5-1		KRP1	KRP2	KRP3	KRP4	KRP5	5-1
S1	0.893	1.170	0.751	1.585	1.829	0.936	BM1	0.426	0.699	0.785	0.804	0.603	0.177
S2	0.732	0.805	1.355	0.773	0.768	0.036	BM2	0.395	0.674	0.893	0.559	0.792	0.397
S3	0.475	0.746	1.128	1.103	0.919	0.444	BM3	0.210	0.448	0.853	0.784	1.015	0.804
S4	0.280	0.939	0.596	0.717	0.696	0.416	BM4	0.578	1.073	0.829	1.094	1.029	0.451
S5	0.328	0.691	0.678	0.663	0.378	0.050	BM5	0.932	1.059	1.445	0.839	1.328	0.396
5-1	-0.565	-0.479	-0.073	-0.922	-1.451		5-1	0.506	0.360	0.661	0.036	0.725	
	EKurt-KRP							MFIK-KRP					
	KRP1	KRP2	KRP3	KRP4	KRP5	5-1		KRP1	KRP2	KRP3	KRP4	KRP5	5-1
EKurt1	0.437	0.606	0.727	1.011	0.955	0.518	MFIK1	1.029	0.882	1.215	0.865	1.612	0.584
EKurt2	0.470	0.765	0.620	1.258	0.804	0.334	MFIK2	0.944	1.285	1.342	1.281	0.977	0.032
EKurt3	0.240	0.745	1.213	1.131	1.033	0.793	MFIK3	0.739	0.928	0.685	0.914	0.396	-0.343
EKurt4	0.317	0.881	0.889	0.995	1.034	0.717	MFIK4	0.625	0.733	0.645	0.868	0.490	-0.135
EKurt5	0.397	0.711	0.818	0.927	0.940	0.543	MFIK5	0.370	0.084	0.496	0.070	0.434	0.064
5-1	-0.040	0.105	0.091	-0.084	-0.015		5-1	-0.659	-0.798	-0.720	-0.795	-1.178	

Table 5.6. Fama-MacBeth Regressions for Realised Returns

The table shows the results for the Fama and MacBeth (1973) regressions of average monthly stock returns on risk premia, firm characteristics and risk factors. The set of these factors includes the variance risk premium (VRP), the skew risk premium (SRP) and the kurtosis risk premium (KRP), market beta (β), idiosyncratic volatility ($IdioVol$), coskewness ($CoSkew$), log of market capitalisation ($ln(ME)$), log of book-to-market-ratio ($ln(BE/ME)$), return momentum ($Momentum$) and illiquidity. The sample period is from January 1996 to December 2012. I report the time-series average of the slope coefficients of the independent variables and t-statistics (shown in brackets). Note: *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
VRP	-0.0075			-0.0109	-0.0054	-0.0122	-0.0070
	(-0.73)			(-0.93)	(-0.63)	(-1.21)	(-0.86)
SRP		-0.0024**		-0.0017**	-0.0014*	-0.0015*	-0.0014*
		(-2.56)		(-1.87)	(-1.84)	(-1.82)	(-1.94)
KRP			0.0006	0.0012**	0.0010***	0.0008**	0.0008**
			(1.29)	(2.50)	(2.71)	(2.15)	(2.26)
β					0.0015		0.0023
					(0.41)		(0.67)
$IdioVol$					0.0006		-0.0002
					(0.39)		(-0.15)
$CoSkew$					0.0000		0.0000
					(-1.00)		(-0.71)
$ln(ME)$						-0.0018*	-0.0021**
						(-1.81)	(-2.47)
$ln(BE/ME)$						0.0005	0.0004
						(0.44)	(0.37)
$Momentum$						0.0084	0.0066
					(0.62)	(0.57)	
$Illiquidity$						-0.0530	-0.0680
						(-0.76)	(-1.17)
Constant	0.0086**	0.0095**	0.0084**	0.0099**	0.0051	0.0183	0.0154
	(2.35)	(2.28)	(2.09)	(2.58)	(1.40)	(1.61)	(1.54)
$Adj-R^2$	0.0209	0.0064	0.0064	0.0346	0.1097	0.0946	0.1487

Table 5.7. Portfolios Sorted by Risk Premia for Expected Stock Returns

The five quintile portfolios are sorted by the variance, skew and kurtosis risk premia. At the end of each month, I sort the stocks into quintile portfolios based on risk premia. The first portfolio then contains the stocks with the lowest risk premia, while the last portfolio contains the stocks with the highest risk premia. I then compute the equally-weighted expected stock returns for each quintile portfolio, month and risk premia. The table reports the time-series average of the equally-weighted portfolio returns. The row '5-1' refers to the average *ex ante* expected stock returns on an arbitrage portfolio with a long position in portfolio 5 and a short position in portfolio 1. In addition, the table provides t-statistics and p-values for the 5-1 return spread to test whether the spread is significant. It also provides p-values, obtained from time-series block bootstrapping, for the Patton and Timmermann (2010) MR test of the hypothesis for monotonically increasing or decreasing relations between risk premia and stock returns.

	1	2	3	4	5	5-1	t-stat	t-pval	MR-p
				Panel A: The Variance Risk Premium					
PTER	21.197	17.572	15.784	15.431	19.177	-2.019	2.646	0.004	1.000
ICC	8.421	7.898	7.668	7.631	8.191	-0.229	1.101	0.135	0.984
				Panel B: The Skew Risk Premium					
PTER	21.055	18.609	17.267	16.769	15.279	-5.776	10.316	0.000	0.000
ICC	8.455	8.021	7.846	7.779	7.644	-0.811	5.472	0.000	0.000
				Panel C: The Kurtosis Risk Premia					
PTER	15.176	17.192	18.125	18.918	19.548	4.372	6.060	0.000	0.000
ICC	7.329	7.767	7.953	8.184	8.544	1.215	6.177	0.000	0.000

Table 5.8. Fama-MacBeth Regressions for Expected Returns
The table shows the results for the Fama and MacBeth (1973) regression of average monthly returns on risk premia, firm characteristics and risk factors. The set of these factors includes the variance risk premium (VRP), the skew risk premium (SRP), the kurtosis risk premium (KRP), market beta (β), idiosyncratic volatility ($IdioVol$), co-skewness ($CoSkew$), log of market capitalisation ($ln(ME)$), log of book-to-market-ratio ($ln(BE/ME)$), return momentum ($Momentum$) and illiquidity. The sample period is from January 1996 to December 2012. I report the time-series average of the slope coefficients of the independent variables and the t-statistics (shown in brackets). Note: *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

Panel A: Price Target Expected Return							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
VRP	-0.0507***			-0.0983***	-0.0726***	-0.0578***	-0.0359**
	(-2.80)			(-4.93)	(-4.06)	(-3.30)	(-2.16)
SRP		-0.0299***		-0.0275***	-0.0271***	-0.0021	-0.0019
		(-15.85)		(-14.80)	(-15.68)	(-1.20)	(-1.18)
KRP			0.0077***	0.0073***	0.0052***	0.0036***	0.0022***
			(8.46)	(8.60)	(7.31)	(6.11)	(3.99)
β					0.0455***		0.0428***
					(7.90)		(8.58)
$IdioVol$					0.0135***		0.0229***
					(5.48)		(10.79)
$CoSkew$					-0.0001***		-0.0001
					(-2.86)		(-1.57)
$ln(ME)$						-0.0011	0.0072***
						(-0.88)	(5.75)
$ln(BE/ME)$						0.0098***	0.0076***
						(7.05)	(6.08)
$Momentum$						-0.5598***	-0.5674***
						(-23.89)	(-29.23)
$Illiquidity$						-1.1362***	-0.6646***
						(-8.15)	(-4.88)
Constant	0.1725***	0.1965***	0.1795***	0.1880***	0.1032***	0.2604***	0.1281***
	(30.82)	(30.31)	(30.68)	(30.51)	(16.63)	(17.89)	(9.50)
$Adj-R^2$	0.0258	0.0242	0.0116	0.0583	0.1309	0.1804	0.2341

Table 5.8---Continued

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Panel B: Implied Cost of Capital							
VRP	-0.0074**			-0.0227***	-0.0210***	-0.0103***	-0.0119***
	(-2.45)			(-6.31)	(-6.25)	(-3.60)	(-4.33)
SRP		-0.0045***		-0.0040***	-0.0034***	-0.0012**	-0.0008*
		(-6.65)		(-5.82)	(-5.85)	(-2.54)	(-1.83)
KRP			0.0023***	0.0022***	0.0015***	0.0009***	0.0007***
			(8.95)	(11.93)	(6.99)	(4.51)	(2.67)
β					0.0043**		0.0030*
					(2.24)		(1.68)
$IdioVol$					0.0074***		0.0054***
					(10.25)		(7.51)
$CoSkew$					0.0001***		0.0001***
					(7.36)		(5.64)
$ln(ME)$						-0.0028***	-0.0020***
						(-10.35)	(-8.08)
$ln(BE/ME)$						0.0190***	0.0186***
						(54.04)	(68.13)
$Momentum$						-0.0359***	-0.0397***
						(-8.96)	(-8.84)
$Illiquidity$						-0.2368***	-0.1873***
						(-7.62)	(-6.50)
Constant	0.0784***	0.0824***	0.0799***	0.0810***	0.0661***	0.2409***	0.2253***
	(96.19)	(59.78)	(79.25)	(64.63)	(39.68)	(60.54)	(98.14)
$Adj-R^2$	0.0218	0.0149	0.0177	0.0528	0.1091	0.3288	0.3493

Table 5.9. Portfolio Analysis of Realised Returns in Subperiods

The five quintile portfolios are sorted by the moment risk premia over the following sample subperiods: 1996-1999, 2000-2002, 2003-2006 and 2007-2012. At the end of each month, I sort the stocks into quintile portfolios based on their risk premia. The first portfolio contains the stocks with the lowest risk premia, while the last portfolio contains the stocks with the highest risk premia. I then compute the value-weighted and equally-weighted monthly returns over the next month for each quintile portfolio, month, subperiod and risk premium measure. The table reports the time-series average of the value-weighted and equally-weighted portfolio returns for each subperiod. The row '5-1' refers to the average monthly return on an arbitrage portfolio with a long position in portfolio 5 and a short position in portfolio 1. In addition, the table provides t-statistics and p-values for the 5-1 return spread to test whether the spread is significant or not. It also provides p-values, obtained from time-series block bootstrapping, for the Patton and Timmermann (2010) MR test of the hypothesis for monotonically increasing or decreasing relations between risk premia and returns. In this table, v-return and e-return represent the value-weighted and equally-weighted stock returns, respectively.

	1	2	3	4	5	5-1	t-stat	t-pval	MR-p
Panel A: The Variance Risk Premium									
1996---1999									
v-return	3.557	2.294	1.578	2.011	1.565	-1.992	2.344	0.010	0.880
e-return	2.387	1.714	1.374	1.299	1.458	-0.929	2.897	0.002	0.284
2000---2002									
v-return	-1.355	-0.951	-1.061	-1.241	-1.689	-0.333	0.251	0.401	0.217
e-return	-0.262	-0.151	-0.065	-0.194	-1.159	-0.897	0.903	0.183	0.196
2003---2006									
v-return	1.725	1.245	1.018	0.782	1.494	-0.231	0.635	0.263	0.951
e-return	1.976	1.422	1.356	1.289	1.896	-0.079	0.281	0.389	0.983
2007---2012									
v-return	0.578	0.567	0.462	0.148	-0.241	-0.818	1.719	0.043	0.039
e-return	0.709	0.752	0.602	0.177	0.461	-0.247	0.519	0.302	0.405
Panel B: The Skew Risk Premium									
1996---1999									
v-return	1.247	2.089	2.247	2.403	2.078	0.832	1.878	0.030	0.572
e-return	1.379	1.969	1.439	1.897	1.552	0.172	0.461	0.322	0.990
2000---2002									
v-return	-0.511	-0.831	-1.547	-1.212	-1.980	-1.470	1.484	0.069	0.241
e-return	0.413	0.058	-0.565	-0.550	-1.191	-1.604	1.810	0.035	0.087
2003---2006									
v-return	1.390	1.255	1.153	0.977	0.970	-0.421	1.482	0.069	0.007
e-return	1.764	1.824	1.551	1.456	1.344	-0.421	1.689	0.046	0.112
2007---2012									
v-return	0.467	0.462	0.219	0.189	-0.037	-0.504	1.763	0.039	0.023
e-return	0.920	0.686	0.523	0.432	0.147	-0.773	2.939	0.002	0.000

Table 5.9---Continued

	1	2	3	4	5	5-1	t-stat	t-pval	MR-p
Panel C: The Kurtosis Risk Premium									
1996---1999									
v-return	2.511	1.879	2.174	1.773	1.465	-1.045	1.948	0.026	0.652
e-return	1.899	1.510	1.831	1.555	1.430	-0.469	1.484	0.069	0.864
2000---2002									
v-return	-1.247	-1.509	-0.159	-1.455	-1.862	-0.615	0.672	0.251	0.996
e-return	-0.992	-0.274	0.197	-0.259	-0.517	0.475	0.788	0.215	0.633
2003---2006									
v-return	0.714	1.095	1.512	1.168	1.385	0.672	1.894	0.029	0.683
e-return	1.201	1.483	1.796	1.586	1.865	0.663	1.939	0.026	0.729
2007---2012									
v-return	0.044	0.218	0.366	0.380	0.416	0.373	1.050	0.147	0.029
e-return	0.185	0.421	0.472	0.785	0.847	0.662	1.560	0.059	0.043

Table 5.10. Portfolio Analysis of Expected Returns in Subperiods

The five quintile portfolios are sorted by risk premia over the following sample subperiods: 1996-1999, 2000-2002, 2003-2006 and 2007-2012. At the end of each month, I sort the stocks into quintile portfolios based on their risk premia. The first portfolio then contains the stocks with the lowest risk premia, while the last portfolio contains the stocks with the highest risk premia. I then compute the equally-weighted expected returns for each quintile portfolio, month, subperiod and risk premium measure. The table reports the time-series average of the equally-weighted portfolio returns for each subperiod. The row '5-1' refers to the average monthly return on an arbitrage portfolio with a long position in portfolio 5 and a short position in portfolio 1. In addition, the table provides t-statistics and p-values for the 5-1 return spread to test whether the spread is significant. It also provides p-values, obtained from time-series block bootstrapping, for the Patton and Timmermann (2010) MR test of the hypothesis for monotonically increasing or decreasing relationships between risk premia and returns.

	1	2	3	4	5	5-1	t-stat	t-pval	MR-p
				Panel A: The Variance Risk Premium					
1996---1999									
PTER	28.560	23.892	20.680	21.640	25.795	-2.765	1.063	0.144	1.000
ICC	6.722	6.299	6.107	6.161	6.457	-0.265	1.751	0.040	0.999
2000---2002									
PTER	34.847	24.123	21.089	21.182	30.613	-4.234	3.903	0.000	1.000
ICC	8.041	7.372	7.203	7.262	7.706	-0.334	1.478	0.070	0.988
2003---2006									
PTER	14.498	13.562	12.337	11.455	12.855	-1.643	2.578	0.005	1.000
ICC	8.049	7.832	7.564	7.417	7.637	-0.413	4.866	0.000	0.999
2007---2012									
PTER	17.890	16.091	14.793	14.371	16.837	-1.053	0.730	0.233	0.969
ICC	9.731	9.021	8.772	8.718	9.718	-0.013	0.025	0.490	0.927
				Panel B: The Skew Risk Premium					
1996---1999									
PTER	27.717	25.101	22.633	22.229	21.856	-5.861	7.633	0.000	0.000
ICC	6.874	6.417	6.194	6.104	6.086	-0.788	7.489	0.000	0.000
2000---2002									
PTER	31.470	26.214	25.394	25.376	23.584	-7.886	6.170	0.000	0.019
ICC	8.125	7.544	7.340	7.266	7.274	-0.850	4.926	0.000	0.054
2003---2006									
PTER	15.229	13.728	12.321	12.290	10.833	-4.396	10.073	0.000	0.008
ICC	7.972	7.752	7.539	7.588	7.627	-0.345	3.797	0.000	0.330
2007---2012									
PTER	18.893	17.177	15.789	14.758	13.191	-5.703	6.190	0.000	0.000
ICC	9.761	9.262	9.152	9.030	8.649	-1.113	3.160	0.001	0.000

Table 5.10---Continued

	1	2	3	4	5	5-1	t-stat	t-pval	MR-p
Panel C: The Kurtosis Risk Premium									
1996---1999									
PTER	21.760	22.442	23.618	24.970	26.198	4.439	4.607	0.000	0.000
ICC	5.762	6.256	6.347	6.481	6.860	1.098	6.103	0.000	0.000
2000---2002									
PTER	21.888	24.301	26.708	28.946	30.218	8.330	6.138	0.000	0.000
ICC	6.635	7.217	7.512	7.845	8.394	1.759	9.484	0.000	0.000
2003---2006									
PTER	12.230	12.827	12.747	13.179	13.416	1.186	2.625	0.004	0.083
ICC	7.493	7.588	7.650	7.773	7.986	0.493	3.445	0.000	0.000
2007---2012									
PTER	12.907	15.847	16.732	16.928	17.429	4.522	4.465	0.000	0.026
ICC	8.382	8.944	9.202	9.494	9.867	1.485	3.341	0.000	0.000

Table 5.11. Portfolio Analysis of Realised Returns for Different Maturities
The five quintile portfolios are sorted by risk premia for different maturities over the sample period from January 1996 to December 2012. At the end of each month, I sort the stocks into quintile portfolios based on their risk premia. The first portfolio then contains the stocks with the lowest risk premia, while the last portfolio contains the stocks with the highest risk premia. I then compute the value-weighted and equally-weighted monthly returns over the next month for each quintile portfolio, month and risk premium measure. The table reports the time-series average of the value-weighted and equally-weighted portfolio returns. The row '5-1' refers to the average monthly return on an arbitrage portfolio with a long position in portfolio 5 and a short position in portfolio 1. In addition, the table provides t-statistics and p-values for the 5-1 return spread to test whether the spread is significant or not. It also provides p-values, obtained from time-series block bootstrapping, for the Patton and Timmermann (2010) MR test of the hypothesis for monotonically increasing or decreasing relations between risk premia and returns. In this table, v-return and e-return represent the value-weighted and equally-weighted stock returns, respectively.

	1	2	3	4	5	5-1	t-stat	t-pval	MR-p
Panel A: The Variance Risk Premium									
60-day Maturity									
v-return	0.990	0.754	0.365	0.472	0.167	-0.823	2.117	0.017	0.350
e-return	1.188	0.890	0.574	0.701	0.635	-0.552	1.778	0.038	0.632
90-day Maturity									
v-return	0.867	0.555	0.459	0.490	0.408	-0.459	1.194	0.116	0.079
e-return	1.048	0.783	0.707	0.695	0.756	-0.293	0.943	0.173	0.116
180-day Maturity									
v-return	0.546	0.747	0.546	0.511	0.233	-0.313	0.724	0.234	0.455
e-return	0.911	0.998	0.725	0.776	0.604	-0.308	0.791	0.214	0.242
Panel B: The Skew Risk Premium									
60-day Maturity									
v-return	0.668	0.460	0.561	0.586	0.176	-0.492	2.206	0.014	0.254
e-return	1.082	0.762	0.897	0.763	0.481	-0.601	2.978	0.001	0.503
90-day Maturity									
v-return	0.712	0.601	0.501	0.614	0.068	-0.644	2.900	0.002	0.285
e-return	1.026	0.942	0.673	0.873	0.470	-0.555	2.873	0.002	0.647
180-day Maturity									
v-return	0.599	0.728	0.676	0.516	0.027	-0.572	2.400	0.008	0.283
e-return	1.012	0.960	0.800	0.736	0.501	-0.511	2.060	0.020	0.013

Table 5.11---Continued

	1	2	3	4	5	5-1	t-stat	t-pval	MR-p
Panel C: The Kurtosis Risk Premium									
60-day Maturity									
v-return	0.447	0.648	0.564	0.422	0.387	-0.060	0.237	0.406	0.540
e-return	0.588	0.836	0.856	0.792	0.914	0.326	1.590	0.056	0.184
90-day Maturity									
v-return	0.342	0.764	0.594	0.360	0.505	0.162	0.802	0.211	0.701
e-return	0.615	0.842	0.850	0.696	0.982	0.367	1.960	0.025	0.554
180-day Maturity									
v-return	0.587	0.508	0.638	0.208	0.413	-0.174	0.749	0.227	0.473
e-return	0.715	0.789	0.942	0.669	0.900	0.185	0.923	0.178	0.957

Table 5.12. Portfolio Analysis for Expected Returns for Different Maturities
The five quintile portfolios are sorted by risk premia for different maturities over the sample period from January 1996 to December 2012. At the end of each month, I sort the stocks into quintile portfolios based on their risk premia. The first portfolio then contains the stocks with the lowest risk premia, while the last portfolio contains the stocks with the highest risk premia. I compute the equally-weighted expected returns for each quintile portfolio, month and risk premium measure. The table reports the time-series average of the equally-weighted portfolio returns. The row '5-1' refers to the average *ex ante* expected return on an arbitrage portfolio with a long position in portfolio 5 and a short position in portfolio 1. In addition, the table provides t-statistics and p-values for the 5-1 return spread to test whether the spread is significant or not. It also provides p-values, obtained from time-series block bootstrapping, for the Patton and Timmermann (2010) MR test of the hypothesis for monotonically increasing or decreasing relations between risk premia and returns.

	1	2	3	4	5	5-1	t-stat	t-pval	MR-p
Panel A: The Variance Risk Premium									
60-day Maturity									
PTER	21.085	17.417	15.567	15.376	19.657	-1.428	1.745	0.040	1.000
ICC	8.343	7.857	7.706	7.614	8.274	-0.070	0.299	0.383	0.992
90-day Maturity									
PTER	21.224	17.396	15.684	15.387	19.424	-1.801	1.949	0.026	0.999
ICC	8.378	7.840	7.656	7.640	8.288	-0.090	0.395	0.346	0.988
180-day Maturity									
PTER	21.345	17.615	15.742	15.389	18.413	-2.932	2.578	0.005	0.998
ICC	8.404	7.869	7.663	7.695	8.149	-0.255	1.255	0.105	0.950
Panel B: The Skew Risk Premium									
60-day Maturity									
PTER	20.987	18.625	17.617	16.376	15.453	-5.534	9.030	0.000	0.000
ICC	8.515	8.019	7.850	7.716	7.634	-0.881	5.054	0.000	0.000
90-day Maturity									
PTER	21.012	18.762	17.508	16.439	15.308	-5.704	9.241	0.000	0.000
ICC	8.601	8.035	7.796	7.701	7.602	-0.999	5.586	0.000	0.000
180-day Maturity									
PTER	20.456	19.187	17.591	16.344	15.067	-5.388	7.751	0.000	0.000
ICC	8.666	8.036	7.841	7.667	7.515	-1.151	6.479	0.000	0.000

Table 5.12---Continued

	1	2	3	4	5	5-1	t-stat	t-pval	MR-p
				Panel C: The Kurtosis Risk Premium					
60-day Maturity									
PTER	15.452	17.513	18.121	18.681	19.376	3.924	5.328	0.000	0.001
ICC	7.341	7.726	8.001	8.228	8.459	1.118	6.659	0.000	0.000
90-day Maturity									
PTER	15.729	17.536	18.186	18.453	19.191	3.462	4.985	0.000	0.004
ICC	7.325	7.747	8.030	8.130	8.530	1.205	6.094	0.000	0.000
180-day Maturity									
PTER	16.509	17.508	17.773	18.265	18.633	2.123	3.189	0.001	0.001
ICC	7.381	7.713	7.964	8.077	8.620	1.239	6.279	0.000	0.000

Chapter 6

Moment Risk Premia and Aggregate Stock Market Returns

6.1 Introduction

The presence of the variance risk premium at the aggregate market level has already been documented extensively in the literature. Bakshi and Kapadia (2003a) propose a nonparametric way to present the variance risk premium by analysing the profits and losses from the Black-Scholes delta-hedged positions in the S&P 500 and S&P 100 index options. They find that the market volatility premium is negative. Bakshi and Kapadia (2003b) show the existence of a negative market volatility risk premium in index options and individual equity options. It has also been documented by Carr and Wu (2009) that there exists a negative average variance risk premium for the S&P 500 index. The negative sign of the variance risk premium indicates that variance buyers are willing to accept a negative average excess return to hedge away upward movements in stock market volatility. In other words, investors dislike increases in market volatility. Jackwerth and Rubinstein (1996) also provide an explanation of why implied volatilities exceed realised volatilities. Market volatility tends to increase when stock market falls. When options are added to a market portfolio, this will help hedge market risk. Hence, this is consistent with a negative volatility risk premium.

Increases in market volatility are less desirable and command high returns as compensation. The variance risk premium is indeed found to help predict future stock market returns at the aggregate market level (see Bollerslev et al., 2009; Drechsler and Yaron, 2011; Bollerslev et al., 2011). Specifically, Bollerslev et al. (2009) find that the variance risk premium, defined as the difference between risk-neutral variance and realised variance, has explanatory power to post-1990 aggregate stock market returns. They support that high values of the variance risk premium can predict high future index returns. Drechsler and Yaron (2011) demonstrate that the variance risk premium, defined as the difference between the squared VIX index and the expected realised variance, is useful for measuring agents' perceptions of uncertainty and the risk of influential shocks to the economic state vector. They show conditions under which the variance risk premium displays significant time variation and future return prediction. Bollerslev et al. (2011) detect significant evidence for the temporal variation in the volatility risk premium, which is directly linked to macro-finance state variables by applying a small-scale Monte Carlo experiment. They find that the volatility risk premium can help predict future stock market returns for the S&P 500 index.

Although standard approaches to asset pricing concentrate largely on the second moment, the third or even the fourth moment of returns have recently become increasingly important for asset pricing and risk management. There is mounting evidence in the literature to suggest the importance of skewness for both individual stocks and for the market as whole (e.g. Kraus and Litzenberger, 1976; Kane, 1982; Harvey and Siddique, 2000). Additionally, investors hold concave preferences and like positive skewness[1]. Bali and Murray (2010) confirm that assets with higher (lower) systematic skewness are more (less) desirable and command lower (higher) expected returns.

Since the importance of the third moment, Kozhan et al. (2013) propose the concept of 'the skew risk premium', which is modelled using skew swaps. They provide strong empirical evidence for the co-existence of both skew and variance risk premia in the equity market. They find that the skew risk premium accounts for the slopes in the implied volatility curve in the S&P 500 market and that skew risk is tightly related to variance risk. The slope of implied volatility is found to have

[1] Kraus and Litzenberger (1976), Kane (1982) and Harvey and Siddique (2000) extend the mean-variance portfolio theory of Markowitz (1952) to incorporate the effect of skewness on valuation. They present a three-moment asset pricing model in which investors prefer positive skewness.

significant predictive power for future stock returns in the previous research. For instance, Atılgan et al. (2010) and Xing et al. (2010) define the shape of the volatility smirk as the difference between the implied volatilities of OTM puts and ATM calls. Atılgan et al. (2010) document a significantly negative link between volatility smirks and expected future returns for the S&P 500 index. Xing et al. (2010) find that stocks with the steepest volatility smirks underperform stocks with the least pronounced volatility smirks. Yan (2011) shows that there is a negative predictive relation between the slope of the implied volatility smile and stock returns.

Motivated by previous research in the variance risk premium in the aggregate stock market by Bollerslev et al. (2009) and the recently proposed skew risk premium measure by Kozhan et al. (2013), I first study a direct relation between the skew and kurtosis risk premia and stock returns at the aggregate market level. The most relevant paper about the variance risk premium in aggregate stock market return prediction is by Bollerslev et al. (2009). I extend this paper by adding another two risk premium measures, named the skew and kurtosis risk premia, and by adding another return measure, *ex ante* expected returns.

In this chapter, I define the moment risk premia as the difference between expected realised moments and risk-neutral moments. The calculation of realised moments follows Amaya et al. (2011) and Choi and Lee (2014). The computation of risk-neutral moments follows the model-free method of Bakshi et al. (2003). The definitions of the moment risk premia are motivated by models of the variance risk premium proposed in previous research. For instance, Bali and Hovakimian (2009) propose the volatility spread (similar to the variance risk premium) as the realised-implied volatility spread. Carr and Wu (2009) propose using the difference between the realised variance and the synthetic variance swap rate to quantify the variance risk premium. On the contrary, Bakshi and Madan (2006) formalise the departure between risk-neutral and physical index return volatilities, termed the volatility spread (similar to the variance risk premium). Bollerslev et al. (2011), define the volatility risk premium as the difference between actual S&P 500 option-implied volatilities (the VIX index) and high-frequency five-minute-based realised volatilities. Bollerslev et al. (2009), Drechsler and Yaron (2011) and Han and Zhou (2012) model the variance risk premium as the difference between implied and realised variances. Using this directly observable proxy for the moment risk premia has the obvious advantage of being simple to implement and completely model-free.

I employ daily options on the S&P 500 Index from 1996 to 2012 for the empirical analysis. I test directly the relationship between the moment risk premia and aggregate stock market returns. I perform the following test procedures. Firstly, I adopt a monthly linear regression to examine the relationship between the moment risk premia and subsequent index returns. I use two return measures: *ex post* realised index returns and *ex ante* expected index returns. Secondly, I include macroeconomic factors, such as inflation, GDP and bond risk premia in the regressions to investigate whether the relationship between the moment risk premia and index returns is robust to these factors.

The contributions of this chapter are summarised as follows. Firstly, I investigate the explanatory power of the variance, skew and kurtosis risk premia with *ex post* realised returns. I document that both the variance and skew risk premia have a negative relationship with subsequent realised returns in the aggregate stock market. However, the variance risk premium has a stronger relationship than the skew risk premium. The negative relationship between the variance and skew risk premia and index returns is robust to macroeconomic factors. For the kurtosis risk premium, I find that it cannot describe realised index returns. I provide the first study on the relationship between the skew and kurtosis risk premia and realised index returns.

Secondly, for *ex ante* expected returns, I am the first to construct the index expected returns using the price target expected return (PTER) and the implied cost of capital (ICC) of all constituents in the S&P 500 Index. It is the first study to investigate the relationship between the moment risk premia and *ex ante* expected stock returns in the aggregate stock market. For the PTER measure, I find that neither the variance risk premium nor the skew risk premium has a robust and significant relationship with expected return, but that the kurtosis risk premium is positively related to the PTER. For another *ex ante* return measure, both the variance and skew risk premia are significantly and positively related to the ICC, while the kurtosis risk premium has a significant negative relationship with the ICC. However, these relationships for the ICC are not robust to macroeconomic variables.

Finally, I test the explanatory power of macroeconomic factors in the aggregate stock market with the *ex ante* and *ex post* return measures. I find that both the PTER and the ICC can be explained by macroeconomic factors, while realised index return cannot be described by macroeconomic factors.

The result contributes to the literature that examines the relationship between the variance risk premium and realised returns in the aggregate stock market. The results for the negative relationship between the variance risk premium and realised index returns are consistent with empirical evidence presented in Bollerslev et al. (2009), who find that the variance risk premium is able to explain a non-trivial fraction of the time-series variation in post-1990 aggregate stock market returns. Bollerslev et al. (2009) define the variance risk premium as the difference between risk-neutral variance and realised variance, and they support a positive relation between the variance risk premium and subsequent index returns. In this empirical analysis, I define the variance risk premium as the difference between realised variance and risk-neutral variance, which is opposite to the definition of Bollerslev et al. (2009). Therefore, the negative relation between the variance risk premium and realised index returns that is documented in this study is consistent with the findings of Bollerslev et al. (2009).

The remainder of the chapter is organised as follows. Section 6.2 shows the calculation of realised and risk-neutral moments, as well as the moment risk premia.

It also describes two *ex ante* expected return measures for index, which are the PTER and the ICC. Section 6.3 describes the data used in the empirical analysis. Section 6.4 shows the test of the relationship between the moment risk premia and index returns. Section 6.5 concludes the main findings of this chapter.

6.2 Methodology

6.2.1 Moments and Moment Risk Premia

In this section, I calculate realised and risk-neutral moments (variance, skewness and kurtosis) using the model-free method. I then describe the approaches to compute the variance, skewness and kurtosis risk premia.

Risk-Neutral Variance, Skewness and Kurtosis

I follow the model-free approach of Bakshi et al. (2003) to compute the risk-neutral variance, skewness and kurtosis of the S&P 500 Index. The detail of the BKM approach is described in Section 3.2.

In this chapter, the time horizon of risk-neutral moments is 30 days. For each day, I calculate risk-neutral moments using options on the S&P 500 Index with different maturities. In each calculation, I require that a minimum of two OTM calls and two OTM puts have valid prices. If insufficient data are available, the observation is discarded. When using daily options with all maturities, I can in principle obtain daily option-implied volatility, skewness and kurtosis with various maturities. I then interpolate linearly to obtain the 30-day VAR, SKEW and KURTOSIS using both contracts with maturity more than 30 days and contracts with maturity less than 30 days. If risk-neutral moment is with only one maturity on a particular day, I do not interpolate and use this to represent the 30-day VAR, SKEW and KURTOSIS on that day.

Realised Variance, Skewness and Kurtosis

The well-known daily realised variance (see Andersen and Bollerslev, 1998; Andersen et al., 2003) is obtained by summing squares of intraday high-frequency returns.

$$RV_t = \sum_{i=1}^{N} R_{t,i}^2 \tag{6.1}$$

where RV_t denotes the realised variance at time t and $R_{t,i}$ represents the daily return on day i.

An appealing characteristic of this variance measure compared with other estimation methods is its model-free nature (see Andersen et al., 2001; Barndorff-Nielsen, 2002 for details).

Following Amaya et al. (2011) and Choi and Lee (2014), I construct realised skewness as [2]

$$RS_t = \frac{\sqrt{N}\sum_{i=1}^{N} R_{t,i}^3}{RV_t^{\frac{3}{2}}} \tag{6.2}$$

where RS_t denotes the realised skewness on day t.

The measure of realised kurtosis is computed as

$$RK_t = \frac{N\sum_{i=1}^{N} R_{t,i}^4}{RV_t^2} \tag{6.3}$$

where RK_t denotes the realised kurtosis at time t.

Since the moment risk premia measure the terminal profit and loss from a long moment swap contract, the realised moments in equations (6.1), (6.2) and (6.3) are historical measures, which cannot represent the future realised moments. Risk-neutral moments carry traders' expectations regarding the distribution of future returns, which is not contained in historical estimates. Following Drechsler and

[2] Compared with the realised skewness by Neuberger (2012), the measure adopted in this thesis is easy and simple to implement. For modelling realised skewness with a short time horizon, this measure is effective. The measure proposed by Neuberger (2012) is better to model the long-horizon realised skewness.

Yaron (2011) and Han and Zhou (2012), I calculate expected future realised moments using regression specifications that include risk-neutral moments in addition to historical realised moments. I adopt a multiple linear regression model to estimate the expected realised moments under the physical measure with lagged risk-neutral moments and historical realised moments. I run the following regressions with one-year of past data:

$$
\begin{aligned}
RV_t &= \alpha_1 + \beta_1 MFIV_{t-1} + \gamma_1 RV_{t-1} + \varepsilon_t^v \\
RS_t &= \alpha_2 + \beta_2 MFIS_{t-1} + \gamma_2 RS_{t-1} + \varepsilon_t^s \\
RK_t &= \alpha_3 + \beta_3 MFIK_{t-1} + \gamma_3 RK_{t-1} + \varepsilon_t^k
\end{aligned}
\tag{6.4}
$$

where $MFIV_t$, $MFIS_t$ and $MFIK_t$ are the model-free implied variance, skewness and kurtosis on day t following the formula of Bakshi et al. (2003), respectively. RV_t, RS_t and RK_t denote the realised variance, skewness and kurtosis on day t, respectively.

I take the physical expected variance, $EVar_t$, the physical expected skewness, $ESkew_t$ and the physical expected kurtosis, $EKurt_t$, as the fitted value from the regressions:

$$
\begin{aligned}
EVar_t &\equiv \widehat{RV}_{t+1} = \widehat{\alpha}_1 + \widehat{\beta}_1 MFIV_t + \widehat{\gamma}_1 RV_t \\
ESkew_t &\equiv \widehat{RS}_{t+1} = \widehat{\alpha}_2 + \widehat{\beta}_2 MFIS_t + \widehat{\gamma}_2 RS_t \\
EKurt_t &\equiv \widehat{RK}_{t+1} = \widehat{\alpha}_3 + \widehat{\beta}_3 MFIK_t + \widehat{\gamma}_3 RK_t
\end{aligned}
\tag{6.5}
$$

In this chapter, I use daily index data instead of high-frequency data to calculate realised variance, skewness and kurtosis. The 30-day realised physical (annualised) variance, skewness and kurtosis are computed using previous one-month daily S&P 500 index returns. For example, RV_t is computed by summing squares of daily returns in the previous one month and it is then annualised by multiplying by 252/20 in the analysis. I thus obtain daily realised and risk-neutral variance, skewness and kurtosis for each day.

The Variance, Skew and Kurtosis Risk Premia

After calculating expected realised moments and option-implied moments, I then compute the moment risk premia, which are the difference between these two measures.

$$
\begin{aligned}
VRP_t &= EVar_t - MFIV_t \\
SRP_t &= ESkew_t - MFIS_t \\
KRP_t &= EKurt_t - MFIK_t
\end{aligned} \tag{6.6}
$$

After obtaining the daily variance, skew and kurtosis risk premia, I select only the observations at the end of each month to represent the monthly variance, skew and kurtosis risk premia. I also select realised and risk-neutral moments observed at the end of each month.

6.2.2 Ex ante Expected Returns

In this section, I present two approaches to calculate *ex ante* expected returns at the aggregate stock market level. The first method is to use the PTER. The second measure is to employ the ICC.

In the literature, the PTER and the ICC are not used for indices. The data used for estimating *ex ante* expected returns of the S&P 500 Index, such as price target and earnings forecast, are not available from the I/B/E/S database. No analysts post a price target for indices. The data for stocks are, however, available in the database. In order to calculate expected returns in the aggregate stock market, I first compute the expected returns for each constituent in the S&P 500 Index. I then calculate the value-weighted expected returns for all constituents.

The estimation of the PTER and the ICC for each constituent is described in Section 5.2.2.

6.3 Data

I employ options on the S&P 500 Index for a sample period from January 1996 to December 2012; a total of 4,278 trading days. The S&P 500 Index serves as a proxy for the US market. The daily index option data are obtained from OptionMetrics. I only retain options with expiration days of at least one week but no more than 700 days. In other words, I exclude options that mature within one week and more than 700 days. Daily index and stock data are taken from CRSP. Treasury bills, as a proxy for risk-free interest rates, are obtained from the CRSP Treasuries database.

The constituents of the S&P 500 Index are obtained from COMPUSTAT. Analyst price target data for the firms in the S&P 500 index are taken from the I/B/E/S unadjusted detail price target database. Since there are no available price target data for the S&P 500 Index, I take all price targets of the firms in the S&P 500 Index with a target horizon of 12 months where both the firm's base currency and the currency of the estimate are in USD. The price target data cover the period from March 1999 to December 2012.

I use data from the I/B/E/S summary history/summary statistics to obtain earnings forecasts for the S&P 500 constituents for the next three years. I/B/E/S analysts supply a one-year-ahead ($FEPS_{t+1}$) and a two-year-ahead ($FEPS_{t+2}$) earnings per share (EPS) forecast, as well as an estimate of the long-term growth rate (Ltg). It also releases a one-year-ahead ($FBPS_{t+1}$) and a two-year-ahead ($FBPS_{t+2}$) book value per share (BPS) forecast. The data sample period is from January 1996 to December 2012. The I/B/E/S earnings forecast summary data are released on the third Thursday of each month.

The macroeconomic data are taken from different sources. Specifically, the CPI data are from the website of the US Bureau of Labor Statistics. The GDP data are obtained from the US Bureau of Economic Analysis. Treasury bills and bonds, Moody Seasoned Baa corporate bonds are from Federal Reserve H15. The data sample period is from January 1996 to December 2012.

Figure 6.1 plots realised and risk-neutral moments and the moment risk premia. Panel A plots the monthly time series of expected realised variance, risk-neutral variance and their differences. During 2004-2008, the two variance time series are very flat and low. Both of the variance measures become somewhat higher during the 2009-2010 part of the sample. The fluctuation of the two measures generally coincides. Risk-neutral variance is generally above expected realised variance, which is consistent with earlier empirical evidence; the spread between expected realised and risk-neutral variance is almost always negative.

Panel B plots the monthly time series of expected realised skewness, risk-neutral skewness, and their differences. Both of the skewness measures keep in the same general variation level during the sample period. There are no distinct spikes in any subperiods. Expected realised skewness is distributed around zero, while risk-neutral skewness fluctuates below expected realised skewness, indicating that the difference between expected realised and implied skewness is positive.

Panel C plots the monthly time series of expected realised kurtosis, risk-neutral kurtosis and the kurtosis risk premium. Compared with risk-neutral kurtosis, expected realised kurtosis is very smoothed. Risk-neutral kurtosis becomes more volatile after 2008; there are even some distinct spikes. From the distribution of expected realised and risk-neutral kurtosis, I find that risk-neutral kurtosis is distributed above expected realised kurtosis, which indicates that the difference between expected realised and risk-neutral kurtosis is positive.

Basic summary statistics for moments, the moment risk premia and *ex ante* expected returns are given in Table 6.1. Panel A reports summary statistics for expected realised and risk-neutral moments and the moment risk premia for the S&P 500 Index. I find that the average expected realised variance is 0.0429 and the average risk-neutral variance is 0.0610. It is obvious that the average risk-neutral variance is higher than the average expected realised variance for the S&P 500 Index, which points out the existence of a negative variance risk premium. The average variance risk premium for the S&P 500 Index is -0.0202, which is more negative than the average variance risk premium for the stocks. For the third moment, the average expected realised skewness is -0.0020 and the average risk-neutral skewness is -1.6788. The average risk-neutral skewness is more negative than the expected realised skewness, indicating the existence of a positive skew risk premium for the S&P 500 Index. The average skew risk premium is 1.6904. For the fourth moment, the average expected realised kurtosis is 2.9671 and the average risk-neutral kurtosis is 9.5801. The average kurtosis risk premium is -6.7627.

Panel B presents summary statistics for *ex ante* expected returns of the S&P 500 index, including the PTER and the ICC. The mean PTER is 0.1482, while the mean ICC is 0.0658. The standard deviation of the ICC is 0.0170, which is much smaller than the standard deviation of the PTER. This is because the ICC is smoothed, which is calculated by solving for the discount rate (r) that equates the current book value of equity plus the present value of expected future earnings to the current stock price.

The result that expected realised variance is less than risk-neutral variance shown in Panel A of Table 6.1 and Figure 6.1 is in line with the previous literature (see, e.g. Bakshi and Kapadia, 2003a; Carr and Wu, 2009; Egloff et al., 2010; Kozhan et al., 2013; Drechsler, 2013,). The result that risk-neutral skewness is more negative than expected realised skewness is consistent with Bakshi et al. (2003) and Kozhan et al. (2013). The result of the kurtosis risk premium has not been reported in the existing literature. I provide the first study.

I investigate whether the index's moment risk premia or index returns are correlated with macroeconomic factors. I use CPI to represent inflation. GDP is the real

GDP level, representing the economic output. The term structure of spread, TS is measured as the difference in the yields to maturity for the 10-year Treasury Bond and the 1-month Treasury Bill. The default risk premia (DRP) is defined as the difference in the yields to maturity between Moody's BAA and the 10-year Treasury bonds.

Table 6.2 reports the correlations of these variables at the aggregate market level. From the second column, I find that realised index returns are negatively correlated with most of these variables. The third column reports that the PTER has a relatively weaker correlation with the variance risk premium (the correlation is 0.0299) or the skew risk premium (the correlation is -0.1036) compared with macroeconomic variables. The PTER has a stronger correlation with the kurtosis risk premium compared with the variance and skew risk premia. In the fourth column, I find a similar result for the ICC. Compared with macroeconomic variables, the ICC seems to have a weaker correlation with the variance risk premium (the correlation is 0.0771) and the skew risk premium (the correlation is 0.1508). The kurtosis risk premium exhibits a stronger correlation than the variance and skew risk premia.

6.4 Moment Risk Premia and Index Return Prediction

In this section, I examine the predictive power of the variance, skew and kurtosis risk premia for index returns. The forecasts of index returns are based on the linear regressions of the S&P 500 Index returns on a different set of lagged predictor variables. I focus on discussing the estimated slope coefficients and their statistical significance as determined by robust t-statistics. I also report the explanatory power of regressions as measured by the corresponding adjusted R^2s.

6.4.1 Main Empirical Findings

I begin by reporting the results in Table 6.3 for the key return regressions with dependent variables of subsequent realised returns and expected returns. These linear regressions provide a simple and effective way to detect the relation between the moment risk premia and index returns.

Simple linear regression formulas for subsequent realised returns are shown below:

$$\begin{aligned} r_{t+1} &= \alpha_1 + \gamma_1 VRP_t + \varepsilon_{1,t} \\ r_{t+1} &= \alpha_2 + \gamma_2 SRP_t + \varepsilon_{2,t} \\ r_{t+1} &= \alpha_3 + \gamma_3 KRP_t + \varepsilon_{3,t} \end{aligned} \tag{6.7}$$

Simple linear regression formulas for $ex\ ante$ expected returns are shown below:

$$\begin{aligned} er_t &= \alpha_4 + \gamma_4 VRP_t + \varepsilon_{4,t} \\ er_t &= \alpha_5 + \gamma_5 SRP_t + \varepsilon_{5,t} \\ er_t &= \alpha_6 + \gamma_6 KRP_t + \varepsilon_{6,t} \end{aligned} \tag{6.8}$$

where r_{t+1} is the realised index return in month $t+1$ and er_t is the expected index return (the PTER or the ICC) in month t, which represents the forecasted index returns in the future. The variance, skew and kurtosis risk premia in month t are denoted by VRP_t, SRP_t and KRP_t, respectively.

Table 6.3 reports the results for simple linear regressions of monthly index returns on the variance, skew and kurtosis risk premia. Panel A presents the regressions with the explanatory variable of the variance risk premium. When regressing monthly realised index returns on the variance risk premium, I find that the coefficient of the variance risk premium is -0.3756 with a t-statistic of -3.99. The robust t-statistic for testing the estimated slope coefficient associated with the variance risk premium exceeds the one sided 1% significance level. I find that the variance risk premium is negatively related to subsequent realised index returns at the 1% significance level. The adjusted R^2 is equal to 7.23%. Bollerslev et al. (2009) find that the variance risk premium is able to explain a nontrivial fraction of the time-series variance in post-1990 aggregate stock market returns with high (low) premia predicting high (low) future returns based on the S&P 500 Index data. They estimate the variance risk premium as the difference between implied and realised variances, which is opposite to the variance risk premium method used in this thesis. Therefore, the negative relation between the variance risk premium and subsequent index returns documented in this study is consistent with Bollerslev et al. (2009). When the dependent variable is the PTER, the slope of the variance risk premium is 0.0423, which is statistically insignificant. For the ICC, the regression of the ICC on the variance risk premium gives a slope coefficient of 0.0792, which is positive and statistically significant at the 5% level.

The regression result with the explanatory variable of the skew risk premium is provided in Panel B. When the dependent variable is monthly realised index return, the coefficient of the skew risk premium is -0.0077, which is statistically significant at the 10% level. The adjusted R^2 is 0.97%. When regressing the PTER on the skew risk premium, the slope is -0.0071 with a t-statistic of -1.40. With the dependent variable of the ICC, the regression gives the coefficient of 0.0031 with a t-statistic of 1.97, which is significant at the 5% level.

Panel C shows the linear regression of index returns on the kurtosis risk premium. When regressing realised index return on the kurtosis risk premium, the coefficient is 0.0006, which is statistically insignificant. When the dependent variable is the PTER, the slope is 0.0013 with a t-statistic of 2.32, which is significant at the 5% level. With the dependent variable of the ICC, I find that the slope is -0.0006, which is statistically significant at the 1% level.

I have a further look at the comparison of the variance, skew and kurtosis risk premia in return prediction with different return measures. For realised index returns, the predictive power of the variance risk premium is stronger than the skew and kurtosis risk premia. The variance risk premium has a more significant coefficient and a bigger value of the adjusted R^2 than the skew and kurtosis risk premia. For the PTER, neither the variance risk premium nor the skew risk premium has explanatory power, while the kurtosis risk premium has a positive and significant relation with the PTER. With the return measure of the ICC, both the variance and skew risk premia have positively explanatory power, while the kurtosis risk premium is significantly and negatively related to the ICC .

In summary, from Table 6.3, I find that at the aggregate market level, both the variance and skew risk premia have a negative and significant relationship with future realised index returns. The variance risk premium has a stronger relationship than the skew risk premium, but the kurtosis risk premium cannot describe realised index returns. For *ex ante* expected returns, neither the variance risk premium nor the skew risk premium can predict the PTER, while the kurtosis risk premium is positively and significantly related to the PTER. Additionally, the variance and skew risk premia are significantly and positively related to the ICC, while the kurtosis risk premium has an inverse and significant relationship with the ICC.

6.4.2 Multiple Linear Regressions with Macroeconomic Control Variables

Index returns may be affected by macroeconomic factors, e.g. economic output (GDP level), inflation (price indices). Dating back to Chen et al. (1986), who find that stock returns can be influenced by a set of economic state variables, many studies have tried to show reliable associations between macroeconomic variables and security returns. The literature, e.g. Flannery and Protopapadakis (2002) has documented that aggregate stock returns are negatively related to inflation and to money growth. Chen et al. (1986) identify five potential macroeconomic factors: *the growth rate of Industrial Production, Expected Inflation, Unexpected Inflation, a bond Default Risk Premium, and a Term Structure Spread*. I include some of these macroeconomic factors in the regressions to see whether they can help predict future index returns. The factors used in the analysis include Inflation (CPI), the real GDP level, a Term Structure of Spread (the difference in the yields to maturity for the 10-year Treasury Bond and the 1-month Treasury Bill), the Default Risk Premia (the difference in the yields to maturity between Moody's BAA and the 10-year Treasury bonds).

Multiple linear regression formulas for subsequent realised index returns are give as follows:

$$r_{t+1} = \gamma_0 + \gamma_1 RP_t + \phi_1' Z_t + \varepsilon_t \tag{6.9}$$

where RP_t denotes the variance, skew or kurtosis risk premium observed in month t and Z_t are macroeconomic factors in month t.

Multiple linear regression formulas for *ex ante* expected returns are given as follows:

$$er_t = \theta_0 + \theta_1 RP_t + \phi_2' Z_t + e_{6,t} \tag{6.10}$$

where RP_t denotes the variance, skew or kurtosis risk premium observed in month t and Z_t are macroeconomic factors in month t.

Table 6.4 reports the results for multiple linear regressions of monthly realised index returns on expected realised and risk-neutral moments, the moment risk premia, as well as macroeconomic variables. When regressing monthly realised index returns on expected realised and risk-neutral moments independently (Models 1-6), I find that expected realised or risk-neutral moments cannot predict monthly realised index returns. Model 7 includes the explanatory variables of the variance risk premium and macroeconomic factors in the linear regression. I find that the coefficient of the variance risk premium remains significantly negative and the value is -0.3567, with a t-statistic of -3.66. In Model 8, the coefficient of the skew risk premium is -0.0082, which is still negative and significant at the 10% level, when including macroeconomic variables in the regression. In Model 9, I regress monthly realised index returns on the kurtosis risk premium and macroeconomic factors. The coefficient on the kurtosis risk premium is insignificant. From Model 7 to Model 9, I also find that macroeconomic factors have almost no relationship, or a very week relationship, with realised index returns.

The regression results for *ex ante* expected returns are shown in Table 6.5. Panel A reports the regressions with the dependent variable of the PTER. From Models 1-4, I find that expected realised, risk-neutral variance and skewness have significant and positive relationships with the PTER. From Models 5 and 6, the coefficients of expected realised and risk-neutral kurtosis are significantly negative. When regressing on the variance risk premium and macroeconomic factors (Model 7), I find that the PTER still has no relationship with the variance risk premium. When including the skew risk premium and the macro control variables in the regression (Model 8), I see that the coefficient of the skew risk premium becomes negative and significant. In Model 9, I find that the significantly positive relationship between the kurtosis risk premium and the PTER is robust to macroeconomic factors. The coefficient of the kurtosis risk premium is 0.0011, which is statistically significant at the 5% level. From Models 7-9, I see that coefficients of macroeconomic factors are significant, which means that the PTER can be explained by macroeconomic variables.

Panel B of Table 6.5 provides multiple regressions with the dependent variable of the ICC. When expected realised and risk-neutral moments are contained in the regressions independently (Models 1-6), the slope coefficients of expected realised and risk-neutral variance and risk-neutral kurtosis are significantly positive, while the slope coefficient of risk-neutral skewness is significantly negative. When running regressions on the variance, skew and kurtosis risk premia and macroeconomic factors (Models 7-9), I find that the coefficient of the variance risk premium is positive, but insignificant. The skew risk premium has a significant and negative coefficient, while the slope of the kurtosis risk premium is significant and positive. Interestingly, I find that most of the coefficients of macroeconomic variables are statistically significant from Models 7-9.

Overall, the results in Table 6.4 and Table 6.5 show that realised index returns cannot be described by the moments, while expected index returns can be explained by expected realised and risk-neutral moments. Realised index returns are mainly negatively related to the variance risk premium. There is also a weakly negative relationship between the skew risk premium and subsequent realised index returns. The kurtosis risk premium has no explanatory power with realised index returns; this is robust to macroeconomic factors. For expected index returns, the variance and skew risk premia have no relationships with the PTER, while the kurtosis risk premium is positively related to the PTER. The result is robust to macroeconomic factors. The PTER is explained mainly by macroeconomic factors. The relationships between the variance, skew and kurtosis risk premia and the ICC are not robust to macroeconomic variables.

6.5 Conclusion

I first explore the direct relation between the moment risk premia (the difference between expected realised moments and risk-neutral moments) and subsequent returns in the aggregate stock market.

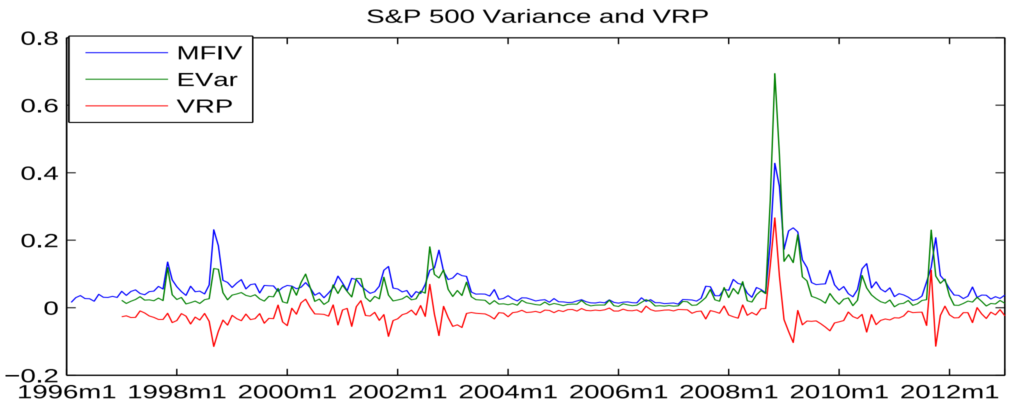
I find that the variance risk premium is negative, which is documented in the previous literature (see, e.g. Bakshi and Kapadia, 2003a; Carr and Wu, 2009; Egloff et al., 2010; Kozhan et al., 2013). The skew risk premium is found to be positive, which is in line with the findings of Bakshi et al. (2003) and Kozhan et al. (2013). I find that the kurtosis risk premium is positive, which is not reported in the literature.

In the aggregate stock market, the variance risk premium can predict subsequent realised index returns. The relationship between the variance risk premium and index returns is negative and robust to macroeconomic variables. This is consistent with the findings of Bollerslev et al. (2009).

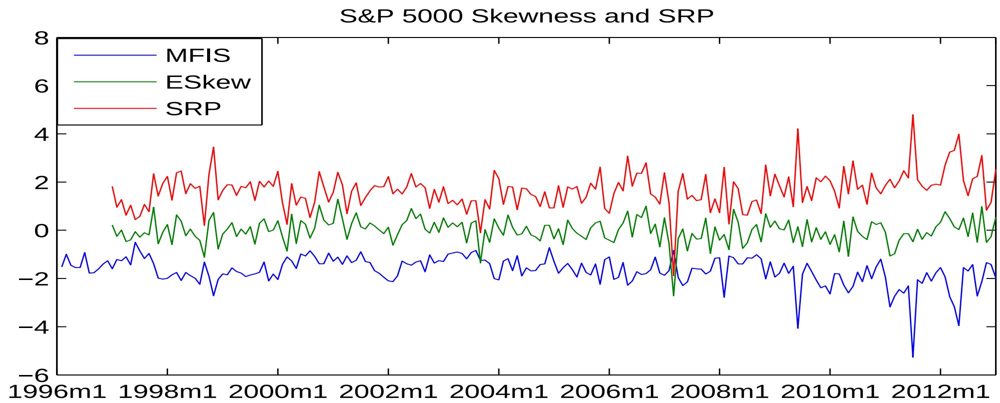
I also find that the skew risk premium is inversely related to subsequent realised index returns, but that it has a weaker relation compared with the variance risk premium. Moreover, the kurtosis risk premium has no relationship with realised index return. This is the first research to explore the predictive ability of the skew and kurtosis risk premia on aggregate market returns.

I am the first to investigate the explanatory power of the variance, skew and kurtosis risk premia on *ex ante* expected returns in the aggregate stock market. For the first *ex ante* expected return measure, neither the variance risk premium nor the skew risk premium is able to explain the PTER, while the kurtosis risk premium is found to have a robust and positive relationship with the PTER. For the second *ex ante* expected return measure, I find that both the variance and skew risk premia are positively related to the ICC when the variance or skew risk premium is the only explanatory variable. I also find that the kurtosis risk premium is inversely and significantly related to the ICC. However, these relationships are not robust to macroeconomic variables.

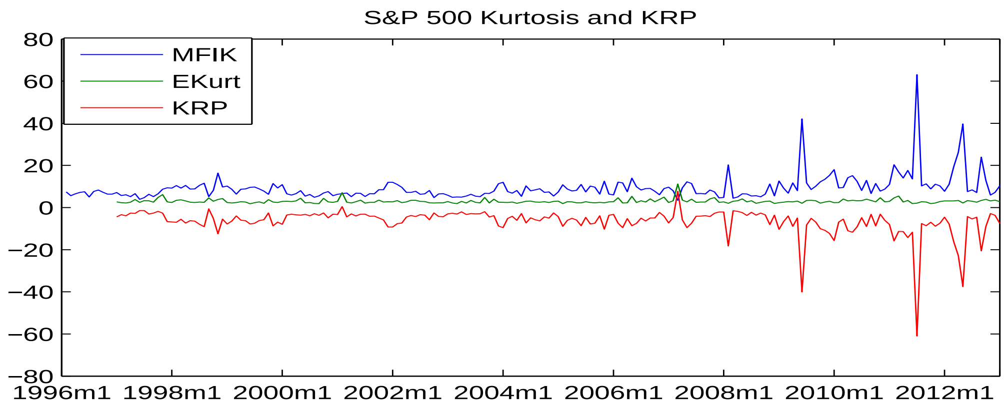
Finally, both the PTER and the ICC are found to be explained by macroeconomic variables, while realised index returns cannot be described by macroeconomic factors.



(a) Panel A: The Variance Risk Premium



(b) Panel B: The Skew Risk Premium



(c) Panel C: The Kurtosis Risk Premium

Figure 6.1. Plot of the S&P 500 Moments and Moment Risk Premia The figure plots expected realised and risk-neutral moments, as well as the moment risk premia from January 1996 to December 2012. The second, third and fourth moments are shown in Panel A, B and C, respectively.

Table 6.1. Summary Statistics on the S&P 500 Moments and Moment Risk Premia

Panel A reports descriptive statistics on realised and risk-neutral moments and the moment risk premia for the S&P 500 Index from January 1996 to December 2012. Panel B provides summary statistics for the PTER and the ICC of the S&P 500 Index. The S&P 500 Index expected return is constructed by the value-weighted expected returns from the index constituents. The data sample for the PTER is from March 1999 to December 2012. The sample period for the ICC is from January 1996 to December 2012. The table reports the mean, median, standard deviation, 25th and 75th percentiles.

Panel A: S&P 500 Moments and Moment Risk Premia						
	Observation	Mean	StDev	25th Percentile	Median	75th Percentile
EVar	4,028	0.0429	0.0706	0.0125	0.0233	0.0439
MFIV	4,278	0.0610	0.0638	0.0286	0.0447	0.0688
VRP	4,028	-0.0202	0.0312	-0.0307	-0.0187	-0.0091
ESkew	4,028	-0.0020	0.4834	-0.3169	-0.0168	0.2967
MFIS	4,278	-1.6788	0.6003	-1.9685	-1.6214	-1.3057
SRP	4,028	1.6904	0.7546	1.2428	1.6676	2.0817
EKurt	4,028	2.9671	0.8588	2.4014	2.7753	3.3126
MFIK	4,278	9.5801	6.7129	6.5615	8.3011	10.7255
KRP	4,028	-6.7627	6.8377	-7.9743	-5.5843	-3.6537
Panel B: S&P 500 Expected Returns						
	Observation	Mean	StDev	25th Percentile	Median	75th Percentile
PTER	166	0.1482	0.0491	0.1144	0.1332	0.1770
ICC	204	0.0658	0.0170	0.0470	0.0708	0.0797

Table 6.2. Correlation of Variables

The table reports the correlation among subsequent monthly realised returns, expected returns, realised and risk-neutral moments, the moment risk premia and macro factors. CPI represents inflation. GDP means the real GDP level. TS is the term structure of spread (the difference in the yields to maturity for the 10-year Treasury Bond and the 1-month Treasury Bill). DRP is the default risk premia (the difference in the yields to maturity between Moody's BAA and the 10-year Treasury bonds).

	RR	PTER	ICC	EVar	MFIV	VRP	ESkew	MFIS	SRP	EKurt	MFIK	KRP	CPI	GDP	TS
PTER	-0.6239														
ICC	-0.0860	-0.2289													
EVar	-0.3735	0.4082	0.2428												
MFIV	-0.4193	0.5171	0.2699	0.8841											
VRP	-0.1121	0.0299	0.0771	0.6763	0.2537										
ESkew	-0.0102	0.1365	-0.1065	0.1208	0.1095	0.0774									
MFIS	-0.1438	0.2413	-0.2743	0.0422	0.0268	0.0450	0.1114								
SRP	0.1101	-0.1036	0.1508	0.0477	0.0525	0.0159	0.5884	-0.7380							
EKurt	0.0820	-0.1210	0.0739	-0.0859	-0.1512	0.0606	-0.2975	0.0326	-0.2285						
MFIK	0.1340	-0.2007	0.2354	-0.0482	-0.0356	-0.0436	-0.0788	-0.9233	0.6978	-0.0630					
KRP	-0.1187	0.1781	-0.2193	0.0342	0.0119	0.0519	0.0321	0.9088	-0.7177	0.2133	-0.9885				
CPI	0.0393	-0.2974	0.9074	0.0856	0.0918	0.0324	-0.1495	-0.4159	0.2369	0.1228	0.3546	-0.3285			
GDP	0.0545	-0.3883	0.8951	0.0071	-0.0370	0.0731	-0.1693	-0.3579	0.1762	0.1559	0.2923	-0.2625	0.9652		
TS	0.0186	-0.0965	0.2633	0.1007	0.2038	-0.1129	-0.0911	-0.1922	0.0945	-0.1600	0.2047	-0.2247	0.2073	0.0737	
DRP	-0.1206	0.2672	0.3841	0.5883	0.7647	0.0124	0.1596	-0.0602	0.1573	-0.1332	0.1202	-0.1379	0.2723	0.0996	0.4098

Table 6.3. Results for Simple Linear Regressions

The table shows the results for simple linear regressions of monthly index returns on the variance risk premium (VRP, Panel A), the skew risk premium (SRP, Panel B) and the kurtosis risk premium (KRP, Panel C). The dependent variables are subsequent realised index returns, the PTER or the ICC, respectively. The table reports the estimated coefficients and the t-statistics of the independent variables. The t-statistics are shown in brackets. *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

Panel A: The Independent Variable is the Variance Risk Premium			
	RR	PTER	ICC
Constant	-0.0024	0.1489***	0.0688***
	(-0.65)	(35.27)	(51.74)
VRP	-0.3756***	0.0423	0.0792**
	(-3.99)	(0.40)	(2.35)
$adj-R^2$	0.0723	-0.0051	0.0231
Panel B: The Independent Variable is the Skew Risk Premium			
	RR	PTER	ICC
Constant	0.0176**	0.1601***	0.0622***
	(2.14)	(17.23)	(21.91)
SRP	-0.0077*	-0.0071	0.0031**
	(-1.71)	(-1.40)	(1.97)
$adj-R^2$	0.0099	0.0058	0.0148
Panel C: The Independent Variable is the Kurtosis Risk Premium			
	RR	PTER	ICC
Constant	0.0090**	0.1570***	0.0636***
	(1.86)	(29.49)	(38.70)
KRP	0.0006	0.0013**	-0.0006***
	(1.21)	(2.32)	(-3.13)
$adj-R^2$	0.0025	0.0259	0.0437

Table 6.4. Results for Monthly Realised Return Regressions

The table shows the results for multiple regressions of monthly realised returns on moments and the moment risk premia, and on macroeconomic factors. The sample period is from January 1996 to December 2012. The table reports the estimated coefficients and the t-statistics of the variables. CPI represents inflation. GDP means the real GDP level, which is scaled by 0.0001. TS is the term structure of spread (the difference in the yields to maturity for the 10-year Treasury Bond and the 1-month Treasury Bill). DRP is the default risk premia (the difference in the yields to maturity between Moody's BAA and the 10-year Treasury bonds). *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Constant	0.0082**	0.0045	0.0047	0.0162	0.0045	0.0117**	-0.4813	-0.9128	-0.9382
	(2.09)	(0.93)	(1.38)	(1.65)	(0.43)	(1.97)	(-0.86)	(-1.58)	(1.59)
EVar	-0.0809*								
	(-1.67)								
MFIV		0.0144							
		(0.24)							
ESkew			-0.0072						
			(-1.07)						
MFIS				0.0065					
				(1.17)					
EKurt					0.0001				
					(0.03)				
MFIK						-0.0007			
						(-1.27)			
VRP							-0.3567***		
							(-3.66)		
SRP								-0.0082*	
								(-1.75)	
KRP									0.0008
									(1.37)
CPI							0.1191	0.2313*	0.2349*
							(0.88)	(1.66)	(1.65)
GDP							-0.0994	-0.1990*	-0.1998*
							(-0.89)	(-1.75)	(-1.74)
TS							-0.0006	-0.0004	0.0003
							(-0.22)	(-0.13)	(0.10)
DRP							-0.0041	-0.0051	-0.0060
							(-0.87)	(-1.06)	(-1.25)
$adj-R^2$	0.0093	-0.0047	0.0008	0.0018	-0.0053	0.0031	0.0593	0.0081	0.0017

Table 6.5. Results for Expected Return Regressions

The table shows the results for multiple regressions of expected returns on moments and the moment risk premia, and on macroeconomic factors. Panel A reports the regression with the PTER. The sample period is from March 1999 to December 2012. Panel B reports the regression with the ICC. The sample period is from January 1996 to December 2012. The table reports the estimated coefficients and the t-statistics (shown in brackets). CPI represents inflation. GDP means the real GDP level, which is scaled by 0.0001. TS is the term structure of spread (the difference in the yields to maturity for the 10-year Treasury Bond and the 1-month Treasury Bill). DRP is the default risk premia (the difference in the yields to maturity between Moody's BAA and the 10-year Treasury bond). *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

	Panel A: PTER								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Constant	0.1365***	0.1212***	0.1483***	0.1811***	0.1653	0.1627***	-2.0391***	-2.2503***	-2.3323***
	(33.85)	(25.39)	(39.16)	(16.62)	(-1.54)	(24.37)	(-2.87)	(-3.15)	(-3.24)
EVar	0.2709***								
	(5.74)								
MFIV		0.4501***							
		(7.75)							
ESkew			0.0125*						
			(1.68)						
MFIS				0.0195***					
				(3.21)					
EKurt					-0.0058***				
					(14.10)				
MFIK						-0.0015***			
						(-2.62)			
VRP							0.0920		
							(1.02)		
SRP								-0.0087**	
								(-1.98)	
KRP									0.0011**
									(2.14)
CPI							0.6132***	0.6647***	0.6811***
							(3.41)	(3.68)	(3.75)
GDP							-0.7601***	-0.7945***	-0.8023***
							(-4.52)	(-4.75)	(-4.80)
TS							-0.0121***	-0.0126***	-0.0118***
							(4.18)	(-4.40)	(-4.10)
DRP							0.0125**	0.0129**	0.0119**
							(2.42)	(2.54)	(2.34)
$adj-R^2$	0.1624	0.2636	0.0110	0.0533	0.0083	0.0345	0.3181	0.3302	0.3329

Table 6.5---Continued

	Panel B: ICC								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Constant	0.0652***	0.0622***	0.0672***	0.0545***	0.0662***	0.0593***	-0.1565***	-0.1741***	-0.1926***
	(48.47)	(35.65)	(57.18)	(15.53)	(17.91)	(27.94)	(-2.87)	(-3.21)	(-3.51)
EVar	0.0482***								
	(2.91)								
MFIV		0.0603***							
		(2.78)							
ESkew			-0.0014						
			(-0.60)						
MFIS				-0.0068***					
				(-3.41)					
EKurt					0.0004				
					(0.30)				
MFIK						0.0007***			
						(3.63)			
VRP							0.0104		
							(1.09)		
SRP								-0.0011**	
								(-2.56)	
KRP									0.0002***
									(3.02)
CPI							0.0175	0.0217*	0.0257*
							(1.33)	(1.65)	(1.94)
GDP							0.0897***	0.0876***	0.0852***
							(8.24)	(8.19)	(7.97)
TS							0.0011***	0.0010***	0.0011***
							(3.62)	(3.44)	(3.89)
DRP							0.0032***	0.0033***	0.0031**
							(6.93)	(7.30)	(7.02)
$adj-R^2$	0.0373	0.032	-0.0034	0.0496	-0.0048	0.0567	0.9258	0.9279	0.929

Chapter 7

Conclusion

7.1 Conclusion

This thesis examines whether the *ex ante* risk measures related to options can explain stock returns. The risk measures employed in this thesis are option-implied betas and the moment risk premia.

I first investigate, in Chapter 4, whether options and downside risk can improve the risk-return relationship implied by the CAPM by using a portfolio analysis and the FM regression. I compare the historical beta and three option-implied betas, named the FGK, CCJV and BV betas, which are modelled using option-implied moments. Consistent with Buss and Vilkov (2012), the BV beta outperforms other beta methods; the BV beta gives the biggest positive high-low return spread through the portfolio analysis. A long-short portfolio buying stocks in the highest BV beta quintile and shorting stocks in the lowest BV beta quintile produces positive average returns. The BV beta has a monotonically increasing relation with the equally-weighted returns. The thesis is the first work to propose implied downside betas, which are defined as the combination of downside risk measures with option-implied betas. Implied downside betas include the FGK and BV downside betas. The BV downside beta performs best among implied downside betas. It offers an improvement of the BV beta for the beta-return relationship. The BV downside beta gives a bigger high-low return spread than the BV beta. The monotonic relation between beta and the equally-weighted return becomes more pronounced. However, the robustness test shows that the implied (downside) beta-return relation is not robust to firm characteristics. The positive beta-return relation for the BV beta and the BV downside beta disappears when other control variables are included in the FM regression.

In Chapter 5, I estimate the moment risk premia as the difference between expected realised moments and risk-neutral moments. The variance risk premium is found to be negative, while the skew risk premium is found to be positive. The kurtosis risk premium is slightly greater than zero; no existing literature provides the sign of the kurtosis risk premium. I examine the determinants of the variance, skew and kurtosis risk premia, and find that they are affected differently by firm-level characteristics (e.g. firm size, book-to-market ratio, momentum and illiquidity) and risk factors (e.g. market beta, idiosyncratic volatility and co-skewness). I investigate the explanatory power of the moment risk premia and find that their effects on realised and expected stock returns are different. For *ex post* realised stock returns, I find that both the variance and skew risk premia have a negative relation with subsequent realised stock returns, while the kurtosis risk premium has a mixed and insignificant relationship with subsequent realised stock returns, which relies on whether the portfolio is value-weighted or equally-weighted. The findings for the skew and kurtosis risk premia have not been reported by earlier studies. For *ex ante* expected stock returns, both the variance and skew risk premia are negatively related to expected stock returns, but the kurtosis risk premium has a positive relation with expected stock returns. The robustness test shows that the relationship between the moment risk premia and stock returns is robust to firm characteristics and risk factors, subperiods, and different maturities.

In Chapter 6, I investigate whether the moment risk premia can explain stock returns in the aggregate stock market. The moment risk premia are defined as the difference between expected realised moments and risk-neutral moments. For the realised return measure, I find that both the variance and skew risk premia are inversely related to subsequent realised index returns, but the skew risk premium has a weaker relation compared with the variance risk premium. The kurtosis risk premium is found to have no relationship with realised index return. The negative relation between the variance risk premium and index returns stil-

I persists when I add macroeconomic variables in the regression. I provide the first study to examine the relationship between the skew and kurtosis risk premia and realised index returns. Moreover, I am the first to investigate the explanatory power of the variance, skew and kurtosis risk premia on *ex ante* expected returns in the aggregate stock market. For the first *ex ante* expected return measure, I find that neither the variance risk premium nor the skew risk premium can explain the PTER, while the kurtosis risk premium is found to have a robust and positive relationship with the PTER. For the second *ex ante* expected return measure, both the variance and skew risk premia are positively related to the ICC when the variance or skew risk premium is the only explanatory variable. I also find that the kurtosis risk premium is inversely and significantly related to the ICC. However, the relationships between the moment risk premia and the ICC are not robust to macroeconomic variables. Interestingly, I also find that both the PTER and the ICC can be explained by macroeconomic variables. The findings for the skew and kurtosis risk premia have not been reported by earlier studies. I provide the first investigation for the relationship between the skew and kurtosis risk premia and index returns with *ex post* realised returns and *ex ante* expected returns.

7.2 Limitations

There are several limitations to this research. Firstly, I mainly consider some representative firm-level and risk factors in the FM regression in this thesis; these variables are commonly used by researchers. However, many firm-level and risk factors are found to be able to explain the cross-section of stock returns in the literature. This thesis does not test whether the risk-return relationship is robust to other firm-level and risk factors.

The moment risk premia used in Chapters 5 and 6 are constructed from realised moments. In order to make the calculation simple and easy to implement, I use daily data instead of intraday high-frequency data to estimate realised variance, skewness and kurtosis. The daily data could possibly be changed to high-frequency data following Bollerslev et al. (2009), who use 5-minute return to estimate realised variance; this makes the calculation more complicated.

For the option and equity sample used in this research, I only employ firms in the S&P 500 index. This is because the estimation of the BV beta in Chapter 4 should be based on the index implied volatility and the implied volatility from the constituents. Therefore, I collect option data on the S&P 500 index and its constituents. The data sample is used in the whole thesis. In Chapter 5, the sample could be expanded to all US exchange-listed equities available from the OptionMetrics database.

In Chapter 6, when I investigate the relationship between the moment risk premia and stock return at the aggregate market level, I adopt only the S&P 500 index to represent the US market. The S&P 500 index is based on the market capitalisations of 500 large companies having common stock listed on the NYSE or NASDAQ. The fact is that the S&P 500 index could not fully represent the US market. In order to have a deep look at the relationship between the moment risk premia and index return in the aggregate market, more index data could be adopted in the thesis.

7.3 Future Research

The directions for future research are addressed as follows.

In Chapter 4, I only compare three option-implied beta methods with the historical beta. Conditional betas could be added in the research to compare further the performance of option-implied betas with conditional betas. For example, Jagannathan and Wang (1996) prove that the conditional CAPM may hold even though stocks are mispriced by the unconditional CAPM. In the conditional CAPM, conditional market betas are time-varying. Therefore, this research could further compare option-implied betas with conditional betas to see which beta method performs better.

Option-implied betas could be considered as *ex ante* risk because they are constructed from option-implied moments. The asset pricing theory states the relationship between *ex ante* risk and *ex ante* stock returns. In Chapter 5, I have estimated *ex ante* stock returns based on the PTER and the ICC. Future research could focus on studying the relationship between option-implied betas and the cross-section of expected stock returns.

In Chapter 5, I only briefly describe the determinants of the variance, skew and kurtosis risk premia. Future research could concentrate on the cross-sectional relation between the variance, skew and kurtosis risk premia and firm-level risk factors. This is because the moment risk premia are constructed from option-implied moments and, in turn, option-implied moments are found to be determined by firm-level and risk factors cross-sectionally. For example, Hansis et al. (2010) investigate that option-implied moments (variance, skewness and kurtosis) are well explained cross-sectionally by a number of firm characteristics. Furthermore, Taylor et al. (2009) investigate the association of various firm-specific and market-wide factors with risk-neutral skewness implied by the prices of individual stock options.

Although the determinants of stock returns have been investigated extensively and heavily, the literature on the determinants of option returns is limited. Recently, researchers have shifted to studying how option returns are derived. Option returns could be explained by the variance risk premium (Bernales and Chen, 2014), idiosyncratic volatility (Cao and Han, 2013), risk-neutral skewness (Bali and Murray, 2010; Boyer and Vorkink, 2014), risk-neutral co-skewness (Chen et al., 2011), and call-put implied volatility spreads (Doran et al., 2013). No existing research studies whether the skew and kurtosis risk premia are priced in option returns. Thus, another future direction would be to explore whether the moment risk premia describe option returns.

Since option returns have nonlinear payoff and an asymmetric distribution, skewness should play a very important role in determining option returns. Risk-neutral skewness is indeed found to be priced in options and stocks. Total skewness is constructed by co-skewness and idiosyncratic skewness. The importance of co-skewness in option pricing has been studied by Chen et al.. For idiosyncratic skewness, Barberis and Huang (2007) and Mitton and Vorkink (2007) develop models in which investors have similar preference for idiosyncratic skewness. Boyer et al. (2010) find that expected idiosyncratic skewness and stock returns are significantly and negatively related. Conrad et al. (2013) find that risk-neutral idiosyncratic skewness is negatively related to stock returns. Conrad et al. (2013) first model the risk-neutral co-skewness of Harvey and Siddique (2000) and then regress the time series of total skewness on co-skewness to estimate risk-neutral idiosyncratic skewness. The effect of risk-neutral idiosyncratic skewness on option returns has not been investigated comprehensively in the existing literature. Future research could focus on studying whether risk-neutral idiosyncratic skewness is priced in options.

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