# Empirical Essays on Option-Implied Information and Asset Pricing

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This thesis is submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Accounting and Finance.

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June 2016

## Abstract

This thesis consists of four empirical essays on option-implied information and asset pricing in the US market.

The **first** essay examines the predictive ability of option-implied volatility measures proposed by previous studies by using firm-level option and stock data. This essay documents significant non-zero returns on long-short portfolios formed on call-put implied volatility spread, and implied volatility skew. Cross-sectional regressions show that the call-put implied volatility spread is the most important factor in predicting one-month ahead stock returns. For two-month and three-month ahead stock returns, “out-minus-at” of calls has stronger predictive ability.

The **second** essay constructs pricing factors by using at-the-money option-implied volatilities and their first differences, and tests whether these pricing factors have significant risk premiums. However, results about significant risk premiums are limited.

The **third** essay focuses on the relationship between an asset’s return and its sensitivity to aggregate volatility risk. First, to separate different market conditions, this study focuses on how VIX spot, VIX futures, and their basis perform different roles in asset pricing. Secondly, this essay decomposes the VIX index into two parts: volatility calculated from out-of-the-money call options and volatility calculated from out-of-the-money put options. The analysis shows that out-of-the-money put options capture more useful information in predicting future stock returns.

The **fourth** essay concentrates on systematic standard deviation (i.e., beta) and skewness (i.e., gamma) by incorporating option-implied information. Portfolio level analysis shows that option-implied gamma performs better than historical gamma in

explaining portfolio returns at longer horizons (five-month or longer). In addition, firm size plays an important role in explaining returns on constituents of the S&P500 index. Finally, cross-sectional regression results confirm the existence of risk premiums on option-implied components for systematic standard deviation and systematic skewness calculation.

# Acknowledgement

I would like to express my gratitude to my supervisor Prof. Mark Shackleton for giving me the opportunity to work with him in the PhD programme as well as for his guidance and encouragement throughout the whole process. I am also grateful to Dr. Eser Arisoy and Dr. Mehmet Umutlu for valuable guidance on the third and fourth chapters, to Dr. Matteo Sandri for helpful comments on the fifth chapter, and to Dr. Yaqiong Yao for beneficial assistance on the sixth chapter.

I would like to thank my parents, Shihong Fu and Wenxiu Zou, and my boyfriend, Qiang Fu, for their unconditional support over the years. Their encouragement and understanding have had a significant impact on my studies and a large part of my motivation stems from them.

# Declaration

I hereby declare that this thesis is completed by myself, and has not been submitted in substantially the same form for the award of a higher degree elsewhere.

Parts of this thesis have been accepted for publication in research journals or presented in conferences. A working paper based on Chapter 3, entitled as "Option-Implied Volatility Measures and Stock Return Predictability" (with Eser Arisoy, Mehemt Umutlu, and Mark Shackleton), was presented in ESRC NWDTC AccFin Pathway Event: PhD Student Workshop in Finance and Accounting in the UK, 2014 Paris Financial Management Conference in France, and The New Financial Reality Seminar at University of Kent.

A paper based on Chapter 5, with the title "Asymmetric Effects of Volatility Risk on Stock Returns: Evidence from VIX and VIX Futures" (with Matteo Sandri, and Mark Shackleton), was accepted by the Journal of Futures Markets (Asymmetric Effects of Volatility Risk on Stock Returns: Evidence from VIX and VIX Futures, Fu, X., Sandri, M., and Shackleton, M. B., The Journal of Futures Markets, forthcoming, DOI: 10.1002/fut.21772, Copyright © 2016 Wiley Periodicals, Inc. Jrl Fut Mark, John Wiley & Sons, Inc). This paper was presented in 1st KoLa Workshop on Finance and Econometrics in the UK, 2014 FEBS International Conference in the UK, EFMA 2014 Conference in Italy, SoFiE Financial Econometrics Spring School 2015 in Belgium, and 7th International IFABS Conference in China.

A working paper based on Chapter 6, entitled as "Risk-Neutral Systematic Risk and Asset Returns", was presented in 2nd KoLa Workshop on Finance and Econometrics in Germany, and EFMA 2015 Conference in Netherlands.

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June 2016

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# Frequently Used Notation

| | |
|---|---|
| $r_i$ | Return on individual asset $i$ |
| $r_f$ | Risk-free rate |
| $r_m$ | Return on market portfolio $m$ |
| $r_0$ | Return on the zero-beta portfolio |
| $r_{5\text{-}1}$ | Return on the "5-1" long-short portfolio |
| $E(\bullet)$ | Expected value |
| $\sigma_i$ | Standard deviation of individual asset $i$ |
| $\sigma_i^2$ | Variance of individual asset $i$ |
| $m_i^3$ | Third central moment of individual asset $i$ |
| $k_i^4$ | Fourth central moment of individual asset $i$ |
| $\sigma_{ij}$ | Covariance between asset $i$ and asset $j$ |
| $\rho_{ij}$ | Correlation between asset $i$ and asset $j$ |
| $\beta_i$ | Market beta of individual asset $i$ |
| $\gamma_i$ | Market gamma of individual asset $i$ |
| $\delta_i$ | Market delta of individual asset $i$ |
| $\lambda_i$ | Risk premium on risk factor $i$ |
| $I_t$ | Information set available in period $t$ |
| $MKT$ | Market excess return |
| $SMB$ | Small-minus-big (i.e., the average return on the three small portfolios minus the average return on the three big portfolios) |
| $HML$ | High-minus-low (i.e., the average return on the two value portfolios minus the average return on the two growth portfolios) |
| $UMD$ | Winner-minus-loser (Up-minus-down) (i.e., the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios) |
| $\mu$ | Mean |
| $h_t$ | Conditional variance |
| $K$ | Strike price of the option |
| $C(T,K)$ | Price of call option with time-to-expiration of $T$ and strike price of $K$ |
| $P(T,K)$ | Price of put option with time-to-expiration of $T$ and strike price of $K$ |
| $V(T,K)$ | Price of the volatility contract with time-to-expiration of $T$ at time $t$ |
| $W(T,K)$ | Price of the cubic contract with time-to-expiration of $T$ at time $t$ |
| $X(T,K)$ | Price of the quartic contract with time-to-expiration of $T$ at time $t$ |
| $MFIV$ | Model-free implied volatility |
| $MFIS$ | Model-free implied skewness |
| $MFIK$ | Model-free implied kurtosis |
| $P$ | Real-world measure |
| $Q$ | Risk-neutral measure |

| | |
|---|---|
| *CPIV* | Call-put implied volatility spread |
| *IVSKEW* | Implied volatility skew |
| *AMB* | Above-minus-below |
| *COMA* | “Out-minus-at” of calls |
| *POMA* | “Out-minus-at” of puts |
| *RVIV* | Realized-implied volatility spread |
| *SPX* | The S&P500 index |
| *VF* | Volatility risk factor |
| *VIX* | The VIX index, which measures the market's expectation of stock market volatility based on the S&P500 index over the next 30-day period |
| *VXO* | The old VIX index, which measures the market's expectation of stock market volatility based on the S&P100 index over the next 30-day period |
| *VXF* | The VIX index futures |
| *VXC* | The volatility index calculated using near-term and next-term out-of-the-money S&P500 call options |
| *VXP* | The volatility index calculated using near-term and next-term out-of-the-money S&P500 put options |
| $Q(K,T)$ | The midpoint of the bid-ask spread for each out-of-the-money call or put option with strike price of $K$ and time-to-expiry of $T$ |
| $\sigma_{C,T}^2$ | Variance calculated by using only out-of-money call options with time-to-expiration of $T$ |
| $\sigma_{P,T}^2$ | Variance calculated by using only out-of-money put options with time-to-expiration of $T$ |
| CAPM | Capital Asset Pricing Model |
| ICAPM | Intertemporal Capital Asset Pricing Model |
| APT | Arbitrage Pricing Theory |
| P/E | Price-to-earnings ratio |
| B/M | Book-to-market ratio |
| GMM | Generalized method of moments |
| ARCH | Autoregressive conditional heteroskedasticity |
| GARCH | Generalized autoregressive conditional heteroskedasticity |

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# Chapter 1 Introduction

## 1.1 Introduction

The Capital Asset Pricing Model (CAPM) developed by Sharpe (1964), Lintner (1965), and Mossin (1966) is one of the most influential theories in finance. The popularity of the CAPM mainly stems from its parsimony and elegance. Based on the CAPM, an asset's expected return can be explained by its systematic risk (i.e., beta), which is equal to the covariance between returns on this asset and returns on the market portfolio divided by the variance of returns on the market portfolio.

However, the CAPM fails to explain many of the time-series and cross-sectional properties of asset returns. Some studies present empirical evidence which is inconsistent with the CAPM. For example, Blume (1970), Blume and Friend (1973), and Fama and MacBeth (1973) suggest that the regression intercept should be higher and the slope should be lower than the CAPM predictions. Also, there are seasonal patterns in financial markets, such as the January effect, and the Weekend effect.[1] Previous literature documents different pricing anomalies related to firm-specific information, as well. Basu (1977) documents a negative relationship between a firm's stock return and its price-to-earnings ratio (i.e., the P/E anomaly). Banz (1981) finds that small firms outperform large firms (i.e., the size effect). Rosenberg, Reid, and Lanstein (1985) present that an asset's return is positively related to its book-to-market ratio (i.e., the value effect).

[1] The January effect indicates that stock prices increase more in January than in any other month. The weekend effect implies that the average return on Mondays is significantly lower than average returns on other four trading days.

Because of the existence of pricing anomalies documented in previous literature and differences between CAPM-predicted prices and empirical observations, it is natural to ask how to improve the asset pricing model in order to capture more relevant information about future market conditions. Thus, after the establishment of the CAPM, a vast number of studies engage in developing asset pricing models from different perspectives.

Some studies try to derive asset pricing models from theoretical perspectives. The CAPM is derived based on Markowitz (1959) mean-variance efficient framework and assumes that investors have a trade-off between mean (i.e., a proxy for expected return) and variance (i.e., a proxy for risk). However, investors' utility functions do not necessarily depend on mean and variance. The failure of the CAPM could be due to omission of other higher moments of stock returns (e.g., skewness or kurtosis). Kraus and Litzenberger (1976), Sears and Wei (1985; 1988), Fang and Lai (1997), Dittmar (2002), and Kostakis, Muhammad and Siganos (2012) introduce factors related to higher moments of return distribution into the asset pricing model and confirm that higher moments are related to asset returns.

Some other studies try to improve asset pricing models by including more pricing factors from empirical perspectives. In order to capture information indicated by different pricing anomalies, Fama and French (1993) introduce two additional return-based factors, Small-Minus-Big ($SMB$) and High-Minus-Low ($HML$), into the asset pricing model.[2] Based on Fama-French three-factor model, Carhart (1997) further includes a momentum factor, Winners-Minus-Losers ($UMD$), into the model.[3]

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[2] Small-Minus-Big ($SMB$) is the average return on the three small portfolios minus the average return on the three big portfolios. High-Minus-Low ($HML$) is the average return on the two value portfolios minus the average return on the two growth portfolios.

[3] Winners-Minus-Losers ($UMD$) is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios.

Although these two models outperform the CAPM in explaining asset returns, they have no theoretical backup.

On the other hand, using historical information to predict expected returns implicitly implies that situations in the future should be quite similar to situations in the past (i.e., returns are drawn from the same distribution). However, if economic conditions change over time, historical data might fail to reflect future market conditions and cause error-in-variables and biased estimation problems. As a remedy to this problem, some empirical studies (Christensen and Prabhala, 1998; Szakmary, Ors, Kim and Davidson, 2003; Poon and Granger, 2005; Kang, Kim and Yoon, 2010; Taylor, Yadav and Zhang, 2010; Yu, Lui and Wang, 2010; and Muzzioli, 2011) use option-implied information in predicting future volatilities. Empirical evidence shows that option-implied information incorporates more useful information in volatility forecasting than historical information does. Some studies (French, Groth and Kolari, 1983; Siegel, 1995; Buss, Schlag and Vilkov, 2009; Buss and Vilkov, 2012; and Chang, Christoffersen, Jacobs and Vainberg, 2012) use forward-looking methods to calculate beta instead of the backward-looking one using historical data. Empirical results confirm that the relationship between an asset's return and its option-implied beta is stronger.

Thus, due to the outperformance of option-implied measures, this thesis aims to improve the asset pricing model in explaining or even predicting asset returns by incorporating option-implied information (i.e., option-implied volatility, skewness and kurtosis) from different perspectives.

## 1.2 The Structure of the Thesis

The thesis is organized as follows. Chapter 2 reviews the relevant literature. First, this chapter discusses the traditional CAPM in detail. Then, different pricing anomalies, which cannot be explained by the CAPM, documented in previous literature are presented. Chapter 2 also takes a look at different multi-factor asset pricing models, including theoretical pricing models other than the CAPM, pricing models with return-based factors, and pricing models with higher moments. Next, this chapter presents how to estimate volatility and higher moments in various ways, by using historical information or forward-looking option-implied information. The final part of Chapter 2 compares the performance of option-implied measures with the performance of historical measures.

Chapter 3, "Option-Implied Volatility Measures and Stock Return Predictability", investigates the relationship between stock return and option-implied volatility measures at firm-level. This chapter constructs six different volatility measures proposed in previous literature. The analysis helps to clarify whether these measures contain different information on volatility curve. This chapter runs analysis among all six volatility measures, and the results give us some hints about the predictive power of each volatility measure. Furthermore, this chapter looks at predictability of volatility measures for different investment horizons.

In Chapter 3, portfolio level analysis confirms a significant and positive relationship between portfolio return and $CPIV$. The analysis also shows that $IVSKEW$ is negatively related to portfolio return. Then, from firm-level cross-sectional regressions, for one-month predictive horizon, $CPIV$ has the most significant predictive power. When extending the predictive horizon to two-month or three-month, the predictive power of $CPIV$ still persists. Meanwhile, $COMA$ gains significant predictive ability. Findings presented in this chapter could provide investors with useful information about how to improve their trading strategies based on the length of their investment horizons in order to boost profits.

Chapter 4, “Option-Implied Factors and Stocks Returns: Indications from At-the-Money Options”, focuses on at-the-money call and put options. Previous studies, such as Ang, Hodrick, Xing and Zhang (2006), construct return-based pricing factors using information at aggregate-level. To contribute beyond previous literature, this chapter extracts useful information from options on individual stocks. This chapter constructs different pricing factors by using implied volatilities extracted from at-the-money call or put options, and then tests whether these factors help to explain time-series and cross-sectional properties of stock returns. However, empirical results provide limited evidence about significant premiums on implied volatility factors constructed in this chapter.

Due to the negative relationship between market index and volatility index and the existence of the market risk premium, Chapter 5, entitled “Asymmetric Effects of Volatility Risk on Stock Returns: Evidence from VIX and VIX Futures”, focuses on the relationship between an asset’s return and its sensitivity to aggregate volatility risk. To measure the aggregate volatility risk, this chapter uses the VIX index, as well as VIX index futures. In addition to the unconditional relationship tested in previous literature (Ang, Hodrick, Xing and Zhang, 2006; Chang, Christoffersen and Jacobs, 2013), this chapter investigates whether the aggregate volatility risk plays different roles in different market scenarios. To separate different market conditions, this chapter uses a dummy variable defined on VIX futures basis (i.e., the difference between VIX spot and VIX futures). Furthermore, the VIX index is decomposed into two parts: volatility calculated by using out-of-money call options and volatility calculated by using out-of-money put options. Such a decomposition helps to shed light on whether the asymmetric effect of volatility risk exists when using ex ante information and whether different kinds of options capture different information about future market conditions.

The empirical analysis in Chapter 5 reveals that there is no significant unconditional relationship between an asset's return and its sensitivity to volatility risk. Nevertheless, by distinguishing different market conditions, it is obvious that an asset's return is significantly and negatively related to its sensitivity to volatility risk in fearful markets. Such a negative relationship does not hold in calm markets. Then, after decomposing the VIX index into two components, results show that put options contain more relevant and useful information in predicting future returns compared with call options. Such results confirm the asymmetric effect of volatility risk by using ex ante information.

Based on the traditional CAPM, in order to explain dynamics of asset returns more adequately, a lot of studies introduce other factors into asset pricing models. Kraus and Litzenberger (1976) propose that higher moments should be taken into consideration in asset pricing. In addition to market beta measuring the systematic standard deviation, market gamma measuring systematic skewness is an important pricing factor. Chapter 6, "Risk-Neutral Systematic Risk and Asset Returns", examines how market beta and market gamma affect asset future returns. In addition to using historical data for beta and gamma estimation, this chapter incorporates option-implied model-free moments. It is expected that options contain forward-looking information which is more relevant to future market conditions. This chapter provides a comparison between beta and gamma calculated using daily historical data and beta and gamma calculated using forward-looking information.

Furthermore, this chapter also tests whether option-implied measures gain significant risk premiums in explaining cross-section of asset returns.

The empirical results in Chapter 6 show that option-implied gamma outperforms historical gamma in explaining portfolio returns over five-month or longer horizons. The analysis also confirm that, compared with beta and gamma, size is a more important pricing factor in explaining returns on components of the S&P500 index. In addition, through Fama-MacBeth cross-sectional regressions, this chapter finds that option-implied components for beta and gamma calculation have significant risk premiums in some cases.

Finally, Chapter 7 summarizes all findings and concludes this thesis. Implications and limitations of the thesis are also discussed.

# Chapter 2 Literature Review

This thesis is motivated by the failure of the CAPM in explaining asset returns. Due to the poor performance of the CAPM, previous literature engages in improving asset pricing models. For example, some studies establish multi-factor asset pricing models from different perspectives. In addition, the development of financial markets makes it possible to extract forward-looking information from different kinds of derivatives (e.g., options and futures).

This chapter provides a detailed literature review. First of all, the CAPM is discussed in detail in section 2.1, followed by a discussion about pricing anomalies that cannot be explained in section 2.2. Then, this chapter reviews some multi-factor asset pricing models derived in previous literature in sections 2.3 and 2.4. After that, sections 2.5 and 2.6 review studies about volatility and higher moments (i.e., skewness and kurtosis) estimation, respectively. The final part of this chapter, section 2.7, discusses studies about the comparison between performance of option-implied measures and performance of historical measures.

## 2.1 The Capital Asset Pricing Model

The CAPM is one of the most influential financial theories. It establishes a linear relationship between an asset's return and its corresponding systematic risk. Investors want to get compensation for bearing systematic risk and the CAPM establishes a simple yet effective framework for this relationship between risk and return. Due to its simplicity, the CAPM is widely used in applications. First of all, some details about the derivation of the CAPM are presented in this section.

The most important foundation of the CAPM is the mean-variance approach proposed by Markowitz (1959). This approach claims that mean and variance of returns can be treated as proxies for return and risk, respectively. If two assets yield the same return, investors will prefer the asset with less risk. If two assets have the same degree of risk, investors will prefer the asset with higher return. In other words, investors prefer more positive first moments (i.e., mean) and are averse to higher second moments (i.e., variance).

Based on the mean-variance approach, Sharpe (1964), Lintner (1965) and Mossin (1966) find a linear relationship between an asset's expected return and its systematic risk. This relationship is later on acknowledged as the Capital Asset Pricing Model (CAPM). On the basis of the mean-variance approach, the CAPM can be written as:

$$E\left(r_i\right) = r_f + \beta_i \left[ E(r_m) - r_f \right] \tag{2.1}$$

where $E\left(r_i\right)$ stands for the expected return on asset $i$, $r_f$ represents the risk-free rate, $E\left(r_m\right)$ measures the expected return on market portfolio $m$, and $\beta_i$ is the beta of asset $i$, which represents the portion of risk that investors care (i.e., undiversifiable risk or systematic risk). More specifically, beta is calculated using the following formula:

$$\beta_i = \frac{\sigma_{im}}{\sigma_m^2} = \frac{\rho_{im}\sigma_i}{\sigma_m} \tag{2.2}$$

where $\rho_{im}$ is the correlation between returns on individual asset $i$ and returns on market portfolio $m$, $\sigma_i$ represents the standard deviation of returns on individual asset $i$, and $\sigma_m$ stands for the standard deviation of returns on market portfolio $m$.

The CAPM is derived based on a set of strong assumptions about capital markets. Thus, if all assumptions hold in capital markets, the CAPM would hold period by period. However, most of these assumptions are fragile. One of the most challenged assumptions is that investors aim to maximize their expected utility functions, which only depend on the first moment (i.e., mean) and the second moment (i.e., variance) of returns on their portfolios. Furthermore, some other assumptions do not hold as well. Transaction costs and personal income taxes do exist in capital markets, and there are indeed restrictions on short sales and limits on the amount of money that can be borrowed or lent. These invalid assumptions of the CAPM could be potential reasons for the failure of the CAPM. The existence of the idiosyncratic risk empirically documented is also a big issue for the CAPM.[4] Due to these real-life frictions, whether the CAPM adequately describes behaviours of stock returns is subject to severe criticism. The next section reviews some studies documenting different pricing anomalies.

## 2.2 Pricing Anomalies in Asset Markets

A vast number of studies focus on empirical tests of the CAPM and many of them document the failure of the CAPM in explaining stock returns. Subsection 2.2.1 discusses some trading strategies generating significant returns. Subsection 2.2.2 looks at anomalies related to firm operation or finance information. The final Subsection 2.2.3 reviews the pricing anomaly about idiosyncratic risk found in recent studies.

### 2.2.1 Trading Strategies Generating Excess Returns

The most famous pricing anomalies about time-series properties of stock returns are the January effect (Rozeff and Kinney, 1976; Keim, 1983) and the Weekend effect (French, 1980).[5] Some other anomalies are related to cross-sectional properties of stock returns, such as P/E effect (Basu, 1977), the size effect (Banz, 1981), and the

[4] See Ang, Hodrick, Xing and Zhang (2006) and Bali and Cakici (2008) for the existence of the idiosyncratic risk.

[5] Keim (1983) maintains that the January effect can be due to the abnormal returns during the first trading week, especially the first trading day.

value effect (Rosenberg, Reid, and Lanstein 1985; Fama and French, 1992).[6] In addition to these well-known pricing anomalies, some trading strategies, which cannot be justified by the CAPM, enable investors to get excess returns.

De Bondt and Thaler (1985 and 1987) claim that past losers outperform past winners during the following 36-month period. Empirical results reveal that, during the period from 1933 to 1980, returns on past losers are 25% higher than returns on past winners even though past winners suffer from more risk than past losers do. Thus, investors can get excess returns if they invest in past losers and sell past winners short at the same time. This zero-cost strategy is known as the contrarian strategy.

More interestingly, the momentum strategy makes investors earn excess returns for shorter future periods. Jegadeesh and Titman (1993) document the existence of the momentum effect in the stock market. According to their results, the momentum strategy which buys past winners and sells past losers can generate significantly positive returns over three-month to 12-month holding periods. Furthermore, they also distinguish that neither the systematic risk nor the lead-lag effect is the potential reason for profits from the momentum strategy.[7]

### 2.2.2 Pricing Anomalies about Firm Operation or Finance Information

Some recent papers document pricing anomalies related to firm operation or finance information.

First of all, Loughran and Ritter (1995) document the existence of the new issues puzzle. Empirical results show that companies issuing stock during 1970 to 1990 (no matter whether it is an initial public offering or a seasoned equity offering) perform

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[6] However, Schwert (2003) documents that some anomalies cannot be detected when using different sample periods, such as the January effect, the weekend effect, the size effect and the value effect.

[7] The lead-lag effect means that one variable (i.e., the leading variable) is closely related to the value of another variable (i.e., the lagging variable) at later times.

poorly during the five-year period after the issue. To be more specific, the average return on companies with an initial public offering is only 5% p.a. and the average return on companies with a seasoned equity offering is only 7% p.a.. In addition, such a puzzle cannot be explained by the value effect.

Diether, Malloy and Scherbina (2002) present empirical evidence about the relationship between dispersion in analysts' earnings forecasts and cross section of future stock returns. The empirical evidence presents that stocks with lower dispersion outperform stocks with higher dispersion significantly, especially for small stocks and stocks that performed badly in the past year.

Titman, Wei and Xie (2004) document a negative relationship between abnormal capital investments and stock returns, especially for firms with greater investment discretion (i.e., the abnormal capital investment anomaly). They find that such a negative relationship is independent of long-term return reversal and secondary equity issue anomalies.

When Petkova and Zhang (2005) investigate the value premium by using the conditional CAPM, they find that the direction of time-varying risk is consistent with a value premium (i.e., value betas tend to covary positively while growth betas tend to covary negatively with the expected market risk premium). However, the evidence also presents that the covariance between value-minus-growth betas and the expected market risk premium is not enough to explain the value premium. Thus, there should be other factors driving the value anomaly.

Daniel and Titman (2006) explore the book-to-market effect. They find that past accounting-based performance cannot help to explain a stock's future return. However, a stock's future return is negatively related to the "intangible" return (i.e., the component of its past return that is orthogonal to the firm's past performance). So they claim that the book-to-market ratio forecasts returns because it is a good proxy for the intangible return. Daniel and Titman (2006) also document that composite stock issuance predicts returns independently (i.e., the composite stock issuance anomaly).

Lyandres, Sun and Zhang (2008) document the evidence of the investment-to-asset ratio anomaly. They show that, if the investment factor is added into the asset pricing model, some anomalies can be explained to some extent. For example, about 40% of the composite issuance effect documented by Daniel and Titman (2006) can be explained after the inclusion of an investment factor into the regression model.

Then, the total asset growth anomaly is documented by Cooper, Gulen and Schill (2008). They find a negative correlation between the total asset growth and the annual return. In addition, they claim that total asset growth even dominates other commonly used pricing factors (e.g., book-to-market ratios, firm capitalization, lagged returns, accruals, and other growth measures).

### 2.2.3 The Idiosyncratic Risk

The CAPM only captures the systematic risk, however, the idiosyncratic risk, which is specific for each asset, is also related to asset returns. Ang, Hodrick, Xing and Zhang (2006) document the existence of the idiosyncratic volatility anomaly. Their paper focuses on the relationship between the idiosyncratic volatility and the asset return. To check whether asset returns are related to the idiosyncratic volatility, they analyze returns on portfolios sorted on idiosyncratic volatility relative to Fama and French three-factor model (1993). The empirical results present that stocks with high idiosyncratic volatility underperform stocks with low idiosyncratic volatility. They also find that many factors, such as size, book-to-market ratio, momentum, and even the dispersion in analysts' earnings forecasts mentioned above, cannot explain low (high) returns on stocks with high (low) idiosyncratic volatility.

In summary, previous studies point out that the CAPM cannot explain time-series and cross-sectional properties of asset returns. After the establishment of the CAPM, many studies aim at improving asset pricing models from different perspectives. Next section reviews some papers deriving multi-factor asset pricing models.

## 2.3 Multi-Factor Asset Pricing Models

This section reviews some classic asset pricing models other than the CAPM, such as the intertemporal CAPM, the Arbitrage Pricing Theory, and the conditional CAPM. Then, this section also discusses empirical studies introducing return-based pricing factors, such as $SMB$, $HML$ and $UMD$.

### 2.3.1 The Intertemporal Capital Asset Pricing Model

Adding to the CAPM, Merton (1973) establishes another asset pricing model, the Intertemporal Capital Asset Pricing Model (ICAPM). First of all, Merton (1973) points out that the CAPM is a one-horizon model and it cannot be used for infinite horizons. He points out that, for continuous time, the choice of the portfolio not only depends on the mean-variance approach but also relates to the uncertainty of the investment opportunity set. So in the ICAPM, there are two pricing factors: the systematic risk and changes in the investment opportunity set. The ICAPM can be written as:

$$E\left(r_i\right) = r_f + \beta_i \left[ E\left(r_m\right) - r_f \right] + \delta_i \left[ E\left(r_0\right) - r_f \right] \tag{2.3}$$

where $E\left(r_0\right)$ is the expected return on the zero-beta portfolio, $\delta_i$ measures how expected return changes for bearing the risk of changes in the investment opportunity set. In this multi-horizon model, investors are able to rebalance their portfolios. Thus, changes in the investment opportunity set affect investors' choices, and investors need to take other risk factors, in addition to beta, into consideration. Furthermore, variables included in models which will be reviewed in later subsections, such as $SMB$ and $HML$, are also related to changes in the investment opportunity set.

### 2.3.2 The Arbitrage Pricing Theory

Another famous multi-factor model is the Arbitrage Pricing Theory (APT) proposed by Ross (1976). The main difference between the CAPM and the APT is that the APT does not require an assumption about the utility function. Ross (1976) proposes that the expected return on an asset should be a linear function of the asset's sensitivities to many different risk factors. The APT can be expressed by the following formula:

$$E(r_i) = r_f + \sum_{j=1}^{J} \beta_{ij} \lambda_j \tag{2.4}$$

where $\beta_{ij}$ measures the sensitivity of stock $i$'s return to risk factor $j$, $\lambda_j$ stands for the expected risk premium on risk factor $j$. The relationship between the APT and the CAPM is that the CAPM can be treated as a special case of the APT, which has only one risk factor, beta. However, the shortcoming of the APT is obvious. Ross (1976) does not identify what exact pricing factors should be used. Which risk factors should be included in the APT remains an open question.

### 2.3.3 The Conditional Capital Asset Pricing Model

Furthermore, previous studies also document that beta and/or the risk premium are not constant, and they vary significantly over time. These variations offer an alternative explanation to the failure of the static CAPM (discussed in section 2.1): the static CAPM is a single-period static model. More particularly, the conditional CAPM establishes the following relationship for each asset $i$ and each period $t$:

$$E\left(r_{i,t} \left| I_{t-1}\right.\right) = \gamma_{0,t-1} + \gamma_{m,t-1}\beta_{i,t-1} \tag{2.5}$$

where $\gamma_{0,t-1}$ stands for the conditional expected return on a zero-beta portfolio, $\gamma_{m,t-1}$ is the conditional market risk premium, and $\beta_{i,t-1}$ means the conditional beta of asset $i$, which can be obtained from

$$\beta_{i,t-1} = \frac{\operatorname{cov}\left(r_{i,t}, r_{m,t} \left| I_{t-1}\right.\right)}{\operatorname{var}\left(r_{m,t} \left| I_{t}\right.\right)} \tag{2.6}$$

If we take unconditional expectations on both sides of the conditional CAPM:

$$E\left(r_{i,t}\right) = \gamma_0 + \gamma_m \overline{\beta_i} + \operatorname{var}\left(\gamma_{m,t-1}\right)\vartheta_i \tag{2.7}$$

where $\gamma_0 = E\left[\gamma_{0,t-1}\right]$ and it is the unconditional expected return on zero-beta portfolio, $\gamma_m = E\left[\gamma_{m,t-1}\right]$ and it is the expected market risk premium, $\overline{\beta_i} = E\left[\beta_{i,t-1}\right]$ and it is the expected beta, and $\vartheta_i$ is the beta-premium sensitivity, which can be calculated by

$$\vartheta_i = \frac{\operatorname{cov}\left(\beta_{i,t-1}, \gamma_{m,t-1}\right)}{\operatorname{var}\left(\gamma_{m,t-1}\right)} \tag{2.8}$$

Thus, in the conditional CAPM, $\vartheta_i$ captures the impact of time-varying betas on expected returns. By using the conditional CAPM, Ferson and Harvey (1991) claim that time variation in the stock market risk premium is very important in predicting expected returns, and it is even more important than changes in betas. Then, Jagannathan and Wang (1996) are the first to test the performance of the conditional CAPM in explaining the cross-section of stock returns. They find that the size effect and statistical rejections of model specifications become weaker under the assumption that betas and expected returns are time-varying. Empirical results in their paper show that the conditional CAPM outperforms the static CAPM in explaining cross-sectional variations in expected returns.

### 2.3.4 Other Multi-Factor Asset Pricing Models

There is a continuous search for factors with the aim to better explain pricing anomalies and asset returns. First, Fama and French (1993) test whether the model including three return-based factors, which are market excess return ( $MKT$ ), Small-Minus-Big ( $SMB$ ) and High-Minus-Low ( $HML$ ), captures risks borne by stocks. The Fama-French three-factor model is as follows:

$$r_i = r_f + \beta_i MKT + s_i SMB + h_i HML + \varepsilon_i \tag{2.9}$$

where $s_i$ and $h_i$ are sensitivities of returns on asset $i$ to $SMB$ and $HML$, respectively. By using time-series regressions, they claim that both firm size and book-to-market ratio are indeed quite important for asset pricing. This three-factor asset pricing model explains the cross-section of average stock returns better than the CAPM does (i.e., two new factors are significant explanatory variables). Furthermore, $SMB$ and $HML$ can be treated as proxies for the investment opportunity set which is the additional factor in the ICAPM. Thus, Fama-French three-factor model is consistent with the ICAPM.

In addition, because of the well-documented momentum effect, Carhart (1997) introduces a momentum factor into the three-factor model established by Fama and French (1993). Thus, four explanatory variables in Carhart's model are $MKT$, $SMB$ and $HML$, and one-year momentum in stock returns ($UMD$). The Carhart four-factor model can be written as:

$$r_i = r_f + \beta_i MKT + s_i SMB + h_i HML + m_i UMD + \varepsilon_i \tag{2.10}$$

where $m_i$ measures the sensitivity of returns on stock $i$ to the momentum risk factor. The empirical findings show that the Carhart four-factor model can well describe both time-series variation and cross-sectional variation in stock returns, and it leads to lower pricing errors than the Fama-French three-factor model does.

Berk, Green and Naik (1999) model asset returns from another perspective. They establish an asset pricing model on the basis of a firm's risk through time. They claim that changes in conditional expected returns are due to the valuation of cash flow from investment decisions and the firm's options to grow in the future time. Thus, a firm's return can be obtained from the sum of the cash flow and the future price divided by the current price. Because the number of ongoing projects is closely related to the firm's life cycle and the interest rate, this model can capture such changes. The simulation results in their paper show that their model helps to explain several time-series and cross-sectional anomalies to some extent, such as the value effect, the size effect, the contrarian effect and the momentum effect.

From previous studies mentioned above, it is obvious that multi-factor asset pricing models perform better in terms of explaining time-series and cross-sectional properties of asset returns.

## 2.4 Asset Pricing Models with Higher Moments

In addition to literature reviewed in the previous section, another strand of studies improves asset pricing models by breaking the assumption of the mean-variance framework.

### 2.4.1 Models Incorporating Systematic Skewness

Kraus and Litzenberger (1976) derive an asset pricing model by incorporating the third moment of return distribution (i.e., skewness). For investors with non-polynomial utility functions (e.g., cubic utility functions), they are averse to standard deviation and they prefer positive skewness. So, in equilibrium, by assuming that the return on the market portfolio is asymmetrically distributed, their study derives a two-factor model (i.e., a three-moment model). In their model, there are two pricing factors, market beta (measuring systematic standard deviation of an asset) and market gamma (measuring systematic skewness of an asset):

$$E\left(r_i\right) = r_f + b_1\beta_i + b_2\gamma_i \tag{2.11}$$

where $\beta_i = \sigma_{im} / \sigma_m^2$, $\gamma_i = m_{imm} / m_m^3$, $b_1 = \left(d\overline{W} / d\sigma_W\right)\sigma_m$, and $b_2 = \left(d\overline{W} / dm_W\right)m_m$ for all investors. $\sigma_m^2 = E\left[\left(r_m - E(r_m)\right)^2\right]$, $m_m^3 = E\left[\left(r_m - E(r_m)\right)^3\right]$, and $k_m^4 = E\left[\left(r_m - E(r_m)\right)^4\right]$ are the second, third, and fourth central moments of the return on the market portfolio. $b_1$ and $b_2$ can be interpreted as risk premiums on market beta and market gamma, respectively. Empirical findings in Kraus and Litzenberger (1976) confirm a significant premium on systematic skewness.

After Kraus and Litzenberger (1976), many studies investigate investors' preference to systematic skewness risk. Friend and Westerfield (1980) provide a more comprehensive test for the Kraus and Litzenberger (1976) model.[8] Compared to previous studies, their study includes bonds as well as stocks into the portfolio. However, they cannot find conclusive evidence about the risk premium related to systematic skewness. Furthermore, they point out that the significance of systematic skewness is sensitive to different market indices and testing and estimation procedures.

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[8] Friend and Westerfield's (1980) paper is also the first using "coskewness" to denote the systematic skewness (measured by market gamma).

Sears and Wei (1985 and 1988) figure out why previous studies have mixed results about the risk premium on systematic skewness. They claim that the potential reason is the nonlinearity in the market risk premium. They incorporate such a nonlinearity in their theoretical framework. Empirical results then provide evidence about investors' preference to higher systematic skewness.

Later, Lim (1989) tests the Kraus and Litzenberger's (1976) model by using Hansen's (1982) generalized method of moments (GMM) and using stock returns at monthly basis. Empirical results confirm the importance of systematic skewness risk in explaining stock returns.

Instead of unconditional systematic skewness used in previous literature, conditional systematic skewness is incorporated in Harvey and Siddique (2000). They find that including systematic skewness into the asset pricing model improves the performance of the model. Investors require higher returns on assets with negative systematic skewness. Furthermore, they find that skewness helps to explain the momentum effect (i.e., skewness of past loser is higher than that of past winner).

### 2.4.2 Models Incorporating Systematic Kurtosis

While confirming the importance of systematic skewness in asset pricing, some studies concentrate on the fourth moment, kurtosis. In order to incorporate the effect of kurtosis into the asset pricing model, Fang and Lai (1997) construct a three-factor model (i.e., a four-moment model):

$$E\left(r_i\right) = r_f + b_1\beta_i + b_2\gamma_i + b_3\delta_i \tag{2.12}$$

where $\delta_i = k_{immm}/k_m^4$ is the systematic kurtosis of asset $i$, and $b_3$ is the market premium on systematic kurtosis. According to the theory, $b_1$ and $b_3$ should be positive, while $b_2$ should have the opposite sign of the market skewness. Empirical results are consistent with theoretical expectations. Fang and Lai (1997) confirm that beta is not the only pricing factor related to asset returns. Systematic skewness and kurtosis affect asset returns as well. Investors are averse to systematic variance and kurtosis, and they require higher expected returns for bearing these two kinds of risks. However, investors are willing to accept lower returns for taking the benefit of increasing the systematic skewness.

Christie-David and Chaudhry (2001) test the four-moment model by looking at 28 futures contracts and nine market proxies. The empirical evidence shows that including systematic skewness and kurtosis improves the performance of asset pricing model in explaining asset returns. This conclusion is robust no matter how the market proxy is constructed.

In summary, previous studies show that the pricing factor proposed in the CAPM (i.e., beta) does not capture enough information related to asset return distribution. In addition to systematic standard deviation risk, higher moments of return distribution are of great importance. Systematic skewness and kurtosis risks should be taken into consideration in asset pricing.

## 2.5 Volatility Estimation

In addition to improving asset pricing models by introducing more factors, some empirical studies estimate risk factors by using more advanced methods. The most widely-tested factor is the volatility factor.

### 2.5.1 The ARCH and GARCH models

Engle (1982) introduces the Autoregressive Conditional Heteroskedasticity (ARCH) model to formulate the time-varying conditional variance of stock returns. First, Engle (1982) defines the conditional distribution of returns as:

$$r_t \left| r_{t-1}, r_{t-2}, r_{t-3} \cdots \sim N\left(\mu, h_t\right) \right. \tag{2.13}$$

where $\mu$ is a constant, and $h_t$ is the time-varying conditional variance which can be expressed as:

$$h_t = \omega + \sum_{j=1}^{q} \alpha_j \left(r_{t-j} - \mu\right)^2 \tag{2.14}$$

where $\omega$ should be positive and $\alpha_j$ should be non-negative in order to ensure that the variance is larger than zero. Thus, from the $\text{ARCH}(q)$ model in Equation (2.14), the conditional variance $h_t$ is known at time $t-1$. The unconditional variance of asset returns can also be obtained:

$$\sigma^2 = \frac{\omega}{1 - \sum_{j=1}^{q} \alpha_j} \tag{2.15}$$

Thus, if $\sum_{j=1}^{q} \alpha_j < 1$, the process of asset returns should be covariance stationary.

Later on, Bollerslev (1986) and Taylor (1986) come up with the Generalised ARCH (GARCH) model simultaneously. In the $\text{GARCH}(p,q)$ model, the conditional variance depends on not only lag differences between returns and the mean but also lag conditional variances:

$$h_t = \omega + \sum_{i=1}^{p} \varphi_i h_{t-i} + \sum_{j=1}^{q} \alpha_j \left(r_{t-j} - \mu\right)^2 \tag{2.16}$$

where $\omega > 0$, the constraints on $\alpha_j$ and $\varphi_i$ are quite complex. For $\text{GARCH}(1,1)$, in order to make the conditional variance non-negative, constraints on $\alpha_j$ and $\varphi_i$ are quite clear: $\alpha_j \geq 0$ and $\varphi_i \geq 0$. The unconditional variance is:

$$\sigma^2 = \frac{\omega}{1 - \sum_{i=1}^{p} \varphi_i - \sum_{j=1}^{q} \alpha_j} \tag{2.17}$$

The $\text{GARCH}(p,q)$ model is covariance stationary when $\sum_{i=1}^{p} \varphi_i + \sum_{j=1}^{q} \alpha_j < 1$.

### 2.5.2 The Option-Implied Volatility

ARCH and GARCH models are popular because they are compatible with stylized facts for asset returns, namely, volatility clustering.[9] However, implied volatility has become a more and more popular rival.

Capital markets developed tremendously in the past 40 years, and more complex financial instruments such as options are now traded actively. One important property of options is that option prices reflect investors' expectations about the evolution of several parameters that investors deem as important in determining their risk and return trade-offs. So, option prices may reveal important information about dynamics of those parameters.

Implied volatility is incorporated in option prices, and it can be obtained by setting market price of an option equal to the price indicated by the option pricing model. Options are forward-looking instruments and they contain more relevant information about future market conditions. Empirical studies document the outperformance of option-implied volatility in forecasting future volatility. Relevant studies are discussed in detail in section 2.7.

### 2.5.3 The Stochastic Volatility

To resolve a shortcoming of the Black–Scholes (1973) model (i.e., the assumption that the underlying volatility is constant over the life of a derivative, and unaffected by changes in the price level of the underlying asset), Heston (1993) proposes the stochastic volatility model. He defines that $Y_t = \log(S_t)$ and $V_t = \sigma_t^2$,

[9] According to Taylor (2005), stylized facts for asset returns are: 1. The distribution of returns is not normal; 2. There is almost no correlation between returns for different days; 3. There is positive dependence between absolute returns on nearby days, and likewise for squared returns.

then if there is no dividend paid during the period, risk-neutral dynamics for an individual asset and its volatility are:

$$dY = \left( r - \frac{1}{2}V \right) dt + \sqrt{V} dW \tag{2.18}$$

$$dV = \left( a - bV \right) dt + \xi \sqrt{V} dZ \tag{2.19}$$

where two Wiener processes $W$ and $Z$ are correlated and the correlation between these two processes is $\rho$. The stochastic volatility makes it possible to model derivatives more accurately. However, it does not capture some features of the implied volatility surface such as volatility smile and skew.

### 2.5.4 The Model-Free Volatility

Even though the stochastic volatility has been developed, option pricing models using the stochastic volatility cannot explain option prices adequately. Britten-Jones and Neuberger (2000) derive a model-free method to adjust the volatility process to fit current option prices exactly. Their study proposes that the risk-neutral forecast of squared volatility only depends on market prices of a continuum of options without depending on an option pricing model. A forecast of squared volatility during time 0 to $T$ can be expressed as:

$$E_0 \left[ \int_0^T \left( \frac{dS_t}{S_t} \right)^2 \right] = 2 \int_0^\infty \frac{C(T,K) - \max(S_0 - K, 0)}{K^2} dK \tag{2.20}$$

where $C(T,K)$ is the price of an European call option with time-to-maturity of $T$ and strike price of $K$, and $S_0$ is the price of the underlying asset at time 0. Based on this framework, Bakshi, Kapadia and Madan (2003) derive how to estimate model-free moments (i.e., variance, skewness and kurtosis) by using out-of-the-money call and put options (as discussed in section 2.6).

### 2.5.5 The High-Frequency Volatility

In addition to volatility estimations discussed in previous subsections, some studies use high-frequency data for volatility estimation. By summing sufficiently finely sampled high-frequency returns, it is possible to construct ex post realized volatility measures. The realized variance for day $t$ is defined as:

$$RV_{t,N}^2 = \sum_{j=1}^{N} \left( r_{t,j,N}^2 \right) \tag{2.21}$$

where $N$ denotes for the total number of observations for high-frequency return data within one trading day.

Andersen, Bollerslev, Diebold and Ebens (2001) claim that realized volatility measures calculated by using high-frequency data are asymptotically free of measurement error. By focusing on components of DJIA, their paper also investigates the distribution of realized volatility. Empirical findings indicate that the distribution of realized variance is right-skewed. In addition, the realized volatility shows strong temporal dependence and appears to be well described by long-memory processes.

By using high-frequency data, Barndorff-Nielsen and Shephard (2004) claim that realized variance can be separated into two parts, the diffusion risk and the jump risk. In addition to power variation, they define the bipower variance as:

$$BV_{t,N}^2 = \frac{\pi}{2} \sum_{j=2}^{N} \left| r_{t,j-1,N} \right| \left| r_{t,j,N} \right| \tag{2.22}$$

The realized variance and the realized bipower converge to the same limit for continuous stochastic volatility semi-martingales process. For stochastic volatility process with jumps, the difference between realized variance and bipower variance can capture the jump risk.[10]

On the basis of stochastic volatility models, Woerner (2005) examines the estimation of the integrated volatility. This study infers the integrated volatility from the power variation by using the high-frequency data. The results give some information about the confidence interval of the integrated volatility. Furthermore, the method in Woerner (2005) allows additions of some processes, such as jump components, into the model without affecting the estimation result of the integrated volatility. Given the possibility of introducing processes into the stochastic volatility model, Woerner's model is more flexible and robust.

Thus, in addition to calculating volatility by using historical data, recent studies develop more advanced methods for volatility estimation. These methods enable us to estimate future volatility more efficiently and more precisely.

## 2.6 Higher Moments Estimation

In addition to volatility estimation, higher moments, such as skewness and kurtosis, receive particular attention. Instead of calculating higher moments using historical data, some studies calculate skewness and kurtosis by incorporating forward-looking information.

Bakshi, Kapadia and Madan (2003) make a great contribution to estimating higher moments and co-moments. In their paper, risk-neutral model-free skewness and kurtosis could be calculated from market prices of out-of-the-money European call and put options:

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[10] Huang and Tauchen (2005) use realized variance and bipower variance to construct jump measures, and provide evidence that jumps account for 7% of stock market price variance.

$$SKEW(t,\tau)=\frac{e^{r\tau}W(t,\tau)-3e^{r\tau}\mu(t,\tau)V(t,\tau)+2\mu(t,\tau)^3}{\left[e^{r\tau}V(t,\tau)-\mu(t,\tau)^2\right]^{3/2}} \tag{2.23}$$

$$KURT(t,\tau)=\frac{e^{r\tau}X(t,\tau)-4e^{r\tau}\mu(t,\tau)W(t,\tau)+6e^{r\tau}\mu(t,\tau)^2V(t,\tau)-3\mu(t,\tau)^4}{\left[e^{r\tau}V(t,\tau)-\mu(t,\tau)^2\right]^{2}} \tag{2.24}$$

where

$$\mu(t,\tau)=e^{r\tau}-1-\frac{e^{r\tau}V(t,\tau)}{2}-\frac{e^{r\tau}W(t,\tau)}{6}-\frac{e^{r\tau}X(t,\tau)}{24} \tag{2.25}$$

$V(t,\tau)$, $W(t,\tau)$, and $X(t,\tau)$ are prices of volatility, cubic, and quartic contracts:

$$V(t,\tau)=\int_{S_t}^{\infty}\frac{2\left(1-\ln\left[\frac{K}{S_t}\right]\right)}{K^2}C(t,\tau;K)\,dK+\int_0^{S_t}\frac{2\left(1+\ln\left[\frac{S_t}{K}\right]\right)}{K^2}P(t,\tau;K)\,dK \tag{2.26}$$

$$\begin{aligned}W(t,\tau)=&\int_{S_t}^{\infty}\frac{6\left(\ln\left[\frac{K}{S_t}\right]\right)-3\left(\ln\left[\frac{K}{S_t}\right]\right)^2}{K^2}C(t,\tau;K)\,dK\\&-\int_0^{S_t}\frac{6\left(\ln\left[\frac{S_t}{K}\right]\right)+3\left(\ln\left[\frac{S_t}{K}\right]\right)^2}{K^2}P(t,\tau;K)\,dK\end{aligned} \tag{2.27}$$

$$\begin{aligned}X(t,\tau)=&\int_{S_t}^{\infty}\frac{12\left(\ln\left[\frac{K}{S_t}\right]\right)^2-4\left(\ln\left[\frac{K}{S_t}\right]\right)^3}{K^2}C(t,\tau;K)\,dK\\&+\int_0^{S_t}\frac{12\left(\ln\left[\frac{S_t}{K}\right]\right)^2+4\left(\ln\left[\frac{S_t}{K}\right]\right)^3}{K^2}P(t,\tau;K)\,dK\end{aligned} \tag{2.28}$$

This method for higher moments estimation derived in Bakshi, Kapadia and Madan (2003) are widely applied in later studies. Conrad, Dittmar and Ghysels (2013) test the relationship between asset future returns and risk-neutral model-free volatility, skewness or kurtosis of individual assets. The empirical results show that stocks with higher volatilities have lower returns in the following month than those with lower volatilities. With respective to skewness, it is negatively related to future returns. That is, stocks with less negative or positive skewness have lower returns. In addition, empirical results confirm a positive relation between asset returns and kurtosis.

## 2.7 The Performance of Option-Implied Measures

Due to the existence of different methods for volatility estimation, it is natural to ask whether these methods perform similarly in predicting future volatility. In recent years, some empirical studies compare the performance of different methods in estimating/forecasting future volatility.

### 2.7.1 Comparison between Option-Implied Volatility and Historical Volatility

Christensen and Prabhala (1998) investigate the comparison between implied volatility and realized volatility by focusing on the S&P100 index. The results show that implied volatility incorporated in call options outperforms realized volatility (i.e., the annualized ex post daily return volatility) in forecasting future volatility.

Blair, Poon and Taylor (2001) compare the information content of implied volatility, ARCH models using daily returns and sums of squares of intraday returns.[11] The in-sample analysis indicates that ARCH models using daily returns have no incremental information beyond that provided by the VIX index of implied volatilities. Information content of historical high-frequency (five-minute) returns is almost subsumed by implied volatilities. Meanwhile, the out-of-the-sample analysis further provides evidence on the outperformance of implied volatility. The VIX index generally performs better than both daily returns and high-frequency returns in forecasting realized volatility.

[11] In Blair, Poon and Taylor (2001), the old VIX index (*VXO*) is used as a proxy of implied volatility of S&P100 index.

Poon and Granger (2005) compare four different methods for volatility estimation, historical volatility, ARCH models, stochastic volatility, and option-implied volatility by looking at the S&P500 index. Empirical results provide evidence that option-implied volatility dominates time-series models, while stochastic volatility underperforms all other three measures. The outperformance of option-implied volatility could be due to the fact that the option market price fully incorporates current information and future volatility expectations.

Focusing on the S&P500 index options, Kang, Kim and Yoon (2010) derive a new method to forecast future volatility by incorporating risk-neutral higher moments. Empirical results support that historical volatility and risk-neutral implied volatility are not unbiased estimators of future volatility. However, the adjusted implied volatility is unbiased and it outperforms other measures in terms of forecasting errors.

Then, Taylor, Yadav and Zhang (2010) compare performance of different volatility measures at different time horizons in the US market. The performance of different measures is sensitive to the length of time horizons. Empirical results show that a historical ARCH model performs the best for one-day-ahead estimation, while option forecasts are more efficient than historical volatility if the prediction horizon is extended until the expiry date of options. Furthermore, Taylor, Yadav and Zhang (2010) show that at-the-money implied volatility generally outperforms the model-free volatility in forecasting future volatility.

Szakmary, Ors, Kim and Davidson (2003) focus on a broad range of futures markets (including stocks, bonds, money market securities, currencies, agricultural commodities, industrial commodities, metals, etc.). The results show that, even though implied volatility is not a completely unbiased predictor of future volatility, it outperforms historical volatility as a predictor of subsequent realized volatility in the underlying futures prices over the remaining life of the option no matter how historical volatility is modelled.

Other than the US market, some studies examine whether the outperformance of option-implied volatility can be found in markets in other countries.

By investigating the DAX index options market, Muzzioli (2011) finds that, among implied volatilities captured by different kinds of options (in-the-money, at-the-money, and out-of-the-money call or put options), at-the-money put implied volatility is an unbiased and efficient forecast, and it subsumes all the information contained in historical volatility.

Yu, Lui and Wang (2010) compare the performance of option-implied volatility with historical volatility and GARCH volatility in Hong Kong and Japanese markets. By investigating options traded in the over-the-counter market, Yu, Lui and Wang (2010) confirm the outperformance of option-implied volatility.

Different volatility estimations have been investigated in foreign exchange markets, as well. Pong, Shackleton, Taylor and Xu (2004) forecast volatility using different measures in foreign exchange markets (GBP/USD, DEM/USD, and JPY/USD) over different horizons from one-day to three-month. Methods used for volatility estimation used in this study are: ARMA and ARFIMA volatility forecasts calculated from high-frequency returns, GARCH volatility forecasts calculated from daily returns, and implied volatilities extracted from option prices. The empirical results in this study show that historical volatility from high-frequency data performs best for one-day and one-week horizons, whereas implied volatilities are at least as accurate as historical forecasts for one-month and three-month horizons.

Thus, previous studies provide supportive evidence about the outperformance of option-implied information in forecasting future volatility.

### 2.7.2 Comparison between Option-Implied Beta and Historical Beta

In addition to volatility estimation, recent studies estimate other factors by using forward-looking information. Even though the CAPM cannot adequately explain asset returns, market beta is still an important risk factor in asset pricing. Several studies improve the method for market beta estimation.

French, Groth and Kolari (1983) incorporate option-implied volatility in beta calculation.

$$\beta_{i,t}^{FGK} = \rho_{im,t}^{P} \times \frac{\sigma_{i,t}^{Q}}{\sigma_{m,t}^{Q}} \tag{2.29}$$

where $\rho_{im,t}^{P}$ is the historical correlation between individual asset $i$ and the market portfolio, $\sigma_{i,t}^{Q}$ is the option-implied volatility of asset $i$, and $\sigma_{m,t}^{Q}$ is the option-implied volatility of the market portfolio. Thus, the beta in French, Groth and Kolari (1983) is a combination of historical and option-implied information.

Siegel (1995) proposes another way for beta estimation incorporating option-implied information.

$$\beta_{i,t}^{S} = \frac{\sigma_{i,t}^{2} + \sigma_{m,t}^{2} - \sigma_{t}^{2}}{2\sigma_{m,t}^{2}} \tag{2.30}$$

where $\sigma_{i,t}^{Q}$ is the instantaneous variance of the return on asset $i$, $\sigma_{m,t}^{Q}$ is the instantaneous variance of the return on the market index, and $\sigma_{t}^{2}$ is the instantaneous variance of the return on $i/m$. To obtain $\sigma_{t}^{2}$, an option that allows the exchange of the firm's stock for shares of a market index is required for calculation. However, such an exchange option is not traded in markets. So, this method cannot be applied.

Chang, Christoffersen, Jacobs and Vainberg (2012) derive a method for beta estimation incorporating higher moments. To be more specific, without using historical correlation, Chang, Christoffersen, Jacobs and Vainberg (2012) calculate correlation between an asset $i$ and the market portfolio by using risk-neutral model-free skewness.

$$\beta_{i,t}^{CCJV} = \left( \frac{MFIS_{i,t}}{MFIS_{m,t}} \right)^{\frac{1}{3}} \times \frac{\sigma_{i,t}^{Q}}{\sigma_{m,t}^{Q}} \tag{2.31}$$

However, this formula only holds under the assumption of zero skewness of the market return residual.

Buss and Vilkov (2012) calculate the option-implied correlation by adjusting the historical correlation and further calculate option-implied beta.

$$\beta_{i,t}^{BV} = \frac{\sigma_{i,t}^{Q} \sum_{j=1}^{N} w_j \sigma_{j,t}^{Q} \rho_{ij,t}^{Q}}{\left(\sigma_{m,t}^{Q}\right)^2} \tag{2.32}$$

where

$$\rho_{ij,t}^{Q} = \rho_{ij,t}^{P} - \alpha_t \left(1 - \rho_{ij,t}^{P}\right) \tag{2.33}$$

$$\alpha_t = -\frac{\left(\sigma_{m,t}^{Q}\right)^2 - \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \sigma_{i,t}^{Q} \sigma_{j,t}^{Q} \rho_{ij,t}^{P}}{\sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \sigma_{i,t}^{Q} \sigma_{j,t}^{Q} \left(1 - \rho_{ij,t}^{P}\right)} \tag{2.34}$$

Furthermore, Buss and Vilkov (2012) provide comprehensive analysis about the performance of historical and option-implied betas (i.e., $\beta_{i,t}^{FGK}$, $\beta_{i,t}^{CCJV}$ and $\beta_{i,t}^{BV}$) by using data for constituents of the S&P500 index. The empirical results show that, compared to historical beta, two option-implied betas, $\beta_{i,t}^{CCJV}$ and $\beta_{i,t}^{BV}$, perform better in explaining risk-return relation. Option-implied beta constructed in their study (i.e., $\beta_{i,t}^{BV}$) performs the best in predicting the realized beta.

Thus, empirical studies provide supportive evidence that, compared to historical information, option-implied information incorporates more useful information about future market conditions.

Based on studies reviewed in this chapter, this thesis uses pricing factors other than market beta in asset pricing models. In addition, this thesis investigates how to extract useful information from options and other derivatives, and how to use the forward-looking information to explain or predict asset returns.

# Chapter 3 Option-Implied Volatility Measures and Stock Return Predictability

## 3.1 Introduction

Options are forward-looking instruments and option-implied measures contain valuable information regarding investors' expectations about return process of the underlying asset. Option-implied volatility has received particular attention due to the time-varying property of volatility and volatility being a widely used parameter in asset pricing. It is now well-documented that implied volatility extracted from option prices is a good forecast of future volatility.[12] Recent studies (Bali and Hovakimian, 2009; Cremers and Weinbaum, 2010; Doran and Krieger, 2010; Xing, Zhang and Zhao, 2010; etc.) propose different option-implied volatility measures and also examine the predictive ability of these volatility measures in the cross-section of stock returns. However, there is no clear understanding of i) whether different option-implied volatility measures capture the same or different information contained in the whole volatility curve, ii) which measures are important for investors in predicting stock returns, and iii) which would outperform as predictive variables in a dynamically managed portfolio. By comparing the predictive ability of alternative option-implied volatility measures proposed in the literature, this chapter highlights whether the proposed option-implied volatility measures are fundamentally different from each other in the context of return predictability over different investment

[12] See Christensen and Prabhala (1998), Blair, Poon and Taylor (2001), Szakmary, Ors, Kim and Davidson (2003), Pong, Shackleton, Taylor and Xu (2004), Poon and Granger (2005), Kang, Kim and Yoon (2010), Taylor, Yadav and Zhang (2010), Yu, Lui and Wang (2010), and Muzzioli (2011) for studies on the predictive ability of option-implied volatility on future volatility.

horizons.[13] If these measures perform differently in predicting asset returns, this chapter sheds light on which measures are better at predicting one-month ahead equity returns and whether their predictive abilities differ by investment horizon.

For tests of predictive ability, this chapter first forms quintile portfolios by sorting stocks with respect to six option-implied volatility measures (i.e., the call-put implied volatility spread ($CPIV$), the implied volatility skew ($IVSKEW$), the "above-minus-below" ($AMB$), the "out-minus-at" of calls ($COMA$), the "out-minus-at" of puts ($POMA$), and the realized-implied volatility spread ($RVIV$)). Then, this chapter constructs long-short portfolios by taking a long position in portfolios that contain stocks with the highest implied volatility measures and a short position in portfolios that contain stocks with the lowest implied volatility measures. Such long-short portfolios enable investors to construct a zero-cost arbitrage strategy. The long-short portfolio will have significantly non-zero average return if there is a statistically significant relationship between stock returns and corresponding option-implied volatility measure. However, portfolio level analysis does not control for effects of other option-implied volatility measures and firm-specific effects simultaneously. Consequently, this chapter performs firm-level cross-sectional regressions to assess the predictive power of all six option-implied volatility measures.

This chapter contributes to the literature in several aspects. Firstly, this chapter compares the predictive ability of six different option-implied volatility measures. To the best of my knowledge, this is the most comprehensive study that compares the predictive power of option-implied volatility measures proposed in the literature. Secondly, this chapter tests the predictive power of different option-implied volatility

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[13] The option-implied volatility measures used in this chapter are: the call-put implied volatility spread ($CPIV$), the implied volatility skew ($IVSKEW$), the "above-minus-below" ($AMB$), the "out-minus-at" of calls ($COMA$), the "out-minus-at" of puts ($POMA$), and the realized-implied volatility spread ($RVIV$). Details about these measures can be found in section 3.4.

measures on stock returns over various horizons. This helps investors better understand the informational content captured by different option-implied volatility measures. Finally, the sample period, from 1996 until 2011, is longer than those used in previous studies. This enables us to analyze whether the predictive power of option-implied volatility measures documented previously is still significant for recent history.

This chapter is organized as follows. Section 3.2 reviews relevant literature. Sections 3.3 and 3.4 discuss data and option-implied volatility measures, respectively. Details about methodology used in this chapter are presented in Section 3.5. Section 3.6 examines the relationship between option-implied volatility measures and one-month ahead stock returns through portfolio level analysis. Section 3.7 presents results for firm-level cross-sectional regressions for one-month holding period. Results for cross-sectional regressions for longer horizons (i.e., two months and three months) are discussed in Section 3.8. Section 3.9 concludes this chapter.

## 3.2 Related Literature

The relationship between option-implied volatility and stock return predictability is of recent interest due to the outperformance of option-implied volatility in predicting future volatility. A vast number of empirical studies use option-implied volatility measures to explain asset returns.[14]

Ang, Hodrick, Xing and Zhang (2006) investigate the relationship between the innovation in aggregate volatility and individual stock returns. In their empirical work,

[14] For example, Arisoy (2014) uses returns on crash-neutral ATM straddles of the S&P500 index as a proxy for the volatility risk, and returns on OTM puts of the S&P500 index as a proxy for the jump risk, and finds that the sensitivity of stock returns to innovations in aggregate volatility and market jump risk can explain the differences between returns on small and value stocks and returns on big and growth stocks. Doran, Peterson and Tarrant (2007) find supportive evidence that there is predictive information content within the volatility skew for short-term horizon.

in addition to market excess return, the daily change in VXO index is used as the other explanatory variable. The results show that stocks with higher sensitivity to innovations in aggregate volatility have lower average returns. Thus, the sensitivity to option-implied aggregate volatility is a significant explanatory factor in asset pricing, and it is negatively correlated with asset returns.

Rather than using option-implied aggregate volatility, An, Ang, Bali and Cakici (2014) focus on the implied volatility of individual options and they document the significant predictive power of implied volatility in predicting the cross-section of stock returns. More specifically, large increases in call (put) implied volatilities are followed by increases (decreases) in one-month ahead stock returns. This indicates that call and put options capture different information about future market conditions.

In order to better understand the information captured by different kinds of options, some studies propose different ways to construct factors by using information captured by different options (i.e., call or put options; out-of-the-money, at-the-money, or in-the-money options).

Bali and Hovakimian (2009) investigate whether realized and implied volatilities can explain the cross-section of monthly stock returns. They construct two volatility measures. The first measure is the difference between at-the-money call implied volatility and at-the-money put implied volatility (i.e., call-put implied volatility spread), and the second measure is the difference between historical realized volatility and at-the-money implied volatility (i.e., realized-implied volatility spread). Empirical results provide evidence that call-put implied volatility spread is positively related to monthly stock returns, while realized-implied volatility spread is negatively related to monthly stock returns.

Cremers and Weinbaum (2010) focus on the predictive power of call-put implied volatility spread at a different time horizon (i.e., one-week). The non-zero call-put implied volatility spread can reflect the deviation from put-call parity. Results provide evidence that the call-put implied volatility spread predicts weekly returns to a greater extent for firms facing a more asymmetric informational environment.

On the other hand, it has been widely documented that option-implied volatility varies across different moneyness levels, also known as the "volatility smile" or "volatility smirk". So, in addition to at-the-money options, out-of-the-money and in-the-money options also capture useful information about future market conditions.

Xing, Zhang and Zhao (2010) look at the implied volatility skew, which is the difference between out-of-the-money put and at-the-money call implied volatilities. They show that a coefficient on the implied volatility skew in firm-level cross-sectional regressions is significantly negative. Furthermore, they find that the predictive power of implied volatility skew persists for at least six months.

Baltussen, Grient, Groot, Hennink and Zhou (2012) include four different implied volatility measures in their study, out-of-the-money volatility skew (the same as the implied volatility skew in Xing, Zhang and Zhao, 2010), realized-implied volatility spread, at-the-money volatility skew (i.e., the difference between the at-the-money put and call implied volatilities), and weekly changes in at-the-money volatility skew. By analysing weekly stock returns, they find negative relationships between weekly returns and all four option-implied measures.

In addition to two common factors used in previous studies (i.e., at-the-money call-put implied volatility spread and out-of-the-money implied volatility skew), Doran and Krieger (2010) construct three other measures based on implied volatilities extracted from call and put options. These three measures are "above-minus-below", “out-minus-at” of calls, and “out-minus-at” of puts. “Above-minus-below” is the difference between the mean implied volatility of in-the-money puts and out-of-the-money calls and the mean implied volatility of in-the-money calls and out-of-the-money puts. “Out-minus-at” of calls (puts) is the difference between the mean implied volatility of out-of-the-money calls (puts) and the mean implied volatility of at-the-money calls (puts). Results in their study show that the difference between at-the-money call and put implied volatilities and the difference between out-of-the-money and at-the-money put implied volatilities both capture relevant information about future equity returns.

From these studies, it is not clear whether separately constructed option-implied volatility measures capture fundamentally different information in the context of return predictability. In the presence of others, some of these volatility measures may be redundant in predicting stock returns. Building on the literature, this chapter compares the ability of various option-implied volatility measures to predict one- to three-month ahead returns. Addressing questions of which option-implied volatility measure(s) outperforms alternative measures in predicting stock returns and whether their predictive abilities persist over different investment horizons is crucial as it has implications for portfolio managers and market participants. These groups can adjust their trading strategies and form portfolios based on option-implied volatility measures that have the strongest predictive power and thus earn returns.

## 3.3 Data

Data used in this chapter come from several different sources. Financial statement data are downloaded from Compustat. Monthly and daily stock return data are from CRSP. Option-implied volatility data are from OptionMetrics.[15] The factors in Fama-French (1993) three-factor model (i.e., $MKT$, $SMB$, and $HML$) are obtained from Kenneth French's online data library.[16]

Following Bali and Hovakimian (2009), only stock data for ordinary common shares (CRSP share codes 10 and 11) are retained. Furthermore, closed-end funds and REITs (SIC codes 6720-6730 and 6798) are excluded. Based on monthly returns, compounded returns for two-month and three-month holding periods are calculated.

In terms of option data, this chapter focuses on the last trading day of each calendar month. This chapter only retains stock options with day-to-maturity greater than 30 but less than 91 days. After deleting options with zero open interest or zero best bid prices and those with missing implied volatility, this chapter further excludes options whose bid-ask spread exceeds 50% of the average of bid and ask prices. To distinguish at-the-money options, this chapter also follows criteria in Bali and Hovakimian (2009). That is, if the absolute value of the natural logarithm of the ratio of the stock price to the exercise price is smaller than 0.1, an option is denoted at-the-money. This chapter denotes options with the natural logarithm of the ratio of the stock price to the exercise price smaller than -0.1 as out-of-the-money call (in-the-money put) options. Options with the natural logarithm of the ratio of the stock price to the exercise price larger than 0.1 are denoted in-the-money call (out-of-the-money put) options. Then, this chapter calculates average implied volatilities across all eligible options and matches the results to stock returns for the following one-month, two-month and three-month periods.[17] Within OptionMetrics,

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[15] Option-implied volatilities are calculated by setting the theoretical option price equal to the market price, which is the midpoint of the option's best closing bid and best closing offer prices.

[16] Available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[17] $|\ln(S/K)| < 0.1$ can be translated to $0.9048 < S/K < 1.1052$. The corresponding range in Doran and Krieger (2010) is [0.95, 1.05]. So moneyness criteria used in Bali and Hovakimian (2009) can expand

data are available from January 1996, so this chapter examines stock returns from February, 1996 to December, 2011 (191 months), but for a sample of 189 months.[18]

## 3.4 Option-Implied Volatility Measures and Firm-Specific Factors

### 3.4.1 Call-Put Implied Volatility Spread

Drawing upon the method documented in Bali and Hovakimian (2009), this chapter constructs the following $CPIV$ :

$$CPIV = IV_{ATM,call} - IV_{ATM,put} \tag{3.1}$$

where $CPIV$ is the call-put implied volatility spread, $IV_{ATM,call}$ is the average of implied volatilities extracted from all at-the-money call options, and $IV_{ATM,put}$ is the average of implied volatilities extracted from all at-the-money put options available on the last trading day of each calendar month.

According to the put-call parity, implied volatilities of call and put options with the same strike price and time-to-maturity should be equal. Thus, $CPIV$ should be zero theoretically. However, a non-zero $CPIV$ does not necessarily indicate the existence of an arbitrage opportunity due to transaction costs, constraints on short-sale, or informed trading. For example, if insider traders get information about decreases in underlying asset price in the near future, they will choose to buy put options and sell call options. In this case, prices of put options will increase while prices of call

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the sample for at-the-money options. Unlike criteria used in Doran and Krieger (2010) for determining the out-of-the money and in-the-money options, criteria used in Bali and Hovakimian (2009) enable to include deep out-of-the money and in-the-money options in the sample. If many deep out-of-the money and in-the-money options exist, criteria in Bali and Hovakimian (2009) can expand the sample for out-of-the-money and in-the-money options as well. That is why this chapter follows moneyness criteria used in Bali and Hovakimian (2009).

[18] The first observation of the implied volatility is available at the end of January, 1996. So the sample for stock returns starts from February, 1996. The last observation of monthly stock returns is the return in December, 2011. Since this chapter uses three-month holding period return in the analysis, the last observation for three-month return should be the return during the period from October, 2011 to December, 2011. So the sample consists of 189 months.

options will decrease. Volatilities implied in put options will be higher than those implied in call options. A more negative $CPIV$ predicts decreases in underlying asset prices (i.e., more negative returns), and vice versa. Thus, it is expected that $CPIV$ should be positively correlated with asset returns. Cremers and Weinbaum (2010) show that the deviation from put-call parity is more likely when the measure of probability of informed trading of Easley, O'Hara and Srinivas (1998) is high, supporting the view that $CPIV$ contains information about future prices of underlying stocks.

### 3.4.2 Implied Volatility Skew

To construct $IVSKEW$ proposed by Xing, Zhang and Zhao (2010), this chapter calculates the difference between the average of implied volatilities extracted from out-of-the-money put options and the average of implied volatilities extracted from at-the-money call options:

$$IVSKEW = IV_{OTM,put} - IV_{ATM,call} \tag{3.2}$$

where $IVSKEW$ is the implied volatility skew, $IV_{OTM,put}$ is the average of implied volatilities extracted from out-of-the-money put options at the end of each calendar month.

If investors expect that there will be a downward movement in underlying asset price, they will choose to buy out-of-the-money put options. Increases in demand of out-of-the-money put options further lead to increases in prices of these options. In this case, the spread between out-of-the-money put implied volatilities and at-the-money call implied volatilities will become larger. $IVSKEW$ actually reflects investors' concern about future downward movements in underlying asset prices. A higher $IVSKEW$ indicates a higher probability of large negative jumps in underlying asset prices. So, $IVSKEW$ is expected to be negatively related to future returns on underlying assets.

### 3.4.3 Above-Minus-Below

$AMB$ represents the difference between average implied volatility of options whose strike prices are above current underlying price and average implied volatility of options whose strike prices are below current underlying price. Following Doran and Krieger (2010), this chapter defines $AMB$ as:

$$AMB = \frac{\left(IV_{ITM,put} + IV_{OTM,call}\right) - \left(IV_{ITM,call} + IV_{OTM,put}\right)}{2} \tag{3.3}$$

where $IV_{ITM,put}$, $IV_{OTM,call}$, $IV_{ITM,call}$, and $IV_{OTM,put}$ are average implied volatilities of all in-the-money put options, all out-of-the-money call options, all in-the-money call options, and all out-of-the-money put options, respectively.

For equity options, it is common to find a "volatility skew".[19] The variable $AMB$ captures the difference between the average implied volatilities of low-strike-price options and the average implied volatilities of high-strike-price options. Thus, $AMB$ captures how skewed the volatility curve is by investigating both tails of the implied volatility curve. More (less) negative values of $AMB$ are indications of more trading of pessimistic (optimistic) investors and thus lower (higher) future stock returns are expected. This suggests a positive relation between $AMB$ and subsequent stock returns.

[19] The phenomenon that the implied volatility of equity options with low strike prices (such as deep out-of-the-money puts or deep in-the-money calls) is higher than that of equity options with high strike prices (such as deep in-the-money puts or deep out-of-the-money calls) is known as volatility skew (Hull, 2012).

### 3.4.4 Out-Minus-At

Doran and Krieger (2010) also introduce two other measures, which capture the difference between out-of-the-money and at-the-money implied volatilities of call/put options.

$$COMA = IV_{OTM,call} - IV_{ATM,call} \tag{3.4}$$

$$POMA = IV_{OTM,put} - IV_{ATM,put} \tag{3.5}$$

All measures in these two equations have the same meanings as in the previous equations (3.1) – (3.3).

In contrast to $AMB$, $COMA$ ($POMA$) uses only out-of-the-money and at-the-money call (put) options to capture the volatility curve asymmetry. In the option market, it is observed that out-of-the-money and at-the-money call and put options are the most liquid and heavily traded whereas in-the-money options are not traded much (Bates, 2000). It is also reported that bullish traders generally buy out-of-the-money calls while bearish traders buy out-of-the-money puts (Gemmill, 1996). To follow a trading strategy based on the volatility curve asymmetry, it is more convenient to construct a measure from the most traded options for which data availability is not a concern. A positive $COMA$ is associated with bullish expectations, indicating an increase in the trading of optimistic investors. However, a positive $POMA$ reflects the overpricing of out-of-the-money puts relative to at-the-money puts due to increased demand for out-of-the-money puts that avoid negative jump risk.

### 3.4.5 Realized-Implied Volatility Spread

In the spirit of Bali and Hovakimian (2009), this chapter calculates realized volatility ($RV$), which is the annualized standard deviation of daily returns over the previous month, and then constructs a realized-implied volatility spread, $RVIV$ , from it:

$$RVIV = RV - IV_{ATM} \tag{3.6}$$

where $IV_{ATM}$ is the average implied volatility of at-the-money call and put options.

The variable $RVIV$ is related to the volatility risk, which has been widely tested in empirical papers. When testing the volatility risk premium, previous literature focuses on the difference between realized volatility and implied volatility (measured by a variance swap rate). However, rather than using a variance swap rate (which is calculated by using options with different moneyness levels), this chapter focuses on at-the-money implied volatility (a standard deviation measure). Due to the shape of volatility curve, at-the-money implied volatility could be different from the standard deviation calculated from variance swap rate. This chapter uses at-the-money implied volatility instead of variance swap rate for two reasons: (1) at-the-money implied volatility is easy for calculation; (2) Taylor, Yadav and Zhang (2010) show that at-the-money implied volatility generally outperforms model-free implied volatility, and Muzzioli (2011) shows that at-the-money implied volatility is unbiased estimation for future volatility.

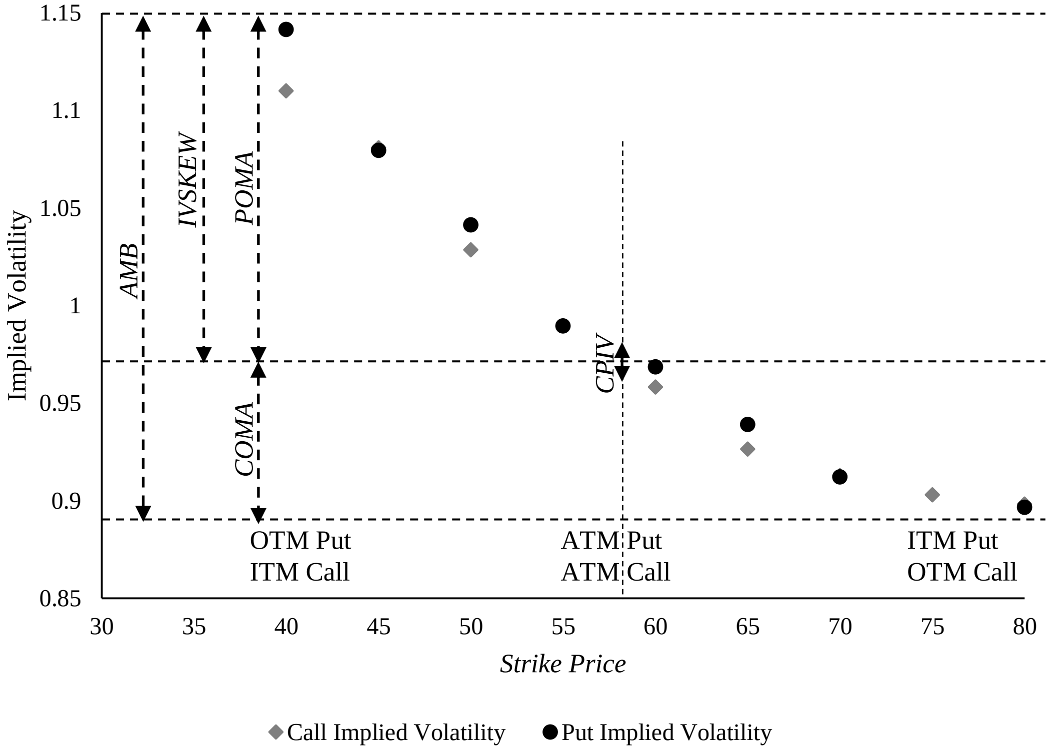
### 3.4.6 Discussion on Option-Implied Volatility Measures

To better show that different option-implied volatility measures (discussed previously) capture different information about the volatility curve, Figure 3.1 plots call and put implied volatilities of Adobe System Inc on December 29, 2000. Options included in this Figure have expiration date of February 17, 2001.

From this Figure, it is clear that $CPIV$ captures the middle of the volatility curve, which reflects small deviations from put-call parity. $IVSKEW$ reflects the left

**Figure 3.1: Implied Volatility Curve**

Notes: This figure plots implied volatility extracted from each call or put option on Adobe Systems Inc on December 29, 2000. To get this figure, only options with expiration date of February 17, 2001 are retained. The closing price for Adobe Systems Inc on December 29, 2000 is 58.1875.



of the put volatility curve and the middle of the call volatility curve. This $AMB$ measure captures the tails of the volatility curve. $COMA$ captures the right side and middle of the volatility curve for call options, while $POMA$ captures the left side and middle of the volatility curve for put options.

From call and put options with the same strike price and time-to-expiration, it is easy to observe deviations from put-call parity. That is, small differences between paired call and put implied volatilities are apparent.

Variables $IVSKEW$, $AMB$, $COMA$ and $POMA$ provide some indications about the shape of the implied volatility curve. Lower $AMB$ and $COMA$ indicate more negatively skewed implied volatility curves. Lower $IVSKEW$ and $POMA$ indicate less negatively skewed implied volatility curves.[20] Thus, it is expected to observe a positive relationship between $AMB$ or $COMA$ and stock returns, but a negative relationship between $IVSKEW$ or $POMA$ and stock returns.

From these points, it is obvious that $CPIV$, $IVSKEW$, $AMB$, $COMA$ and $POMA$ capture different parts of the volatility curve. Therefore, it is interesting to test whether they possess different predictive powers about asset returns.

Variables $CPIV$, $IVSKEW$, $AMB$, $COMA$ and $POMA$ are constructed at firm-level. Taken together, all five option-implied volatility measures capture much of the information contained in the cross-section of implied volatilities (Doran and Krieger, 2010). They are of course interdependent, e.g., $IVSKEW = POMA - CPIV$. So, all these three measures cannot be included in the same model as independent factors. In addition to these measures, this chapter further includes another volatility

[20] Compared to $POMA$, $IVSKEW$ uses at-the-money call options, which are more liquid than at-the-money put options and are seen as the investors' consensus on the firm's uncertainty (Xing, Zhang and Zhao, 2010).

measure used in Bali and Hovakimian (2009), $RVIV$, which is discussed in previous Subsection 3.4.5.

### 3.4.7 Firm-Specific Variables

In order to see whether option-implied volatility measures can predict stock returns after controlling for known firm-specific effects, the empirical analysis also includes several firm-level control variables. To control for the size effect documented by Banz (1981), this chapter uses the natural logarithm of a company's market capitalization (in 1,000,000s) on the last trading day of each month. As suggested by Fama and French (1992), this chapter also uses the book-to-market ratio as another firm-level control variable. Jegadeesh and Titman (1993) document the existence of a momentum effect (i.e., past winners, on average, outperform past losers in short future periods). This chapter uses past one-month return to capture the momentum effect. Stock trading volumes are included as another variable (measured in 100,000,000s of shares traded in the previous month). The market beta reflects the historical systematic risk and is calculated by using daily returns available in the previous month with respect to the CAPM. The bid-ask spread is used to control for liquidity risk. It is defined as the mean daily bid-ask spread over the previous month where the bid-ask spread is the difference between ask and bid prices scaled by the mean of the bid and ask prices. Pan and Poteshman (2006) find strong evidence that option trading volume contains information about future stock prices. Doran, Peterson and Tarrant (2007) incorporate option trading volume when analyzing whether the shape of implied volatility skew can predict the probability of market crash or spike. Thus, controlling for option volume could also be important. This chapter uses the total option trading volume (in 100,000s) in the previous month as another control variable.

## 3.5 Methodology

### 3.5.1 Portfolio Level Analysis

First, this chapter examines the relation between quintile portfolio returns and each option-implied volatility measure. To be more specific, from the data universe, this chapter sorts stocks into quintiles by each volatility measure and then calculates both equally- and value-weighted average returns on each quintile portfolio for the following month. By assuming that investors rebalance these portfolios on the last trading day of each month, this chapter constructs a “5-1” long-short portfolio by taking a long position in the portfolio with the highest volatility measure and a short position in the portfolio with the lowest volatility measure. Thus, such a long-short trading strategy enables investors to construct a zero-cost investment. If stock returns are sensitive to different option-implied volatility measures, quintile portfolios with different option-implied volatility measures are expected to have different returns. So, the long-short portfolio is expected to have a non-zero mean return if there is a significant relationship between stock returns and an option-implied volatility measure.

Having formed portfolios based on different option-implied measure, this chapter then calculates monthly raw returns and Jensen’s alphas with respect to the Fama-French three-factor model for the quintile portfolios as well as the long-short portfolio. Raw returns represent returns which are not adjusted for any risk factors. Jensen’s alphas are the returns on quintile portfolios adjusted for Fama-French three factors, and they are obtained from the following model:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i MKT_t + s_i SMB_t + h_i HML_t + \varepsilon_{i,t} \tag{3.7}$$

where the intercept, $\alpha_i$, is the Jensen's alpha for asset $i$. However, for the "5-1" long-short portfolio, Jensen's alpha calculation is as follows:

$$r_{5-1,t} = \alpha_{5-1} + \beta_{5-1} MKT_t + s_{5-1} SMB_t + h_{5-1} HML_t + \varepsilon_{5-1,t} \qquad (3.8)$$

If raw return or Jensen's alpha on the long-short portfolio is significantly non-zero, it means that investors can earn excess returns from the long-short trading strategy without or with controlling for Fama-French risk factors.

### 3.5.2 Firm-Level Cross-Sectional Regressions

Though portfolio level analysis helps us to understand the relation between quintile portfolio returns and each option-implied volatility measure, such analysis does not allow controlling for effects of other option-implied volatility measures and firm-specific control variables simultaneously. In order to examine the relationship between monthly stock returns and option-implied volatility measures in more detail and to avoid potential problems with the aggregation process at the portfolio level, this chapter performs cross-sectional regressions at firm-level for one-month holding period. First, this chapter estimates coefficients on option-implied volatility measures cross-sectionally for each calendar month. Furthermore, the analysis also includes several firm-level control variables in regression models: size, book-to-market ratio, past one-month return, stock trading volume, historical market beta, bid-ask spread, and option trading volume. The model can be written as follows:

$$r_i = a_i + \sum_j b_j IVmeasure_{ij} + \sum_k c_k controlvar_{ik} + \varepsilon_i \qquad (3.9)$$

where $IVmeasure$ includes $CPIV$, $IVSKEW$, $AMB$, $COMA$, $POMA$, and $RVIV$, and $IVmeasure$ is the $j$ th measure in all six volatility measures for stock $i$. $controlvar$ includes size, book-to-market ratio, past one-month return, stock trading volume, market beta, bid-ask spread, and option trading volume, and $controlvar_{ik}$ is the $k$th variable in all seven control variables for stock $i$.

To be more specific, this chapter runs both univariate and multivariate cross-sectional regressions in later sections. If $CPIV$ is the only explanatory variable in the model, the model can be written as:

$$r_i = a_i + b_i^{CPIV} CPIV_i + \varepsilon_i \tag{3.10}$$

This model is Model *I* in tables 3.3 to 3.6. With respect to multivariate models, to avoid the multicollinearity problem (discussed in detail in later sections), $IVSKEW$ and $AMB$ are excluded from the model. So, the full model including all control variables is written as:

$$\begin{aligned} r_i = {} & a_i + b_i^{CPIV} CPIV_i + b_i^{COMA} COMA_i + b_i^{POMA} POMA_i + b_i^{RVIV} RVIV_i \\ & + c_i^{size} size_i + c_i^{B/M} \, B/M_i + c_i^{mom} mom_i + c_i^{stockvol} stockvol_i + c_i^{beta} beta_i \\ & + c_i^{bid-askspread} bid-askspread_i + c_i^{optionvol} optionvol_i + \varepsilon_i \end{aligned} \tag{3.11}$$

This model refers to Model *XX* in tables 3.4 to 3.6. Details about these two models are presented in sections 3.7 and 3.8.

From monthly regressions, there are 189 estimations for each coefficient. Then, this chapter tests the null hypothesis that the average slope on each option-implied volatility measure is equal to zero in order to shed light on the relationship between stock returns and each option-implied volatility measure.

This chapter also extends the holding period to two months and three months in order to see whether these volatility measures still have significant predictability in stock returns for longer horizons and to clarify which measure can best predict cross-section of stock returns at firm-level for longer horizons. Under the assumption of one-month holding period, dependent variables used in firm-level cross-sectional regressions are one-month ahead stock returns. If the holding period is extended to two or three months, dependent variables in firm-level cross-sectional regressions are two- or three-month ahead compounded returns.

Next section presents results for the quintile portfolio level analysis.

## 3.6 Results for Portfolio Level Analysis

### 3.6.1 Descriptive Results for Option-Implied Volatility Measures

Table 3.1 presents some summary statistics, such as mean, standard deviation, minimum, percentiles, median, and maximum of each volatility measure, sample size available for each measure, as well as pairwise correlations.[21]

Panel A of Table 3.1 reports descriptive statistics for each option-implied volatility measure on the basis of all available observations on the last trading day of each month during the sample period. It is observed that $CPIV$, $AMB$, $COMA$ and $RVIV$ have negative means (-0.0083, -0.0787, -0.0178 and -0.0161, respectively), while $IVSKEW$ and $POMA$ have positive means (0.0669 and 0.0563, respectively). The last column of Panel A shows that, the sample size for $CPIV$ is the largest (i.e., 201,842), while the sample size for $AMB$ is the smallest (i.e., 65,919). $CPIV$ is constructed by using near-the-money call and put options, while $AMB$ is constructed by using deep out-of-the-money and in-the-money call and put options. It is known that the number of available near-the-money options is larger than that of deep out-of-the-money and in-the-money options. So the larger sample size for $CPIV$ and the much smaller sample size for $AMB$ are reasonable.

[21] The numbers for volatility measures presented in Table 3.1 are decimal numbers not percentage numbers. In this table, there are some extreme numbers for minimum and maximum values of each volatility measure. This could be due to the effect of some outliers, since 5th percentile and 95th percentile of each option-implied volatility measure are acceptable. These descriptive statistics in Table 3.1 are comparable to summary statistics presented in Table 1 of Doran and Krieger (2010), who present option-implied volatility measures in percentage. Also, the inclusion of deep in-the-money and out-of-money options in the sample and the wide rage to distinguish at-the-money options could affect the summary statistics.

The minima and maxima of different volatility measures in Panel A are driven by extreme outliers. The maximum of *CPIV* is obtained in July, 2000 and the corresponding firm is Techne Corp. For Techne Corp, at the end of July, 2000, at-the-money call implied volatility was 3.6439, and at-the-money put implied volatility was 0.3700. Such a large difference between at-the-money call and put implied volatilities could be due to the increase in company's share price from $30 to $160 in 10-month period. Prior to this period, the company's chairman, CEO, and president avoided media attention. In late 1999, investors discovered this company and pushed share price up. Positive information about the firm's prospects made the at-the-money call implied volatility high and the at-the-money put implied volatility low, and further drove up the call-put implied volatility spread.

For Sterling Software Inc, in August 1996, the out-of-the-money put implied volatility was 2.4253, the at-the-money call implied volatility was 0.3921, and the at-the-money put implied volatility was 0.3809. The high out-of-the-money put implied volatility of Sterling Software Inc led to the high value of *IVSKEW* and *POMA* (i.e., 2.0332 and 2.0444, respectively). The high out-of-the-money put implied volatility could be driven by negative jumps in underlying asset prices.

For Microcom Inc, in August 1996, the out-of-the-money call implied volatility was 1.0098, the in-the-money put implied volatility was 2.0705, the out-of-the-money put implied volatility was 0.8936, and the in-the-money call implied volatility was 0.8718. These implied volatilities of different kinds of options led to the maximum value of *AMB* in the sample (i.e., 0.6575). As discussed in section 3.4, higher implied volatilities for options with high strike prices and lower implied volatilities for options with lower strike prices could be due to more trading of optimistic investors.

With respect to $COMA$, the maximum value is the observation for Cytec Inds Inc in May 1996. The out-of-the-money call implied volatility was 2.7738 and the at-the-money call implied volatility was 0.2495. The extremely high out-of-the-money call implied volatility was driven by the positive information that the company began to shed businesses and properties, discarding assets that no longer matched its priorities in May 1996.

The maximum of $RVIV$ is the observation for Vanda Pharmaceuticals Inc in May 2009. This extreme value was driven by the announcement of the approval of Fanapt™ by the US Food and Drug Administration (FDA) on May 7th, 2009. The daily return on May 7th, 2009 was extremely high, which drove the realized volatility up sharply, and further increased the value of $RVIV$.

The minima of different volatility measures are also driven by outliers. The minimum value of $CPIV$ is the $CPIV$ for Secure Computing Corp in November, 2004. The corresponding at-the-money call implied volatility was 0.5573, and the at-the-money put implied volatility was 2.9817. The high at-the-money put implied volatility yielded a more negative value of $CPIV$.

The minimum value of $IVSKEW$ is driven by the extremely high value of the at-the-money call implied volatility of Techne Corp in July, 2000 (i.e., 3.6439). Meanwhile, out-of-the-money put implied volatility was 0.5907. As discussed before, the outperformance of the company’s share resulted in such a high at-the-money call implied volatility, and further led to an extremely small value of $IVSKEW$.

Then, for Savient Pharmaceuticals Inc, in November, 2007, the out-of-the-money call implied volatility was 1.3590, the in-the-money put implied volatility was 1.4149, the out-of-the-money put implied volatility was 2.5122, and the in-the-money call implied volatility was 2.3816. Higher values of out-of-the-money put and in-the-money call implied volatilities made the $AMB$ of the company more negative.

In April 1996, for Johns Manville Corp, the out-of-the-money call implied volatility was 1.9033, and the at-the-money call implied volatility was very high, 3.6645. The high at-the-money call implied volatility yielded the minimum value of $COMA$ during the sample period. The company changed its name to Schuller Corporation in 1996. Such a name can be easily recognized by fewer people. So, in 1997, the company changed its name back. The change of name made investors expect better performance of the company's share.

The minimum value of $POMA$ is $POMA$ for Samsonite Corp in May 1998. The out-of-the-money put implied volatility was 2.6787, and the at-the-money put implied volatility was 3.5953. In May 1998, Samsonite Corp announced a recapitalization plan, which positively affected the performance of the company's share, and further affected the implied volatility indicated by options.

For $RVIV$, the minimum value of the realized-implied volatility spread is the $RVIV$ for AtheroGenics Inc in February 2007. In that month, the at-the-money call implied volatility was 3.1533, the at-the-money put implied volatility was 3.8719, whereas the realized volatility was only 0.4900. In February 2007, Investors were waiting for the upcoming trial data on its heart drug in the following month. The future volatility of the underlying asset, which is captured by option data, should be relatively high. This explains why $RVIV$ had a more negative value here.

Panel B reports descriptive statistics of the intersection sample. The intersection sample consists of stocks with all the six option-implied volatility measures available and has 61,331 stock-month observations. The intersection sample in Doran and Krieger (2010) consists of 62076 company months during the period from January

**Table 3.1: Summary Statistics (January, 1996 - September, 2011)**

Notes: Table 3.1 shows the descriptive statistics for the full sample in Panel A. Panel B is for the intersection sample, in which all observations have available data to construct each measure. Panel C presents the pairwise correlation for one-month holding period.

*Panel A: Full Sample*

| | Mean | Std | Min | 5th Pct | 25th Pct | Median | 75th Pct | 95th Pct | Max | Sample Size |
|---|---|---|---|---|---|---|---|---|---|---|
| *CPIV* | -0.0083 | 0.0540 | -2.4244 | -0.0731 | -0.0205 | -0.0055 | 0.0079 | 0.0499 | 3.2740 | 201842 |
| *IVSKEW* | 0.0669 | 0.0709 | -3.0532 | -0.0090 | 0.0317 | 0.0564 | 0.0887 | 0.1755 | 2.0332 | 113466 |
| *AMB* | -0.0787 | 0.0947 | -1.0599 | -0.2381 | -0.1252 | -0.0699 | -0.0246 | 0.0513 | 0.6575 | 65919 |
| *COMA* | -0.0178 | 0.0493 | -1.7611 | -0.0771 | -0.0367 | -0.0185 | -0.0008 | 0.0424 | 2.5243 | 111839 |
| *POMA* | 0.0563 | 0.0537 | -0.8965 | -0.0060 | 0.0259 | 0.0482 | 0.0764 | 0.1464 | 2.0444 | 108146 |
| *RVIV* | -0.0161 | 0.1936 | -3.0225 | -0.2386 | -0.1036 | -0.0379 | 0.0413 | 0.2791 | 21.0411 | 201842 |

*Panel B: Intersection Sample (Sample Size=61331)*

| | Mean | Std | Min | 5th Pct | 25th Pct | Median | 75th Pct | 95th Pct | Max |
|---|---|---|---|---|---|---|---|---|---|
| *CPIV* | -0.0108 | 0.0466 | -1.5332 | -0.0720 | -0.0181 | -0.0054 | 0.0052 | 0.0335 | 0.6255 |
| *IVSKEW* | 0.0724 | 0.0709 | -0.5534 | -0.0074 | 0.0343 | 0.0608 | 0.0965 | 0.1886 | 1.9825 |
| *AMB* | -0.0814 | 0.0940 | -1.0599 | -0.2411 | -0.1276 | -0.0721 | -0.0270 | 0.0467 | 0.6312 |
| *COMA* | -0.0235 | 0.0368 | -0.5469 | -0.0804 | -0.0397 | -0.0219 | -0.0055 | 0.0280 | 0.8764 |
| *POMA* | 0.0616 | 0.0550 | -0.2875 | -0.0047 | 0.0285 | 0.0525 | 0.0834 | 0.1585 | 1.1071 |
| *RVIV* | 0.0003 | 0.2250 | -2.0498 | -0.2486 | -0.1052 | -0.0310 | 0.0694 | 0.3540 | 11.1502 |

(Continued)

| *Panel C: Correlation Table for the Intersection Sample* | | | | | | |
|---|---|---|---|---|---|---|
| | *CPIV* | *IVSKEW* | *AMB* | *COMA* | *POMA* | *RVIV* |
| *IVSKEW* | -0.6189 | | | | | |
| *AMB* | -0.3256 | -0.2492 | | | | |
| *COMA* | -0.2390 | -0.0548 | 0.5786 | | | |
| *POMA* | 0.0808 | 0.7079 | -0.6124 | -0.2887 | | |
| *RVIV* | 0.0393 | -0.0355 | 0.0465 | 0.0851 | -0.0118 | |
| ln(*size*) | 0.1127 | 0.0323 | -0.0978 | -0.0166 | 0.1401 | 0.0673 |
| *B/M Ratio* | 0.0111 | 0.0033 | 0.0410 | 0.0487 | 0.0177 | 0.0054 |
| *Momentum* | -0.0538 | 0.0695 | -0.0653 | -0.0114 | 0.0389 | 0.1145 |
| *Stock Volume* | 0.0490 | 0.0659 | -0.0484 | 0.0210 | 0.1304 | 0.1118 |
| *Market Beta* | -0.0023 | 0.0560 | -0.0664 | -0.0934 | 0.0672 | 0.2907 |
| *Bid-Ask Spread* | -0.1424 | 0.0631 | 0.0837 | 0.0684 | -0.0410 | -0.0373 |
| *Option Volume* | 0.0200 | 0.1217 | -0.0745 | 0.0130 | 0.1751 | 0.0640 |

1996 to September 2008. Thus, the size of our intersection sample is smaller than that of Doran and Krieger (2010). This can be due to different moneyness criteria and more control variables used in this chapter. Averages of $CPIV$, $AMB$, and $COMA$ are still negative (-0.0108, -0.0814, and -0.0235, respectively), while averages of $IVSKEW$, $POMA$, and $RVIV$ are positive (0.0724, 0.0616 and 0.0003, respectively). Signs of means of $CPIV$, $IVSKEW$, $AMB$, $COMA$, and $POMA$ are consistent with the results in Doran and Krieger (2010). The negative average of $CPIV$ shows that put options of individual stocks tend to have higher average implied volatility than that of call options. Individual firms tend to have negative implied volatility smirks as seen by the positive average of $POMA$ and $IVSKEW$ and negative averages of $AMB$ and $COMA$. $IVSKEW$ is the difference between $POMA$ and $CPIV$. So 14.92 percent of the value of the negative smirk stems from the difference between at-the-money implied volatility of puts and at-the-money implied volatility of calls ($CPIV$), and the other 85.08 percent can be due to the difference between out-of-the-money implied volatility and at-the-money implied volatility of puts ($POMA$). Given the positive relationship between stock returns and $CPIV$ and the negative relationship between stock returns and $IVSKEW$ documented in previous studies (Bali and Hovakimian, 2009; Cremers and Weinbaum, 2010; Doran and Krieger, 2010; and Xing, Zhang and Zhao, 2010), it is able to infer whether $POMA$ (which represents the right-hand side of the put implied volatility skew), plays a significant role in predicting stock returns. If there is no empirical evidence in favour of significant predictive ability of $POMA$, the predictive power of $IVSKEW$ should be driven by the difference between the at-the-money put implied volatilities and the at-the-money call implied volatilities (i.e., $CPIV$).

Panel C presents pairwise correlations. There are four high average correlations. The correlation between *CPIV* and *IVSKEW* is -0.6189, the correlation between *IVSKEW* and *POMA* is 0.7079, the correlation between *AMB* and *COMA* is 0.5786, and the correlation between *AMB* and *POMA* is -0.6124. Other pairwise correlations are small, all between -0.35 and 0.35. These high correlations indicate that there might be some information overlap in option-implied volatility measures. Thus, this chapter takes into account potential multicollinearity problem when conducting multivariate firm-level cross-sectional regressions by minimizing these intersections.

### 3.6.2 Option-Implied Volatility Measures and Quintile Portfolios

As mentioned before, this chapter forms quintile portfolios on the basis of each option-implied volatility measure, and further constructs a long-short portfolio in order to examine the relationship between quintile portfolio returns and each volatility measure. This subsection presents results for quintile portfolio level analysis.

In order to form quintile portfolios, all stocks are sorted into quintiles based on each volatility measure on the last trading day of the previous month. Quintile 1 consists of stocks with the lowest option-implied volatility measure and quintile 5 consists of stocks with the highest option-implied volatility measure. Then, equally- and value-weighted returns are calculated for the following one-month holding period. Table 3.2 reports the results for portfolio level analysis. Panel A shows the results for equally-weighted portfolios, while Panel B documents results for value-weighted portfolios. The column “5-1” refers to results for long-short portfolio consisting of a long position in portfolio 5 and a short position in portfolio 1. Rows “Return” include data about raw returns on different portfolios, and rows “Alpha” present Jensen’s alphas with respect to Fama-French three-factor model for different portfolios.

## Table 3.2: Results for Quintile Portfolios Sorted on Option-Implied Volatility Measures

Notes: Quintile portfolios are formed every month by sorting stocks on each option-implied volatility measure at the end of the previous month. Quintile 1 (5) denotes the portfolio of stocks with the lowest (highest) volatility measure. The column "5-1" refers to long-short portfolio with a long position in portfolio 5 and a short position in portfolio 1. Rows "Return" document raw returns on portfolios, and rows "Alpha" show Jensen's alpha with respect to Fama-French three-factor model. The sample consists of all stocks with available data and covers the February 1996 – October 2011 period. *, **, and *** denote for significance at 10%, 5% and 1% levels, respectively.

| Panel A: Equally-Weighted Portfolios | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 5-1 | p-value |
| *CPIV* | *Return* | 0.0012 | 0.0057 | 0.0083 | 0.0086 | 0.0139 | 0.0127*** | (0.0000) |
| | *Alpha* | -0.0085 | -0.0029 | 0.0000 | 0.0002 | 0.0046 | 0.0131*** | (0.0000) |
| *IVSKEW* | *Return* | 0.0100 | 0.0076 | 0.0052 | 0.0045 | -0.0007 | -0.0107*** | (0.0000) |
| | *Alpha* | 0.0011 | -0.0008 | -0.0031 | -0.0044 | -0.0104 | -0.0116*** | (0.0000) |
| *AMB* | *Return* | 0.0039 | 0.0084 | 0.0070 | 0.0046 | 0.0009 | -0.0030 | (0.2803) |
| | *Alpha* | -0.0050 | -0.0009 | -0.0021 | -0.0046 | -0.0087 | -0.0036 | (0.1933) |
| *COMA* | *Return* | 0.0052 | 0.0094 | 0.0092 | 0.0066 | 0.0060 | 0.0008 | (0.7456) |
| | *Alpha* | -0.0047 | 0.0004 | 0.0002 | -0.0022 | -0.0034 | 0.0014 | (0.5660) |
| *POMA* | *Return* | 0.0034 | 0.0090 | 0.0068 | 0.0061 | 0.0037 | 0.0003 | (0.9077) |
| | *Alpha* | -0.0056 | 0.0007 | -0.0018 | -0.0024 | -0.0057 | -0.0001 | (0.9806) |
| *RVIV* | *Return* | 0.0095 | 0.0095 | 0.0067 | 0.0072 | 0.0047 | -0.0048* | (0.0986) |
| | *Alpha* | 0.0002 | 0.0010 | -0.0014 | -0.0014 | -0.0051 | -0.0053* | (0.0536) |
| Panel B: Value-Weighted Portfolios | | | | | | | | |
| | | 1 | 2 | 3 | 4 | 5 | 5-1 | p-value |
| *CPIV* | *Return* | 0.0004 | 0.0037 | 0.0077 | 0.0079 | 0.0118 | 0.0114*** | (0.0000) |
| | *Alpha* | -0.0072 | -0.0028 | 0.0018 | 0.0018 | 0.0053 | 0.0125*** | (0.0000) |
| *IVSKEW* | *Return* | 0.0115 | 0.0107 | 0.0061 | 0.0039 | 0.0039 | -0.0076*** | (0.0050) |
| | *Alpha* | 0.0052 | 0.0043 | 0.0002 | -0.0023 | -0.0026 | -0.0078*** | (0.0037) |
| *AMB* | *Return* | 0.0067 | 0.0059 | 0.0056 | 0.0068 | 0.0010 | -0.0057 | (0.1309) |
| | *Alpha* | 0.0006 | -0.0006 | -0.0011 | 0.0003 | -0.0065 | -0.0071* | (0.0535) |
| *COMA* | *Return* | 0.0053 | 0.0100 | 0.0066 | 0.0078 | 0.0023 | -0.0029 | (0.4167) |
| | *Alpha* | -0.0021 | 0.0035 | 0.0000 | 0.0019 | -0.0039 | -0.0018 | (0.5824) |
| *POMA* | *Return* | 0.0052 | 0.0096 | 0.0062 | 0.0070 | 0.0042 | -0.0009 | (0.7394) |
| | *Alpha* | -0.0020 | 0.0031 | 0.0000 | 0.0009 | -0.0018 | 0.0002 | (0.9271) |
| *RVIV* | *Return* | 0.0096 | 0.0096 | 0.0065 | 0.0053 | 0.0031 | -0.0064 | (0.1120) |
| | *Alpha* | 0.0022 | 0.0031 | 0.0009 | -0.0008 | -0.0040 | -0.0062 | (0.1184) |

This subsection starts with analyzing the effect of $CPIV$ on stock returns. In the first two rows in Panel A of Table 3.2, where the results for equally-weighted returns are presented, it can be seen that the equally-weighted average monthly return increases monotonically from quintile portfolio 1 (0.12%) to quintile portfolio 5 (1.39%). Investors can earn positive excess returns on the long-short portfolio no matter whether Fama-French three factors are controlled for or not. The long-short portfolio generates an average raw return of 1.27% per month with a p-value of $10^{-4}$ and a Jensen's alpha with respect to Fama-French three-factor model of 1.31% with a p-value of $10^{-4}$. The first two rows in Panel B show that, for one-month holding period, the same pattern can be observed. The value-weighted average monthly return increases monotonically from quintile portfolio 1 (0.04%) to quintile portfolio 5 (1.18%). The average return on "5-1" long-short portfolio is 1.14% per month and it is significantly different from zero with a p-value of $10^{-4}$. After controlling for Fama-French three factors, the average risk-adjusted return on "5-1" long-short portfolio increases to 1.25% per month, and it is significantly different from zero with a p-value of $10^{-4}$. Thus, the trading strategy of holding a long position in the portfolio with the highest $CPIV$ and a short position in the portfolio with the lowest $CPIV$ generates significantly positive returns. So portfolio level analysis on $CPIV$ confirms a positive relation between quintile portfolio returns and $CPIV$. Results from equally-weighted and value-weighted average returns for one-month holding period in Table 3.2 are compatible with results in Bali and Hovakimian (2009), who document that the equally-weighted (value-weighted) raw returns on the long-short portfolio are 1.425% (1.045%) with a t-statistic of 7.9 (4.2) and the equally-weighted (value-weighted) Jensen's alpha on the long-short portfolio is 1.486% (1.140%) with a t-statistic of 8.6 (4.5).

Next, this subsection forms quintile portfolios by sorting stocks on $IVSKEW$ at the end of the each month. The third and fourth rows in Panel A of Table 3.2 present results for equally-weighted portfolios. Equally-weighted returns on quintile portfolios decrease monotonically, and the average return on quintile portfolio 5 (-0.07%) is significantly smaller than the average return on quintile portfolio 1 (1.00%). More specifically, the average monthly return on the long-short portfolio is significantly negative (-1.07% with a p-value of $10^{-4}$). After controlling for three Fama-French factors, the average risk-adjusted return on the long-short portfolio is still significantly negative (-1.16% with a p-value of $10^{-4}$). Similar results are found for value-weighted portfolios (the third and fourth rows in Panel B of Table 3.2). The average monthly return and the Jensen's alpha on the value-weighted long-short portfolio are both significantly negative (-0.76% with a p-value of 0.0050, and -0.78% with a p-value of 0.0037, respectively). So, the significantly negative average return on the long-short portfolio suggests that quintile portfolio returns are negatively related to $IVSKEW$. The negative relationship is significant even after controlling for market excess returns ($MKT$), size ($SMB$) and book-to-market ratio ($HML$).

Next, this subsection sorts stocks on three measures documented in Doran and Krieger (2010) and form quintile portfolios accordingly. First, the relationship between quintile portfolio returns and $AMB$ is examined. Equally-weighted and value-weighted average returns on quintile portfolios are presented in the fifth and sixth rows in Panel A and Panel B of Table 3.2, respectively. Equally-weighted and value-weighted returns yield very similar results. Average returns on quintile portfolio 1 to quintile portfolio 4 are higher than the average return on quintile portfolio 5 in fifth and sixth rows in both Panel A and Panel B of Table 3.2. The average monthly return on the "5-1" long-short portfolio is not significantly different from zero (-0.30%

with a p-value of 0.2803 for the equally-weighted return and -0.57% with a p-value of 0.1309 for the value-weighted return). Controlling for Fama-French three factors exacerbates the equally-weighted 5-1 spread to -0.36% with a p-value of 0.1933 and the value-weighted 5-1 spread to -0.71% with a p-value of 0.0535. That is, the Jensen's alpha for the value-weighted long-short portfolio is marginally significant at a 10% significance level. Holding a long position in the value-weighted quintile portfolio with the highest $AMB$ and a short position in the value-weighted quintile portfolio with the lowest $AMB$ generates marginally significant risk-adjusted returns with respect to the Fama-French three-factor model. For Doran and Krieger's (2010) long-short portfolio constructed on $AMB$, the Jensen's alpha with respect to Fama-French three-factor model is -0.77% (statistically significant at a 1% significance level). In order to check for consistency, a subsample from January 1996 to September 2008 is used to calculate the Jensen's alpha on the long-short portfolio. Results show that the Jensen's alpha is -0.92% with a p-value of 0.0364. Thus, subsample results are comparable to results in Doran and Krieger (2010). This indicates that the predictability of $AMB$ becomes weaker after extending sample period to include more recent data.

Then, Table 3.2 presents results about the relationship between quintile portfolio returns and $COMA$. The seventh and eighth rows in Panel A show that the raw average one-month return on the equally-weighted "5-1" long-short portfolio is negative but not significantly different from zero (0.08% with a p-value of 0.7456). Controlling for Fama-French three factors increases Jensen's alpha to 0.14% with a p-value of 0.5660. So, returns on extreme portfolios are not significantly different from each other. Using value-weighted returns does not change results qualitatively (raw monthly return of -0.29% with a p-value of 0.4167 and Jensen's alpha of -0.18%

with a p-value of 0.5824, respectively). Results indicate no evidence that the return on the value-weighted long-short portfolio is significantly different from zero. Thus, there is no evidence in favour of a significant relationship between quintile portfolio returns and $COMA$.

This subsection also forms quintile portfolios by sorting stocks on $POMA$. As evident in the ninth and tenth rows in Panel A and B of Table 3.2, regardless of the weighting scheme, the average one-month return on the long-short portfolio is not significantly different from zero. After controlling for Fama-French three factors, Jensen's alpha is still not significant (-0.01% with a p-value of 0.9806 for the equally-weighted long-short portfolio, and 0.02% with a p-value of 0.9271 for the value-weighted long-short portfolio). Thus, empirical results indicate that investing in a long-short portfolio based on $POMA$ cannot produce significantly non-zero returns.

Finally, quintile portfolios are formed based on $RVIV$. The information about these quintile portfolios can be found in the last two rows in Panel A and Panel B of Table 3.2. When using the equally-weighted scheme, the raw return on the long-short portfolio is -0.48% per month with a p-value of 0.0986, and the Jensen's alpha on the long-short portfolio is -0.53% with a p-value of 0.0536 (marginally significant). So, after controlling for Fama-French three factors, investors can earn marginally significant positive returns if they hold a short position in portfolio 5 and a long position in portfolio 1 constructed based on $RVIV$. For value-weighted portfolios, even though the average monthly return decreases from quintile portfolio 1 to quintile portfolio 5, the average monthly return on the long-short portfolio is insignificantly negative (-0.64% with a p-value of 0.1120). Meanwhile, the Jensen's alpha on the "5-1" long-short portfolio is also insignificantly negative (-0.62% with a p-value of

0.1184). Thus, results about risk-adjusted returns in this subsection are comparable to results in Bali and Hovakimian (2009). Bali and Hovakimian (2009) document that Jensen's alpha for the long-short portfolio constructed on $RVIV$ is -0.587% with a significant t-statistic of -2.5 when using the equally-weighted scheme, and -0.642% with a significant t-statistic of -2.2 when using the value-weighted scheme.

### 3.6.3 Discussion

To summarize, results in Table 3.2 confirm the existence of a positive relation between quintile portfolio returns and $CPIV$, and a negative relation between quintile portfolio returns and $IVSKEW$. Also, there is weak evidence about a negative relationship between portfolio returns and $AMB$ or $RVIV$. These findings are consistent with the findings of previous studies. However, results for $AMB$ are different from our expectations. This indicates that in-the-money options may not capture information as expected due to infrequent trading activities. The results suggest that some of the option-implied volatility measures are helpful in explaining future returns. However, there is no significant relation between quintile portfolio returns and $COMA$ or $POMA$. This can be due to different moneyness criteria used in this chapter. The range of $S/K$ for determining at-the-money options in this chapter is the same as that used in Bali and Hovakimian (2009) but it is wider than that used in Doran and Krieger (2010). So, more options are recognized as at-the-money options in this chapter as compared to Doran and Krieger (2010).

Although portfolio level analysis helps to determine potential candidates among several option-implied volatility measures in predicting stock returns, it does not allow us to control for firm-specific effects. There may be important size or book-to-market ratio differences between extreme portfolios. The relationship between portfolio returns and volatility measures could be affected by size or book-to-market ratio. For example, if portfolios are constructed on $IVSKEW$, the firm size increases from quintile portfolio 1 to quintile portfolio 4, while firm size of quintile portfolio 5 is a bit smaller than that of quintile portfolio 4. Thus, the negative relationship between quintile portfolio returns and $IVSKEW$ can be driven by the size effect. In addition, for portfolios constructed on $AMB$, the firm size decreases from quintile portfolio 1 to quintile portfolio 5, and the book-to-market ratio is highest for quintile portfolio 5 and lowest for quintile portfolio 2. There are size differences between quintiles, but the extreme portfolios have similar book-to-market ratios. These results suggest that size, but not book-to-market ratio, may drive the relation between future returns and $AMB$. For portfolios constructed on $RVIV$, size exhibits a U shape across quintiles. The book-to-market ratio decreases monotonically from quintile portfolio 1 to quintile portfolio 5. These results suggest that book-to-market ratio, not size, may drive the relation between future returns and $RVIV$.

The analysis for size or book-to-market ratio suggests that these two factors may drive some of observed relationships. Some other firm-specific effects may also play a role in explaining stock returns. To check, this chapter performs firm-level cross-sectional regressions in the following section.

## 3.7 Firm-Level Cross-Sectional Regressions

As mentioned above, portfolio level analysis does not allow controlling for firm-specific variables (i.e., size, book-to-market ratio, momentum, stock trading volume, market beta, bid-ask spread, and option trading volume) simultaneously. However, firm-level cross-sectional regressions enable us to cope with this issue; these regressions allow including all option-implied volatility measures in the same model, and further allow comparing the predictive power of different measures.

This section first performs univariate cross-sectional regressions at firm-level by using the full sample. The univariate cross-sectional regressions include each of several option-implied volatility measures, such as $CPIV$, $IVSKEW$, $AMB$, $COMA$, $POMA$, and $RVIV$. Then, this section conducts univariate cross-sectional regressions at firm-level by using the intersection sample to examine whether findings obtained by using the full sample still hold. Moreover, several option-implied volatility measures are included in the same model (i.e., multivariate regressions) in order to compare the predictive power of each measure. Such an analysis sheds light on which measure is the most useful in predicting individual stock returns.

Findings in this section can help us to understand which option-implied volatility measure has the strongest predictive power when competing with other measures.

### 3.7.1 Cross-Sectional Regressions for Full Sample over One-Month Holding Period

First, this subsection uses firm-level cross-sectional regressions to shed light on the relationship between one-month ahead stock returns and each volatility measure using the full sample. The results can be found in Table 3.3.

Model *I* and Model *II* in Table 3.3 present firm-level cross-sectional regression results for $CPIV$. These two models show that $CPIV$ has significantly positive average slopes (around 0.10 with extremely small p-values) no matter whether models control for size, book-to-market ratio, momentum, volume, market beta and bid-ask spread or not. These results are consistent with the findings in Bali and Hovakimian (2009). So, empirical results confirm a significant and positive relation between stock returns and $CPIV$. Also, in Panel A of Table 3.1, the average of $CPIV$ is equal to -0.83%. Thus, the coefficient of 0.1084 (0.0935 after controlling for firm-specific effects) on $CPIV$ translates to a future monthly return of -9.00 (-7.76) bps for the average value of $CPIV$.

**Table 3.3: Firm-Level Cross-Sectional Regression Results by Using the Full Sample**

Notes: Table 3.3 presents the firm-level cross-sectional regression results for the full sample for the period from Feb 1996 to Oct 2011. P-values are reported in parentheses. *, **, and *** denote for significance at 10%, 5% and 1% levels, respectively.

| | *I* | *II* | *III* | *IV* | *V* | *VI* | *VII* | *VIII* | *IX* | *X* | *XI* | *XII* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Intercept* | 0.0085* | 0.0131 | 0.0100* | 0.0077 | 0.0050 | 0.0036 | 0.0076 | 0.0075 | 0.0069 | 0.0077 | 0.0083* | 0.0123 |
| | (0.0875) | (0.2567) | (0.0547) | (0.5369) | (0.4117) | (0.7887) | (0.1681) | (0.5556) | (0.1824) | (0.5495) | (0.0834) | (0.2817) |
| *CPIV* | 0.1084*** | 0.0935*** | | | | | | | | | | |
| | (0.0000) | (0.0000) | | | | | | | | | | |
| *IVSKEW* | | | -0.0750*** | -0.0626*** | | | | | | | | |
| | | | (0.0000) | (0.0000) | | | | | | | | |
| *AMB* | | | | | -0.0038 | 0.0024 | | | | | | |
| | | | | | (0.7659) | (0.8401) | | | | | | |
| *COMA* | | | | | | | 0.0239 | 0.0392 | | | | |
| | | | | | | | (0.3819) | (0.1011) | | | | |
| *POMA* | | | | | | | | | -0.0243 | -0.0208 | | |
| | | | | | | | | | (0.1556) | (0.1686) | | |
| *RVIV* | | | | | | | | | | | -0.0052 | -0.0028 |
| | | | | | | | | | | | (0.2839) | (0.4759) |
| ln(*size*) | | -0.0006 | | 0.0003 | | 0.0009 | | 0.0004 | | 0.0002 | | -0.0006 |
| | | (0.6279) | | (0.7682) | | (0.4972) | | (0.7594) | | (0.8859) | | (0.6196) |
| *B/M Ratio* | | 0.0024 | | 0.0025 | | 0.0020 | | 0.0025 | | 0.0021 | | 0.0025 |
| | | (0.2427) | | (0.4087) | | (0.5399) | | (0.3262) | | (0.5081) | | (0.2131) |
| *Momentum* | | -0.0079 | | -0.0043 | | -0.0009 | | -0.0068 | | -0.0040 | | -0.0081 |
| | | (0.3080) | | (0.6122) | | (0.9208) | | (0.4142) | | (0.6301) | | (0.2951) |
| *Stock Volume* | | 0.0000 | | -0.0022 | | -0.0044 | | -0.0019 | | -0.0025 | | 0.0016 |
| | | (0.9866) | | (0.3764) | | (0.1110) | | (0.4998) | | (0.3044) | | (0.5614) |
| *Market Beta* | | 0.0007 | | 0.0015 | | 0.0012 | | 0.0009 | | 0.0015 | | 0.0009 |
| | | (0.7383) | | (0.4944) | | (0.6020) | | (0.6730) | | (0.5099) | | (0.7006) |
| *Bid-Ask Spread* | | -1.1091** | | -1.5720** | | -2.6772*** | | -2.3906*** | | -2.2973*** | | -1.3993*** |
| | | (0.0221) | | (0.0417) | | (0.0088) | | (0.0070) | | (0.0069) | | (0.0057) |
| *Option Volume* | | 0.0000 | | 0.0031 | | 0.0008 | | -0.0016 | | 0.0023 | | -0.0018 |
| | | (0.9842) | | (0.1718) | | (0.7813) | | (0.5285) | | (0.3085) | | (0.4352) |

Then, this subsection analyzes the relation between cross-section of stock returns and $IVSKEW$ at firm level (Model *III* and Model *IV*). The average slope on $IVSKEW$ is significantly negative (-0.0750 with a p-value of $10^{-4}$ excluding control variables, and -0.0626 with a p-value of $10^{-4}$ including control variables, respectively). Our findings about $IVSKEW$ are consistent with previous studies (e.g., Xing, Zhang and Zhao, 2010; and Doran and Krieger, 2010). Results are economically significant as well. Without controlling for firm-specific effects, a coefficient of -0.0750 on $IVSKEW$ indicates that, if a stock has an average $IVSKEW$ of 6.69 percent, its future monthly return should be 50.18 bps lower. After including control variables in the model, a coefficient of -0.0626 on $IVSKEW$ leads to a future monthly return of -41.88 bps for the average value of $IVSKEW$.

Next, three measures introduced by Doran and Krieger (2010), $AMB$, $COMA$, and $POMA$ (Models *V* to *X*), are investigated. There is an insignificant average slope on $AMB$. The average slope on $COMA$ is positive but insignificant, and the average slope on $POMA$ is insignificantly negative.

Finally, $RVIV$ is included in cross-sectional regressions. The results in Model *XI* and Model *XII* present negative average slopes on $RVIV$. However, the average slope is not significant no matter whether control variables are included in the regression model or not. This subsection also uses the subsample for the period from February 1996 to January 2005. The subsample analysis by using the full sample yields a significantly negative average slope for the realized-implied volatility spread without including any control variables (-0.0135 with a p-value of 0.0410). The results for the subsample analysis are consistent with the finding in Bali and Hovakimian (2009). Thus, the significance of the negative average slope on $RVIV$ disappears when using a longer sample period with more recent data.

To sum up, firm-level cross-sectional regression results show that the average slope on $CPIV$ is significantly positive (around 0.10) and the average slope on $IVSKEW$ is significantly negative (around -0.07). These average slopes confirm the positive relation between stock returns and $CPIV$ and the negative relation between stock returns and $IVSKEW$. Additionally, there is no significant average slope for $AMB$, $COMA$, $POMA$, or $RVIV$. Thus, based on the full sample, there is no significant relation between stock returns and $AMB$, $COMA$, $POMA$, or $RVIV$.

### 3.7.2 Cross-Sectional Regressions for Intersection Sample over One-Month Holding Period

After the analysis using the full sample, this subsection conducts firm-level cross-sectional regressions by using the intersection sample. As mentioned previously, $POMA$ is equal to the sum of $IVSKEW$ and $CPIV$, so these three measures cannot be included in the same model. In Panel C of Table 3.1, a highly negative correlation between $CPIV$ and $IVSKEW$, a highly positive correlation between $IVSKEW$ and $POMA$, a highly positive correlation between $AMB$ and $COMA$, and a highly negative correlation between $AMB$ and $POMA$ are documented. So, in multivariate cross-sectional regressions, the potential multicollinearity problem should be eliminated. In the first multivariate cross-sectional regression model, $POMA$ is excluded. Then, in the second model, $IVSKEW$ is excluded. In the third multivariate regression model, $AMB$ and $POMA$ are excluded. Finally, in the fourth model, both $IVSKEW$ and $AMB$ are excluded. Thus, in the fourth model, correlations between any two explanatory variables are low, and results obtained from the fourth model are less affected by a multicollinearity problem.

Under the assumption of one-month holding period, this subsection performs univariate and multivariate cross-sectional regressions at firm-level by using the

**Table 3.4: Firm-Level Cross-Sectional Regression Results by Using the Intersection Sample for One-Month Holding Period**

Notes: Table 3.4 presents the firm-level cross-sectional regression results for the intersection sample (N=61331) for the period from Feb 1996 to Oct 2011. P-values are reported in parentheses. *, **, and *** denote for significance at 10%, 5% and 1% levels, respectively.

Panel A: Univariate Firm-Level Cross-Sectional Regression Models

| | *I* | *II* | *III* | *IV* | *V* | *VI* | *VII* | *VIII* | *IX* | *X* | *XI* | *XII* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Intercept* | 0.0064 | 0.0074 | 0.0110* | 0.0074 | 0.0056 | 0.0071 | 0.0056 | 0.0072 | 0.0079 | 0.0064 | 0.0067 | 0.0047 |
| | (0.2874) | (0.5910) | (0.0613) | (0.5874) | (0.3433) | (0.6071) | (0.3324) | (0.6007) | (0.1712) | (0.6408) | (0.2467) | (0.7292) |
| *CPIV* | 0.1234*** | 0.1000*** | | | | | | | | | | |
| | (0.0000) | (0.0008) | | | | | | | | | | |
| *IVSKEW* | | | -0.0926*** | -0.0740*** | | | | | | | | |
| | | | (0.0000) | (0.0000) | | | | | | | | |
| *AMB* | | | | | 0.0001 | 0.0062 | | | | | | |
| | | | | | (0.9969) | (0.6255) | | | | | | |
| *COMA* | | | | | | | 0.0248 | 0.0340 | | | | |
| | | | | | | | (0.5207) | (0.3421) | | | | |
| *POMA* | | | | | | | | | -0.0573** | -0.0481** | | |
| | | | | | | | | | (0.0127) | (0.0311) | | |
| *RVIV* | | | | | | | | | | | 0.0010 | 0.0037 |
| | | | | | | | | | | | (0.8881) | (0.5704) |
| ln(*size*) | | 0.0005 | | 0.0008 | | 0.0006 | | 0.0006 | | 0.0008 | | 0.0007 |
| | | (0.6908) | | (0.5178) | | (0.6603) | | (0.6568) | | (0.5544) | | (0.5785) |
| *B/M Ratio* | | 0.0016 | | 0.0020 | | 0.0017 | | 0.0021 | | 0.0020 | | 0.0015 |
| | | (0.6798) | | (0.6206) | | (0.6706) | | (0.5987) | | (0.6146) | | (0.6971) |
| *Momentum* | | 0.0019 | | 0.0026 | | 0.0012 | | 0.0018 | | 0.0010 | | 0.0010 |
| | | (0.8433) | | (0.7895) | | (0.9026) | | (0.8472) | | (0.9129) | | (0.9158) |
| *Stock Volume* | | -0.0054** | | -0.0053** | | -0.0048* | | -0.0051** | | -0.0051** | | -0.0047* |
| | | (0.0320) | | (0.0376) | | (0.0651) | | (0.0479) | | (0.0431) | | (0.0552) |
| *Market Beta* | | 0.0008 | | 0.0011 | | 0.0011 | | 0.0010 | | 0.0012 | | 0.0017 |
| | | (0.7528) | | (0.6497) | | (0.6489) | | (0.6800) | | (0.6252) | | (0.5116) |
| *Bid-Ask Spread* | | -1.6331 | | -1.5474 | | -2.7998*** | | -3.0435*** | | -2.5439** | | -2.1081** |
| | | (0.1117) | | (0.1253) | | (0.0096) | | (0.0056) | | (0.0205) | | (0.0429) |
| *Option Volume* | | 0.0027 | | 0.0032 | | 0.0015 | | 0.0022 | | 0.0022 | | 0.0010 |
| | | (0.3484) | | (0.2705) | | (0.6096) | | (0.4500) | | (0.4404) | | (0.7216) |

(Continued)

| Panel B: Multivariate Firm-Level Cross-Sectional Regression Models | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | *XIII* | *XIV* | *XV* | *XVI* | *XVII* | *XVIII* | *XIX* | *XX* |
| *Intercept* | 0.0110** | 0.0092 | 0.0110** | 0.0092 | 0.0108** | 0.0084 | 0.0108** | 0.0084 |
| | (0.0455) | (0.4979) | (0.0455) | (0.4979) | (0.0480) | (0.5360) | (0.0480) | (0.5360) |
| *CPIV* | 0.0844* | 0.0885* | 0.1412*** | 0.1205*** | 0.0914*** | 0.0768** | 0.1424*** | 0.1172*** |
| | (0.0689) | (0.0624) | (0.0000) | (0.0002) | (0.0091) | (0.0325) | (0.0000) | (0.0001) |
| *IVSKEW* | -0.0568** | -0.0320 | | | -0.0510** | -0.0404* | | |
| | (0.0430) | (0.2527) | | | (0.0204) | (0.0669) | | |
| *AMB* | -0.0120 | 0.0053 | -0.0120 | 0.0053 | | | | |
| | (0.5420) | (0.7779) | (0.5420) | (0.7779) | | | | |
| *COMA* | 0.0479 | 0.0438 | 0.0479 | 0.0438 | 0.0394 | 0.0499 | 0.0394 | 0.0499 |
| | (0.2795) | (0.2798) | (0.2795) | (0.2798) | (0.3135) | (0.1686) | (0.3135) | (0.1686) |
| *POMA* | | | -0.0568** | -0.0320 | | | -0.0510** | -0.0404* |
| | | | (0.0430) | (0.2527) | | | (0.0204) | (0.0669) |
| *RVIV* | -0.0029 | -0.0010 | -0.0029 | -0.0010 | -0.0028 | -0.0011 | -0.0028 | -0.0011 |
| | (0.6744) | (0.8724) | (0.6744) | (0.8724) | (0.6871) | (0.8612) | (0.6871) | (0.8612) |
| ln(*size*) | | 0.0005 | | 0.0005 | | 0.0005 | | 0.0005 |
| | | (0.7014) | | (0.7014) | | (0.6736) | | (0.6736) |
| *B/M Ratio* | | 0.0022 | | 0.0022 | | 0.0023 | | 0.0023 |
| | | (0.5837) | | (0.5837) | | (0.5594) | | (0.5594) |
| *Momentum* | | 0.0051 | | 0.0051 | | 0.0050 | | 0.0050 |
| | | (0.5990) | | (0.5990) | | (0.6099) | | (0.6099) |
| *Stock Volume* | | -0.0052** | | -0.0052** | | -0.0049** | | -0.0049** |
| | | (0.0238) | | (0.0238) | | (0.0305) | | (0.0305) |
| *Market Beta* | | 0.0020 | | 0.0020 | | 0.0021 | | 0.0021 |
| | | (0.4319) | | (0.4319) | | (0.4149) | | (0.4149) |
| *Bid-Ask Spread* | | -1.7040* | | -1.7040* | | -1.6002 | | -1.6002 |
| | | (0.0820) | | (0.0820) | | (0.1046) | | (0.1046) |
| *Option Volume* | | 0.0022 | | 0.0022 | | 0.0018 | | 0.0018 |
| | | (0.4234) | | (0.4234) | | (0.4872) | | (0.4872) |

intersection sample. The regression results are presented in Table 3.4.

Model *I* and Model *II* present firm-level cross-sectional regression results for $CPIV$. The coefficient on $CPIV$ is 0.1000 with a p-value of $10^{-4}$ after controlling for size, book-to-market ratio, momentum, stock trading volume, market beta, bid-ask spread, and option trading volume. That is, if a stock has an average difference between the call and put volatilities of -1.08 percent, then on average the month-ahead return will be 10.8 bps lower. Model *III* and Model *IV* present significantly negative average slopes on $IVSKEW$. The average slope is -0.0926 with a p-value of $10^{-4}$ without including control variables, and it is -0.0740 with a p-value of $10^{-4}$ after controlling for control variables mentioned before. The interpretation of the economic significance is that a coefficient of -0.0926 (-0.0740) on $IVSKEW$ translates to a future monthly return of -67.04 (-53.58) bps for the average value of $IVSKEW$ (7.24 percent). Models *V* to *VIII* show that average slopes on $AMB$ and $COMA$ are positive but not significant, while average slopes on $POMA$ are significantly negative (-0.0481 with p-value of 0.0311 after including control variables in regression Model *X*). The final two univariate regression models (Model *XI* and Model *XII*) yield insignificant average slopes for $RVIV$. Thus, the results are consistent with those obtained in the previous section by using the full sample (except the results for $POMA$).

Panel B presents the results of eight models used in multivariate firm-level cross-sectional regressions. If $POMA$ is excluded (Model *XIII* and Model *XIV*), average slopes on $CPIV$ and $IVSKEW$ remain significant. Without including control variables, the average slope for $CPIV$ is 0.0844 with a p-value of 0.0689, and the average slope for $IVSKEW$ is -0.0568 with a p-value of 0.0430. After controlling for size, book-to-market ratio, momentum, stock trading volume, market beta, bid-ask spread and option trading volume, the significance of the average slope for *IVSKEW* disappears. Only the average slope on *CPIV* is still marginally significant (0.0885 with a p-value of 0.0624). Other volatility measures do not have significant average slopes. In these two models, the average slope on *CPIV* is marginally significant at a 10% significance level. The significant average slope on *CPIV* in Model *XIV* indicates that, if a stock has an average *CPIV* of -1.08 percent, the return will, on average, be 9.56 bps lower in the following month. From Panel C of Table 3.1, the correlation between *CPIV* and *IVSKEW* is -0.6189. These two variables are highly correlated, so results could be driven by this high correlation.

If *IVSKEW* is excluded instead of *POMA* (Model *XV* and Model *XVI*), there is a significantly positive average slope on *CPIV* no matter whether control variables are included in regression models or not. The average slope on *CPIV* is 0.1205 with a p-value of 0.0002 after controlling for several firm-specific effects (in Model *XVI*). With respect to the economic significance, from Model *XVI*, if the average difference between at-the-money call and put implied volatilities is -1.08 percent, the return in the following month is expected to be 13.01 bps lower. These two models include *AMB*, *COMA* and *POMA* in the model. Panel C of Table 3.1 documents that the correlation between *AMB* and *COMA* is 0.5786, and the correlation between *AMB* and *POMA* is -0.6124. Thus, the multicollinearity issue could affect the accuracy of results.

Then, both *AMB* and *POMA* are excluded in the next two models (Model *XVII* and Model *XVIII*). Results of these two models show that *CPIV* has a significantly positive average slope while *IVSKEW* has a significantly negative average slope no matter whether control variables are included or not. Without including control variables, the average slope on *CPIV* is 0.0914 with a p-value of

0.0091, and the average slope on *IVSKEW* is -0.0510 with a p-value of 0.0204. After including control variables, the average slope on *CPIV* is 0.0768 with a p-value of 0.0325, and the average slope on *IVSKEW* is -0.0404 with a p-value of 0.0669. In these two models, the predictive power of *CPIV* is stronger than that of *IVSKEW*. When it comes to economic significance, after controlling for firm-specific effects, if *CPIV* increases by 1%, one-month ahead return is expected to increase by 7.68 bps, which corresponds to 0.92% per annum. If *IVSKEW* increases by 1%, one-month ahead return is expected to decrease by 4.04 bps, which corresponds to -0.48% per annum. Again, these two multivariate regression models may suffer from the multicollinearity problem because of the high correlation between *CPIV* and *IVSKEW*.

It is seen that the results for six models above may be affected by the multicollinearity issue, so the final two sets of models try to eliminate this problem. In these two models (Model *XIX* and Model *XX*), both *IVSKEW* and *AMB* are excluded so that pairwise correlations in these models are not very high. From the last two sets of models, there is a significantly positive average slope on *CPIV* (0.1172 with a p-value of 0.0001 after controlling for firm-specific effects) and a marginally significant negative average slope for *POMA* (-0.0404 with a p-value of 0.0669 after including control variables). With respect to the economic significance, if a stock has an average *CPIV* (*POMA*) of 1.08 (6.16) percent, one-month ahead return will, on average, be 12.66 (24.89) bps lower with other variables remaining the same. So, results from these two models confirm a significant positive relation between stock returns and *CPIV*. The negative relationship between stock returns and *POMA* is marginally significant at a 10% significance level.

*IVSKEW* can capture both *CPIV* and *POMA*. In multivariate regression models of *XIV* and *XVI*, the only difference is that Model *XIV* contains *IVSKEW* whereas Model *XVI* contains *POMA*. The coefficient on *IVSKEW* in Model *XIV* and that on *POMA* in Model *XVI* are the same. The coefficient on *CPIV* in Model *XVI* is equal to the difference between the coefficient on *CPIV* and the coefficient on *IVSKEW* in Model *XIV*. So, the influence of *IVSKEW* can be split into two parts, the influence of *CPIV* and the influence of *POMA*. Similar results are found when comparing Model *XVIII* and Model *XX*. Furthermore, if the average slope on *POMA* is significant/insignificant (Model *XVI/XX*), the coefficient on *IVSKEW* is also significant/insignificant in the paired model (Model *XIV/XVIII*). For the intersection sample, the significance of the average slope on *IVSKEW* is affected by *POMA*. Furthermore, Model *XX* shows that differences between at-the-money call implied volatilities and at-the-money put implied volatilities (*CPIV*) and between the out-of-the-money put implied volatilities and at-the-money put implied volatilities (*POMA*) both capture valuable information about future equity returns. The predictive power of *CPIV* has stronger statistical significance, while the predictive power of *POMA* has stronger economic significance.

Thus, among all option-implied volatility measures, the predictive power of *CPIV* is stronger than those of other measures over one-month holding period. Empirical results in this subsection confirm a positive relationship between monthly stock returns and *CPIV*, a negative relationship between monthly stock returns and *IVSKEW*, and a weak negative relationship between monthly stock returns and *POMA*. Moreover, empirical results indicate that, among all six option-implied volatility measures, *CPIV* has stronger predictive power than any other volatility measure over one-month investment horizon.

Section 3.8 performs additional tests by extending the holding period to two months and three months in order to investigate whether the predictive power of each option-implied volatility measure persists for longer horizons.

## 3.8 Tests for Longer Holding Periods

### 3.8.1 Cross-Sectional Regressions for Intersection Sample over Two-Month Holding Period

This subsection extends the holding period to two months, and then performs univariate and multivariate cross-sectional regressions at firm-level by using the intersection sample. The regression results for two-month holding period are documented in Table 3.5.

Model *I* and Model *II* show a significantly positive average slope on $CPIV$ (0.0970 with a p-value of 0.0169 after controlling for size, book-to-market ratio, momentum, stock trading volume, beta, bid-ask spread and option trading volume in Model *II*). That is, if a stock has an average $CPIV$ of -1.08 percent, then the following two-month return will be 10.48 bps lower on average. Also, there is a significantly negative slope on $IVSKEW$. After including control variables, the average slope on $IVSKEW$ is -0.0951 with a p-value of 0.0002 in Model *IV*, implying economic significance as well. If $IVSKEW$ increases by 1%, the two-month ahead return is expected to decrease by 9.51 bps, which corresponds to -0.57% per annum. Then, this subsection investigates three measures documented in Doran and Krieger (2010). The average slope on $AMB$ is insignificant in Model *V* and Model *VI*. However, the average slope on $COMA$ is significantly positive at a 10% significance level after including control variables in Model *VIII* (0.0867 with a p-value of 0.0703). That is, if a stock has an average $COMA$ of -2.35 percent, the

## Table 3.5: Firm-Level Cross-Sectional Regression Results by Using the Intersection Sample for Two-Month Holding Period

Notes: Table 3.5 presents the firm-level cross-sectional regression results for the intersection sample (N=61197) for the period from Feb 1996 to Oct 2011. P-values are reported in parentheses. *, **, and *** denote for significance at 10%, 5% and 1% levels, respectively.

Panel A: Univariate Firm-Level Cross-Sectional Regression Models

| | *I* | *II* | *III* | *IV* | *V* | *VI* | *VII* | *VIII* | *IX* | *X* | *XI* | *XII* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Intercept* | 0.0102 | 0.0071 | 0.0160* | 0.0081 | 0.0086 | 0.0087 | 0.0095 | 0.0092 | 0.0121 | 0.0087 | 0.0111 | 0.0052 |
| | (0.2310) | (0.7344) | (0.0532) | (0.6962) | (0.2976) | (0.6767) | (0.2429) | (0.6571) | (0.1411) | (0.6781) | (0.1848) | (0.8014) |
| *CPIV* | 0.1218*** | 0.0970** | | | | | | | | | | |
| | (0.0029) | (0.0169) | | | | | | | | | | |
| *IVSKEW* | | | -0.1090*** | -0.0951*** | | | | | | | | |
| | | | (0.0001) | (0.0002) | | | | | | | | |
| *AMB* | | | | | -0.0052 | 0.0078 | | | | | | |
| | | | | | (0.7932) | (0.6647) | | | | | | |
| *COMA* | | | | | | | 0.0690 | 0.0867* | | | | |
| | | | | | | | (0.2107) | (0.0703) | | | | |
| *POMA* | | | | | | | | | -0.0685* | -0.0680* | | |
| | | | | | | | | | (0.0602) | (0.0548) | | |
| *RVIV* | | | | | | | | | | | -0.0040 | -0.0011 |
| | | | | | | | | | | | (0.6548) | (0.8994) |
| ln(*size*) | | 0.0016 | | 0.0020 | | 0.0015 | | 0.0016 | | 0.0017 | | 0.0017 |
| | | (0.3791) | | (0.2846) | | (0.4309) | | (0.3997) | | (0.3617) | | (0.3461) |
| *B/M Ratio* | | 0.0037 | | 0.0037 | | 0.0036 | | 0.0033 | | 0.0038 | | 0.0034 |
| | | (0.5084) | | (0.5101) | | (0.5270) | | (0.5576) | | (0.5002) | | (0.5414) |
| *Momentum* | | -0.0022 | | -0.0006 | | -0.0030 | | -0.0030 | | -0.0027 | | -0.0003 |
| | | (0.8664) | | (0.9596) | | (0.8172) | | (0.8101) | | (0.8320) | | (0.9797) |
| *Stock Volume* | | -0.0060 | | -0.0064 | | -0.0057 | | -0.0066* | | -0.0065 | | -0.0059 |
| | | (0.1189) | | (0.1024) | | (0.1520) | | (0.0962) | | (0.1002) | | (0.1380) |
| *Market Beta* | | 0.0007 | | 0.0013 | | 0.0011 | | 0.0011 | | 0.0013 | | 0.0028 |
| | | (0.8067) | | (0.6522) | | (0.7201) | | (0.7134) | | (0.6674) | | (0.3812) |
| *Bid-Ask Spread* | | -3.4628** | | -3.5728** | | -5.2132*** | | -5.4727*** | | -5.1568*** | | -4.7496*** |
| | | (0.0161) | | (0.0138) | | (0.0005) | | (0.0003) | | (0.0008) | | (0.0011) |
| *Option Volume* | | 0.0090* | | 0.0099** | | 0.0082 | | 0.0092* | | 0.0096** | | 0.0082* |
| | | (0.0667) | | (0.0403) | | (0.1095) | | (0.0644) | | (0.0442) | | (0.0934) |

(Continued)

| Panel B: Multivariate Firm-Level Cross-Sectional Regression Models | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | *XIII* | *XIV* | *XV* | *XVI* | *XVII* | *XVIII* | *XIX* | *XX* |
| *Intercept* | 0.0146* | 0.0096 | 0.0146* | 0.0096 | 0.0148* | 0.0089 | 0.0148* | 0.0089 |
| | (0.0607) | (0.6398) | (0.0607) | (0.6398) | (0.0576) | (0.6637) | (0.0576) | (0.6637) |
| *CPIV* | 0.0556 | 0.0608 | 0.1396*** | 0.1269*** | 0.0999** | 0.0802 | 0.1457*** | 0.1282*** |
| | (0.3951) | (0.3506) | (0.0013) | (0.0023) | (0.0434) | (0.1150) | (0.0002) | (0.0007) |
| *IVSKEW* | -0.0840* | -0.0661 | | | -0.0458 | -0.0481 | | |
| | (0.0620) | (0.1285) | | | (0.1961) | (0.1756) | | |
| *AMB* | -0.0522* | -0.0281 | -0.0522* | -0.0281 | | | | |
| | (0.0615) | (0.2702) | (0.0615) | (0.2702) | | | | |
| *COMA* | 0.1214** | 0.1240** | 0.1214** | 0.1240** | 0.0787 | 0.1033** | 0.0787 | 0.1033** |
| | (0.0432) | (0.0221) | (0.0432) | (0.0221) | (0.1592) | (0.0339) | (0.1592) | (0.0339) |
| *POMA* | | | -0.0840* | -0.0661 | | | -0.0458 | -0.0481 |
| | | | (0.0620) | (0.1285) | | | (0.1961) | (0.1756) |
| *RVIV* | -0.0091 | -0.0084 | -0.0091 | -0.0084 | -0.0090 | -0.0085 | -0.0090 | -0.0085 |
| | (0.2937) | (0.3017) | (0.2937) | (0.3017) | (0.3017) | (0.3007) | (0.3017) | (0.3007) |
| ln(*size*) | | 0.0015 | | 0.0015 | | 0.0016 | | 0.0016 |
| | | (0.4403) | | (0.4403) | | (0.4050) | | (0.4050) |
| *B/M Ratio* | | 0.0040 | | 0.0040 | | 0.0038 | | 0.0038 |
| | | (0.4733) | | (0.4733) | | (0.4949) | | (0.4949) |
| *Momentum* | | 0.0047 | | 0.0047 | | 0.0049 | | 0.0049 |
| | | (0.7143) | | (0.7143) | | (0.7023) | | (0.7023) |
| *Stock Volume* | | -0.0068 | | -0.0068 | | -0.0067* | | -0.0067* |
| | | (0.1010) | | (0.1010) | | (0.0899) | | (0.0899) |
| *Market Beta* | | 0.0033 | | 0.0033 | | 0.0033 | | 0.0033 |
| | | (0.2828) | | (0.2828) | | (0.2830) | | (0.2830) |
| *Bid-Ask Spread* | | -3.6126** | | -3.6126** | | -3.5948** | | -3.5948** |
| | | (0.0123) | | (0.0123) | | (0.0129) | | (0.0129) |
| *Option Volume* | | 0.0098* | | 0.0098* | | 0.0096** | | 0.0096** |
| | | (0.0516) | | (0.0516) | | (0.0412) | | (0.0412) |

following two-month return will be 20.37 bps lower on average. The marginal significance of negative average slope on *POMA* remains a bit lower than 0.07 as shown in Model *IX* and Model *X*. If the average difference between out-of-the-money and at-the-money put implied volatilities is 6.16 percent, the two-month ahead return will be 41.89 bps lower. *RVIV* has an insignificantly negative average slope in Model *XI* and Model *XII*. Thus, results for the univariate firm-level cross-sectional regression models indicate that two-month ahead returns are positively correlated with *CPIV*, and they are negatively correlated with *IVSKEW*. *COMA* and *POMA* are weakly related to two-month ahead stock returns, as well. The difference between results for one-month holding period and results for two-month holding period is the marginal significance of relationship between two-month stock returns and *COMA*.

This subsection proceeds with multivariate cross-sectional regressions to see whether the predictive power of *COMA* is strong when competing with other variables. Results for multivariate firm-level cross-sectional regressions for two-month holding period are slightly different compared to those for one-month holding period. In addition to the significantly positive average slope on *CPIV* presented in models *XV* to *XX* (the average slope is around 0.10 with very small p-value), there is a significantly positive average slope on *COMA*.[22] The average slope on *COMA* is higher than 0.10 with a p-value smaller than 5% after controlling for several firm-specific effects (models *XIV*, *XVI*, *XVIII* and *XX*). Model *XX* shows that a coefficient of 0.1033 on *COMA* indicates a two-month ahead return of -24.28 bps for the average *COMA*. Also, without including control variables, there is a marginally significant and negative average slope on *AMB* in Model *XIII* and Model

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[22] There is no significant average slope for *CPIV* in Model *XIII* and Model *XIV*. This could be due to the high correlation between *CPIV* and *IVSKEW* presented in Panel C of Table 3.1.

*XV* at a 10% significance level (-0.0522 with a p-value of 0.0615 in both models), implying a future two-month return of 42.49 bps for the average value of *AMB*.

Thus, the predictive power of *CPIV* is strong for two-month holding period as well. However, compared with the results for one-month holding period, *COMA* becomes an important measure in predicting two-month ahead stock returns.

### 3.8.2 Cross-Sectional Regressions for Intersection Sample over Three-Month Holding Period

This subsection performs cross-sectional regressions at firm-level by using the intersection sample for three-month holding period. Table 3.6 documents regression results.

In univariate firm-level cross-sectional regression models, the average slope on *CPIV*, *IVSKEW*, *COMA* or *POMA* remains statistically significant (0.0932 with a p-value of 0.0281, -0.1149 with a p-value of 0.0001, 0.1667 with a p-value of 0.0026, and -0.0958 with a p-value of 0.0244 after including control variables, respectively). With respect to the economic significance, the average slope on *CPIV* / *IVSKEW* / *COMA* / *POMA* translates to future three-month returns of -10.07/-83.19/-39.17/-59.01 bps for the average value of the option-implied volatility measures, respectively. There is no significant average slope on *AMB* or *RVIV* again. So, results for three-month holding period still document a positive relationship between stock returns and *CPIV* or *COMA*, and a negative relationship between stock returns and *IVSKEW* or *POMA*. These findings are consistent with findings for two-month holding period in previous subsection.

In multivariate firm-level cross-sectional regression models, results for three-month holding period are very similar to the results obtained for two-month

**Table 3.6: Firm-Level Cross-Sectional Regression Results by Using the Intersection Sample for Three-Month Holding Period**

Notes: Table 3.6 presents the firm-level cross-sectional regression results for the intersection sample (N=61020) for the period from Feb 1996 to Oct 2011. P-values are reported in parentheses. *, **, and *** denote for significance at 10%, 5% and 1% levels, respectively.

| Panel A: Univariate Firm-Level Cross-Sectional Regression Models | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *I* | *II* | *III* | *IV* | *V* | *VI* | *VII* | *VIII* | *IX* | *X* | *XI* | *XII* |
| *Intercept* | 0.0161 | 0.0035 | 0.0237** | 0.0045 | 0.0151 | 0.0048 | 0.0170* | 0.0065 | 0.0196* | 0.0052 | 0.0175* | 0.0066 |
| | (0.1278) | (0.8909) | (0.0205) | (0.8597) | (0.1417 | (0.8542) | (0.0938) | (0.8003) | (0.0570) | (0.8416) | (0.0959 | (0.7993) |
| *CPIV* | 0.1285** | 0.0932** | | | | | | | | | | |
| | (0.0036) | (0.0281) | | | | | | | | | | |
| *IVSKEW* | | | -0.1386** | -0.1149** | | | | | | | | |
| | | | (0.0000) | (0.0001) | | | | | | | | |
| *AMB* | | | | | 0.0012 | 0.0158 | | | | | | |
| | | | | | (0.9607 | (0.4694) | | | | | | |
| *COMA* | | | | | | | 0.1428* | 0.1667*** | | | | |
| | | | | | | | (0.0310) | (0.0026) | | | | |
| *POMA* | | | | | | | | | -0.1029* | -0.0958** | | |
| | | | | | | | | | (0.0217) | (0.0244) | | |
| *RVIV* | | | | | | | | | | | 0.0114 | 0.0138 |
| | | | | | | | | | | | (0.2881 | (0.1875) |
| ln(*size*) | | 0.0029 | | 0.0034 | | 0.0029 | | 0.0029 | | 0.0031 | | 0.0027 |
| | | (0.2084) | | (0.1425) | | (0.2109) | | (0.2002) | | (0.1797) | | (0.2414) |
| *B/M Ratio* | | 0.0032 | | 0.0031 | | 0.0036 | | 0.0027 | | 0.0034 | | 0.0031 |
| | | (0.6507) | | (0.6565) | | (0.6071) | | (0.7036) | | (0.6236) | | (0.6635) |
| *Momentum* | | 0.0081 | | 0.0094 | | 0.0078 | | 0.0069 | | 0.0074 | | 0.0089 |
| | | (0.5886) | | (0.5264) | | (0.6030) | | (0.6438) | | (0.6175) | | (0.5592) |
| *Stock Volume* | | -0.0070* | | -0.0074* | | -0.0072* | | -0.0078* | | -0.0075* | | -0.0089** |
| | | (0.0997) | | (0.0866) | | (0.0984) | | (0.0737) | | (0.0798) | | (0.0472) |
| *Market Beta* | | 0.0037 | | 0.0044 | | 0.0043 | | 0.0046 | | 0.0045 | | 0.0053 |
| | | (0.3217) | | (0.2313) | | (0.2390) | | (0.2073) | | (0.2136) | | (0.1670) |
| *Bid-Ask* | | -6.0853** | | -6.1184** | | -8.1657** | | -8.5077** | | -8.1403** | | -8.0511** |
| | | (0.0014) | | (0.0018) | | (0.0000) | | (0.0000) | | (0.0001) | | (0.0001) |
| *Option Volume* | | 0.0109* | | 0.0115** | | 0.0103* | | 0.0113** | | 0.0114** | | 0.0121** |
| | | (0.0626) | | (0.0438) | | (0.0916) | | (0.0572) | | (0.0466) | | (0.0348) |

(Continued)

| Panel B: Multivariate Firm-Level Cross-Sectional Regression Models | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | *XIII* | *XIV* | *XV* | *XVI* | *XVII* | *XVIII* | *XIX* | *XX* |
| *Intercept* | 0.0228** | 0.0104 | 0.0228** | 0.0104 | 0.0234** | 0.0102 | 0.0234** | 0.0102 |
| | (0.0194) | (0.6838) | (0.0194) | (0.6838) | (0.0171) | (0.6920) | (0.0171) | (0.6920) |
| *CPIV* | 0.0383 | 0.0460 | 0.1545*** | 0.1290*** | 0.0883 | 0.0655 | 0.1580*** | 0.1289*** |
| | (0.6162) | (0.5257) | (0.0016) | (0.0035) | (0.1382) | (0.2647) | (0.0004) | (0.0017) |
| *IVSKEW* | -0.1162** | -0.0830* | | | -0.0698 | -0.0634 | | |
| | (0.0234) | (0.0938) | | | (0.1024) | (0.1317) | | |
| *AMB* | -0.0681** | -0.0366 | -0.0681** | -0.0366 | | | | |
| | (0.0256) | (0.1949) | (0.0256) | (0.1949) | | | | |
| *COMA* | 0.1849** | 0.1822*** | 0.1849** | 0.1822*** | 0.1321* | 0.1596*** | 0.1321* | 0.1596*** |
| | (0.0104) | (0.0039) | (0.0104) | (0.0039) | (0.0539) | 0.0056) | (0.0539) | (0.0056) |
| *POMA* | | | -0.1162** | -0.0830* | | | -0.0698 | -0.0634 |
| | | | (0.0234) | (0.0938) | | | (0.1024) | (0.1317) |
| *RVIV* | 0.0048 | 0.0038 | 0.0048 | 0.0038 | 0.0050 | 0.0040 | 0.0050 | 0.0040 |
| | (0.6452) | (0.6984) | (0.6452) | (0.6984) | (0.6315) | (0.6934) | (0.6315) | (0.6934) |
| ln(*size*) | | 0.0026 | | 0.0026 | | 0.0027 | | 0.0027 |
| | | (0.2708) | | (0.2708) | | (0.2467) | | (0.2467) |
| *B/M Ratio* | | 0.0031 | | 0.0031 | | 0.0024 | | 0.0024 |
| | | (0.6581) | | (0.6581) | | (0.7318) | | (0.7318) |
| *Momentum* | | 0.0121 | | 0.0121 | | 0.0129 | | 0.0129 |
| | | (0.4193) | | (0.4193) | | (0.3939) | | (0.3939) |
| *Stock Volume* | | -0.0095** | | -0.0095** | | -0.0095** | | -0.0095** |
| | | (0.0409) | | (0.0409) | | (0.0355) | | (0.0355) |
| *Market Beta* | | 0.0063* | | 0.0063* | | 0.0063* | | 0.0063* |
| | | (0.0879) | | (0.0879) | | (0.0906) | | (0.0906) |
| *Bid-Ask Spread* | | -6.2884*** | | -6.2884*** | | -6.3008*** | | -6.3008*** |
| | | (0.0013) | | (0.0013) | | (0.0013) | | (0.0013) |
| *Option Volume* | | 0.0124** | | 0.0124** | | 0.0126** | | 0.0126** |
| | | (0.0310) | | (0.0310) | | (0.0236) | | (0.0236) |

holding period.[23] If *CPIV* and *IVSKEW* are not included in the same model, there is a significantly positive average slope on *CPIV* in models *XV*, *XVI*, *XIX* and *XX* (higher than 0.15 without control variables and higher than 0.12 with control variables). The average slope on *AMB* remains significant without including control variables in Model *XIII* and Model *XV* at a 5% significance level (-0.0681 with a p-value of 0.0256). Finally, average slopes for *COMA* are statistically significant and positive in all multivariate cross-sectional regressions. These average slopes are higher than 0.13 and significant at a 5% significance level, and some of them are even significant at a 1% significance level. As mentioned in the previous section, Model *XX* yields stronger results. For this model, if a stock has an average *CPIV* of -1.08 percent, the following three-month ahead return should be -13.92 bps lower on average. If a stock has an average *COMA* of -2.35 percent, the three-month ahead return will, on average, be 37.51 bps lower. Thus, average slopes on these two variables are not only statistically significant but also economically significant.

The results for three-month holding period indicate that the predictive power of *CPIV* is still strong when the holding period is extended to three months, as well as the predictive power of *COMA*. Furthermore, in some models, the average slope on *CPIV* is not significant while the average slope on *COMA* is highly significant. The predictive power of *COMA* seems to be the strongest when competing with other option-implied volatility measures in explaining three-month ahead holding period returns.

As the length of holding period increases, *COMA* becomes more and more important in predicting stock returns. It is known that the intrinsic value of the

[23] The main different result for the three-month holding period is that the average slope on the realized-implied volatility spread becomes positive. However, the average slope is still insignificant. So, there is no significant relationship between stock returns and realized-implied volatility spread for all three holding periods.

out-of-the-money call option is zero. The out-of-the-money call option only has extrinsic or time value. Because there is only a small chance that the stock price will increase by a significant amount, out-of-the-money call options tend to trade at significantly low prices. If an out-of-the-money call option becomes in-the-money on the expiration date, the out-of-the-money call option will be exercised; if not, the option expires worthless and the investor loses the premium. This chapter includes the deep out-of-the-money call options to calculate $COMA$. In a short holding period (i.e., one-month), there is a very small probability that the out-of-the-money call option becomes in-the-money, making it a very risky strategy when the option is close-to-expiry. However, in a longer holding period (i.e., two-month or three-month), it is more likely that the out-of-the-money call will be in-the-money. The significant predictive power of $COMA$ for longer horizons is an indication of this difference and implies that the left hand side of the call volatility skew plays an important role in predicting stock returns over two- and three-month holding periods.

In summary, previous two subsections show that, if the holding period is extended to two months or even three months, the significance of the average slope on $CPIV$ persists. Meanwhile, $COMA$ becomes an important factor in predicting stock returns because it always has a significantly positive average slope.

## 3.9 Conclusions

This chapter focuses on the relationship between stock returns and six option-implied volatility measures. First, this chapter performs portfolio level analysis, which sheds light on whether the long-short portfolio constructed by holding a long position in the quintile portfolio with the highest volatility measure and a short position in the quintile portfolio with the lowest volatility measure can earn significantly non-zero monthly raw or risk-adjusted returns. The portfolio level analysis confirms a positive relation between one-month ahead stock returns and $CPIV$ and a negative relation between one-month ahead stock returns and $IVSKEW$. The results also confirm a marginally significant and negative relation between one-month ahead stock returns and $AMB$ or $RVIV$. However, there is no significant relationship between one-month ahead stock returns and $COMA$ or $POMA$ in portfolio level analysis.

Portfolio level analysis does not control for firm-specific effects and other option-implied volatility measures simultaneously. This chapter performs firm-level cross-sectional regressions over one-month holding period. The firm-level cross-sectional regression results indicate that $CPIV$ has a significantly positive average slope while $IVSKEW$ and $POMA$ have significantly negative average slopes. However, in the multivariate cross-sectional regressions, over one-month holding period, $CPIV$ has a significantly positive average slope after controlling for size, book-to-market ratio, momentum, volume, beta and bid-ask spread.

Finally, this chapter extends investors' holding period to two months and three months in order to investigate whether the predictive power of $CPIV$ persists and whether other variables are significantly correlated with stock returns over longer horizons. In these tests, the significance of the average slope on $CPIV$ persists. Furthermore, $COMA$ has a significantly positive average slope. Thus, the predictive power of $CPIV$ is still strong over longer horizons, and the predictive power of $COMA$ becomes stronger when the holding period is extended. This chapter also probes into more detailed reason for the predictive power of $COMA$. If the holding period is longer, out-of-the-money call options are more likely to become in-the-money. Investors will take the out-of-the-money call implied volatility into consideration when forming their trading strategies over longer investment horizons. This can explain why the predictive ability of $COMA$ is stronger over longer holding periods.

# Chapter 4 Option-Implied Factors and Stocks Returns: Indications from At-the-Money Options

## 4.1 Introduction

The CAPM establishes a parsimonious relationship between risk and return. However, it fails to explain the time-series and cross-sectional properties of asset returns. Many previous studies document the existence of pricing anomalies (as discussed in section 2.2). In order to better explain asset returns, theoretical and empirical studies are continuously looking for improvements on asset pricing models from different aspects.

For example, Ang, Hodrick, Xing and Zhang (2006) investigate whether the aggregate implied volatility can help to explain time-series and cross-section of stock returns, while An, Ang, Bali and Cakici (2014) focus on the predictive power of implied volatility in cross-section of stock returns at firm-level. Thus, whether the option-implied volatility can help explain time-series and cross-sectional properties of expected asset returns is worth to be studied. The goal of this chapter is to shed light on this issue.

This chapter applies the method documented in Ang, Hodrick, Xing and Zhang (2006) to construct return-based implied volatility factors ( *IVF*s ). To differentiate this chapter from previous studies, rather than using information at aggregate index level, this chapter uses option-implied information at individual firm level. The analysis also follows the way in Ang, Hodrick, Xing and Zhang (2006) to form 25 portfolios in cross-sectional regressions. To be more specific, this chapter employs firm-level implied volatility measures by using implied volatilities extracted from at-the-money call and put options. This chapter uses the cross-sectional regression documented in

Fama and MacBeth (1973) to test the significance of the risk premium on each $IVF$. This sheds light on whether investors are willing to pay compensation or buy insurance for $IVF$s. However, results in this chapter provide limited evidence that $IVF$s have significant risk premiums.

This chapter is organised as follows. Section 4.2 gives a detailed review of the relevant literature. Section 4.3 and 4.4 discuss data and methodology, respectively. Empirical results are presented in Section 4.5, followed by concluding remarks in Section 4.6.

## 4.2 Related Literature

Studies so far focus on pricing implications of aggregate volatility risk in cross-section of stock returns. Ang, Hodrick, Xing and Zhang (2006) document that first difference of the VXO index, which is used as a proxy for aggregate volatility risk, is an important factor in explaining the cross section of stock returns even after controlling for size, value, momentum, and liquidity effects. Their study constructs a return-based factor which can capture the aggregate volatility risk and find supportive evidence that aggregate volatility risk has a significantly negative risk premium. Furthermore, Ang, Hodrick, Xing and Zhang (2006) document that the cross-sectional price for aggregate volatility risk is about -1% per annum.

Recently, An, Ang, Bali and Cakici (2014) focus on the implied volatility of individual options and document the significant predictive power of the implied volatility in cross-section of stock returns at firm-level. More specifically, large increases in call (put) implied volatilities are followed by increases (decreases) in next-month stock returns. These results are robust to the inclusion of control variables, such as beta, size, book-to-market ratio, momentum and illiquidity, in regression models for asset pricing tests.

Compared with studies discussed above in this field, the innovation of this chapter lies in the fact that return-based factors are constructed by using firm-level implied volatility. These factors can be used as common risk factors (similar as $MKT$, $SMB$, and $HML$) and they can capture the influence of the option-implied volatility. This chapter sheds light on whether investors are willing to pay risk premiums on $IVF$s and expand the literature about the predictive power of $IVF$s. The following two sections introduce data and methodology used in this chapter in detail.

## 4.3 Data

The data used in this chapter are obtained from different sources. Stock return data are downloaded from CRSP. Fama-French three factors are available from Kenneth French's online data library.

Option data are obtained from "Volatility Surface" file in OptionMetrics.[24] This chapter investigates whether at-the-money implied volatilities contain useful information in explaining stock returns. Rather than using non-standardized historical option price data (from which it is difficult to get exactly at-the-money options with fixed day-to-maturities), this chapter uses standardized at-the-money option data (with delta equal to 0.5 for call options and -0.5 for put options) from "Volatility Surface" file. To construct return-based risk factors, "5-1" long-short portfolios are formed

[24] The "Volatility Surface" file contains the interpolated volatility surface for each security on each day, using a methodology based on a kernel smoothing algorithm. In order to get the volatility surface through interpolation, three factors are included in the kernel function: time-to-maturity of the option, "call-equivalent delta" of the option (delta for a call, one plus delta for a put), and the call/put identifier of the option. A standardized option is only included if there exists enough option price data on that date to accurately interpolate the required values. After the interpolation, OptionMetrics provides data for standardized options with expirations of 30, 60, 91, 122, 152, 182, 273, 365, 547, and 730 calendar days and deltas of 0.20, 0.25, 0.30, 0.35, 0.40, 0.45, 0.50, 0.55, 0.60, 0.65, 0.70, 0.75, and 0.80 (negative deltas for puts).

based on implied volatility and first difference in implied volatility at end of each calendar month. Furthermore, following Ang, Hodrick, Xing and Zhang (2006), this chapter constructs return-based risk factors by using monthly stock returns after portfolio formation. To ensure that the predictive period indicated by standardized option data (i.e., day-to-maturity of options) matches the period used for return-based risk factors calculation, this chapter focuses on option data with 30 day-to-maturity. Thus, this chapter uses implied volatility data extracted from standardized at-the-money call and put options with 30 day-to-maturity.

The sample period starts from January 1996 and ends in December 2010. During the sample period, this chapter examines whether information extracted from at-the-money options helps to explain stock returns.

## 4.4 Methodology

By assuming that investors can rebalance their portfolios without any transaction cost, this chapter aims to analyze whether factors constructed by using at-the-money option-implied volatility have significant risk premiums in explaining cross-section of monthly stock returns.

### 4.4.1 Implied Volatility Factors Construction

First, under the assumption that investors rebalance their portfolios every month, the implied volatilities of at-the-money call or put options with 30 day-to-maturity are extracted on the last trading day of each calendar month. Then, on that day, the information of the market capitalization for each stock is obtained. This chapter excludes stocks which do not have data available in all previous 36 months, and then sorts remaining stocks based on implied volatility and forms quintile portfolios. The analysis calculates both equally-weighted and value-weighted average return on each quintile portfolio during the following one-month period. After obtaining quintile portfolios, this chapter calculates the difference between the return on the portfolio with the highest implied volatility (i.e., portfolio 5) and the return on the portfolio with the lowest implied volatility (i.e., portfolio 1). This difference (return on "5-1" long-short portfolio) is used as the *IVF* in this chapter.

Furthermore, this chapter also uses change in implied volatility for *IVF* construction. After obtaining the implied volatility on the last trading day before portfolio construction, this chapter gets the implied volatility on the last trading day one month ago, which facilitates the calculation of change in implied volatility in the previous one month. This chapter sorts stocks on the change in implied volatility during previous one month, and forms quintile portfolios. Equally-weighted average return for each quintile portfolio is calculated, as well as value-weighted average return. The difference between the return on the portfolio with the highest change in implied volatility (i.e., portfolio 5) and the return on the portfolio with the lowest change in implied volatility (i.e., portfolio 1) is also used as the *IVF* in later cross-sectional regressions.

Given portfolio formation process discussed above, there are eight *IVF*s .[25]

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[25] There are four *IVF*s constructed from at-the-money call options: (1) the difference between the equally-weighted average return on the portfolio with the highest implied volatility and the equally-weighted average return on the portfolio with the lowest implied volatility; (2) the difference between the value-weighted average return on the portfolio with the highest implied volatility and the value-weighted average return on the portfolio with the lowest implied volatility; (3) the difference between the equally-weighted average return on the portfolio with the highest change in implied volatility and the equally-weighted average return on the portfolio with the lowest change in implied volatility; (4) the difference between the value-weighted average return on the portfolio with the highest change in implied volatility and the value-weighted average return on the portfolio with the lowest change in implied volatility. Furthermore, there are other four *IVF*s constructed from at-the-money put options by using the same process. These *IVF*s are available from March, 1999 to December, 2010.

### 4.4.2 Portfolios Formation in Cross-Sectional Regressions

Fama-MacBeth cross-sectional regressions can shed light on whether *IVF*s constructed in this chapter have significant risk premiums in explaining cross-section of stock returns. Constructing portfolios before the analysis is quite important and how to construct these portfolios has implications in asset pricing tests. Here, this chapter follows the way documented in Ang, Hodrick, Xing and Zhang (2006) and forms 25 portfolios for later cross-sectional regressions.

First of all, at the end of each month, this chapter estimates the following univariate regression for each individual stock which has monthly data available in all previous 36 months:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^m \left( r_{m,t} - r_{f,t} \right) + \varepsilon_{i,t} \tag{4.1}$$

where $r_{i,t}$ is the monthly return on each stock, $r_{m,t}$ is the value-weight monthly return on all NYSE, AMEX, and NASDAQ stocks, and $r_{f,t}$ is the monthly risk-free rate. After estimating the coefficient on the market excess return, $\beta_i^m$, all individual stocks are sorted into five quintiles by $\beta_i^m$. Then, the following bivariate regression is estimated for each individual stock during previous 36 months:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^m \left( r_{m,t} - r_{f,t} \right) + \beta_i^{IVF} IVF_t + \varepsilon_{i,t} \tag{4.2}$$

where $IVF_t$ stands for implied volatility factors discussed in Subsection 4.4.1. Then, within each $\beta_i^m$ quintile, stocks are sorted into five quintiles by the coefficient on $IVF_t$ ($\beta_i^{IVF}$). Thus, there are 25 portfolios in total.[26] Both equally-weighted average returns and value-weighted average returns on these 25 portfolios are calculated for later cross-sectional regressions.

[26] These 25 portfolios are available from March, 2002 to December, 2010.

### 4.4.3 Fama-MacBeth Cross-Sectional Regressions

This subsection discusses how to use cross-sectional regressions in empirical analysis. This chapter uses both full-window and rolling-window methods.

For the full-window method, in the first step, time-series regression for each portfolio among 25 portfolios is estimated for the whole period from March, 2002 to December, 2010. Factor loadings obtained in the first step will be used as explanatory variables in the second-step regressions for risk premium estimation.

Then, this chapter allows time variation in factor loadings in first-step regressions, (i.e., 60-month rolling-window and 36-month rolling-window methods). In each calendar month, first-step time-series regression is estimated for each portfolio during previous 60 or 36 months. This enables us to take into account the time-variation in betas. Then, second-step cross-sectional regressions help to make sure whether risk premiums on different factors are statistically significant.

## 4.5 Results

Following the process illustrated in section 4.4, this chapter constructs $IVF$s and uses these factors for portfolio formation. Then, this chapter uses these portfolios in cross-sectional regressions. The results are presented in this section.

### 4.5.1 Descriptive Summary

As introduced in Subsection 4.4.1, there are eight different $IVF$s constructed on the basis of either at-the-money call or put options. Details with regard to quintile portfolios and $IVF$s are presented in this subsection.

Table 4.1 reports summary statistics for quintile portfolios sorted on implied volatilities on the last trading day of the previous month. To be more specific, in Panel A, quintile portfolios are sorted on implied volatility extracted from at-the-money call options and formed by using equally-weighted scheme. Panel B presents details of value-weighted quintile portfolios sorted on implied volatility extracted from at-the-money call options. The remaining two panels (Panels C and D) report the information for equally-weighted and value-weighted quintile portfolios sorted on implied volatility extracted from at-the-money put options, respectively.

From Table 4.1, it is clear that portfolios with higher implied volatilities always bring higher returns to investors, while portfolios with lower implied volatilities always obtain lower returns (except for the second portfolio in Panel B and the fourth portfolio in Panel D). The standard deviation of returns increases among five quintile portfolios in all four panels. With regard to CAPM alphas, portfolios with higher implied volatilities normally have higher CAPM alphas than those with lower implied volatilities, even though there are several exceptions in Panels B, C, and D. That is, based on the CAPM, risk-adjusted returns on portfolios with higher implied volatilities are normally higher than risk-adjusted returns on portfolios with lower implied volatilities. However, for Fama-French three-factor (FF3F) alphas, there is no trend. That is, FF3F alphas fluctuate among these quintile portfolios in all panels.

Even though it is easy to find that, in all panels, portfolios with higher implied volatilities always have higher returns, differences between returns on portfolios with the highest implied volatility and returns on portfolios with the lowest implied volatility (average returns on "5-1" long-short portfolios) are not significantly different from zero (0.82%, 0.62%, 0.51%, and 0.27% in Panels A, B, C and D).[27] So the mean return on the portfolio with the highest implied volatility is not significantly higher than that on the portfolio with the lowest implied volatility. For CAPM and FF3F alphas on "5-1" long-short portfolios, in Panels A, B and C, controlling for the

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[27] These four kinds of "5-1" long-short returns represent four *IVF*s for later cross-sectional analysis.

**Table 4.1: Quintile Portfolios Sorted on the Implied Volatility**

Notes: This table reports details about quintile portfolios and implied volatility factors. Panel A and Panel B report summary statistics for quintile portfolios sorted on implied volatility extracted from at-the-money call options. Panel C and Panel D report summary statistics for quintile portfolios sorted on implied volatility extracted from at-the-money put options. The row "5-1" refers to the difference in monthly returns between the portfolio with the highest implied volatility and the portfolio with the lowest implied volatility, and the "5-1" return is used as $IVF$s in later analysis. The Alpha columns report alpha with respect to the CAPM or the Fama-French (1993) three-factor model which are estimated by using previous 36-month monthly data. Hereafter, *, **, and *** denote for statistical significance at 10%, 5% and 1% significance levels, respectively. The figures in the parentheses present p-values for the t-test with the null hypothesis that the mean is significantly different from zero.

| Rank | Mean | Std | CAPM $\alpha$ | FF3F $\alpha$ |
|---|---|---|---|---|
| Panel A: Portfolios Sorted on ATM Call Implied Volatility (Equally-Weighted) | | | | |
| 1 | 0.0062 | 0.0376 | 0.0050 | 0.0038 |
| 2 | 0.0089 | 0.0486 | 0.0072 | 0.0049 |
| 3 | 0.0105 | 0.0588 | 0.0084 | 0.0050 |
| 4 | 0.0121 | 0.0788 | 0.0092 | 0.0053 |
| 5 | 0.0144 | 0.1155 | 0.0105 | 0.0047 |
| 5-1 | 0.0082 | 0.0997 | 0.0055 | 0.0010 |
| p-value | (0.3280) | | (0.3614) | (0.8180) |
| Panel B: Portfolios Sorted on ATM Call Implied Volatility (Value-Weighted) | | | | |
| 1 | 0.0023 | 0.0354 | 0.0012 | 0.0019 |
| 2 | 0.0056 | 0.0513 | 0.0037 | 0.0042 |
| 3 | 0.0050 | 0.0661 | 0.0026 | 0.0026 |
| 4 | 0.0078 | 0.0908 | 0.0046 | 0.0055 |
| 5 | 0.0085 | 0.1220 | 0.0044 | 0.0021 |
| 5-1 | 0.0062 | 0.1097 | 0.0031 | 0.0002 |
| p-value | (0.5015) | | (0.6287) | (0.9671) |
| Panel C: Portfolios Sorted on ATM Put Implied Volatility (Equally-Weighted) | | | | |
| 1 | 0.0070 | 0.0377 | 0.0058 | 0.0048 |
| 2 | 0.0088 | 0.0497 | 0.0071 | 0.0049 |
| 3 | 0.0103 | 0.0589 | 0.0082 | 0.0051 |
| 4 | 0.0110 | 0.0803 | 0.0080 | 0.0048 |
| 5 | 0.0121 | 0.1153 | 0.0082 | 0.0027 |
| 5-1 | 0.0051 | 0.1000 | 0.0023 | -0.0021 |
| p-value | (0.5433) | | (0.6944) | (0.6290) |
| Panel D: Portfolios Sorted on ATM Put Implied Volatility (Value-Weighted) | | | | |
| 1 | 0.0032 | 0.0355 | 0.0021 | 0.0029 |
| 2 | 0.0043 | 0.0517 | 0.0025 | 0.0030 |
| 3 | 0.0049 | 0.0673 | 0.0024 | 0.0022 |
| 4 | 0.0066 | 0.0908 | 0.0034 | 0.0050 |
| 5 | 0.0059 | 0.1221 | 0.0017 | -0.0009 |
| 5-1 | 0.0027 | 0.1103 | -0.0004 | -0.0038 |
| p-value | (0.7740) | | (0.9546) | (0.4534) |

## Table 4.2: Quintile Portfolios Sorted on the Change in Implied Volatility

Notes: This table reports details about quintile portfolios and implied volatility factors. Panel A and Panel B report summary statistics for quintile portfolios sorted on the change in implied volatility extracted from at-the-money call options. Panel C and Panel D report summary statistics for quintile portfolios sorted on the change in implied volatility extracted from at-the-money put options. The row "5-1" refers to the difference in monthly returns between the portfolio with the highest change in implied volatility and the portfolio with the lowest change in implied volatility, and the "5-1" return is used as $IVF$s in later analysis. The Alpha columns report alpha with respect to the CAPM or the Fama-French (1993) three-factor model which are run by using previous 36-month monthly data.

| Rank | Mean | Std | CAPM $\alpha$ | FF3F $\alpha$ |
|---|---|---|---|---|
| Panel A: Portfolios Sorted on Change in ATM Call Implied Volatility (Equally-Weighted) | | | | |
| 1 | 0.0073 | 0.0726 | 0.0047 | 0.0011 |
| 2 | 0.0087 | 0.0569 | 0.0066 | 0.0038 |
| 3 | 0.0094 | 0.0547 | 0.0074 | 0.0049 |
| 4 | 0.0113 | 0.0585 | 0.0092 | 0.0061 |
| 5 | 0.0148 | 0.0808 | 0.0120 | 0.0072 |
| 5-1 | 0.0075*** | 0.0324 | 0.0073*** | 0.0061** |
| p-value | (0.0065) | | (0.0075) | (0.0267) |
| Panel B: Portfolios Sorted on Change in ATM Call Implied Volatility (Value-Weighted) | | | | |
| 1 | 0.0000 | 0.0657 | -0.0023 | -0.0023 |
| 2 | 0.0033 | 0.0487 | 0.0015 | 0.0025 |
| 3 | 0.0054 | 0.0439 | 0.0038 | 0.0043 |
| 4 | 0.0057 | 0.0489 | 0.0040 | 0.0046 |
| 5 | 0.0072 | 0.0685 | 0.0048 | 0.0027 |
| 5-1 | 0.0072* | 0.0504 | 0.0071* | 0.0050 |
| p-value | (0.0932) | | (0.0969) | (0.2335) |
| Panel C: Portfolios Sorted on Change in ATM Put Implied Volatility (Equally-Weighted) | | | | |
| 1 | 0.0093 | 0.0732 | 0.0067 | 0.0036 |
| 2 | 0.0102 | 0.0573 | 0.0081 | 0.0057 |
| 3 | 0.0105 | 0.0556 | 0.0085 | 0.0061 |
| 4 | 0.0089 | 0.0591 | 0.0068 | 0.0039 |
| 5 | 0.0097 | 0.0808 | 0.0069 | 0.0026 |
| 5-1 | 0.0004 | 0.0313 | 0.0002 | -0.0011 |
| p-value | (0.8805) | | (0.9371) | (0.6828) |
| Panel D: Portfolios Sorted on Change in ATM Put Implied Volatility (Value-Weighted) | | | | |
| 1 | 0.0034 | 0.0657 | 0.0011 | 0.0022 |
| 2 | 0.0057 | 0.0492 | 0.0040 | 0.0047 |
| 3 | 0.0044 | 0.0442 | 0.0028 | 0.0036 |
| 4 | 0.0038 | 0.0499 | 0.0021 | 0.0025 |
| 5 | 0.0037 | 0.0692 | 0.0013 | 0.0000 |
| 5-1 | 0.0003 | 0.0505 | 0.0001 | -0.0022 |
| p-value | (0.9480) | | (0.9776) | (0.5971) |

market factor decreases “5-1” spreads to 0.55%, 0.31%, and 0.23% per month, while controlling for the Fama-French three factors decreases “5-1” spreads to 0.10%, 0.02%, and -0.21% per month, respectively. In Panel D, controlling for the market factor decreases the “5-1” spread to -0.04% per month, while controlling for Fama-French three factors exacerbates the “5-1” spread to -0.38% per month.

In addition to quintile portfolios sorted on the implied volatility, this chapter also forms quintile portfolios by sorting stocks on the change in implied volatility during previous one month. Thus, following the same method mentioned above, there are other four $IVF$s .

Table 4.2 shows summary statistics for quintile portfolios sorted on the change in implied volatility during the previous month before portfolio construction. Panel A reports information of equally-weighted quintile portfolios sorted on the change in at-the-money call implied volatility. In Panel B, quintile portfolios are formed by using value-weighted scheme and by sorting on the change in at-the-money call implied volatility. The remaining two panels report the information for equally-weighted and value-weighted quintile portfolios sorted on the change in at-the-money put implied volatility.

In the first two panels in Table 4.2, returns on quintile portfolios increase with the increasing change in implied volatility. That is, portfolios with lower changes in implied volatility also have lower returns than those with higher changes in implied volatility. Furthermore, in these two panels, CAPM alphas and FF3F alphas also always increase with the change in implied volatility, except for the FF3F alpha for quintile portfolio 5 in Panel B. However, in Panels C and D, returns on quintile portfolios do not change monotonically. Meanwhile, there is no trend in CAPM alphas and FF3F alphas in these two panels. When it comes to the standard deviation, in all these four panels, the standard deviation performs a U-shape. The third quintile portfolio has the smallest standard deviation while portfolios with extremely high or low change in implied volatility have higher standard deviations.

In Table 4.2, for “5-1” long-short portfolios, statistical significance of returns, CAPM alphas and FF3F alphas are quite different from Table 4.1. In Panel A and Panel B of Table 4.2, the average return on “5-1” long-short portfolio is different from zero (0.75% with a p-value of 0.0065 and 0.72% with a marginally significant p-value of 0.0932, respectively). So portfolios with the highest change in at-the-money call implied volatility earn significantly higher monthly returns than those with the lowest change in implied volatility. Furthermore, in Panel A, CAPM alpha and FF3F alpha on the “5-1” long-short portfolio are also significantly positive. In Panel A, controlling the $MKT$ decreases the “5-1” spread to 0.73% per month, and controlling for Fama-French three factors decreases the “5-1” spread to 0.61% per month. In Panel B, controlling for the $MKT$ decreases the “5-1” spread to 0.71% per month, and controlling for Fama-French three factors makes the “5-1” spread insignificant and decreases it to 0.50% per month. Meanwhile, in Panel C and Panel D, average returns, CAPM alphas and FF3F alphas of “5-1” portfolios are all insignificantly different from zero. In Panel C and Panel D, controlling the $MKT$ decreases the “5-1” spread to 0.02% and 0.01% per month, respectively, while controlling $MKT$, $SMB$, and $HML$ exacerbates the “5-1” spread to -0.11% and -0.22% per month, respectively.

Returns on “5-1” long-short portfolios are used as $IVF$s in cross-sectional regressions. Later analysis discusses whether these factors have significant risk premiums and whether investors are willing to pay compensation or buy insurance for these factors.

### 4.5.2 Cross-Sectional Regression Results

To shed light on whether implied volatility is priced by investors, this chapter uses the mimicking volatility factor, $IVF$s, to run cross-sectional regressions. This chapter first constructs a set of test portfolios whose factor loadings on volatility risk are sufficiently disperse in order to make sure that cross-sectional regressions have reasonable power (see details about portfolio construction in previous Subsection 4.4.2).

This section runs cross-sectional regressions following the method documented in Fama and MacBeth (1973), and forms six models for cross-sectional regressions. Model *I* and *II* are univariate models which include $IVF$s or $MKT$, respectively. Model *III* includes two variables, which are $IVF$s and $MKT$. Model *IV*, *V* and *VI* take $SMB$ and $HML$ into consideration. Model *IV* includes the $IVF$s, $SMB$ and $HML$, Model *V* includes $MKT$, $SMB$ and $HML$, and Model *VI* incorporates all four variables.

As introduced above, cross-sectional analysis uses the full-window method, the 60-month rolling-window method and the 36-month rolling-window method. Following three subsections present regression results obtained by using these three methods, respectively.

#### 4.5.2.1 Cross-Sectional Regression Results Using Full-Window Method

Table 4.3 presents cross-sectional regression results obtained using the full-window method under the assumption that there is no time variation in beta estimation in first-step time-series regressions. Thus, there are 106 lambda estimations (risk premiums on different explanatory factors). The sample period for cross-sectional regressions using the full-window method is from March, 2002 to December, 2010.

**Table 4.3: Cross-Sectional Regression Results Using Full-Window Method**

Notes: This table reports cross-sectional regression results by using the full-window method. Panel A (B) shows results when using $IVF$ obtained by using equally-weighted (value-weighted) quintile portfolios sorted on the implied volatility extracted from at-the-money call options. Panel C (D) presents results obtained by using $IVF$ constructed by using equally-weighted (value-weighted) quintile portfolios sorted on the implied volatility extracted from at-the-money put options. Panel E (F) shows results when using $IVF$ obtained by using equally-weighted (value-weighted) quintile portfolios sorted on the change in implied volatility extracted from at-the-money call options. Panel G (H) presents results got by using $IVF$ constructed by using equally-weighted (value-weighted) quintile portfolios sorted on the change in implied volatility extracted from at-the-money put options. Six models including different variables ($IVF$, $MKT$, $SMB$ and $HML$) in different combinations are estimated to test whether risk premiums on relative factors are significantly different from zero.

| | I | II | III | IV | V | VI |
|---|---|---|---|---|---|---|
| Panel A: Cross-Sectional Regression Results by Using $IVF$ Constructed by Using Portfolios Sorted on $IV$ Extracted from ATM **Call** Options (Equally-Weighted) | | | | | | |
| *Intercept* | 0.0038 | 0.0038 | 0.0017 | 0.0052 | 0.0021 | 0.0011 |
| p-value | (0.2899) | (0.2899) | (0.6938) | (0.1134) | (0.5841) | (0.8185) |
| $\lambda_{IVF}$ | 0.0059 | | 0.0055 | 0.0051 | | 0.0035 |
| p-value | (0.4800) | | (0.5158) | (0.5323) | | (0.6797) |
| $\lambda_{MKT}$ | | 0.0059 | 0.0048 | | 0.0063 | 0.0074 |
| p-value | | (0.4800) | (0.4839) | | (0.3592) | (0.3560) |
| $\lambda_{SMB}$ | | | | -0.0020 | -0.0031 | -0.0030 |
| p-value | | | | (0.6680) | (0.5679) | (0.5700) |
| $\lambda_{HML}$ | | | | -0.0009 | -0.0014 | -0.0019 |
| p-value | | | | (0.8469) | (0.7584) | (0.7100) |
| Panel B: Cross-Sectional Regression Results by Using $IVF$ Constructed by Using Portfolios Sorted on $IV$ Extracted from ATM **Call** options (Value-Weighted) | | | | | | |
| *Intercept* | 0.0018 | 0.0001 | 0.0002 | 0.0016 | 0.0005 | 0.0001 |
| p-value | (0.6078) | (0.9816) | (0.9691) | (0.6001) | (0.8896) | (0.9740) |
| $\lambda_{IVF}$ | 0.0056 | | 0.0055 | 0.0057 | | 0.0051 |
| p-value | (0.5353) | | (0.5470) | (0.5183) | | (0.5671) |
| $\lambda_{MKT}$ | | 0.0041 | 0.0041 | | 0.0037 | 0.0041 |
| p-value | | (0.5199) | (0.5410) | | (0.5413) | (0.5331) |
| $\lambda_{SMB}$ | | | | 0.0018 | 0.0014 | 0.0015 |
| p-value | | | | (0.6641) | (0.7499) | (0.7196) |
| $\lambda_{HML}$ | | | | 0.0008 | 0.0004 | 0.0003 |
| p-value | | | | (0.8609) | (0.9193) | (0.9489) |

(Continued)

| Panel C: Cross-Sectional Regression Results by Using $IVF$ Constructed by Using Portfolios Sorted on $IV$ Extracted from ATM **Put** Options (Equally-Weighted) | | | | | | |
|---|---|---|---|---|---|---|
| *Intercept* | 0.0037 | 0.0020 | 0.0031 | 0.0041 | 0.0002 | 0.0030 |
| p-value | (0.3069) | (0.6619) | (0.4623) | (0.2553) | (0.9515) | (0.4635) |
| $\lambda_{IVF}$ | 0.0058 | | 0.0057 | 0.0052 | | 0.0049 |
| p-value | (0.4872) | | (0.4947) | (0.5279) | | (0.5605) |
| $\lambda_{MKT}$ | | 0.0044 | 0.0032 | | 0.0082 | 0.0055 |
| p-value | | (0.4856) | (0.6225) | | (0.2138) | (0.4448) |
| $\lambda_{SMB}$ | | | | -0.0050 | -0.0046 | -0.0052 |
| p-value | | | | (0.2871) | (0.3704) | (0.2998) |
| $\lambda_{HML}$ | | | | 0.0024 | 0.0011 | 0.0022 |
| p-value | | | | (0.6329) | (0.8168) | (0.6789) |
| Panel D: Cross-Sectional Regression Results by Using $IVF$ Constructed by Using Portfolios Sorted on $IV$ Extracted from ATM **Put** Options (Value-Weighted) | | | | | | |
| *Intercept* | 0.0008 | -0.0012 | 0.0010 | 0.0002 | 0.0001 | 0.0017 |
| p-value | (0.8249) | (0.7941) | (0.8219) | (0.9528) | (0.9870) | (0.6842) |
| $\lambda_{IVF}$ | 0.0069 | | 0.0069 | 0.0077 | | 0.0084 |
| p-value | (0.4439) | | (0.4451) | (0.3897) | | (0.3533) |
| $\lambda_{MKT}$ | | 0.0051 | 0.0029 | | 0.0039 | 0.0023 |
| p-value | | (0.4422) | (0.6617) | | (0.5169) | (0.7166) |
| $\lambda_{SMB}$ | | | | 0.0041 | 0.0046 | 0.0040 |
| p-value | | | | (0.3263) | (0.2572) | (0.3367) |
| $\lambda_{HML}$ | | | | 0.0018 | 0.0016 | 0.0024 |
| p-value | | | | (0.7091) | (0.7366) | (0.6252) |
| Panel E: Cross-Sectional Regression Results by Using $IVF$ Constructed by Using Portfolios Sorted on $\Delta IV$ Extracted from ATM **Call** Options (Equally-Weighted) | | | | | | |
| *Intercept* | 0.0000 | 0.0021 | -0.0006 | -0.0012 | -0.0014 | -0.0021 |
| p-value | (0.9939) | (0.6471) | (0.8927) | (0.7603) | (0.7721) | (0.6537) |
| $\lambda_{IVF}$ | 0.0123 | | 0.0078* | 0.0056 | | 0.0055 |
| p-value | (0.2581) | | (0.0674) | (0.1610) | | (0.1706) |
| $\lambda_{MKT}$ | | 0.0044 | 0.0056 | | 0.0062 | 0.0066 |
| p-value | | (0.4833) | (0.3708) | | (0.3530) | (0.3157) |
| $\lambda_{SMB}$ | | | | 0.0046 | 0.0030 | 0.0032 |
| p-value | | | | (0.3563) | (0.4353) | (0.4160) |
| $\lambda_{HML}$ | | | | 0.0055 | 0.0071 | 0.0062 |
| p-value | | | | (0.2858) | (0.1482) | (0.2189) |

(Continued)

| | | | | | | |
|---|---|---|---|---|---|---|
| Panel F: Cross-Sectional Regression Results by Using $IVF$ Constructed by Using Portfolios Sorted on $\Delta IV$ Extracted from ATM **Call** Options (Value-Weighted) | | | | | | |
| *Intercept* | 0.0055 | -0.0004 | 0.0018 | 0.0014 | -0.0026 | -0.0018 |
| p-value | (0.3593) | (0.9346) | (0.6745) | (0.7054) | (0.5442) | (0.6797) |
| $\lambda_{IVF}$ | -0.0122 | | -0.0065 | -0.0060 | | -0.0076 |
| p-value | (0.3567) | | (0.3033) | (0.3724) | | (0.2610) |
| $\lambda_{MKT}$ | | 0.0046 | 0.0024 | | 0.0068 | 0.0059 |
| p-value | | (0.4764) | (0.7041) | | (0.2844) | (0.3580) |
| $\lambda_{SMB}$ | | | | 0.0028 | 0.0017 | -0.0019 |
| p-value | | | | (0.6317) | (0.7212) | (0.6935) |
| $\lambda_{HML}$ | | | | 0.0041 | 0.0052 | 0.0046 |
| p-value | | | | (0.3995) | (0.2854) | (0.3425) |
| Panel G: Cross-Sectional Regression Results by Using $IVF$ Constructed by Using Portfolios Sorted on $\Delta IV$ Extracted from ATM **Put** Options (Equally-Weighted) | | | | | | |
| *Intercept* | 0.0024 | 0.0018 | 0.0021 | 0.0028 | 0.0010 | 0.0015 |
| p-value | (0.5637) | (0.6899) | (0.6290) | (0.4785) | (0.8351) | (0.7520) |
| $\lambda_{IVF}$ | 0.0064 | | -0.0017 | -0.0021 | | -0.0027 |
| p-value | (0.5049) | | (0.6873) | (0.6181) | | (0.5229) |
| $\lambda_{MKT}$ | | 0.0044 | 0.0046 | | 0.0045 | 0.0043 |
| p-value | | (0.4791) | (0.4660) | | (0.4988) | (0.5178) |
| $\lambda_{SMB}$ | | | | 0.0040 | 0.0021 | 0.0019 |
| p-value | | | | (0.4324) | (0.6211) | (0.6474) |
| $\lambda_{HML}$ | | | | 0.0016 | 0.0024 | 0.0030 |
| p-value | | | | (0.8076) | (0.6945) | (0.6262) |
| Panel H: Cross-Sectional Regression Results by Using $IVF$ Constructed by Using Portfolios Sorted on $\Delta IV$ Extracted from ATM **Put** Options (Value-Weighted) | | | | | | |
| *Intercept* | 0.0065 | -0.0005 | 0.0013 | 0.0015 | -0.0021 | -0.0005 |
| p-value | (0.3082) | (0.9053) | (0.7642) | (0.6923) | (0.6438) | (0.9074) |
| $\lambda_{IVF}$ | -0.0096 | | -0.0063 | -0.0050 | | -0.0057 |
| p-value | (0.2327) | | (0.2896) | (0.3951) | | (0.3453) |
| $\lambda_{MKT}$ | | 0.0046 | 0.0027 | | 0.0062 | 0.0045 |
| p-value | | (0.4765) | (0.6654) | | (0.3460) | (0.4726) |
| $\lambda_{SMB}$ | | | | 0.0037 | 0.0029 | 0.0011 |
| p-value | | | | (0.4888) | (0.5226) | (0.8064) |
| $\lambda_{HML}$ | | | | 0.0035 | 0.0046 | 0.0043 |
| p-value | | | | (0.5430) | (0.4156) | (0.4505) |

From Table 4.3, it can be seen that there is only one marginally significant risk premium. That is, risk premium on *IVF* in Model *III* in Panel E is significantly positive at the 10% significance level. The risk premium is 0.78% per month with a p-value of 0.0674. Furthermore, when Fama-French three factors are included in Model *VI*, the significance of the risk premium on *IVF* disappears.

*IVF*s used in Panel A to Panel D are always highly correlated with *MKT* and *SMB* (correlations are around 0.5). This high correlation may affect the significance of results obtained in cross-sectional regressions. However, in Panel E to Panel H, factors used in regressions are not highly correlated (all correlations are smaller than 0.35). Thus, the disappearance of the significance of the risk premium on *IVF* in Model *VI* of Panel E cannot be due to the collinearity problem.

So, under the assumption that factor loadings are constant from March, 2002 to December, 2010, the evidence that investors are willing to pay compensation or buy insurance for implied volatility factors constructed in this chapter is very limited.

#### 4.5.2.2 Cross-Sectional Regression Results Using 60-Month Rolling-Window Method

Since results from cross-sectional regressions by using the full-window method do not provide any strong evidence about risk premiums on *IVF*s, this chapter further assumes that factor loadings from time-series regressions could be time-varying. Thus, this subsection estimates factor loadings every month by using previous 60-month data. That is, this subsection runs the first-step time-series regression every month by using previous 60-month data. Thus, there are only 47 lambda estimations in total, from February, 2007 to December, 2010. Table 4.4 documents results from cross-sectional regressions when using the 60-month rolling-window method.

**Table 4.4: Cross-Sectional Regression Results Using 60-Month Rolling-Window Method**

Notes: This table reports cross-sectional regression results by using 60-month rolling-window method. Panel A (B) shows results when using $IVF$ obtained by using equally-weighted (value-weighted) quintile portfolios sorted on the implied volatility extracted from at-the-money call options. Panel C (D) presents results obtained by using $IVF$ constructed by using equally-weighted (value-weighted) quintile portfolios sorted on the implied volatility extracted from at-the-money put options. Panel E (F) shows results when using $IVF$ obtained by using equally-weighted (value-weighted) quintile portfolios sorted on the change in implied volatility extracted from at-the-money call options. Panel G (H) presents results got by using $IVF$ constructed by using equally-weighted (value-weighted) quintile portfolios sorted on the change in implied volatility extracted from at-the-money put options. Six models including different variables ($IVF$, $MKT$, $SMB$ and $HML$) in different combinations are estimated to test whether risk premiums on relative factors are significantly different from zero.

| | I | II | III | IV | V | VI |
|---|---|---|---|---|---|---|
| Panel A: Cross-Sectional Regression Results by Using $IVF$ Constructed by Using Portfolios Sorted on $IV$ Extracted from ATM **Call** Options (Equally-Weighted) | | | | | | |
| *Intercept* | -0.0068 | -0.0100 | 0.0030 | 0.0008 | 0.0033 | 0.0049 |
| p-value | (0.2173) | (0.1476) | (0.6585) | (0.8876) | (0.6430) | (0.3783) |
| $\lambda_{IVF}$ | 0.0153 | | 0.0151 | 0.0112 | | 0.0119 |
| p-value | (0.2290) | | (0.2225) | (0.4206) | | (0.3723) |
| $\lambda_{MKT}$ | | 0.0114 | -0.0025 | | -0.0023 | -0.0040 |
| p-value | | (0.3335) | (0.8362) | | (0.8674) | (0.7495) |
| $\lambda_{SMB}$ | | | | 0.0047 | 0.0066 | 0.0059 |
| p-value | | | | (0.4209) | (0.3099) | (0.3334) |
| $\lambda_{HML}$ | | | | -0.0039 | -0.0037 | -0.0029 |
| p-value | | | | (0.6030) | (0.6073) | (0.6909) |
| Panel B: Cross-Sectional Regression Results by Using $IVF$ Constructed by Using Portfolios Sorted on $IV$ Extracted from ATM **Call** options (Value-Weighted) | | | | | | |
| *Intercept* | -0.0050 | -0.0039 | 0.0079 | 0.0020 | 0.0123* | 0.0101 |
| p-value | (0.3974) | (0.5607) | (0.2080) | (0.6959) | (0.0652) | (0.1259) |
| $\lambda_{IVF}$ | 0.0111 | | 0.0122 | -0.0002 | | 0.0010 |
| p-value | (0.4189) | | (0.3649) | (0.9913) | | (0.9443) |
| $\lambda_{MKT}$ | | 0.0060 | -0.0061 | | -0.0105 | -0.0084 |
| p-value | | (0.5956) | (0.6207) | | (0.4033) | (0.4633) |
| $\lambda_{SMB}$ | | | | 0.0128*** | 0.0123** | 0.0138*** |
| p-value | | | | (0.0088) | (0.0107) | (0.0066) |
| $\lambda_{HML}$ | | | | -0.0102* | -0.0057 | -0.0091 |
| p-value | | | | (0.0876) | (0.3342) | (0.1153) |

(Continued)

| Panel C: Cross-Sectional Regression Results by Using $IVF$ Constructed by Using Portfolios Sorted on $IV$ Extracted from ATM **Put** Options (Equally-Weighted) | | | | | | |
|---|---|---|---|---|---|---|
| $Intercept$ | -0.0063 | -0.0088 | 0.0051 | 0.0028 | 0.0050 | 0.0077 |
| p-value | (0.2438) | (0.2065) | (0.4132) | (0.6379) | (0.4394) | (0.1904) |
| $\lambda_{IVF}$ | 0.0144 | | 0.0149 | 0.0105 | | 0.0110 |
| p-value | (0.2599) | | (0.2374) | (0.4513) | | (0.4205) |
| $\lambda_{MKT}$ | | 0.0102 | -0.0049 | | -0.0041 | -0.0058 |
| p-value | | (0.3891) | (0.6640) | | (0.7400) | (0.6206) |
| $\lambda_{SMB}$ | | | | 0.0014 | 0.0065 | 0.0022 |
| p-value | | | | (0.8296) | (0.3255) | (0.7158) |
| $\lambda_{HML}$ | | | | -0.0042 | -0.0036 | -0.0038 |
| p-value | | | | (0.6065) | (0.6421) | (0.6310) |
| Panel D: Cross-Sectional Regression Results by Using $IVF$ Constructed by Using Portfolios Sorted on $IV$ Extracted from ATM **Put** Options (Value-Weighted) | | | | | | |
| $Intercept$ | -0.0068 | -0.0076 | 0.0027 | 0.0005 | 0.0066 | 0.0035 |
| p-value | (0.2650) | (0.3154) | (0.5769) | (0.9287) | (0.3412) | (0.5123) |
| $\lambda_{IVF}$ | 0.0138 | | 0.0155 | 0.0031 | | 0.0040 |
| p-value | (0.3390) | | (0.2661) | (0.8481) | | (0.7948) |
| $\lambda_{MKT}$ | | 0.0091 | -0.0013 | | -0.0049 | -0.0019 |
| p-value | | (0.4420) | (0.9098) | | (0.7011) | (0.8694) |
| $\lambda_{SMB}$ | | | | 0.0132*** | 0.0131** | 0.0137*** |
| p-value | | | | (0.0088) | (0.0141) | (0.0067) |
| $\lambda_{HML}$ | | | | -0.0068 | -0.0025 | -0.0059 |
| p-value | | | | (0.3158) | (0.6923) | (0.3799) |
| Panel E: Cross-Sectional Regression Results by Using $IVF$ Constructed by Using Portfolios Sorted on $\Delta IV$ Extracted from ATM **Call** Options (Equally-Weighted) | | | | | | |
| $Intercept$ | -0.0080 | -0.0108 | -0.0087 | -0.0048 | -0.0068 | -0.0029 |
| p-value | (0.1632) | (0.1331) | (0.1984) | (0.4242) | (0.2962) | (0.6504) |
| $\lambda_{IVF}$ | 0.0098 | | 0.0037 | 0.0030 | | 0.0038 |
| p-value | (0.2879) | | (0.5619) | (0.5988) | | (0.4754) |
| $\lambda_{MKT}$ | | 0.0118 | 0.0096 | | 0.0079 | 0.0042 |
| p-value | | (0.3136) | (0.3917) | | (0.5190) | (0.7328) |
| $\lambda_{SMB}$ | | | | 0.0080 | 0.0032 | 0.0033 |
| p-value | | | | (0.2410) | (0.6044) | (0.5925) |
| $\lambda_{HML}$ | | | | 0.0001 | 0.0009 | -0.0004 |
| p-value | | | | (0.9858) | (0.8990) | (0.9592) |

(Continued)

| Panel F: Cross-Sectional Regression Results by Using $IVF$ Constructed by Using Portfolios Sorted on $\Delta IV$ Extracted from ATM **Call** Options (Value-Weighted) | | | | | | |
|---|---|---|---|---|---|---|
| *Intercept* | 0.0013 | -0.0055 | -0.0046 | -0.0008 | 0.0064 | 0.0059 |
| p-value | (0.8960) | (0.4433) | (0.5298) | (0.8939) | (0.3457) | (0.3871) |
| $\lambda_{IVF}$ | 0.0025 | | 0.0023 | -0.0021 | | 0.0002 |
| p-value | (0.8989) | | (0.8120) | (0.8419) | | (0.9839) |
| $\lambda_{MKT}$ | | 0.0071 | 0.0063 | | -0.0050 | -0.0044 |
| p-value | | (0.5445) | (0.5908) | | (0.7163) | (0.7423) |
| $\lambda_{SMB}$ | | | | 0.0049 | 0.0039 | 0.0038 |
| p-value | | | | (0.5257) | (0.4794) | (0.4871) |
| $\lambda_{HML}$ | | | | -0.0001 | -0.0029 | -0.0022 |
| p-value | | | | (0.9942) | (0.7152) | (0.7692) |
| Panel G: Cross-Sectional Regression Results by Using $IVF$ Constructed by Using Portfolios Sorted on $\Delta IV$ Extracted from ATM **Put** Options (Equally-Weighted) | | | | | | |
| *Intercept* | -0.0080 | -0.0108 | -0.0099 | -0.0029 | -0.0015 | -0.0032 |
| p-value | (0.2040) | (0.1493) | (0.1662) | (0.6030) | (0.8275) | (0.6249) |
| $\lambda_{IVF}$ | 0.0118 | | 0.0038 | 0.0060 | | 0.0039 |
| p-value | (0.2025) | | (0.5126) | (0.3244) | | (0.4791) |
| $\lambda_{MKT}$ | | 0.0116 | 0.0112 | | 0.0030 | 0.0048 |
| p-value | | (0.3313) | (0.3694) | | (0.8197) | (0.7109) |
| $\lambda_{SMB}$ | | | | 0.0087 | 0.0029 | 0.0040 |
| p-value | | | | (0.1840) | (0.5898) | (0.4449) |
| $\lambda_{HML}$ | | | | -0.0025 | -0.0024 | -0.0026 |
| p-value | | | | (0.7318) | (0.7354) | (0.6988) |
| Panel H: Cross-Sectional Regression Results by Using $IVF$ Constructed by Using Portfolios Sorted on $\Delta IV$ Extracted from ATM **Put** Options (Value-Weighted) | | | | | | |
| *Intercept* | 0.0068 | -0.0058 | -0.0035 | -0.0029 | 0.0002 | 0.0012 |
| p-value | (0.4292) | (0.4130) | (0.5634) | (0.5834) | (0.9724) | (0.8196) |
| $\lambda_{IVF}$ | -0.0027 | | 0.0032 | 0.0029 | | 0.0018 |
| p-value | (0.8603) | | (0.7909) | (0.7929) | | (0.8729) |
| $\lambda_{MKT}$ | | 0.0072 | 0.0049 | | 0.0011 | 0.0001 |
| p-value | | (0.5412) | (0.6433) | | (0.9327) | (0.9922) |
| $\lambda_{SMB}$ | | | | 0.0103 | 0.0062 | 0.0044 |
| p-value | | | | (0.1618) | (0.2845) | (0.3966) |
| $\lambda_{HML}$ | | | | 0.0018 | 0.0000 | -0.0029 |
| p-value | | | | (0.7864) | (0.9991) | (0.6699) |

In Table 4.4, there is no significant risk premium on $IVF$s in all eight panels. However, in Panel B and Panel D, $SMB$ has a significant risk premium in models *IV*, *V* and *VI*. In both panels, the risk premium on $SMB$ is significantly positive at a 5% significance level (in models *IV* and *VI*, the risk premium is even significantly positive at a 1% significance level). Furthermore, the risk premium on $SMB$ in these six models is quite persistent, around 1.3% per month. Meanwhile, in other panels, there is no significant result for these factors.

Pairwise correlations show that correlations between $IVF$s in Panels A to D and other three factors (all higher than 0.45) are higher than those between $IVF$s in Panels E to H and other three factors (all lower than 0.42). Furthermore, correlations between $IVF$s and other factors are higher in this period than those in the period from March, 2002 to December, 2010. In addition, correlations between any two variables among $MKT$, $SMB$ and $HML$ are also higher in the period from February, 2007 to December, 2010 than those correlations in the period from March, 2002 to December, 2010. Thus, insignificant cross-sectional results in Table 4.4 are probably caused by high correlations between any two explanatory variables.

Discussion above indicates that, during the period from February, 2007 to December, 2010, $SMB$ is the only factor which has a significant risk premium. The significant risk premium is found when value-weighted portfolios are formed by using the implied volatility extracted from both the at-the-money call option and the at-the-money put option. Forming value-weighted portfolios takes the market capitalization of each firm into consideration. $SMB$ is a factor which can be seen as a proxy for risk captured by firm size. Thus, value-weighted portfolios can enhance the significance of the risk premium on $SMB$ in cross-sectional regressions.

#### 4.5.2.3 Cross-Sectional Regression Results Using 36-Month Rolling-Window Method

From the previous subsection, *IVF*s do not have significant risk premiums when using the 60-month rolling-window method in cross-sectional regressions. It is natural to ask whether these results are sensitive to the selection of window length. So, in this subsection, the time-series regression (i.e., the first step of the Fama-MacBeth regression) is estimated at monthly frequency by using previous 36 months' monthly data. There are 71 lambda estimations to test whether the relative risk premium is significantly positive or negative. Thus, the sample period is from February, 2005 to December, 2010. Results obtained from cross-sectional regressions using the 36-month rolling-window method are documented in Table 4.5.

In Table 4.5, marginally significant risk premium on *IVF* at a 10% significance level is documented in Panel E. The risk premium on *IVF* is 0.61% per month, while the corresponding average of this *IVF* is 0.19% per month. In addition, Panel D shows that risk premium on *SMB* (around 0.60% per month) is significantly positive at a 10% significance level in model *V* and *VI*. The average of *SMB* during the period from February, 2005 to December, 2010 is 0.30% per month. Furthermore, different from cross-sectional regression results in Table 4.3 and Table 4.4, in Panels B, C, D, F and G in Table 4.5, cross-sectional regressions yield significantly positive intercepts. That is, there should be other factors which can help to explain cross-section of portfolio returns under the assumption that factor loadings from time-series regressions change every 36 months.

Similarly, correlations between *IVF*s in Panels A to D and other three factors are higher than those between *IVF*s in Panels E to H and other three factors. Furthermore, correlations between *IVF*s and other factors are higher in this period than those in the period from February, 2007 to December, 2010, but they are lower

**Table 4.5: Cross-Sectional Regression Results Using 36-Month Rolling-Window Method**

Notes: This table reports cross-sectional regression results by using 36-Month Rolling-Window method. Panel A (B) shows results when using $IVF$ obtained by using equally-weighted (value-weighted) quintile portfolios sorted on the implied volatility extracted from at-the-money call options. Panel C (D) presents results obtained by using $IVF$ constructed by using equally-weighted (value-weighted) quintile portfolios sorted on the implied volatility extracted from at-the-money put options. Panel E (F) shows results when using $IVF$ obtained by using equally-weighted (value-weighted) quintile portfolios sorted on the change in implied volatility extracted from at-the-money call options. Panel G (H) presents results got by using $IVF$ constructed by using equally-weighted (value-weighted) quintile portfolios sorted on the change in implied volatility extracted from at-the-money put options. Six models including different variables ($IVF$, $MKT$, $SMB$ and $HML$) in different combinations are estimated to test whether risk premiums on relative factors are significantly different from zero.

| | I | II | III | IV | V | VI |
|---|---|---|---|---|---|---|
| Panel A: Cross-Sectional Regression Results by Using $IVF$ Constructed by Using Portfolios Sorted on $IV$ Extracted from ATM **Call** Options (Equally-Weighted) | | | | | | |
| *Intercept* | 0.0007 | -0.0017 | 0.0030 | 0.0036 | 0.0036 | 0.0035 |
| p-value | (0.8513) | (0.7221) | (0.5281) | (0.2908) | (0.4022) | (0.3140) |
| $\lambda_{IVF}$ | 0.0088 | | 0.0114 | 0.0072 | | 0.0080 |
| p-value | (0.3391) | | (0.1996) | (0.4451) | | (0.3818) |
| $\lambda_{MKT}$ | | 0.0061 | -0.0005 | | -0.0006 | -0.0004 |
| p-value | | (0.4803) | (0.9503) | | (0.9469) | (0.9587) |
| $\lambda_{SMB}$ | | | | 0.0034 | 0.0035 | 0.0036 |
| p-value | | | | (0.3841) | (0.4031) | (0.3457) |
| $\lambda_{HML}$ | | | | 0.0016 | 0.0015 | 0.0016 |
| p-value | | | | (0.7356) | (0.7447) | (0.7285) |
| Panel B: Cross-Sectional Regression Results by Using $IVF$ Constructed by Using Portfolios Sorted on $IV$ Extracted from ATM **Call** options (Value-Weighted) | | | | | | |
| *Intercept* | 0.0003 | 0.0018 | 0.0076* | 0.0050 | 0.0090*** | 0.0081** |
| p-value | (0.9324) | (0.6978) | (0.0831) | (0.1178) | (0.0074) | (0.0188) |
| $\lambda_{IVF}$ | 0.0058 | | 0.0072 | -0.0016 | | -0.0010 |
| p-value | (0.5432) | | (0.4331) | (0.8646) | | (0.9130) |
| $\lambda_{MKT}$ | | 0.0023 | -0.0037 | | -0.0054 | -0.0044 |
| p-value | | (0.7802) | (0.6397) | | (0.4875) | (0.5202) |
| $\lambda_{SMB}$ | | | | 0.0041 | 0.0041 | 0.0038 |
| p-value | | | | (0.2235) | (0.2068) | (0.2472) |
| $\lambda_{HML}$ | | | | -0.0042 | -0.0040 | -0.0043 |
| p-value | | | | (0.2851) | (0.3193) | (0.2663) |

(Continued)

| | | | | | | |
|---|---|---|---|---|---|---|
| Panel C: Cross-Sectional Regression Results by Using *IVF* Constructed by Using Portfolios Sorted on *IV* Extracted from ATM **Put** Options (Equally-Weighted) | | | | | | |
| *Intercept* | 0.0008 | -0.0011 | 0.0045 | 0.0044 | 0.0045 | 0.0067** |
| p-value | (0.8248) | (0.8146) | (0.2554) | (0.2082) | (0.2211) | (0.0455) |
| $\lambda_{IVF}$ | 0.0085 | | 0.0110 | 0.0067 | | 0.0079 |
| p-value | (0.3474) | | (0.2105) | (0.4812) | | (0.3940) |
| $\lambda_{MKT}$ | | 0.0055 | -0.0021 | | -0.0013 | -0.0030 |
| p-value | | (0.5273) | (0.7925) | | (0.8733) | (0.6914) |
| $\lambda_{SMB}$ | | | | 0.0021 | 0.0033 | 0.0018 |
| p-value | | | | (0.5787) | (0.4080) | (0.6317) |
| $\lambda_{HML}$ | | | | 0.0011 | 0.0012 | 0.0011 |
| p-value | | | | (0.8256) | (0.8032) | (0.8218) |
| Panel D: Cross-Sectional Regression Results by Using *IVF* Constructed by Using Portfolios Sorted on *IV* Extracted from ATM **Put** Options (Value-Weighted) | | | | | | |
| *Intercept* | -0.0009 | -0.0003 | 0.0044 | 0.0048 | 0.0087** | 0.0083*** |
| p-value | (0.8116) | (0.9521) | (0.2051) | (0.1429) | (0.0232) | (0.0045) |
| $\lambda_{IVF}$ | 0.0074 | | 0.0098 | -0.0028 | | -0.0017 |
| p-value | (0.4659) | | (0.3184) | (0.7859) | | (0.8680) |
| $\lambda_{MKT}$ | | 0.0041 | -0.0005 | | -0.0050 | -0.0045 |
| p-value | | (0.6223) | (0.9369) | | (0.5440) | (0.5268) |
| $\lambda_{SMB}$ | | | | 0.0055 | 0.0064* | 0.0060* |
| p-value | | | | (0.1232) | (0.0739) | (0.0898) |
| $\lambda_{HML}$ | | | | -0.0034 | -0.0028 | -0.0034 |
| p-value | | | | (0.4395) | (0.5009) | (0.4219) |
| Panel E: Cross-Sectional Regression Results by Using *IVF* Constructed by Using Portfolios Sorted on $\Delta IV$ Extracted from ATM **Call** Options (Equally-Weighted) | | | | | | |
| *Intercept* | -0.0006 | -0.0030 | -0.0023 | 0.0011 | 0.0001 | 0.0024 |
| p-value | (0.8876) | (0.5534) | (0.6242) | (0.7807) | (0.9824) | (0.5439) |
| $\lambda_{IVF}$ | 0.0078 | | 0.0065 | 0.0054 | | 0.0061* |
| p-value | (0.2054) | | (0.1136) | (0.1591) | | (0.0950) |
| $\lambda_{MKT}$ | | 0.0070 | 0.0059 | | 0.0040 | 0.0014 |
| p-value | | (0.4082) | (0.4479) | | (0.6150) | (0.8564) |
| $\lambda_{SMB}$ | | | | 0.0039 | 0.0014 | 0.0017 |
| p-value | | | | (0.3852) | (0.7245) | (0.6588) |
| $\lambda_{HML}$ | | | | 0.0033 | 0.0018 | 0.0021 |
| p-value | | | | (0.4622) | (0.6970) | (0.6327) |

(Continued)

| | | | | | | |
|---|---|---|---|---|---|---|
| Panel F: Cross-Sectional Regression Results by Using $IVF$ Constructed by Using Portfolios Sorted on $\Delta IV$ Extracted from ATM **Call** Options (Value-Weighted) | | | | | | |
| *Intercept* | 0.0047 | 0.0006 | 0.0031 | 0.0063 | 0.0056 | 0.0069* |
| p-value | (0.5062) | (0.8974) | (0.5238) | (0.1638) | (0.1769) | (0.0901) |
| $\lambda_{IVF}$ | -0.0026 | | -0.0018 | -0.0073 | | -0.0048 |
| p-value | (0.8280) | | (0.7620) | (0.2421) | | (0.3889) |
| $\lambda_{MKT}$ | | 0.0032 | 0.0007 | | -0.0020 | -0.0032 |
| p-value | | (0.6980) | (0.9270) | | (0.8249) | (0.6983) |
| $\lambda_{SMB}$ | | | | 0.0016 | 0.0016 | 0.0005 |
| p-value | | | | (0.7051) | (0.6585) | (0.8796) |
| $\lambda_{HML}$ | | | | -0.0014 | 0.0002 | -0.0009 |
| p-value | | | | (0.7543) | (0.9591) | (0.8400) |
| Panel G: Cross-Sectional Regression Results by Using $IVF$ Constructed by Using Portfolios Sorted on $\Delta IV$ Extracted from ATM **Put** Options (Equally-Weighted) | | | | | | |
| *Intercept* | -0.0028 | -0.0032 | -0.0013 | 0.0015 | 0.0072* | 0.0074* |
| p-value | (0.5403) | (0.5536) | (0.7922) | (0.6729) | (0.0730) | (0.0746) |
| $\lambda_{IVF}$ | 0.0078 | | 0.0044 | 0.0044 | | 0.0030 |
| p-value | (0.1714) | | (0.2273) | (0.2307) | | (0.3840) |
| $\lambda_{MKT}$ | | 0.0070 | 0.0052 | | -0.0032 | -0.0033 |
| p-value | | (0.4173) | (0.5586) | | (0.7101) | (0.7014) |
| $\lambda_{SMB}$ | | | | 0.0022 | 0.0028 | 0.0034 |
| p-value | | | | (0.5935) | (0.4577) | (0.3565) |
| $\lambda_{HML}$ | | | | 0.0000 | -0.0015 | -0.0026 |
| p-value | | | | (0.9924) | (0.7672) | (0.5702) |
| Panel H: Cross-Sectional Regression Results by Using $IVF$ Constructed by Using Portfolios Sorted on $\Delta IV$ Extracted from ATM **Put** Options (Value-Weighted) | | | | | | |
| *Intercept* | 0.0086 | 0.0000 | 0.0020 | 0.0029 | 0.0037 | 0.0038 |
| p-value | (0.1794) | (0.9961) | (0.6271) | (0.3939) | (0.3207) | (0.2508) |
| $\lambda_{IVF}$ | -0.0098 | | -0.0029 | -0.0018 | | -0.0029 |
| p-value | (0.2104) | | (0.6484) | (0.7842) | | (0.6310) |
| $\lambda_{MKT}$ | | 0.0036 | 0.0014 | | -0.0002 | -0.0004 |
| p-value | | (0.6570) | (0.8528) | | (0.9837) | (0.9548) |
| $\lambda_{SMB}$ | | | | 0.0039 | 0.0019 | 0.0001 |
| p-value | | | | (0.3766) | (0.6198) | (0.9807) |
| $\lambda_{HML}$ | | | | 0.0023 | -0.0004 | -0.0012 |
| p-value | | | | (0.5611) | (0.9254) | (0.7523) |

than those in the period from March, 2002 to December, 2010. In addition, correlations between any two variables among $MKT$, $SMB$ and $HML$ are also higher in the period from February, 2005 to December, 2010 than those correlations in the period from February, 2007 to December, 2010. Thus, insignificant cross-sectional results in Table 4.5 can probably be due to high correlations between any two explanatory variables.

Based on results discussed in this subsection, there is very limited evidence about the significant risk premium on $IVF$s. $SMB$ is the factor which has a marginally significant risk premium in some cases. Furthermore, during the sample period from February, 2005 to December, 2010, there should be other factors which can help to explain cross-section of portfolio returns under the assumption that factor loadings from time-series regressions change every 36 months.

## 4.6 Conclusions

It is well acknowledged that the CAPM cannot explain asset returns adequately. Theoretical and empirical studies try to improve asset pricing models from different aspects. One aspect to improve these models is to find an alternative to realized volatility, which is often used in asset pricing tests. This chapter focuses on an alternative to realized volatility, the implied volatility extracted from options. This chapter aims to check whether $IVF$s constructed by using firm-level information help to explain time-series and cross-sectional properties of stock returns.

This chapter follows the method in Ang, Hodrick, Xing and Zhang (2006) to construct eight different $IVF$s and form 25 portfolios. This chapter uses three methods to run cross-sectional regressions for asset pricing tests, the full-window method, the 60-month rolling-window method and the 36-month rolling-window method. Furthermore, cross-sectional regressions include $IVF$s, $MKT$, $SMB$ and $HML$.

Results in this chapter indicate that, among eight $IVF$s constructed in this chapter, only two factors have significantly positive mean during the period from March, 1999 to December, 2010. One is the difference between the return on equally-weighted quintile portfolio with the highest change in at-the-money call implied volatility and the return on equally-weighted quintile portfolio with the lowest change in at-the-money call implied volatility. The other one is constructed by calculating the difference between these two extreme portfolios but using value-weighted scheme (but only marginally significant at a 10% significance level). These two positive mean values of $IVF$s indicate that two corresponding “5-1” long-short portfolios can bring weakly positive return to investors during the 11-year period from March, 1999 to December, 2010.

However, the evidence that $IVF$s have significant risk premiums is quite limited. That is, this chapter does not find strong evidence that investors are willing to pay compensation or buy insurance for $IVF$s. There is some weak evidence about a significant risk premium on $SMB$ by using the 60-month rolling-window method and the 36-month rolling-window method to run cross-sectional regressions. To be more specific, using the 60-month or 36-month rolling-window method, the risk premium on $SMB$ is around 1.3% per month or 0.6% per month. Since $SMB$ is a proxy for risk captured by firm size, these results indicate that investors are willing to pay compensation for risk related to market capitalization.

However, this chapter still has some constraints. Because of the limitation of data, data available for this chapter starts from 1996. The sample period in this chapter is not very long. This period also covers two crises, the dot-com bubble and the

2008-2010 crisis. It is not sure whether insignificant risk premiums are due to dynamic market conditions during the sample period. Furthermore, this chapter uses monthly data. If daily data are used to construct implied-volatility factors, results could be different.

# Chapter 5 Asymmetric Effects of Volatility Risk on Stock Returns: Evidence from VIX and VIX Futures[28]

## 5.1 Introduction

Since the introduction of the Capital Asset Pricing Model (CAPM) by Sharpe (1964), Lintner (1965) and Mossin (1966), the market risk premium, defined as the compensation required by investors to bear market risk, has been investigated. In addition to the market risk premium, various empirical studies (Arisoy, Salih and Akdeniz, 2007; Bakshi and Kapadia, 2003; Bollerslev, Gibson and Zhou, 2011; Bollerslev, Tauchen and Zhou, 2009; Carr and Wu, 2009; Mo and Wu, 2007) document the existence of a premium for bearing volatility risk; this supports the hypothesis that volatility is another important pricing factor in equity markets. Ang, Hodrick, Xing and Zhang (2006) and Chang, Christoffersen and Jacobs (2013) show that the aggregate volatility risk (measured by changes in volatility indices) is important in explaining the cross-section of returns: stocks that fall less as volatility rises have low average returns because they provide protection against crisis movements in financial markets.

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[28] As stated in the Declaration, a paper based on this chapter was accepted for publication by the Journal of Futures Markets. Compared to the published version, some changes are made: (1) In the published version, the “Introduction” section provides literature review, whereas in this Chapter 5, a more detailed literature review is provided in section 5.2. Ammann and Buesser (2013), and Hung, Shackleton and Xu (2004) are included in section 5.2. (2) Footnote 1 in the published version is not included in this chapter, since similar discussions have been included in previous chapters. (3) In the published version, data and methodology are discussed in the section 2 of the article, “DATA AND METHODOLOGY”, whereas in this chapter, data and methodology are presented in two separate sections, sections 5.3 and 5.4, respectively. (4) Footnote 23 in the published version is moved to the main text in this chapter (Subsection 5.4.3). This chapter includes discussions about the cost of carry relationship between the VIX index and VIX futures, and more detailed discussions about “contango” and “backwardation” compared to footnote 23 in the published version. Also, a figure about the relationship between VIX futures basis and the VIX index (Figure 5.3) is included in this chapter to make the discussions more clear. (5) For consistency, the format of tables in this chapter is different from the format used in the published version.

Additionally, many empirical studies also reveal that the influence of market risk is not symmetric. Given that the market risk has an asymmetric effect on equity returns, it is interesting to ask whether the influence of volatility risk on equity returns is also asymmetric.

This chapter first concentrates on the unconditional relationship between an asset's return and its sensitivity to volatility risk through a quintile portfolio level analysis. This chapter uses the VIX index itself to construct a volatility factor, that is, innovations in the squared VIX index. In addition, this chapter introduces VIX index futures into asset pricing models. Thus, this chapter uses innovations in squares of the VIX index or VIX futures to measure changes in the volatility risk, and further tests the unconditional relationship between portfolio returns and sensitivity to volatility risk factors.

This chapter also focuses on the asymmetric effect of volatility risk. In order to do so, the empirical analysis follows the method used in DeLisle, Doran and Peterson (2011) and defines a dummy variable to distinguish different situations. To contribute beyond previous studies, this chapter defines a dummy variable based on the VIX futures basis (i.e., the difference between the VIX spot and VIX futures) instead of daily changes in the VIX index. Daily innovations in the VIX index reflect how it changes from its level on the previous trading day. However, the VIX futures basis reflects how the spot VIX index deviates from its risk-neutral market expectation; the VIX futures basis captures more relevant ex ante information and is better at predicting future trends in volatility than time series models. To test whether volatility risk plays the same role in explaining asset returns under different scenarios, this chapter investigates the relationship between an asset's return and sensitivity to volatility risk in each market scenario.

Furthermore, this chapter also decomposes the aggregate volatility index into two components: volatility calculated either from out-of-the-money call options only or from out-of-the-money puts. The innovations in squares of volatility terms are used as separate volatility factors in the analysis. Such a decomposition enables us to test for an asymmetric effect of volatility risk from using ex ante information, and to highlight whether investors treat information captured by different kinds of options in different ways.

This chapter contributes to previous literature in several areas. First, this chapter introduces VIX futures into asset pricing models. Previous literature (Ang, Hodrick, Xing and Zhang, 2006; Chang, Christoffersen and Jacobs, 2013; DeLisle, Doran and Peterson, 2011) uses VIX index to construct a proxy for volatility risk.[29] However, the new VIX index is a model-free aggregate implied volatility index, and is a spot index. In order to replicate the VIX index, investors need to trade out-of-the-money options. However, such a replication is costly. Instead, VIX futures are tradable in derivative markets, and they reflect the market expectation of this volatility index at a future date. Few studies have used VIX futures in asset pricing and they only focus on theoretical pricing, the existence of a term structure, or causality between VIX spot and VIX futures.[30] Trading on the VIX futures provides investors with an expectation of the VIX index itself at a future expiration; so movements in the square of VIX futures reflect changes in market expectations of variance (i.e., implied volatility squared) at expiration. Rather than changes in the squared VIX spot index, introducing

[29] Here, the VIX index refers to both old VXO index and new VIX index. The old VXO index is CBOE S&P100 volatility index, and is an average of the Black-Scholes implied volatilities on eight near-the-money S&P100 options at the two nearest maturities. The new VIX index is CBOE S&P500 volatility index, and is a weighted sum of a broader range of strike prices on out-of-the-money S&P500 options at the two nearest maturities.

[30] For example, Lin (2007) and Zhang and Zhu (2006) focus on the pricing of the VIX index futures. Huskaj and Nossman (2013) and Lu and Zhu (2010) both investigate the term structure of VIX index futures. Shu and Zhang (2012) and Karagiannis (2014) look at the causal relationship between the VIX index and its futures.

factors constructed from VIX futures into asset pricing models is expected to help improve a model's ability to forecast returns through a volatility premium. Such an analysis also highlights the importance of VIX futures in asset pricing.

Secondly, this chapter contributes to the use of risk-neutral volatility measures in empirical tests of volatility risk premium. Historical data show a negative relationship between the market and the volatility index. An increase in the market index is often accompanied by a decrease in the volatility index, whereas a downward movement of the market frequently comes together with a sharp increase in the volatility index. Additionally, such a relationship is time-varying, and is stronger during periods of financial turmoil (Campbell, Forbes, Koedijk and Kofman, 2008). In light of this, Jackwerth and Vilkov (2015) find the existence of a negative risk premium on the index-to-volatility correlation.[31] Thus, in addition to the market risk premium, volatility or variance risk premiums are commonly tested empirically.

Thirdly, this chapter takes an asymmetric effect of the volatility risk into consideration. Although small increments in the market index and consequent reductions in the volatility index are consistent with investors' expectations, decreases in the market or increases in the volatility indices are perceived as shocks with negative news for investors. Separating these different cases through dummy variables enables us to analyze the role of volatility risk in asset pricing under different scenarios. Furthermore, the way to separate different scenarios used in this chapter is new compared to previous literature. In DeLisle, Doran and Peterson (2011), dummy variables are defined based on innovations in the VIX spot (they define dummy variables based on a lagged variable). This chapter separates different scenarios based

[31] Jackwerth and Vilkov (2015) estimate the implied index-to-volatility correlation from the out-of-the-money option on S&P500 index and VIX index. By comparing the implied correlation with its realized counterpart, they find a significantly negative and time-varying risk premium on the correlation risk.

on the sign of the VIX futures basis, which is an ex ante measure. Such a definition captures information about ex ante market conditions. Then this chapter investigates the effect of volatility risk in different situations.

Fourthly, this chapter decomposes the VIX index and distinguishes two different components of aggregate volatility. Volatility calculated by using out-of-the-money call options captures information conditional on increases in price of the underlying asset, whereas volatility calculated by using out-of-the-money put options captures information conditional on decreases in price of the underlying asset. By using these two components to construct separate volatility factors, this chapter investigates the asymmetric effect of volatility risk by using ex ante information. Such an analysis also sheds light on whether investors treat information captured by out-of-the-money call and put options (i.e., up and down market conditions) differently. If investors think one kind of option is more informative or more influential than the other, they can seek higher premiums by constructing trading strategies based on this kind of options alone. Thus, empirical results in this chapter give investors an indication of how to improve their trading strategies and capture premiums from their portfolios.

The rest of this chapter is organized as follows. Section 5.2 reviews literature in details. Sections 5.3 and 5.4 discuss details of data and methodology, respectively. Results for portfolio level analysis using VIX spot and VIX futures are presented in section 5.5. Section 5.6 documents results obtained by using two components of aggregate volatility (i.e., volatility terms calculated by using out-of-the-money call or put options). Finally, section 5.7 concludes.

## 5.2 Related Literature

Various empirical studies document the existence of a premium for bearing volatility risk; this supports the hypothesis that volatility is another important pricing factor in equity markets. For instance, by using delta-hedged option portfolios, Bakshi and Kapadia (2003) provide evidence in supportive of a negative volatility risk premium. Arisoy, Salih and Akdeniz (2007) use zero-beta at-the-money straddle returns on the S&P500 index to capture volatility risk. Empirical results in their study show that volatility risk helps to explain size and book-to-market anomalies. By investigating three countries (the US, the UK, and Japan), Mo and Wu (2007) find that investors are willing to forgo positive premiums in order to avoid increases in volatility. Carr and Wu (2009) use the difference between realized and implied variances to quantify the variance risk premium, and they find that the average variance risk premium is strongly negative for the S&P500, the S&P100, and the DJIA. Bollerslev, Tauchen and Zhou (2009) use the difference between model-free implied and realized variances to estimate the volatility risk premium and show that such a difference helps to explain the variation of quarterly stock market returns. Using the same definition, Bollerslev, Gibson and Zhou (2011) also document that the volatility risk premium is relevant in predicting the return on the S&P500 index. Ammann and Buesser (2013) follow the same approach in order to investigate the importance of the variance risk premium in foreign exchange markets. These empirical studies show that volatility risk could be an important pricing factor in equity markets.

Furthermore, the only pricing factor considered in the CAPM setup (i.e., the beta) is assumed to be constant and not dependent on upward or downward movements of the market. In contrast, some studies reveal that the influence of the market's realization is not symmetric. Hung, Shackleton and Xu (2004) find that, after controlling for different realized risk premiums in up and down markets, beta has highly significant power in explaining the cross−section of UK stock returns and it remains significant even when the Fama-French factors are included in the analysis. Ang, Chen and Xing (2006) show the existence of a downside risk premium (approximately 6% per annum), where stocks with higher market covariance during recession periods provide higher average returns compared to those that exhibit lower covariance with the market.[32] Some studies investigate whether volatility risk plays different roles under different market conditions. By using delta-hedged option portfolios, Bakshi and Kapadia (2003) provide evidence in support of an overall negative volatility risk premium. These empirical results also reveal time-variation of the volatility risk premium (i.e., the underperformance of delta-hedged strategies is greater during times of high volatilities). DeLisle, Doran and Peterson (2011) use innovations in the VIX index to measure volatility risk and focus on its asymmetric effect. To be more specific, their study shows that sensitivity to VIX innovations is negatively related to stock returns when volatility is expected to increase, but it is unrelated when volatility is expected to decrease. Based on the ICAPM (Merton, 1973), Campbell (1993 and 1996) and Chen (2003) argue that an increment in aggregate volatility can be interpreted as a worsening of the investment opportunity set. More recently, Farago and Tédongap (2015) claim that investors' disappointment aversion is relevant to asset pricing theory, conjecturing that a worsening opportunity set may result either from a decrease in the market index or from an increase in the volatility index. Empirical results in their study show that these undesirable changes

[32] The measure of downside risk used in Ang, Chen and Xing (2006) was originally introduced by Bawa and Lindenberg (1977).

(decreases in market and increases in volatility indices) motivate significant premiums in the cross-section of stock returns. In order to understand the asymmetric effect due to market or volatility risks, it is important to distinguish between different cases: positive or negative market returns, and increments or reductions in the aggregate volatility, especially by using forward-looking measures of volatility.

On the other hand, after the introduction of VIX futures contracts in March 26th, 2004, many studies investigate in VIX futures (as discussed in footnote 30). However, most of them focus on theoretical pricing, the existence of a term structure, or causality relationship between VIX spot and VIX futures. So, this chapter introduces VIX futures into asset pricing and compares VIX spot and VIX futures in predicting asset returns.

## 5.3 Data

### 5.3.1 Data Resources

This chapter focuses on the effect of aggregate volatility risk factors on individual stock returns in the US markets. Daily individual stock returns for ordinary common shares (share codes of 10, 11 and 12) are downloaded from CRSP.[33] When forming volatility factors, this chapter uses the VIX spot ($VIX$) and VIX futures ($VXF$), which are obtained from the CBOE official website.[34] Furthermore, in order to decompose the aggregate volatility index, this chapter uses data for options written on the S&P500 index ($SPX$), which are available from OptionMetrics. The analysis also needs other factors, such as the market excess return ($MKT$), the size factor

[33] Following DeLisle, Doran and Peterson (2011), this chapter only keeps stocks with CRSP share codes 10, 11 and 12 in the sample.

[34] This chapter converts the VIX index and VIX futures from percentage to decimal numbers, that is, 20%=0.20. In later equations, volatility terms, $VIX$, $VXF$, $VXC$, and $VXP$, are all decimal numbers too not percentage numbers.

($SMB$), the book-to-market factor ($HML$), and the momentum factor ($UMD$). Data for these factors are all available from Kenneth French's data library.[35]

### 5.3.2 Data Description

The first part of this chapter separates different market scenarios based on a dummy variable defined from the VIX futures basis (i.e., periods with positive or negative VIX futures basis). The VIX futures basis is defined as the difference between VIX spot ($VIX$) and VIX futures ($VXF$). The $VXF$ started trading on the CBOE in March 26, 2004; however, only after October 2005, did VIX futures contracts expiring in each calendar month appear. So the sample period used in the first part of the empirical analysis in this chapter runs from October 2005 until December 2014. Figure 5.1 plots levels of $VIX$, $VXF$, $SPX$, and $MKT$ during the period from March 26, 2004 to December 31, 2014.[36]

In Panel A of Figure 5.1, it is clear that $VIX$ and $VXF$ are very close, and they increase or decrease together.[37] There is a negative relationship between $SPX$ and $VIX$ or $VXF$. When the $SPX$ increases, $VIX$ and $VXF$ decrease, and vice versa. This phenomenon is even stronger during the financial crisis: for instance, from the beginning of September 2008 to the end of October 2008, the $SPX$ decreased

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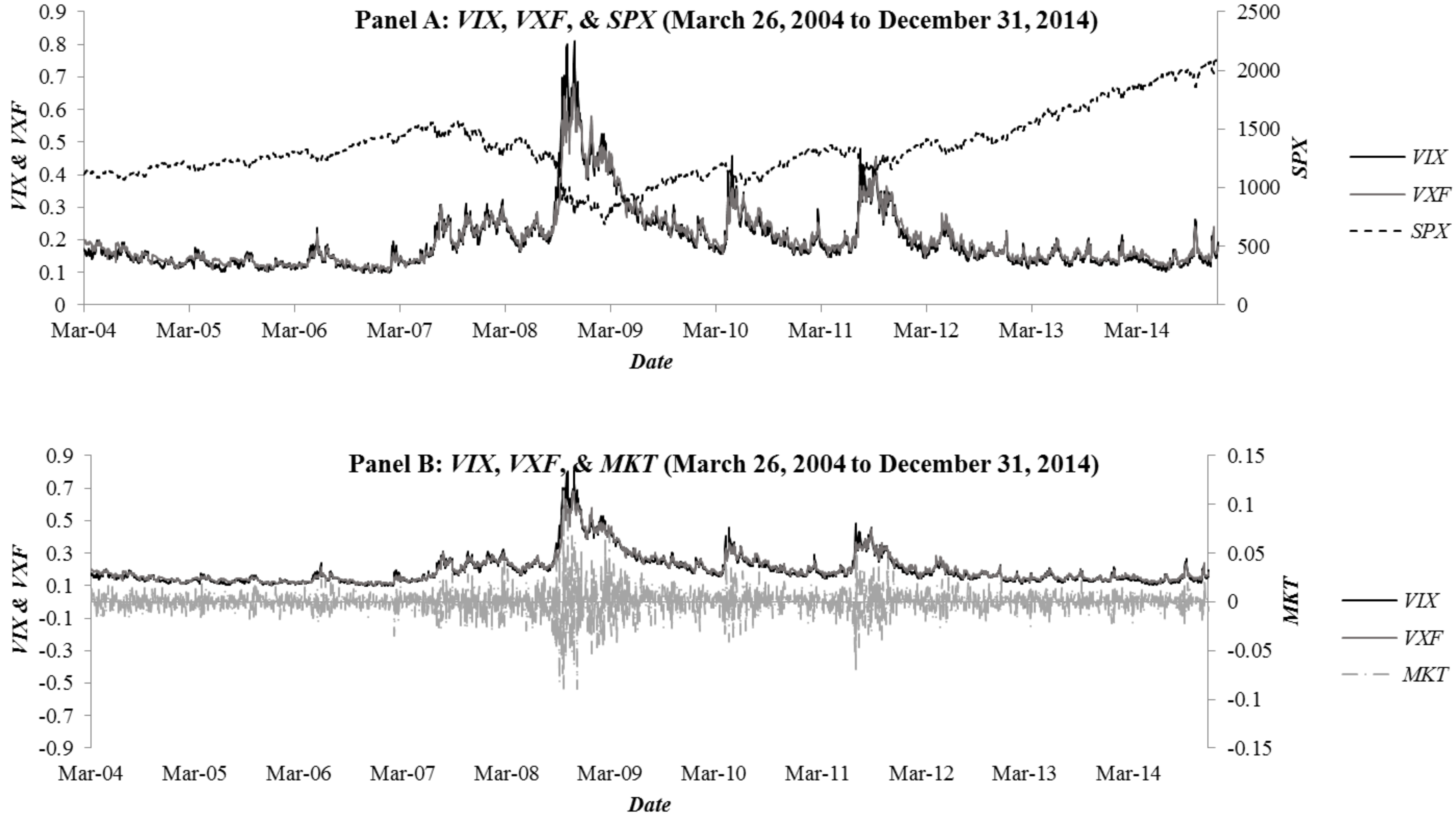
[35] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html for more details. $MKT$ is the excess return on the market, value-weighted return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11 at the beginning of month $t$, good shares and price data at the beginning of $t$, and good return data for $t$ minus the one-month Treasury bill rate (from Ibbotson Associates). $SMB$ (small-minus-big) is the average return on the three small portfolios minus the average return on the three big portfolios. $HML$ (high-minus-low) is the average return on the two value portfolios minus the average return on the two growth portfolios. $UMD$ (winners-minus-losers) is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolio.

[36] March 26, 2004 is the first trading day with VIX futures data available, whereas December 31, 2014 is the last trading day of the sample period. In order to draw the figure and get the summary statistics for VIX index futures, Figure 5.1 and Table 5.1 use the settlement price of futures contract with near-term expiration.

[37] The lead-lag relationship between spot and futures markets is an important topic. However, this chapter is not looking at the causal relationship between VIX spot and VIX futures.

**Figure 5.1: VIX Index (*VIX* ), VIX Index Futures (*VXF* ), S&P500 Index ( *SPX* ), and Market Excess Returns ( *MKT* )**



dramatically from 1277.58 to 968.75, whereas the $VIX$ ($VXF$) increased from 0.2199 (0.2208) to 0.5989 (0.5457). Then, in Panel B, it is clear that both $VIX$ and $VXF$ are good forward-looking proxies for measuring aggregate volatility of the market.[38] Levels of $VIX$ and $VXF$ are higher when the market becomes more volatile.

In addition, it can be easily seen that $VIX$ spot is less stable than its futures, $VXF$. The minimum value for $VIX$ (0.0989) is slightly smaller than the minimum value for $VXF$ (0.0995), whereas the maximum value for $VIX$ (0.8086) is much larger than the maximum value for $VXF$ (0.6795). The range of $VIX$ is wider than that of $VXF$.[39] Correlations in Panel B of Table 5.1 indicate that $VIX$ and $VXF$ are highly correlated (with the correlation of 0.9846). There is a negative relationship between the market excess returns and the aggregate volatility risk.

By using ex ante information, the second part of this chapter investigates whether volatility risk has an asymmetric effect. This part also answers whether call or put options capture different information concerning future market conditions. This part replicates the VIX index and decomposes it into two components, that is, volatility calculated from out-of-the-money call options ($VXC$) or volatility calculated from out-of-the-money put options ($VXP$).[40] In the second part, the sample period covers the period from January 1996 to September 2014.[41]

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[38] Panel B of Figure 5.1 plots the market factor ($MKT$) together with $VIX$ and $VXF$. This chapter also calculates the daily simple returns and logarithmic returns on the S&P500 index. The data indicate that daily simple returns and logarithmic returns on the S&P500 index are highly correlated with $MKT$ (with correlations of 0.9917 and 0.9918, respectively). This chapter concentrates on market-based pricing factors. So, rather than using return on S&P500 index, this chapter uses the market excess return provided by French's online data library.

[39] The descriptive statistics of different variables presented in Table 5.1 are all calculated at daily frequency. For example, the mean of daily market excess returns is 0.04% (Panel A of Table 5.1), which translates to around 13.65% p.a. using continuous compounding.

[40] Details about the decomposition are discussed in section 5.4.4.

[41] The regression model in equation (5.1) is estimated until the end of August 2014. Then, quintile portfolios are constructed by using monthly returns in September 2014.

**Table 5.1: Descriptive Statistics**

**Panel A: Summary Statistics during the Period from March 26, 2004 to December 31, 2014**

| | $SPX$ | $MKT$ $(Daily)$ | $VIX$ | $\Delta(VIX^2)$ | $VXF$ | $\Delta(VXF^2)$ |
|---|---|---|---|---|---|---|
| Mean | 1336.5 | 0.0004 | 0.1969 | 0.0000 | 0.2012 | -0.0000 |
| Median | 1294.0 | 0.0009 | 0.1660 | -0.0002 | 0.1727 | -0.0002 |
| Standard Deviation | 274.4 | 0.0126 | 0.0971 | 0.0155 | 0.0894 | 0.0098 |
| Minimum | 676.5 | -0.0895 | 0.0989 | -0.2140 | 0.0995 | -0.1472 |
| Maximum | 2090.6 | 0.1135 | 0.8086 | 0.2030 | 0.6795 | 0.1186 |

**Panel B: Pairwise Correlations during the Period from March 26, 2004 to December 31, 2014**

| | $SPX$ | $MKT$ | $VIX$ | $\Delta(VIX^2)$ | $VXF$ | $\Delta(VXF^2)$ |
|---|---|---|---|---|---|---|
| $SPX$ | 1 | | | | | |
| $MKT$ | 0.0329 | 1 | | | | |
| $VIX$ | -0.5367 | -0.1222 | 1 | | | |
| $\Delta(VIX^2)$ | -0.0080 | -0.7528 | 0.0841 | 1 | | |
| $VXF$ | -0.5550 | -0.0812 | 0.9846 | 0.0390 | 1 | |
| $\Delta(VXF^2)$ | -0.0069 | -0.6768 | 0.0888 | 0.8173 | 0.0660 | 1 |

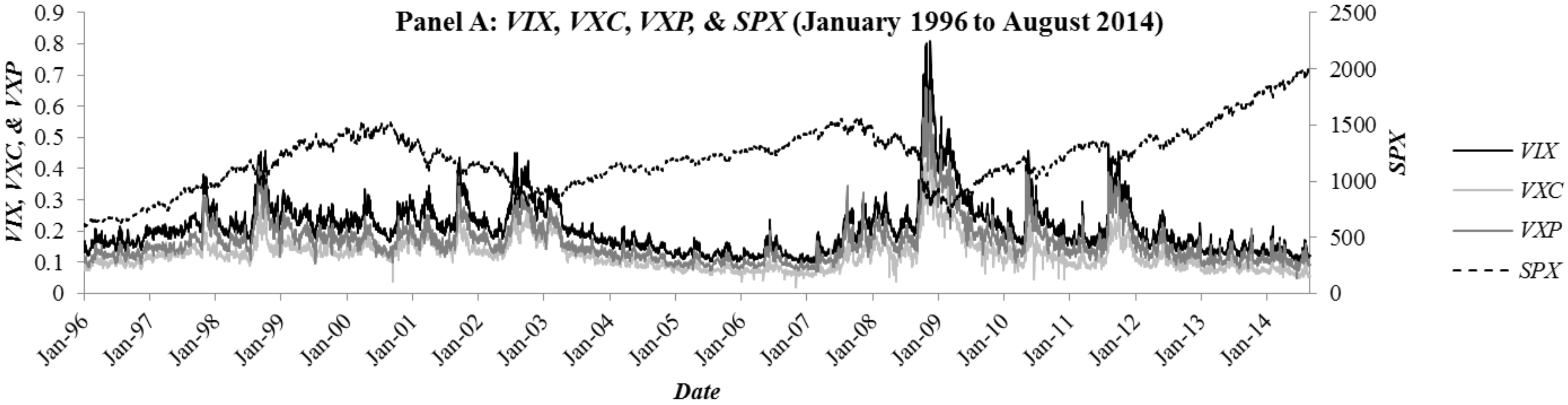
**Panel C: Summary Statistics during the Period from January 1996 to August 2014**

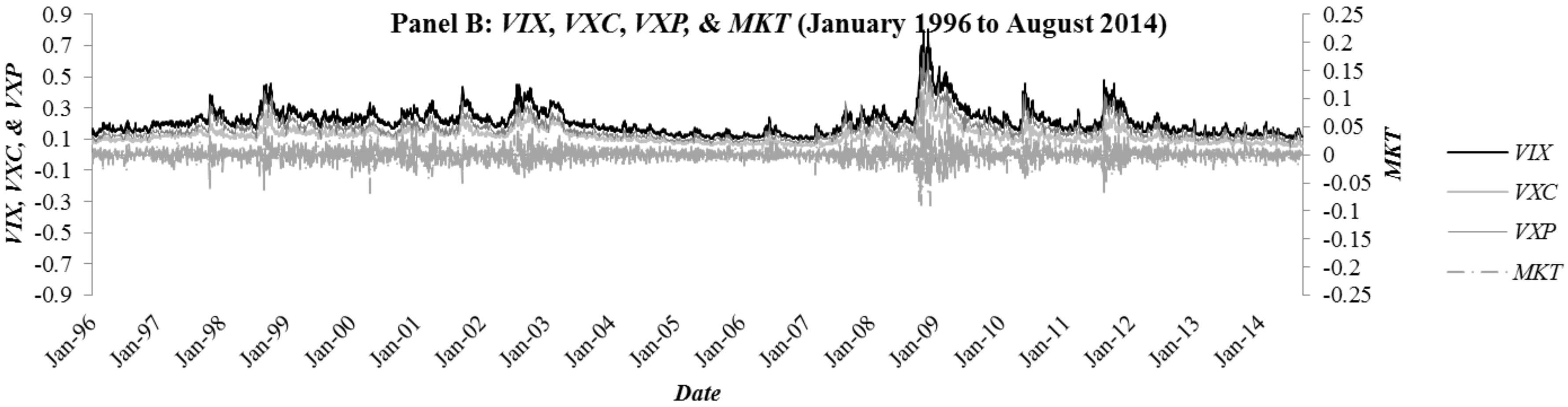
| | $SPX$ | $MKT$ $(Daily)$ | $VIX$ | $\Delta(VIX^2)$ | $VXC$ | $\Delta(VXC^2)$ | $VXC$ | $\Delta(VXP^2)$ |
|---|---|---|---|---|---|---|---|---|
| Mean | 1206.3 | 0.0003 | 0.2131 | 0.0000 | 0.1252 | -0.0000 | 0.1646 | -0.0000 |
| Median | 1204.5 | 0.0008 | 0.1984 | -0.0002 | 0.1180 | -0.0000 | 0.1502 | -0.0001 |
| Standard Deviation | 274.3 | 0.0125 | 0.0845 | 0.0130 | 0.0506 | 0.0065 | 0.0686 | 0.0099 |
| Minimum | 598.5 | -0.0895 | 0.0989 | -0.2140 | 0.0209 | -0.1018 | 0.0486 | -0.1357 |
| Maximum | 2003.4 | 0.1135 | 0.8086 | 0.2030 | 0.4635 | 0.1159 | 0.6600 | 0.1507 |

| Panel D: Pairwise Correlations during the Period from January 1996 to August 2014 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | $SPX$ | $MKT$ | $VIX$ | $\Delta\left(VIX^2\right)$ | $VXC$ | $\Delta\left(VXC^2\right)$ | $VXC$ | $\Delta\left(VXP^2\right)$ |
| $SPX$ | 1 | | | | | | | |
| $MKT$ | 0.0234 | 1 | | | | | | |
| $VIX$ | -0.3845 | -0.1249 | 1 | | | | | |
| $\Delta\left(VIX^2\right)$ | -0.0107 | -0.7267 | 0.0886 | 1 | | | | |
| $VXC$ | -0.4217 | -0.1199 | 0.9611 | 0.0768 | 1 | | | |
| $\Delta\left(VXC^2\right)$ | -0.0067 | -0.4613 | 0.0554 | 0.6006 | 0.1463 | 1 | | |
| $VXP$ | -0.3483 | -0.1266 | 0.9840 | 0.0924 | 0.9116 | 0.0209 | 1 | |
| $\Delta\left(VXP^2\right)$ | -0.0090 | -0.6215 | 0.0730 | 0.8522 | 0.0261 | 0.2706 | 0.1139 | 1 |

| Panel E: Augmented Dickey-Fuller Unit Root Tests ($H_0$: there is a unit root in time series data) | | |
|---|---|---|
| | *p-value* | *T-statistic* |
| **Sample Period: March 26, 2004 to December 31, 2014** | | |
| *VIX* | (0.0128) | (-3.3518) |
| *VXF* | (0.0326) | (-3.0269) |
| $\Delta\left(VIX^2\right)$ | (0.0000) | (-18.3054) |
| $\Delta\left(VXF^2\right)$ | (0.0000) | (-32.8952) |
| **Sample Period: January 1996 to August 2014** | | |
| *VIX* | (0.0001) | (-4.7915) |
| *VXC* | (0.0001) | (-4.6040) |
| *VXP* | (0.0000) | (-4.8263) |
| $\Delta\left(VIX^2\right)$ | (0.0000) | (-23.9694) |
| $\Delta\left(VXC^2\right)$ | (0.0000) | (-38.1739) |
| $\Delta\left(VXP^2\right)$ | (0.0000) | (-15.4873) |

**Figure 5.2: VIX Index (*VIX*), Call VIX Index (*VXC*), Put VIX Index (*VXP*), S&P500 Index (*SPX*), and Market Excess Returns (*MKT*)**



In Panel A and Panel B of Figure 5.2, $VXC$ and $VXP$ have similar trends to $VIX$. $VXC$ and $VXP$ are both negatively related to $SPX$ (they are both risk neutral parts of the aggregate volatility).[42] Panel C of Table 5.1 presents summary statistics of $VIX$, $VXC$ and $VXP$. It is clear that $VXP$ is always higher than $VXC$. Then, in Panel D, both $VXC$ and $VXP$ are highly correlated with $VIX$ (with correlation of 0.9611 and 0.9840, respectively). Meanwhile, $VXC$ and $VXP$ are both negatively correlated with the market.

## 5.4 Methodology

In order to investigate the relationship between asset returns and sensitivity to aggregate volatility risk, this chapter uses a quintile portfolio level analysis among individual stock returns. Such an analysis enables us to test whether stocks with more negative correlations between returns and volatility changes outperform those with less negative correlations.

To test whether there is an asymmetric effect of volatility risk on asset returns, this chapter uses two different methods. First, this chapter separates different market conditions by defining a dummy variable and analyzes the relationship under two different situations. Secondly, this chapter decomposes $VIX$ into two parts and uses forward-looking information to capture future market conditions. Then, this chapter examines whether the asymmetric effect of volatility risk exists if ex ante information is used. Details about methodologies are discussed in the following subsections.

[42] Due to the existence of volatility risk premium, there is a bias when using risk-neutral volatility.

### 5.4.1 Volatility Factor Construction

First, it should be highlighted that this chapter focuses on market-based pricing factors. That is, this chapter concentrates on pricing factors constructed at aggregate level, and uses pricing factors which are common for all individual assets in the market rather than firm-specific factors.

From existing literature, in addition to systematic market risk captured by beta, coskewness (or systematic skewness) is also an important pricing factor in asset pricing (Fang and Lai, 1997; Harvey and Siddique, 2000; Kraus and Litzenberger, 1976; Scott and Horvath, 1980; Sears and Wei, 1985 and 1988). Coskewness refers to how an individual asset's return co-moves with the second moment of the market return.[43] By using historical data, previous papers calculate ex post estimates of systematic market risk and coskewness risk, and document that coskewness helps to explain asset returns.

Rather than using historical data, recent studies use option-implied information to measure the risk-neutral expected second moment of the market return, and further calculate coskewness for individual stocks. In empirical studies, due to potential non-stationarity issue, the first difference of the volatility index, instead of the level of the volatility index, is commonly used to measure the volatility risk.[44] For example,

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[43] For example, according to Kraus and Litzenberger (1976), the relation between returns and risk is given by:

$$E[r_i] - r_f = b_1\beta_i + b_2\gamma_i$$

where $r_i$ is the return on the $i$th asset, $\beta_i = \sigma_{im} / \sigma_m^2$ is the market beta or systematic standard deviation of the $i$th asset, $\gamma_i = m_{imm} / m_m^3$ is the market gamma or systematic skewness of the $i$th asset ($\sigma_m$ and $m_m$ are the standard deviation and the cube root of third moment, respectively). Factor loading $b_1$ can be interpreted as the risk premium on beta, and $b_2$ can be interpreted as the risk premium on gamma.

[44] Panel E of Table 5.1 present results for Augmented Dickey-Fuller unit root tests for both levels of each volatility index ($VIX$, $VXF$, $VXC$ and $VXP$) and changes in variance terms ($\Delta(VIX^2)$, $\Delta(VXF^2)$, $\Delta(VXC^2)$ and $\Delta(VXP^2)$). The results indicate that by using first differences in variance terms to measure the volatility risk, the autocorrelation in variables of interest could be controlled.

in order to measure the second moment of market returns, Ang, Hodrick, Xing and Zhang (2006) use daily innovations in the old volatility index ($VXO$), and Chang, Christoffersen and Jacobs (2013) use daily changes in the VIX index (the replacement for $VXO$). Rather than using change in aggregate volatility, this chapter uses changes in aggregate variance (i.e., changes in the square of volatility).

The first part of this chapter separates different market scenarios by defining a dummy variable and investigates the asymmetric effect of aggregate volatility risk. This part uses $\Delta\left(VIX^2\right)$ and $\Delta\left(VXF^2\right)$ as factors that capture variance changes.[45] Then, the second part of this chapter uses forward-looking information to check an asymmetric effect, and concentrates on whether out-of-the-money call or put options capture different information about future return prediction. This chapter decomposes the VIX index into two parts and then uses innovations in each variance term (i.e., $\Delta\left(VXC^2\right)$ and $\Delta\left(VXP^2\right)$) as risk factors. The construction of $\Delta\left(VXC^2\right)$ and $\Delta\left(VXP^2\right)$ and the relationship between $VXC$, $VXP$ and $VIX$ are discussed in Subsection 5.4.4 in detail.

### 5.4.2 Quintile Portfolio Level Analysis

In order to test if there is a significant relationship between an asset's return and its sensitivity to volatility factors, this chapter uses a quintile portfolio level analysis

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[45] The VIX index measures market index volatility at 30-day horizon. $\Delta\left(VIX^2\right)$ is the daily change in the square of $VIX$. Thus, $\Delta\left(VIX^2\right)$ measures the daily change in the aggregate variance on each trading day. If $\Delta\left(VIX^2\right) > 0$, aggregate variance increases compared to the closing level on the previous trading day, and vice versa. For VIX index futures, this chapter uses the settlement price of the futures contract. $VXF$ reflects the expectation of $VIX$ at expiration. $\Delta\left(VXF^2\right)$ is the daily change in the square of $VXF$. So, $\Delta\left(VXF^2\right)$ reflects the daily change in expectation of aggregate variance during the 30-day period after expiration. If $\Delta\left(VXF^2\right) > 0$, the settlement price of $VXF$ increases compared to the previous trading day, and vice versa.

for individual stocks. To be more specific, this chapter first estimates the following time-series regressions using daily data for each individual stock $i$:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{VF} VF_t + \varepsilon_{i,t} \tag{5.1}$$

$$VF \in \left[ \Delta\left(VIX^2\right), \Delta\left(VXF^2\right), \Delta\left(VXC^2\right), \Delta\left(VXP^2\right) \right]$$

where $r_{i,t}$ stands for daily returns on each individual stock, $r_{f,t}$ is the daily risk-free rate, $MKT$ denotes daily market excess returns, and $VF$ is one proxy for the volatility risk (i.e., $\Delta\left(VIX^2\right)$, $\Delta\left(VXF^2\right)$, $\Delta\left(VXC^2\right)$ or $\Delta\left(VXP^2\right)$).[46]

As the first part of this chapter compares $VIX$ to $VXF$, the volatility factors ($VF_t$) are defined in different ways: $\Delta\left(VIX^2\right)$ (daily changes in square of VIX spot), and $\Delta\left(VXF^2\right)$ (daily changes in square of VIX futures). As the final settlement date of VIX futures contracts is normally the third Wednesday in each month, the period used for the above regression model (equation (5.1)) starts from the next trading day with data available for the VIX future contracts expiring two months later and ends on the final settlement date of the corresponding VIX futures contract (i.e., around 40 observations for each time-series regression). For example, the third Wednesday in January 2008 is January 16, 2008, and the third Wednesday in March 2008 is March 19, 2008. To run a regression model during the period from January 2008 to March 2008, daily settlement prices of VIX futures contracts expiring in March 2008 are used. Such contracts started trading from January 17, 2008. In order to form quintile portfolios in March 2008, the empirical analysis uses the data of VIX futures contracts expiring in March 2008, during the period from January 17, 2008 to March 19, 2008.

[46] In addition to two explanatory variables in equation (5.1) (i.e., $MKT$ and $VF$), $SMB$, $HML$, or other factors could be included. However, this chapter principally uses forward looking information about volatility not historical regressors. So, only $MKT$ and $VF$ are included in one regression model.

The second part of our analysis distinguishes information captured by out-of-the-money call and put options. Two components of VIX squared, $\Delta\left(VXC^{2}\right)$ and $\Delta\left(VXP^{2}\right)$, are used to represent $VF$, the volatility factor. To be consistent with the first part of this chapter, the second part estimates equation (5.1) at firm level at the end of each calendar month by using previous two-month daily data. Then, to avoid data overlaps for time-series regressions in different calendar months, this part also uses previous one-month daily data for regression model presented in equation (5.1) at the end of each month.

After estimating equation (5.1) and obtaining beta coefficients on $MKT$ and $VF$ ( $\beta_i^{MKT}$ and $\beta_i^{VF}$ ) for each individual stock, among all stocks available, equally-weighted or value-weighted quintile portfolios are formed based on $\beta_i^{VF}$.[47] Portfolio 1 consists of the 20% of stocks with the lowest $\beta_i^{VF}$, whereas portfolio 5 consists of the 20% of stocks with the highest $\beta_i^{VF}$; that is, stocks in portfolio 1 have the lowest sensitivity to aggregate volatility risk, whereas stocks in portfolio 5 have the highest sensitivity. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. The first part of this chapter assumes that investors hold portfolios for 10-day, 20-day and 30-day horizons after construction, and calculates the return on each portfolio during these holding periods.[48] The second part of this chapter calculates portfolio returns in the following one calendar month. The empirical analysis calculates whether the "5-1" long-short

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[47] For equally-weighted portfolios, the weight for each constituent is determined by the total number of stocks included in the portfolio, whereas for value-weighted portfolios, the weight of each constituent depends on the market capitalization of stocks in the portfolio.

[48] It is known that $VIX$ reflects the market's expectation of stock market volatility over the next 30-day period. $VIX$ is calculated by using near-term and next-term options with maturities longer than 7 days. Here, "10-day", "20-day", and "30-day" refer to trading days, and correspond to 2-, 4-, and 6-week periods. So lengths of holding periods used in this chapter are consistent with predictive periods indicated by options used for $VIX$ calculations.

portfolio has a significant non-zero mean return or Jensen's alpha with respect to the market-factor model, the Fama-French three-factor model, or the Carhart four-factor model (i.e., risk-adjusted return after controlling for $MKT$, $SMB$, $HML$ and $UMD$).[49] If the "5-1" long-short portfolio has a significant and negative mean return, overall asset sensitivity to volatility factors is negatively related to returns.

However, if the realization of $MKT$ or $VF$ is close to zero, it is difficult to find significant non-zero average return on any portfolio. Thus, by distinguishing periods with different market conditions, it is possible to detect statistically significant mean returns on the "5-1" long-short portfolio. Also, such an analysis sheds light on whether the volatility risk plays different roles under different market conditions.

### 5.4.3 Asymmetric Quintile Portfolio Level Analysis

By using $\Delta\left(VIX^2\right)$ and $\Delta\left(VXF^2\right)$ to capture volatility risk, although previous models (equation (5.1)) detail relationships between asset returns and sensitivities to volatility factors, these models ignore asymmetric effects of volatility risk. Financial markets may react differently to positive or negative volatility shocks, thus, this chapter incorporates an asymmetric effect of volatility risk.

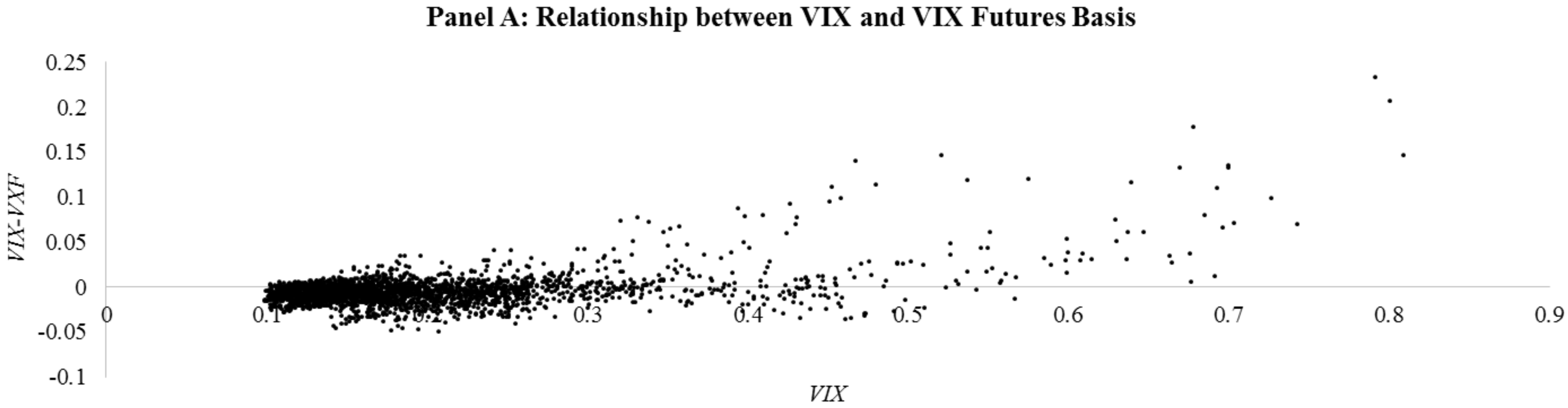
In order to separate different cases, this chapter follows the method used in DeLisle, Doran and Peterson (2011) and includes dummy variables into the time-series regression model. DeLisle, Doran and Peterson (2011) define dummy variables based on daily innovations in $VIX$. However, $\Delta VIX$ is a lagged variable and it reflects how aggregate volatility changes from its level on the previous trading day. It does not capture expectations in aggregate volatility. So instead of using the

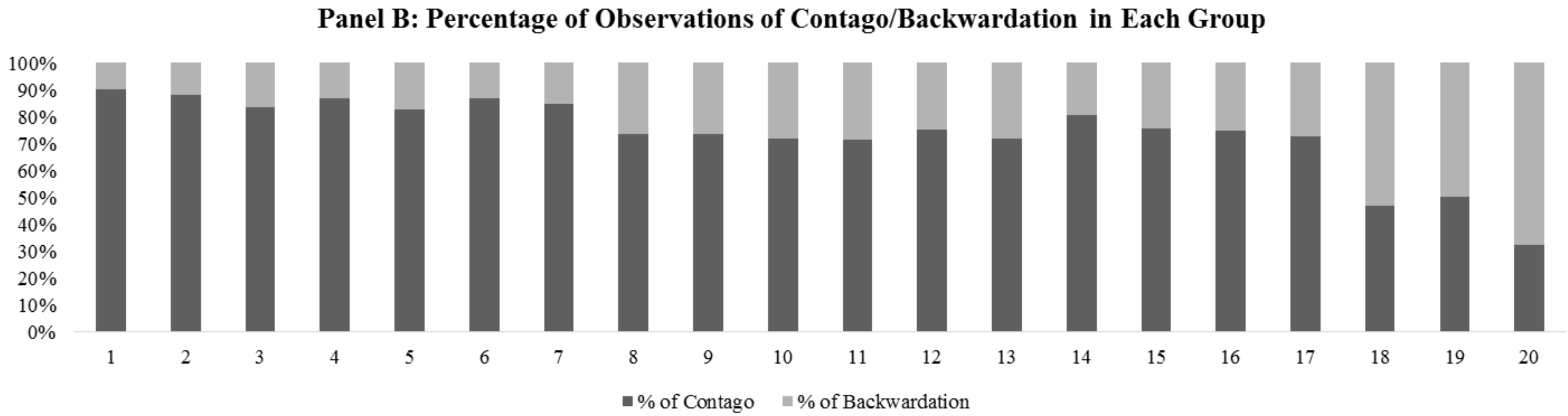
[49] In empirical analysis of this chapter, p-values reported in Tables 5.2 to 5.7 are calculated after controlling for autocorrelation (i.e., adjusted by using the Newey-West method).

innovation in VIX index or VIX futures, this chapter uses the difference between $VIX$ and $VXF$ (i.e., the VIX futures basis), $VIX - VXF$. Both $VIX$ and $VXF$ are forward looking and capture information about aggregate volatility levels in the near future but $VXF$ represents an expectation as to the level of volatility at future expiry.

As highlighted in CBOE official website, VIX futures are contracts on forward 30-day "model-free" implied volatilities. The price of a VIX futures contract can be lower, equal to or higher than VIX index, depending on whether the market expects volatility to be lower, equal to or higher in the 30-day forward period covered by the VIX futures contract than in the 30-day spot period covered by VIX index. The VIX index is a volatility forecast, not an individual asset. Hence, it is very expensive for investors to create a position equivalent to one in VIX futures by buying a portfolio of options to replicate VIX index and holding the position to futures expiration date while financing the transaction. VIX futures are not tied by the usual cost of carry relationship that connects other indices and index futures (Lin, 2007; Shu and Zhang, 2012). In this chapter, a positive VIX futures basis refers to "backwardation", whereas a negative VIX futures basis refers to "contango". Within the sample, there are more observations of "contango". However, when the VIX index becomes higher, there are more observations of "backwardation" (as shown in Panel A of Figure 5.3). This chapter also divides all available daily observations of VIX futures basis into 20 groups based on the VIX index on each day. Panel B of Figure 5.3 shows that, within each group, there are observations of both "backwardation" and "contango". In less volatile groups, there are more observations of "contango", whereas in more volatile groups, there are more observations of "backwardation". Thus, "backwardation" reflects highly volatile periods. For example, in the most volatile 2% trading days during the period from March 26, 2004 to December 31, 2014, 92.59% of

**Figure 5.3: Relationship between VIX Futures Basis and the VIX index (*VIX*)**



observations refer to "backwardation", whereas 7.41% of them refer to "contango". When $VIX$ is higher than 0.5676, $VIX - VXF$ is positive in all cases.

If $VIX$ is lower than $VXF$ (i.e., a negative futures basis), it indicates that the current aggregate volatility index is below what is expected by the market in the future. Risk-averse investors would prefer such conditions since they present less risk. For example, as shown in Panel A of Figure 5.4, during the period from March 22, 2007 to May 16, 2007, the $SPX$ increases from 1434.54 to 1514.14. During this period, in 28 out of 39 trading days, $VXF$ was higher than $VIX$. If $VIX$ is higher than $VXF$ (i.e., positive futures basis), it means that the current aggregate volatility index is higher than its market expectation. In this case, the current period is relatively more volatile for investors compared to future prospects. In Panel B of Figure 5.4, it is clear that $VIX$ was higher than $VXF$ in 31 out of 44 trading days during the period from August 21, 2008 to October 22, 2008. During this highly volatile period, $SPX$ dropped sharply from 1277.72 to 896.78.

Thus, a negative futures basis captures attractiveness to investors, whereas a positive futures basis indicates bad current conditions. In this chapter, the dummy variable $D_t$ is defined to be 1 if the futures basis is positive and 0 otherwise. The regression model incorporating an asymmetric effect is specified as follows:

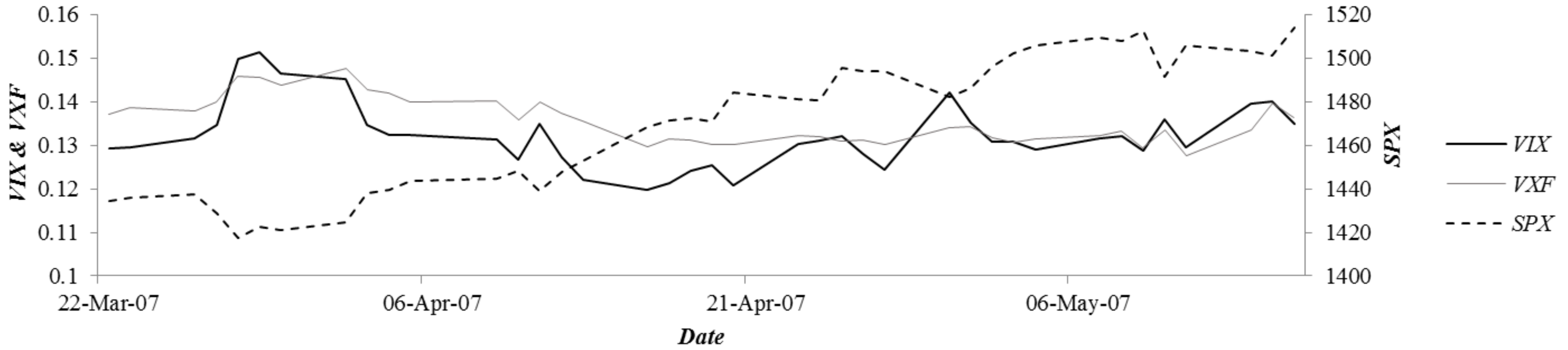
$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{VF} VF_t + \beta_i^{D} D_t VF_t + \varepsilon_{i,t} \tag{5.2}$$

where $VF$ is either $\Delta\left(VIX^2\right)$ or $\Delta\left(VXF^2\right)$. After running the regression shown in equation (5.2) by using previous approximately 40-day daily data points at the final settlement date in each month, quintile portfolios and "5-1" long-short portfolios are formed separately in two different situations ($D_t = 0$ and $D_t = 1$).[50] In other words,

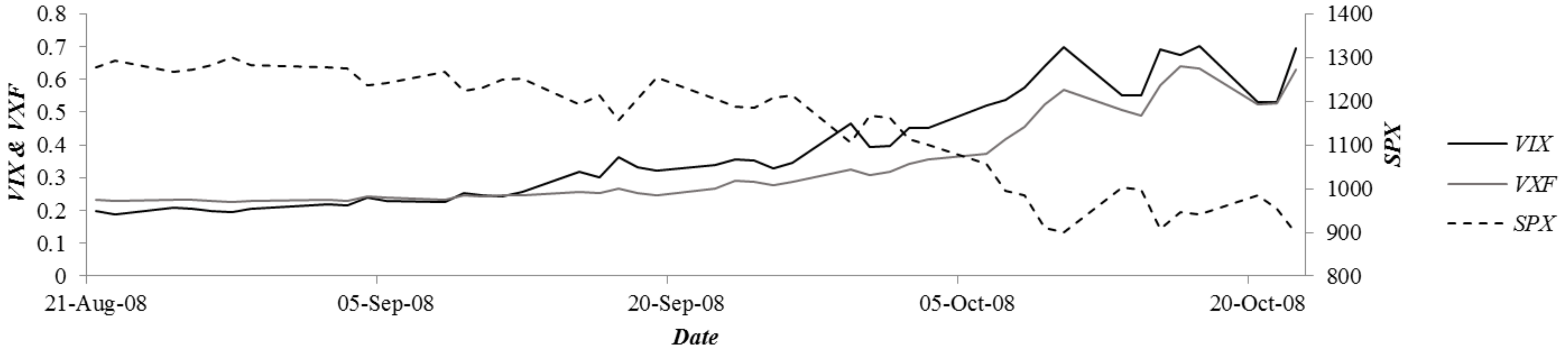
[50] A small fraction of observations is omitted because the dummy variable does not change value.

**Figure 5.4: Relationship between VIX Futures Basis and S&P500 Index ( *SPX* )**

**Panel A: *VIX*, *VXF*, & *SPX* (March 22, 2007 to May 16, 2007)**




**Panel B: *VIX*, *VXF*, & *SPX* (August 21, 2008 to October 22, 2008)**



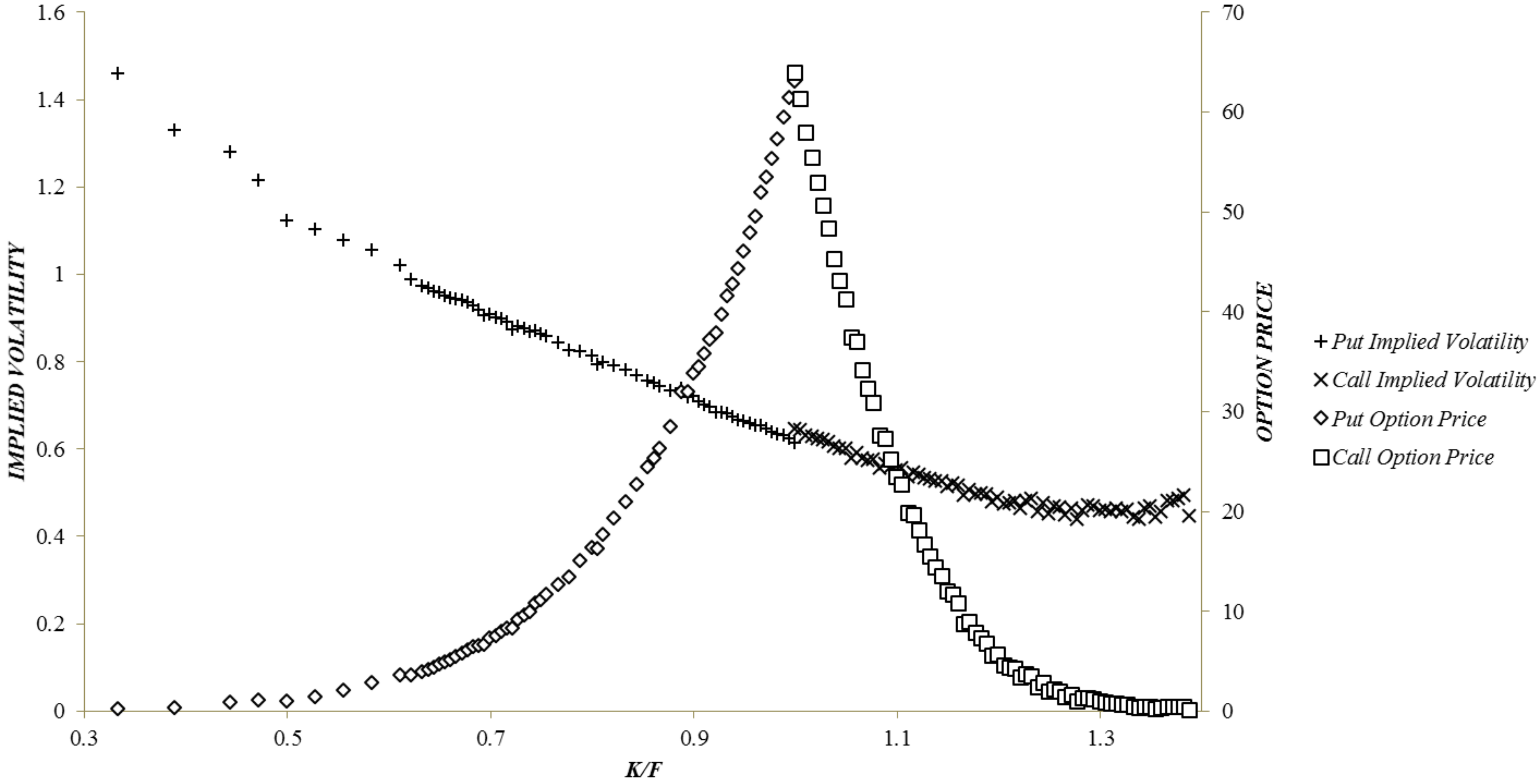
this chapter forms portfolios on $\beta_i^{VF}$ when $D_t = 0$ (i.e., only considering information about the volatility risk during the period with negative VIX futures basis), whereas this chapter forms portfolios on $\left(\beta_i^{VF} + \beta_i^{D}\right)$ when $D_t = 1$ (i.e., only considering information about volatility risk during period with positive VIX futures basis). Furthermore, for the "5-1" long-short portfolios, Jensen's alphas with respect to the market-factor model, the Fama-French three-factor model or the Carhart four-factor model are calculated to see whether, in different scenarios, the relationships between an asset's return and sensitivity to volatility factors are significant even after taking $MKT$, $SMB$, $HML$ and $UMD$ factors into consideration. This analysis enables us to verify whether the asymmetric effect of volatility risk on asset returns is determined by existing factors.

### 5.4.4 Decomposition of the VIX Index

The VIX index measures the market's expectation of 30-day aggregate volatility implied by both out-of-the-money call and put options of S&P500 index. Nevertheless, out-of-the-money call and put options reflect information captured by different parts of the option cross section.

Figure 5.5 indicates that out-of-the-money put options capture information conditional on future stock prices being lower than stock index forward, whereas out-of-the-money call options capture information conditional on future stock prices being higher. This chapter separates different market conditions based on ex ante information. Information contained in out-of-the-money put options reflects state prices from bad news conditions, whereas information contained in out-of-the-money call options reflects state prices from good news conditions. Decomposing $VIX^2$ into two parts (i.e., $VXC^2$ and $VXP^2$) enables us to test whether information captured by

**Figure 5.5: Prices of Out-of-the-Money Options $Q(K,T)$ and Implied Volatilities on October 22, 2008 (31 Day-to-Maturity)**



different options affects asset returns in different ways and to test the asymmetric effect of volatility risk using ex ante information. If information captured by one kind of options is more important and relevant to asset returns, investors could improve their trading strategies by only incorporating such information and avoid bearing unnecessary risk. Details about the decomposition are presented as follows.

According to the VIX Whitepaper from CBOE's website,[51] the "model-free" variance is calculated using the following formula:

$$\sigma_T^2 = \frac{2}{T}\sum_i \frac{\Delta K_i}{K_i^2} e^{rT} Q\left(K_i, T\right) - \frac{1}{T}\left[\frac{F_{0,T}}{K_0} - 1\right]^2 \tag{5.3}$$

where $T$ refers to time to expiration, $F_{0,T}$ is the forward index level derived from index option prices, $K_0$ is the first strike below the forward index level, $K_i$ is the strike price of the $i$th out-of-the-money option, $Q\left(K_i, T\right)$ is the midpoint of the bid-ask spread for each out-of-the-money call or put option with strike price of $K_i$ and time-to-expiry of $T$ (i.e., $Q\left(K_i, T\right) = \min\left(C\left(K_i, T\right), P\left(K_i, T\right)\right)$ where $C\left(K_i, T\right)$ is the midpoint of the bid-ask spread for out-of-the-money call option, and $P\left(K_i, T\right)$ is the midpoint of the bid-ask spread for out-of-the-money put option). This chapter decomposes $\sigma_T^2$ into $\sigma_{C,T}^2$ and $\sigma_{P,T}^2$, which separates information extracted from out-of-the-money call and put options, respectively. Variances $\sigma_{C,T}^2$ and $\sigma_{P,T}^2$ can be written as:

$$\sigma_{C,T}^2 = \frac{2}{T}\sum_i^{K_i \geq K_0} \frac{\Delta K_i}{K_i^2} e^{rT} C\left(K_i, T\right) - \frac{1}{2T}\left[\frac{F_{0,T}}{K_0} - 1\right]^2 \tag{5.4}$$

[51] Available from: https://www.cboe.com/micro/vix/vixwhite.pdf.

$$\sigma_{P,T}^2 = \frac{2}{T} \sum_{i}^{K_i \le K_0} \frac{\Delta K_i}{K_i^2} e^{rT} P\left(K_i, T\right) - \frac{1}{2T}\left[\frac{F_{0,T}}{K_0} - 1\right]^2 \tag{5.5}$$

The variance $\sigma_{C,T}^2$ is calculated by using only out-of-the-money call options with time-to-expiration of $T$, and $\sigma_{P,T}^2$ is calculated by using only out-of-the-money put options with time-to-expiration of $T$. Then, $VXC^2$ and $VXP^2$ are linear interpolation of near-term ($T_1$) and next term ($T_2$) variances.

$$VXC^2 = \left\{ T_1 \sigma_{C,T_1}^2 \left[\frac{N_{T_2} - N_{30}}{N_{T_2} - N_{T_1}}\right] + T_2 \sigma_{C,T_2}^2 \left[\frac{N_{30} - N_{T_1}}{N_{T_2} - N_{T_1}}\right] \right\} \times \frac{N_{365}}{N_{30}} \tag{5.6}$$

$$VXP^2 = \left\{ T_1 \sigma_{P,T_1}^2 \left[\frac{N_{T_2} - N_{30}}{N_{T_2} - N_{T_1}}\right] + T_2 \sigma_{P,T_2}^2 \left[\frac{N_{30} - N_{T_1}}{N_{T_2} - N_{T_1}}\right] \right\} \times \frac{N_{365}}{N_{30}} \tag{5.7}$$

Hence, $VXC^2$ and $VXP^2$ sum up to $VIX^2$. After decomposing $VIX$ into two components ($VXC$ and $VXP$), this chapter constructs $VF$ in equation (5.1) by using $VXC$ or $VXP$ (i.e., $\Delta\left(VXC^2\right)$ or $\Delta\left(VXP^2\right)$).

## 5.5 Results for Portfolio Level Analysis Using $\Delta\left(VIX^2\right)$ and $\Delta\left(VXF^2\right)$

The results obtained by using $\Delta\left(VIX^2\right)$ and $\Delta\left(VXF^2\right)$ are presented in this section in detail. First of all, this section shows results for portfolio level analysis obtained by using $\Delta\left(VIX^2\right)$ and $\Delta\left(VXF^2\right)$ without incorporating an asymmetric effect. Then, this section incorporates the asymmetric effect into empirical analysis by including a dummy variable and checks whether volatility risk plays a significant role in explaining asset returns in different market conditions.

### 5.5.1 Results for Portfolio Level Analysis Using $\Delta\left(VIX^{2}\right)$ and $\Delta\left(VXF^{2}\right)$

First of all, the results for quintile portfolio level analysis by using $\Delta\left(VIX^{2}\right)$ and $\Delta\left(VXF^{2}\right)$ without incorporating asymmetric effects are presented. This subsection first estimates equation (5.1) on the final settlement date in each calendar month by using previous two-month daily data on each individual stock.[52] Then, quintile portfolios are constructed based on the beta coefficients of volatility factors (i.e., $\beta_i^{VF}$). The "5-1" long-short portfolio is formed by holding a long position in quintile portfolio 5 and a short position in quintile portfolio 1. The corresponding results obtained when using $\Delta\left(VIX^{2}\right)$ are found in Table 5.2.

Panels A and B of Table 5.2 present results for equally- and value-weighted portfolios, respectively. In these two panels, no matter what holding period horizon is used after portfolio formation, there is no significant relationship between an asset's sensitivity to $\Delta\left(VIX^{2}\right)$ and its return.

As well as using $\Delta\left(VIX^{2}\right)$, the analysis uses $\Delta\left(VXF^{2}\right)$ as the volatility factor. The results are shown in Table 5.3. Two panels of Table 5.3 show that there is no significant relationship between an asset's sensitivity to $\Delta\left(VXF^{2}\right)$ and its return.

The insignificant relationship between an asset's sensitivity to volatility factors and its return could be due to the fact that the sample period of this chapter is from October 2005 to December 2014. The sample period is relatively short but it covers the recent financial crisis, where asset markets were relatively volatile and dynamic.

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[52] When using $\Delta\left(VIX^{2}\right)$ in equation (5.1), the average adjusted $R^2$ of the regression model among all individual stocks is 20.53%. Among all individual stocks, 7.75% of them have significant non-zero intercept at a 10% significance level. When switching to use $\Delta\left(VXF^{2}\right)$ in equation (5.1), the average adjusted $R^2$ is 20.45%. The percentage of individual stocks with significant non-zero intercept is 7.69%.

**Table 5.2: Results for Quintile Portfolio Level Analysis by Using $\Delta\left(VIX^2\right)$**

Notes: The following time-series regression is estimated on the final settlement date in each calendar month by using daily data:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta(VIX^2)} \Delta\left(VIX^2\right)_t + \varepsilon_{i,t}$$

Equally- and value-weighted quintile portfolios are constructed based on $\beta_i^{\Delta(VIX^2)}$. Portfolio 5 consists of stocks with the highest $\beta_i^{\Delta(VIX^2)}$, whereas portfolio 1 consists of stocks with the lowest $\beta_i^{\Delta(VIX^2)}$. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. Then, this chapter calculates the return for each portfolio during the holding period (10-, 20-, and 30-day) after the portfolio formation.

**Panel A: Results for Equally-weighted Quintile Portfolios**

| | 10-Day Holding Period | | | | 20-Day Holding Period | | | | 30-Day Holding Period | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ |
| 1 | 0.0122 | 0.0053 | 0.0064 | 0.0063 | 0.0153 | 0.0070 | 0.0073 | 0.0074 | 0.0281 | 0.0101 | 0.0121 | 0.0145 |
| 2 | 0.0089 | 0.0025 | 0.0032 | 0.0031 | 0.0106 | 0.0030 | 0.0033 | 0.0034 | 0.0204 | 0.0048 | 0.0062 | 0.0073 |
| 3 | 0.0080 | 0.0016 | 0.0024 | 0.0023 | 0.0107 | 0.0032 | 0.0034 | 0.0035 | 0.0191 | 0.0037 | 0.0050 | 0.0060 |
| 4 | 0.0092 | 0.0023 | 0.0031 | 0.0031 | 0.0113 | 0.0032 | 0.0035 | 0.0036 | 0.0204 | 0.0039 | 0.0055 | 0.0068 |
| 5 | 0.0129 | 0.0051 | 0.0062 | 0.0061 | 0.0145 | 0.0057 | 0.0061 | 0.0062 | 0.0268 | 0.0080 | 0.0103 | 0.0126 |
| 5-1 | 0.0007 | -0.0001 | -0.0002 | -0.0002 | -0.0007 | -0.0013 | -0.0012 | -0.0012 | -0.0013 | -0.0021 | -0.0018 | -0.0019 |
| p-value | (0.5259) | (0.8689) | (0.8734) | (0.8622) | (0.7143) | (0.4539) | (0.5090) | (0.5129) | (0.5239) | (0.2784) | (0.3829) | (0.3621) |

**Panel B: Results for Value-Weighted Quintile Portfolios**

| | 10-Day Holding Period | | | | 20-Day Holding Period | | | | 30-Day Holding Period | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ |
| 1 | 0.0058 | -0.0010 | -0.0004 | -0.0004 | 0.0068 | -0.0016 | -0.0015 | -0.0015 | 0.0160 | -0.0002 | 0.0001 | 0.0005 |
| 2 | 0.0047 | -0.0007 | -0.0007 | -0.0007 | 0.0067 | -0.0003 | -0.0003 | -0.0004 | 0.0127 | -0.0001 | -0.0002 | -0.0003 |
| 3 | 0.0062 | 0.0007 | 0.0006 | 0.0006 | 0.0076 | 0.0011 | 0.0011 | 0.0011 | 0.0136 | 0.0011 | 0.0010 | 0.0011 |
| 4 | 0.0081 | 0.0019 | 0.0018 | 0.0018 | 0.0084 | 0.0011 | 0.0013 | 0.0013 | 0.0150 | 0.0006 | 0.0008 | 0.0013 |
| 5 | 0.0087 | 0.0006 | 0.0009 | 0.0009 | 0.0072 | -0.0016 | -0.0011 | -0.0010 | 0.0161 | -0.0006 | 0.0002 | 0.0014 |
| 5-1 | 0.0030 | 0.0016 | 0.0013 | 0.0013 | 0.0004 | -0.0000 | 0.0004 | 0.0005 | 0.0001 | -0.0004 | 0.0001 | 0.0009 |
| p-value | (0.3777) | (0.5499) | (0.6147) | (0.6152) | (0.9137) | (0.9959) | (0.9154) | (0.8948) | (0.9718) | (0.9184) | (0.9776) | (0.8266) |

**Table 5.3: Results for Quintile Portfolio Level Analysis by Using $\Delta\left(VXF^2\right)$**

Notes: The following time-series regression is estimated on the final settlement date in each calendar month by using daily data:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta\left(VXF^2\right)} \Delta\left(VXF^2\right)_t + \varepsilon_{i,t}$$

Equally- and value-weighted quintile portfolios are constructed based on $\beta_i^{\Delta\left(VXF^2\right)}$. Portfolio 5 consists of stocks with the highest $\beta_i^{\Delta\left(VXF^2\right)}$, whereas portfolio 1 consists of stocks with the lowest $\beta_i^{\Delta\left(VXF^2\right)}$. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. Then, this chapter calculates the return for each portfolio during the holding period (10-, 20-, and 30-day) after the portfolio formation.

**Panel A: Results for Equally-weighted Quintile Portfolios**

| | 10-Day Holding Period | | | | 20-Day Holding Period | | | | 30-Day Holding Period | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ |
| 1 | 0.0130 | 0.0056 | 0.0067 | 0.0065 | 0.0149 | 0.0064 | 0.0068 | 0.0070 | 0.0270 | 0.0085 | 0.0106 | 0.0129 |
| 2 | 0.0093 | 0.0025 | 0.0033 | 0.0032 | 0.0110 | 0.0032 | 0.0035 | 0.0035 | 0.0205 | 0.0045 | 0.0061 | 0.0072 |
| 3 | 0.0083 | 0.0020 | 0.0027 | 0.0026 | 0.0107 | 0.0032 | 0.0034 | 0.0035 | 0.0196 | 0.0046 | 0.0059 | 0.0068 |
| 4 | 0.0088 | 0.0022 | 0.0030 | 0.0030 | 0.0104 | 0.0025 | 0.0028 | 0.0029 | 0.0201 | 0.0039 | 0.0054 | 0.0067 |
| 5 | 0.0119 | 0.0046 | 0.0057 | 0.0056 | 0.0154 | 0.0067 | 0.0071 | 0.0073 | 0.0278 | 0.0091 | 0.0111 | 0.0138 |
| 5-1 | -0.0010 | -0.0009 | -0.0010 | -0.0009 | 0.0004 | 0.0003 | 0.0003 | 0.0003 | 0.0009 | 0.0005 | 0.0006 | 0.0009 |
| p-value | (0.5670) | (0.6041) | (0.5605) | (0.5576) | (0.8209) | (0.8827) | (0.8865) | (0.8716) | (0.7096) | (0.8067) | (0.7978) | (0.6584) |

**Panel B: Results for Value-Weighted Quintile Portfolios**

| | 10-Day Holding Period | | | | 20-Day Holding Period | | | | 30-Day Holding Period | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ |
| 1 | 0.0076 | 0.0002 | 0.0006 | 0.0006 | 0.0069 | -0.0016 | -0.0015 | -0.0015 | 0.0149 | -0.0017 | -0.0012 | -0.0008 |
| 2 | 0.0062 | 0.0003 | 0.0003 | 0.0003 | 0.0068 | -0.0003 | -0.0002 | -0.0002 | 0.0131 | 0.0001 | -0.0001 | -0.0002 |
| 3 | 0.0060 | 0.0006 | 0.0004 | 0.0004 | 0.0069 | 0.0003 | 0.0003 | 0.0003 | 0.0131 | 0.0009 | 0.0008 | 0.0008 |
| 4 | 0.0057 | 0.0001 | 0.0001 | 0.0001 | 0.0066 | -0.0004 | -0.0005 | -0.0005 | 0.0136 | -0.0000 | 0.0000 | 0.0002 |
| 5 | 0.0084 | 0.0009 | 0.0013 | 0.0012 | 0.0092 | 0.0006 | 0.0008 | 0.0009 | 0.0187 | 0.0006 | 0.0014 | 0.0032 |
| 5-1 | 0.0008 | 0.0006 | 0.0006 | 0.0007 | 0.0023 | 0.0022 | 0.0023 | 0.0024 | 0.0038 | 0.0024 | 0.0026 | 0.0040 |
| p-value | (0.7628) | (0.8009) | (0.8072) | (0.7915) | (0.6080) | (0.6209) | (0.6075) | (0.5546) | (0.5309) | (0.6670) | (0.6250) | (0.3949) |

Insignificant relationships between quintile portfolio returns and sensitivity to $\Delta\left(VIX^2\right)$ or $\Delta\left(VXF^2\right)$ may be due to crash factors.

### 5.5.2 Results for Asymmetric Portfolio Level Analysis Using $\Delta\left(VIX^2\right)$

Without separating market scenarios, the previous subsection does not detect any significant relationship between an asset's sensitivity to volatility risk and its return. So, this subsection includes a dummy variable in the time-series regression model to separate different market conditions (see equation (5.2)).[53] Such an analysis enables us to investigate the asymmetric effect of the volatility risk. First, this subsection focuses on the asymmetric effect of $\Delta\left(VIX^2\right)$; the corresponding results are presented in Table 5.4.

The results show the asymmetric effect of aggregate volatility risk reflected by $\Delta\left(VIX^2\right)$. From Panels A and C, investors do not earn premiums from the "5-1" long-short portfolio if they only take into account the information during the periods with negative futures basis (i.e., $D_t = 0$). From Panels B and D of Table 5.4, it is shown that, if investors construct their trading strategies based on information during the period with positive futures basis, they lose money by holding a long position in portfolios with the highest beta on $\Delta\left(VIX^2\right)$ and short selling portfolios with the

[53] When using $\Delta\left(VIX^2\right)$ in equation (5.2), the average adjusted $R^2$ of the regression model among all individual stocks is 20.17%. After incorporating the asymmetric effect of volatility risk, at a 10% significance level, 7.27% of individual stocks have significant non-zero intercept, and 8.85% of individual stocks have significant factor loading on the dummy variable, $\beta_i^D$. When using $\Delta\left(VXF^2\right)$ in equation (5.2), similar results are obtained. The average adjusted $R^2$ of the regression model is 20.11%. 7.24% of individual stocks have significant non-zero intercept, and 9.06% have significant $\beta_i^D$. A significant intercept indicates the failure of the asset pricing model. Although incorporating the asymmetric effect does not increase the adjusted $R^2$ of the model (compared with the results discussed in footnote 52), it does decrease cases with significant intercept.

## Table 5.4: Results for Asymmetric Quintile Portfolio Level Analysis by Using $\Delta\left(VIX^2\right)$

Notes: The following time-series regression is estimated on the final settlement date in each calendar month by using daily data:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta\left(VIX^2\right)} \Delta\left(VIX^2\right)_t + \beta_i^D D_t \Delta\left(VIX^2\right)_t + \varepsilon_{i,t}$$

where $D_t$=1 if VIX future basis is positive and zero otherwise. Then, equally- and value-weighted quintile portfolios are constructed in two different situations, $D_t$=0 and $D_t$=1. Portfolio 5 consists of stocks with the highest $\beta_i^{\Delta\left(VIX^2\right)}$ or $\left(\beta_i^{\Delta\left(VIX^2\right)} + \beta_i^D\right)$, whereas portfolio 1 consists of stocks with the lowest $\beta_i^{\Delta\left(VIX^2\right)}$ or $\left(\beta_i^{\Delta\left(VIX^2\right)} + \beta_i^D\right)$. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. Then, this chapter calculates the return for each portfolio during the holding period (10-, 20-, and 30-day) after the portfolio formation. *, **, and *** denote for significance at 10%, 5% and 1% levels, respectively.

**Panel A: Results for Equally-weighted Quintile Portfolios Formed When $D_t = 0$**

| | 10-Day Holding Period | | | | 20-Day Holding Period | | | | 30-Day Holding Period | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ |
| 1 | 0.0084 | 0.0040 | 0.0055 | 0.0056 | 0.0118 | 0.0051 | 0.0057 | 0.0062 | 0.0226 | 0.0081 | 0.0098 | 0.0123 |
| 2 | 0.0059 | 0.0017 | 0.0027 | 0.0029 | 0.0082 | 0.0019 | 0.0023 | 0.0026 | 0.0172 | 0.0043 | 0.0056 | 0.0067 |
| 3 | 0.0053 | 0.0013 | 0.0023 | 0.0024 | 0.0083 | 0.0022 | 0.0027 | 0.0029 | 0.0159 | 0.0037 | 0.0049 | 0.0059 |
| 4 | 0.0062 | 0.0020 | 0.0030 | 0.0032 | 0.0089 | 0.0025 | 0.0030 | 0.0032 | 0.0166 | 0.0033 | 0.0047 | 0.0062 |
| 5 | 0.0086 | 0.0040 | 0.0053 | 0.0055 | 0.0116 | 0.0047 | 0.0054 | 0.0059 | 0.0220 | 0.0068 | 0.0086 | 0.0117 |
| 5-1 | 0.0002 | -0.0000 | -0.0001 | -0.0001 | -0.0001 | -0.0004 | -0.0003 | -0.0003 | -0.0006 | -0.0013 | -0.0012 | -0.0006 |
| p-value | (0.8615) | (0.9808) | (0.9200) | (0.9333) | (0.9525) | (0.8436) | (0.8959) | (0.8991) | (0.8396) | (0.6409) | (0.6720) | (0.8438) |

**Panel B: Results for Equally-weighted Quintile Portfolios Formed When $D_t = 1$**

| | 10-Day Holding Period | | | | 20-Day Holding Period | | | | 30-Day Holding Period | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ |
| 1 | 0.0098 | 0.0055 | 0.0069 | 0.0071 | 0.0134 | 0.0066 | 0.0073 | 0.0078 | 0.0252 | 0.0104 | 0.0120 | 0.0148 |
| 2 | 0.0060 | 0.0020 | 0.0029 | 0.0030 | 0.0088 | 0.0026 | 0.0030 | 0.0033 | 0.0171 | 0.0045 | 0.0058 | 0.0069 |
| 3 | 0.0050 | 0.0010 | 0.0019 | 0.0020 | 0.0069 | 0.0009 | 0.0012 | 0.0015 | 0.0147 | 0.0024 | 0.0036 | 0.0045 |
| 4 | 0.0056 | 0.0014 | 0.0025 | 0.0026 | 0.0085 | 0.0020 | 0.0026 | 0.0029 | 0.0159 | 0.0026 | 0.0040 | 0.0055 |
| 5 | 0.0079 | 0.0032 | 0.0047 | 0.0049 | 0.0112 | 0.0041 | 0.0048 | 0.0053 | 0.0213 | 0.0063 | 0.0082 | 0.0110 |
| 5-1 | -0.0019* | -0.0022** | -0.0022** | -0.0022** | -0.0022 | -0.0025* | -0.0025 | -0.0025 | -0.0038** | -0.0041** | -0.0038** | -0.0039* |
| p-value | (0.0776) | (0.0191) | (0.0187) | (0.0256) | (0.1601) | (0.0958) | (0.1099) | (0.1158) | (0.0348) | (0.0254) | (0.0430) | (0.0544) |

(Continued)

| Panel C: Results for Value-Weighted Quintile Portfolios Formed When $D_t = 0$ | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 10-Day Holding Period | | | | 20-Day Holding Period | | | | 30-Day Holding Period | | | |
| | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ |
| 1 | 0.0031 | -0.0013 | -0.0009 | -0.0008 | 0.0049 | -0.0020 | -0.0019 | -0.0017 | 0.0126 | -0.0017 | -0.0015 | -0.0006 |
| 2 | 0.0038 | -0.0000 | -0.0000 | -0.0000 | 0.0056 | -0.0002 | -0.0001 | -0.0001 | 0.0122 | 0.0012 | 0.0011 | 0.0011 |
| 3 | 0.0044 | 0.0010 | 0.0009 | 0.0008 | 0.0065 | 0.0010 | 0.0010 | 0.0009 | 0.0118 | 0.0016 | 0.0015 | 0.0014 |
| 4 | 0.0045 | 0.0008 | 0.0008 | 0.0008 | 0.0062 | 0.0004 | 0.0005 | 0.0005 | 0.0112 | 0.0000 | 0.0002 | 0.0006 |
| 5 | 0.0032 | -0.0012 | -0.0008 | -0.0008 | 0.0049 | -0.0019 | -0.0017 | -0.0017 | 0.0099 | -0.0036 | -0.0031 | -0.0021 |
| 5-1 | 0.0001 | 0.0001 | 0.0001 | 0.0000 | -0.0000 | 0.0001 | 0.0002 | -0.0000 | -0.0027 | -0.0018 | -0.0016 | -0.0015 |
| p-value | (0.9527) | (0.9572) | (0.9546) | (0.9987) | (0.9969) | (0.9822) | (0.9453) | (0.9986) | (0.5349) | (0.6889) | (0.7348) | (0.7404) |

| Panel D: Results for Value-Weighted Quintile Portfolios Formed When $D_t = 1$ | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 10-Day Holding Period | | | | 20-Day Holding Period | | | | 30-Day Holding Period | | | |
| | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ |
| 1 | 0.0054 | 0.0010 | 0.0016 | 0.0015 | 0.0085 | 0.0016 | 0.0018 | 0.0016 | 0.0176 | 0.0044 | 0.0045 | 0.0052 |
| 2 | 0.0034 | -0.0003 | -0.0003 | -0.0003 | 0.0065 | 0.0007 | 0.0007 | 0.0007 | 0.0118 | 0.0009 | 0.0008 | 0.0007 |
| 3 | 0.0042 | 0.0007 | 0.0006 | 0.0006 | 0.0062 | 0.0008 | 0.0008 | 0.0007 | 0.0109 | 0.0006 | 0.0005 | 0.0004 |
| 4 | 0.0048 | 0.0009 | 0.0009 | 0.0009 | 0.0053 | -0.0005 | -0.0005 | -0.0004 | 0.0104 | -0.0010 | -0.0009 | -0.0004 |
| 5 | 0.0022 | -0.0024 | -0.0018 | -0.0018 | 0.0008 | -0.0061 | -0.0058 | -0.0054 | 0.0071 | -0.0071 | -0.0065 | -0.0045 |
| 5-1 | -0.0032 | -0.0034 | -0.0034 | -0.0033 | -0.0076** | -0.0077** | -0.0075* | -0.0071** | -0.0105** | -0.0115*** | -0.0110*** | -0.0096*** |
| p-value | (0.1806) | (0.1600) | (0.1284) | (0.1365) | (0.0469) | (0.0418) | (0.0505) | (0.0360) | (0.0148) | (0.0042) | (0.0067) | (0.0093) |

lowest beta on $\Delta\left(VIX^2\right)$ for different investment horizons. If investors construct an equally-weighted "5-1" long-short portfolio and hold the portfolio for the following 10 trading days, Jensen's alpha with respect to the Carhart four-factor model (controlling for $MKT$, $SMB$, $HML$ or $UMD$) is -0.22% (with a p-value of 0.0256). If investors hold the "5-1" long-short portfolio for a longer period, 30 trading-day, the risk-adjusted return with respect to Carhart four-factor model becomes -0.39% (with a p-value of 0.0544). For the value-weighted "5-1" long-short portfolio, the risk-adjusted return with respect to Carhart four-factor model is -0.71% (with a p-value of 0.0360) for a 20 trading-day period, and is -0.96% (with a p-value of 0.0093) for a 30 trading-day period.

The asymmetric effect of the volatility risk constructed by using $VIX$ is also documented in DeLisle, Doran and Peterson (2011); findings in this subsection are consistent with their paper.

### 5.5.3 Results for Asymmetric Portfolio Level Analysis Using $\Delta\left(VXF^2\right)$

After confirming the existence of the asymmetric effect of volatility risk by using $VIX$, this subsection investigates whether the traded derivative, VIX index futures ($VXF$), plays a similar role in separating the asymmetric effect of the volatility risk. Instead of using $\Delta\left(VIX^2\right)$, this subsection uses $\Delta\left(VXF^2\right)$ as a proxy for the volatility risk in the portfolio level analysis with the asymmetric effect incorporated. Table 5.5 shows corresponding results.

In Panels A and C of Table 5.5, when only taking into consideration the information during the period with negative futures basis, there is no significant relationship between a stock's sensitivity to $\Delta\left(VXF^2\right)$ and quintile portfolio return. However, from Panels B and D, it is easy to find that under the assumption of a

30-day holding period, there is a significant and negative relationship between an asset's sensitivity to $\Delta\left(VXF^2\right)$ and its return considering the information during the period with positive futures basis. For example, under the assumption of a 30 trading-day holding period after portfolio formation, for the equally-weighted "5-1" long-short portfolio, the risk-adjusted mean return with respect to Carhart four-factor model is -0.35% (with a p-value of 0.0637); for the value-weighted "5-1" long-short portfolio, the risk-adjusted mean return with respect to Carhart four-factor model is -0.85% (with a p-values of 0.0461).

Thus, the asymmetric effect of the volatility risk still exists if $\Delta\left(VXF^2\right)$ is used to measure volatility risk. When only considering information about volatility risk in the period with positive futures basis (i.e., fearful markets), there is a negative relationship between an asset's return and its sensitivity to $\Delta\left(VXF^2\right)$. However, such a relationship is insignificant when only considering information about volatility risk in the period with negative futures basis (i.e., calm markets).

### 5.5.4 Discussions for Asymmetric Portfolio Analysis Using $\Delta\left(VIX^2\right)$ or $\Delta\left(VXF^2\right)$

From the above analysis, it is obvious that sensitivity to $\Delta\left(VIX^2\right)$ or $\Delta\left(VXF^2\right)$ is significantly and negatively correlated with quintile portfolio return when incorporating an asymmetric effect of the volatility risk into the empirical analysis (Panels B and D in Tables 5.4 and 5.5). During periods with positive futures basis, the market is relatively more volatile, and the return on the market portfolio is negative. If individual stock returns are highly correlated with volatility during such periods, investors will take into consideration the correlation between stock returns and volatility risk, and returns on these stocks will be lower over a short horizon.

## Table 5.5: Results for Asymmetric Quintile Portfolio Level Analysis by Using $\Delta\left(VXF^2\right)$

Notes: The following time-series regression is estimated on the final settlement date in each calendar month by using daily data:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta\left(VXF^2\right)} \Delta\left(VXF^2\right)_t + \beta_i^D D_t \Delta\left(VXF^2\right)_t + \varepsilon_{i,t}$$

where $D_t$=1 if VIX future basis is positive and zero otherwise. Then, equally- and value-weighted quintile portfolios are constructed in two different situations, $D_t$=0 and $D_t$=1. Portfolio 5 consists of stocks with the highest $\beta_i^{\Delta\left(VXF^2\right)}$ or $\left(\beta_i^{\Delta\left(VXF^2\right)} + \beta_i^D\right)$, whereas portfolio 1 consists of stocks with the lowest $\beta_i^{\Delta\left(VXF^2\right)}$ or $\left(\beta_i^{\Delta\left(VXF^2\right)} + \beta_i^D\right)$. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. Then, this chapter calculates the return for each portfolio during the holding period (10-, 20-, and 30-day) after the portfolio formation. *, **, and *** denote for significance at 10%, 5% and 1% levels, respectively.

**Panel A: Results for Equally-weighted Quintile Portfolios Formed When $D_t = 0$**

| | 10-Day Holding Period | | | | 20-Day Holding Period | | | | 30-Day Holding Period | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ |
| 1 | 0.0077 | 0.0032 | 0.0047 | 0.0049 | 0.0115 | 0.0046 | 0.0053 | 0.0058 | 0.0223 | 0.0076 | 0.0094 | 0.0119 |
| 2 | 0.0058 | 0.0016 | 0.0027 | 0.0028 | 0.0084 | 0.0021 | 0.0026 | 0.0028 | 0.0172 | 0.0044 | 0.0057 | 0.0067 |
| 3 | 0.0054 | 0.0014 | 0.0023 | 0.0024 | 0.0086 | 0.0026 | 0.0030 | 0.0032 | 0.0163 | 0.0040 | 0.0052 | 0.0060 |
| 4 | 0.0064 | 0.0023 | 0.0034 | 0.0035 | 0.0086 | 0.0023 | 0.0028 | 0.0030 | 0.0167 | 0.0036 | 0.0050 | 0.0065 |
| 5 | 0.0090 | 0.0045 | 0.0058 | 0.0059 | 0.0116 | 0.0047 | 0.0053 | 0.0059 | 0.0219 | 0.0067 | 0.0084 | 0.0116 |
| 5-1 | 0.0013 | 0.0013 | 0.0010 | 0.0010 | 0.0001 | 0.0000 | 0.0000 | 0.0001 | -0.0004 | -0.0008 | -0.0010 | -0.0003 |
| p-value | (0.2522) | (0.2780) | (0.3776) | (0.3905) | (0.9548) | (0.9920) | (0.9872) | (0.9529) | (0.8632) | (0.6906) | (0.6421) | (0.8899) |

**Panel B: Results for Equally-weighted Quintile Portfolios Formed When $D_t = 1$**

| | 10-Day Holding Period | | | | 20-Day Holding Period | | | | 30-Day Holding Period | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ |
| 1 | 0.0100 | 0.0056 | 0.0069 | 0.0071 | 0.0131 | 0.0064 | 0.0071 | 0.0075 | 0.0245 | 0.0100 | 0.0118 | 0.0145 |
| 2 | 0.0064 | 0.0023 | 0.0034 | 0.0035 | 0.0093 | 0.0030 | 0.0035 | 0.0038 | 0.0182 | 0.0053 | 0.0065 | 0.0077 |
| 3 | 0.0051 | 0.0011 | 0.0020 | 0.0021 | 0.0075 | 0.0014 | 0.0018 | 0.0020 | 0.0149 | 0.0027 | 0.0039 | 0.0048 |
| 4 | 0.0050 | 0.0008 | 0.0019 | 0.0020 | 0.0074 | 0.0009 | 0.0014 | 0.0017 | 0.0154 | 0.0020 | 0.0033 | 0.0048 |
| 5 | 0.0078 | 0.0033 | 0.0046 | 0.0048 | 0.0114 | 0.0044 | 0.0051 | 0.0057 | 0.0213 | 0.0062 | 0.0080 | 0.0110 |
| 5-1 | -0.0022 | -0.0023 | -0.0023 | -0.0023 | -0.0017 | -0.0020 | -0.0020 | -0.0019 | -0.0033* | -0.0038** | -0.0038** | -0.0035* |
| p-value | (0.1690) | (0.1417) | (0.1480) | (0.1397) | (0.3297) | (0.2297) | (0.2387) | (0.2536) | (0.0866) | (0.0389) | (0.0444) | (0.0637) |

(Continued)

| Panel C: Results for Value-Weighted Quintile Portfolios Formed When $D_t = 0$ | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 10-Day Holding Period | | | | 20-Day Holding Period | | | | 30-Day Holding Period | | | |
| | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ |
| 1 | 0.0025 | -0.0020 | -0.0015 | -0.0013 | 0.0027 | -0.0042 | -0.0039 | -0.0037 | 0.0115 | -0.0021 | -0.0016 | -0.0008 |
| 2 | 0.0039 | 0.0001 | 0.0001 | 0.0001 | 0.0067 | 0.0010 | 0.0011 | 0.0011 | 0.0136 | 0.0028 | 0.0028 | 0.0028 |
| 3 | 0.0041 | 0.0007 | 0.0005 | 0.0005 | 0.0063 | 0.0010 | 0.0009 | 0.0009 | 0.0112 | 0.0010 | 0.0009 | 0.0008 |
| 4 | 0.0038 | 0.0001 | 0.0000 | -0.0001 | 0.0052 | -0.0007 | -0.0008 | -0.0009 | 0.0098 | -0.0018 | -0.0016 | -0.0015 |
| 5 | 0.0044 | 0.0001 | 0.0006 | 0.0005 | 0.0049 | -0.0018 | -0.0017 | -0.0016 | 0.0112 | -0.0025 | -0.0020 | -0.0009 |
| 5-1 | 0.0019 | 0.0021 | 0.0021 | 0.0019 | 0.0022 | 0.0024 | 0.0022 | 0.0021 | -0.0003 | -0.0004 | -0.0004 | -0.0001 |
| p-value | (0.4707) | (0.4480) | (0.4260) | (0.4615) | (0.5779) | (0.5539) | (0.5830) | (0.6197) | (0.9390) | (0.9305) | (0.9223) | (0.9726) |

| Panel D: Results for Value-Weighted Quintile Portfolios Formed When $D_t = 1$ | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 10-Day Holding Period | | | | 20-Day Holding Period | | | | 30-Day Holding Period | | | |
| | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ |
| 1 | 0.0055 | 0.0012 | 0.0016 | 0.0016 | 0.0076 | 0.0010 | 0.0012 | 0.0011 | 0.0167 | 0.0040 | 0.0044 | 0.0049 |
| 2 | 0.0043 | 0.0005 | 0.0005 | 0.0005 | 0.0069 | 0.0010 | 0.0009 | 0.0009 | 0.0135 | 0.0026 | 0.0024 | 0.0022 |
| 3 | 0.0037 | 0.0003 | 0.0001 | 0.0001 | 0.0065 | 0.0011 | 0.0011 | 0.0011 | 0.0115 | 0.0013 | 0.0012 | 0.0012 |
| 4 | 0.0046 | 0.0008 | 0.0009 | 0.0009 | 0.0046 | -0.0014 | -0.0013 | -0.0012 | 0.0097 | -0.0020 | -0.0019 | -0.0015 |
| 5 | 0.0040 | -0.0006 | -0.0003 | -0.0002 | 0.0031 | -0.0039 | -0.0036 | -0.0033 | 0.0085 | -0.0062 | -0.0056 | -0.0036 |
| 5-1 | -0.0016 | -0.0018 | -0.0019 | -0.0018 | -0.0045 | -0.0049 | -0.0048 | -0.0044 | -0.0082 | -0.0102** | -0.0100** | -0.0085** |
| p-value | (0.5336) | (0.4637) | (0.4500) | (0.4583) | (0.3119) | (0.2397) | (0.2495) | (0.2445) | (0.1209) | (0.0317) | (0.0345) | (0.0461) |

However, if stock returns are correlated with the volatility risk in calm markets, investors in the market will ignore such correlations and future stock returns will not be affected.

Furthermore, profits from holding a long position in portfolio 1 and a short position in portfolio 5 constructed based on $\left(\beta_i^{\Delta\left(VXF^2\right)} + \beta_i^D\right)$ when $D_t = 1$ (around 0.35% for equally-weighted portfolio and around 0.85% for value-weighted portfolio for a 30-day holding period) are comparable with those obtained from holding a long position in portfolio 1 and a short position in portfolio 5 based on $\left(\beta_i^{\Delta\left(VIX^2\right)} + \beta_i^D\right)$ when $D_t = 1$ (around 0.40% for equally-weighted portfolio and around 0.95% for value-weighted portfolio for a 30-day holding period). The asymmetric effect found from using $\Delta\left(VXF^2\right)$ is also significant. So, from the comparison, this chapter confirms the importance of $VXF$ in stock pricing and returns.

## 5.6 Results for Portfolio Level Analysis Using $\Delta\left(VXC^2\right)$ and $\Delta\left(VXP^2\right)$

The full VIX index contains information captured by both out-of-the-money call and put options. This section separates information captured by each kind of options (i.e., decomposes $VIX^2$ into $VXC^2$ and $VXP^2$) and investigates the asymmetric effect of volatility risk ($\Delta\left(VXC^2\right)$ and $\Delta\left(VXP^2\right)$) by using ex ante information.

### 5.6.1 Results for Quintile Portfolio Level Analysis

At the end of each calendar month, this subsection regresses an individual asset's return on market excess return ($MKT$) and volatility risk factors ($\Delta\left(VIX^2\right)$, $\Delta\left(VXC^2\right)$, and $\Delta\left(VXP^2\right)$) by using previous two-month daily data (shown in equation (5.1)) during the period from January 1996 to August 2014.[54] Then, this subsection constructs quintile portfolios based on factor loadings of volatility risk factors ( $\beta_i^{\Delta(VIX^2)}$, $\beta_i^{\Delta(VXC^2)}$ and $\beta_i^{\Delta(VXP^2)}$) in the following calendar month and uses a quintile portfolio level analysis to clarify the relationship between an asset's sensitivity to volatility risk factors and its return.

From columns 1 to 4 of Table 5.6, it is obvious that, by using $\Delta(VIX^2)$ as a proxy for aggregate volatility risk, there is a significant and negative relationship between quintile portfolio returns and sensitivity to volatility risk. After controlling for $MKT$, $SMB$, $HML$ and $UMD$, the average return on equally-weighted "5-1" long-short portfolio is -0.37% (with a p-value of 0.0345).

The remaining eight columns of Table 5.6 give us indications of the negative drivers between an asset's return and its sensitivity to volatility risk. From columns 5 to 8, if $\Delta(VXC^2)$ is used as a proxy for aggregate volatility risk, there is no evidence that the "5-1" long-short portfolio has significant and non-zero mean return.

However, if quintile portfolios are formed based on factor loading on $\Delta(VXP^2)$, there is a significant and negative relationship between an asset's return and its sensitivity to $\Delta(VXP^2)$. To be more specific, by using the equally-weighted scheme, the mean return on the "5-1" long-short portfolio is -0.23% per month (with a p-value of 0.0796). After controlling for commonly used pricing factors, Jensen's alpha with respect to the Carhart four-factor model is -0.37% per month (with a p-value of 0.0087) for equally-weighted "5-1" long-short portfolio, and it is -0.58% per month

[54] When using $\Delta(VIX^2)$ in equation (5.1), the average adjusted $R^2$ of the regression model among all individual stocks is 14.10%. Using $\Delta(VXC^2)$ or $\Delta(VXP^2)$ in equation (5.1) gives the average adjusted $R^2$ of 14.10% and 14.07%, respectively.

### Table 5.6: Results for Two-Month Quintile Portfolio Level Analysis

Notes: The following time-series regressions are estimated at the end of each calendar month by using previous two-month daily data:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta(VIX^2)} \Delta\left(VIX^2\right)_t + \varepsilon_{i,t}$$

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta(VXC^2)} \Delta\left(VXC^2\right)_t + \varepsilon_{i,t}$$

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta(VXP^2)} \Delta\left(VXP^2\right)_t + \varepsilon_{i,t}$$

Equally- and value-weighted quintile portfolios are constructed based on $\beta_i^{\Delta(VIX^2)}$, $\beta_i^{\Delta(VXC^2)}$, or $\beta_i^{\Delta(VXP^2)}$. Portfolio 5 consists of stocks with the highest $\beta_i^{\Delta(VIX^2)}$, $\beta_i^{\Delta(VXC^2)}$, or $\beta_i^{\Delta(VXP^2)}$, whereas portfolio 1 consists of stocks with the lowest $\beta_i^{\Delta(VIX^2)}$, $\beta_i^{\Delta(VXC^2)}$, or $\beta_i^{\Delta(VXP^2)}$. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. Then, this chapter calculates the return for each portfolio during the following one-month after the portfolio formation. *, **, and *** denote for significance at 10%, 5% and 1% levels, respectively.

**Panel A: Results for Equally-weighted Quintile Portfolios**

| | $\Delta(VIX^2)$ | | | | $\Delta(VXC^2)$ | | | | $\Delta(VXP^2)$ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ |
| 1 | 0.0124 | 0.0028 | 0.0021 | 0.0052 | 0.0109 | 0.0013 | 0.0005 | 0.0031 | 0.0130 | 0.0034 | 0.0027 | 0.0056 |
| 2 | 0.0120 | 0.0039 | 0.0023 | 0.0037 | 0.0104 | 0.0022 | 0.0006 | 0.0018 | 0.0117 | 0.0034 | 0.0019 | 0.0034 |
| 3 | 0.0112 | 0.0036 | 0.0019 | 0.0028 | 0.0116 | 0.0039 | 0.0023 | 0.0032 | 0.0110 | 0.0034 | 0.0017 | 0.0025 |
| 4 | 0.0105 | 0.0023 | 0.0006 | 0.0015 | 0.0116 | 0.0034 | 0.0018 | 0.0029 | 0.0102 | 0.0019 | 0.0002 | 0.0013 |
| 5 | 0.0103 | 0.0003 | -0.0006 | 0.0016 | 0.0119 | 0.0020 | 0.0012 | 0.0038 | 0.0107 | 0.0007 | -0.0002 | 0.0020 |
| 5-1 | -0.0021 | -0.0025* | -0.0027* | -0.0037** | 0.0009 | 0.0007 | 0.0007 | 0.0008 | -0.0023* | -0.0026** | -0.0029** | -0.0037*** |
| p-value | (0.1324) | (0.0853) | (0.0605) | (0.0345) | (0.3384) | (0.4910) | (0.5141) | (0.4663) | (0.0796) | (0.0414) | (0.0219) | (0.0087) |

(Continued)

| Panel B: Results for Value-weighted Quintile Portfolios | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\Delta\left(VIX^2\right)$ | | | | $\Delta\left(VXC^2\right)$ | | | | $\Delta\left(VXP^2\right)$ | | | |
| | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ |
| 1 | 0.0073 | -0.0016 | -0.0018 | -0.0002 | 0.0053 | -0.0040 | -0.0039 | -0.0032 | 0.0078 | -0.0016 | -0.0011 | 0.0010 |
| 2 | 0.0081 | 0.0005 | 0.0005 | 0.0008 | 0.0083 | 0.0009 | 0.0009 | 0.0006 | 0.0092 | 0.0014 | 0.0011 | 0.0016 |
| 3 | 0.0085 | 0.0010 | 0.0008 | 0.0006 | 0.0075 | 0.0001 | -0.0002 | -0.0004 | 0.0084 | 0.0011 | 0.0008 | 0.0005 |
| 4 | 0.0075 | -0.0005 | -0.0007 | -0.0009 | 0.0096 | 0.0016 | 0.0014 | 0.0016 | 0.0058 | -0.0020 | -0.0022 | -0.0027 |
| 5 | 0.0046 | -0.0053 | -0.0050 | -0.0050 | 0.0073 | -0.0028 | -0.0024 | -0.0015 | 0.0048 | -0.0049 | -0.0046 | -0.0048 |
| 5-1 | -0.0027 | -0.0038 | -0.0033 | -0.0048 | 0.0021 | 0.0012 | 0.0015 | 0.0017 | -0.0030 | -0.0033 | -0.0035 | -0.0058* |
| p-value | (0.4365) | (0.2961) | (0.3936) | (0.1876) | (0.4382) | (0.6422) | (0.5972) | (0.5162) | (0.3345) | (0.3312) | (0.2887) | (0.0739) |

**Table 5.7: Results for One-Month Quintile Portfolio Level Analysis**

Notes: The following time-series regressions are estimated at the end of each calendar month by using previous one-month daily data:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta\left(VIX^2\right)} \Delta\left(VIX^2\right)_t + \varepsilon_{i,t}$$

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta\left(VXC^2\right)} \Delta\left(VXC^2\right)_t + \varepsilon_{i,t}$$

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{\Delta\left(VXP^2\right)} \Delta\left(VXP^2\right)_t + \varepsilon_{i,t}$$

Equally- and value-weighted quintile portfolios are constructed based on $\beta_i^{\Delta\left(VIX^2\right)}$, $\beta_i^{\Delta\left(VXC^2\right)}$, or $\beta_i^{\Delta\left(VXP^2\right)}$. Portfolio 5 consists of stocks with the highest $\beta_i^{\Delta\left(VIX^2\right)}$, $\beta_i^{\Delta\left(VXC^2\right)}$, or $\beta_i^{\Delta\left(VXP^2\right)}$, whereas portfolio 1 consists of stocks with the lowest $\beta_i^{\Delta\left(VIX^2\right)}$, $\beta_i^{\Delta\left(VXC^2\right)}$, or $\beta_i^{\Delta\left(VXP^2\right)}$. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. Then, this chapter calculates the return for each portfolio during the following one-month after the portfolio formation. *, **, and *** denote for significance at 10%, 5% and 1% levels, respectively.

**Panel A: Results for Equally-weighted Quintile Portfolios**

| | $\Delta\left(VIX^2\right)$ | | | | $\Delta\left(VXC^2\right)$ | | | | $\Delta\left(VXP^2\right)$ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ |
| 1 | 0.0132 | 0.0035 | 0.0026 | 0.0056 | 0.0111 | 0.0014 | 0.0005 | 0.0031 | 0.0130 | 0.0034 | 0.0026 | 0.0055 |
| 2 | 0.0115 | 0.0034 | 0.0018 | 0.0033 | 0.0108 | 0.0026 | 0.0010 | 0.0020 | 0.0123 | 0.0041 | 0.0027 | 0.0040 |
| 3 | 0.0108 | 0.0032 | 0.0014 | 0.0023 | 0.0117 | 0.0041 | 0.0025 | 0.0034 | 0.0113 | 0.0037 | 0.0020 | 0.0029 |
| 4 | 0.0106 | 0.0023 | 0.0007 | 0.0016 | 0.0116 | 0.0032 | 0.0016 | 0.0028 | 0.0102 | 0.0019 | 0.0002 | 0.0012 |
| 5 | 0.0108 | 0.0007 | -0.0002 | 0.0019 | 0.0117 | 0.0017 | 0.0008 | 0.0035 | 0.0100 | -0.0001 | -0.0011 | 0.0011 |
| 5-1 | -0.0024 | -0.0028* | -0.0029* | -0.0037** | 0.0006 | 0.0003 | 0.0003 | 0.0003 | -0.0031* | -0.0034** | -0.0037** | -0.0044** |
| p-value | (0.1180) | (0.0620) | (0.0537) | (0.0480) | (0.6173) | (0.8323) | (0.7938) | (0.7767) | (0.0544) | (0.0263) | (0.0237) | (0.0102) |

(Continued)

| Panel B: Results for Value-weighted Quintile Portfolios | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\Delta\left(VIX^2\right)$ | | | | $\Delta\left(VXC^2\right)$ | | | | $\Delta\left(VXP^2\right)$ | | | |
| | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ | Return | MKT $\alpha$ | FF3F $\alpha$ | CH4F $\alpha$ |
| 1 | 0.0082 | -0.0010 | -0.0008 | 0.0004 | 0.0051 | -0.0044 | -0.0042 | -0.0041 | 0.0102 | 0.0008 | 0.0014 | 0.0031 |
| 2 | 0.0083 | 0.0007 | 0.0006 | 0.0009 | 0.0079 | 0.0004 | 0.0003 | 0.0002 | 0.0103 | 0.0027 | 0.0025 | 0.0030 |
| 3 | 0.0080 | 0.0007 | 0.0003 | 0.0002 | 0.0085 | 0.0012 | 0.0010 | 0.0008 | 0.0073 | -0.0002 | -0.0005 | -0.0007 |
| 4 | 0.0079 | -0.0003 | -0.0005 | -0.0009 | 0.0088 | 0.0006 | 0.0005 | 0.0006 | 0.0062 | -0.0017 | -0.0020 | -0.0025 |
| 5 | 0.0055 | -0.0046 | -0.0044 | -0.0040 | 0.0079 | -0.0022 | -0.0018 | -0.0010 | 0.0030 | -0.0068 | -0.0067 | -0.0068 |
| 5-1 | -0.0027 | -0.0036 | -0.0036 | -0.0044 | 0.0027 | 0.0022 | 0.0024 | 0.0032 | -0.0072** | -0.0076** | -0.0081** | -0.0100*** |
| p-value | (0.3678) | (0.2512) | (0.2436) | (0.1514) | (0.2315) | (0.3728) | (0.3317) | (0.1888) | (0.0173) | (0.0132) | (0.0118) | (0.0020) |

(with a p-value of 0.0739) for value-weighted “5-1” long-short portfolio.

In order to construct quintile portfolios, prior analysis uses previous two-month daily data for time-series regressions. Thus, there is some data overlap for time-series regressions in different calendar months. In order to avoid this issue, this subsection next uses previous one-month daily data for regression model presented in equation (5.1).[55]

Table 5.7 documents similar results to those shown in Table 5.6. If $\Delta\left(VIX^2\right)$ is used to measure the volatility risk, after controlling for common-used pricing factors, there is a significant and negative relationship between an asset’s return and its sensitivity to $\Delta\left(VIX^2\right)$ (columns 1 to 4). The Jensen’s alpha with respect to Carhart four-factor model is -0.37% (with a p-value of 0.0480) for equally-weighted “5-1” long-short portfolio.

The results obtained by using $\Delta\left(VXC^2\right)$ and $\Delta\left(VXP^2\right)$ in Table 5.7 confirm that out-of-the-money put options drive the negative relationship between an asset’s return and its sensitivity to volatility risk. To be more specific, if $\Delta\left(VXC^2\right)$ is used to measure volatility risk, there is no significant mean return or risk-adjust return on “5-1” long-short portfolios (columns 5 to 8).

Nevertheless, if $\Delta\left(VXP^2\right)$ is used to measure volatility risk, the average return on equally-weighted “5-1” long-short portfolio is -0.31% (with a p-value of 0.0544). After controlling for $MKT$, $SMB$, $HML$ or $UMD$, greater significance and more negative premiums are obtained from the equally-weighted “5-1” long-short portfolio

[55] When using previous one-month daily returns to estimate equation (5.1), the average adjusted $R^2$ are almost the same. When using $\Delta\left(VIX^2\right)$, the average adjusted $R^2$ is 14.15%. When using $\Delta\left(VXC^2\right)$, the average adjusted $R^2$ is 14.24%. When using $\Delta\left(VXP^2\right)$, the average adjusted $R^2$ is 14.17%.

(-0.34% with a p-value of 0.0263 for Jensen's alpha with respect to the market-factor model, -0.37% with a p-value of 0.0237 for Jensen's alpha with respect to the Fama-French three-factor model, and -0.44% with a p-value of 0.0102 with respect to the Carhart four-factor model). By switching to a value-weighted scheme, the average return and Jensen's alpha on the "5-1" long-short portfolio become more negative. The average return without controlling factors on the value-weighted "5-1" long-short portfolio is -0.72% per month (with a p-value of 0.0173). Controlling for common-used pricing factors makes the Jensen's alphas more negative. For example, the risk-adjusted return with respect to Carhart four-factor model on the "5-1" long-short portfolio is -1.00% per month (with a p-value of 0.0020).

In summary, there is a significant and negative relationship between quintile portfolio return and sensitivity to volatility risk factors constructed from $VIX$ . However, if separating the information captured by out-of-the-money call and put options, the negative relationship between quintile portfolio return and sensitivity to volatility risk becomes more statistically significant when using out-of-the-money put options only (i.e., $\Delta\left(VXP^2\right)$). When using $\Delta\left(VXC^2\right)$ to measure the volatility risk, there is no significant and negative relationship between portfolio return and sensitivity to volatility risk.[56]

[56] This chapter follows the method documented in VIX Whitepaper from CBOE for VIX replication. To obtain the results presented in this subsection, this chapter uses equations (5.4) to (5.7) to construct $\Delta\left(VXC^2\right)$ and $\Delta\left(VXP^2\right)$ rather than using the method with interpolation across strike prices documented by Bakshi, Kapadia, and Madan (2003). This chapter also calculates $\Delta\left(VXC^2\right)$ and $\Delta\left(VXP^2\right)$ by using the method with interpolation. The results are different from what I find in this subsection. Thus, results presented here are sensitive to the method used for volatility factor calculation.

### 5.6.2 Discussions for Asymmetric Portfolio Analysis Using Ex Ante Information

As discussed in section 5.5, there is no evidence of a negative relationship between an asset's return and its sensitivity to volatility risk during the period from October 2005 to December 2014. This could be due to the fact that the market is under stress during the relatively short sample period used in section 5.5. In Subsection 5.6.1, the sample period is longer, from January 1996 to September 2014. During this period, this chapter provides evidence on the negative relationship between an asset's return and its sensitivity to aggregate volatility risk when using $\Delta\left(VIX^2\right)$ as a proxy.

The comparison between results obtained by using $\Delta\left(VXC^2\right)$ and those results obtained from $\Delta\left(VXP^2\right)$ indicates that out-of-the-money put options capture more relevant information about future asset returns. Different results obtained from using $\Delta\left(VXC^2\right)$ and $\Delta\left(VXP^2\right)$ also reflect the asymmetric effect of aggregate volatility risk. Out-of-the-money put options capture information about the potential future market with downward movements in market index and upward movements in aggregate volatility, whereas out-of-the-money call options capture information about the potential future market with upward movements in market index and downward movements in aggregate volatility. Thus, information captured by put options represents negative shocks for investors, whereas information captured by call options is consistent with investors' positive news. Results discussed in Subsection 5.6.1 provide evidence of this asymmetric effect of aggregate volatility risk obtained by using forward-looking information. Holding a long position in portfolio 1 and a short position in portfolio 5 constructed on put options brings more statistically significant and higher premiums than the strategy using the VIX index does.

Furthermore, if investors use previous one-month daily data for portfolio construction rather than use previous two-month daily data, the average return and Jensen's alphas on arbitrage portfolios are more statistically significant. This indicates that more immediate data captures relevant information about future market conditions.

## 5.7 Conclusions

From the analysis presented previously, during the period from October 2005 to December 2014, it is difficult to find any unconditional significant relationship between an asset's sensitivity to volatility risk and its return by using innovations in square of VIX index or VIX futures ($\Delta\left(VIX^2\right)$ or $\Delta\left(VXF^2\right)$) as a proxy for the volatility risk. This could be due to the fact that the sample period covers the recent financial crisis; during the sample period, asset markets were more stressed. Furthermore, the average return on the market portfolio and the average volatility change are close to zero. So, it is difficult to detect an unconditional relationship between an asset's sensitivity to volatility risk and its return.

However, this chapter tests whether volatility risk plays different roles in different market conditions. This chapter uses a dummy variable defined on the VIX futures basis to distinguish different expectations. The empirical results provide evidence supporting the asymmetric effect of volatility risk on asset returns. When only taking into consideration the information during the period with positive VIX futures basis (i.e., period with VIX spot higher than VIX futures), stocks with higher sensitivities to volatility risk have significantly lower returns than those with lower sensitivities to volatility risk. That is, an asset's return is significantly and negatively related to its sensitivity to volatility risk measured by $\Delta\left(VIX^2\right)$ or $\Delta\left(VXF^2\right)$ but only if quintile portfolios are formed on information during periods with positive VIX futures basis.

Finally, this chapter decomposes the VIX index into two components. One component is the volatility calculated from out-of-the-money call options ($VXC$), and the other component is the volatility calculated from out-of-the-money put options ($VXP$). Such a decomposition enables us to test if information captured by one type of option is more important to investors in verifying the existence of the asymmetric effect by using ex ante information. Such an analysis reveals that the asymmetric negative relationship between an asset's sensitivity to volatility risk and its return is more significant when using $\Delta\left(VXP^2\right)$. Information captured by out-of-the-money put options is the main driver of the negative relationship between asset return and sensitivity to aggregate volatility risk. Put options contain more useful information about negative news in future market conditions. Such findings are expected to give indications to investors about how to design their trading strategies to capture premiums.

# Chapter 6 Risk-Neutral Systematic Risk and Asset Returns

## 6.1 Introduction

Previous empirical studies show the failure of the CAPM in explaining asset returns (as discussed in section 2.2). Brennan (1971) claims that the failure of the CAPM could be due to the divergent borrowing and lending rate.

Kraus and Litzenberger (1976) find another potential reason for such a phenomenon. Starting with the assumption that investors' utility functions are non-polynomial, they extend the traditional CAPM to a two-factor model incorporating the effect of systematic skewness. The empirical results confirm that, in addition to the systematic standard deviation risk (i.e., beta), the systematic skewness risk (i.e., gamma) is another important pricing factor. Stocks with higher systematic skewness risk have lower returns than those with lower systematic skewness risk. By using historical data, later studies also provide supportive evidence of a positive skewness preference and confirm that investors require higher returns on assets with negative systematic skewness (Scott and Horvath, 1980; Sears and Wei, 1985 and 1988; Fang and Lai, 1997; Harvey and Siddique, 2000).

In Kraus and Litzenberger (1976), the systematic skewness risk is measured as the comovement of an asset's return with the return variance of the market portfolio. Given the importance of forward-looking instruments, empirical studies incorporate forward-looking information in explaining why systematic skewness risk is important and shedding light on the relationship between systematic skewness and asset returns. Some studies (Ang, Hodrick, Xing and Zhang, 2006; Chang, Christoffersen and Jacobs, 2013) use factors constructed by using risk-neutral aggregate volatility to measure the second moment of the market portfolio for gamma calculation.

Albuquerque (2012) interprets the information content captured by aggregate skewness. He decomposes aggregate skewness into three different components (details are discussed in section 6.4.2) and empirical results show that cross-sectional heterogeneity in firm announcement events is the main driver of the aggregate skewness.

This chapter focuses on the systematic standard deviation risk (i.e., market beta) and the systematic skewness risk (i.e., market gamma) of individual stocks. In the theoretical part, this chapter decomposes skewness of the portfolio in a different way compared with the method used in Albuquerque (2012). This chapter sticks to the two-factor model proposed by Kraus and Litzenberger (1976), and calculates beta and gamma by using historical information or by partially incorporating option-implied information.

Then, in the empirical part, this chapter calculates historical and option-implied beta and gamma for constituents of the S&P500 index, and investigates how beta and gamma help to explain future asset returns. This chapter examines the relationship between asset returns and beta or gamma through portfolio level analysis among constituents of the S&P500 index. The analysis also looks at different investment time-horizons to see whether predictive power of each factor (i.e., beta or gamma) changes over time. In portfolio level analysis, option-implied gamma performs better in predicting asset returns during longer periods than historical gamma does.

Constructing portfolios on one factor does not allow us to control for effects of other risk factors. Option-implied beta and gamma used in this chapter are both calculated by using coefficients obtained from regressions using daily historical data (as discussed in Subsection 6.4.3). It is expected that option-implied beta and gamma should be highly correlated cross-sectionally. Thus, this chapter controls for the effect of gamma/beta when investigating the relationship between option-implied beta/gamma and asset returns by using a double-sorting method. Also, this chapter investigates how firm size affects stock returns with option-implied beta/gamma controlled.

After investigating the relationship between portfolio returns and option-implied beta or gamma through portfolio level analysis, this chapter uses cross-sectional regressions at firm-level to examine whether beta and gamma gain significant risk premiums in explaining cross-section of individual stock returns. Such an analysis also includes firm-specific control variables, such as size (market capitalization), value (book-to-market ratio), momentum (historical return in previous 12 to two months and historical return in previous one month), and liquidity (bid-ask spread and trading volume in previous one month). The inclusion of control variables enables us to ensure whether the predictive power of beta or gamma is significant after considering firm-specific risk factors.

In addition, in order to make sure whether option-implied components of beta and gamma have significant risk premiums, this chapter uses 25 portfolios constructed on size or book-to-market ratio to run Fama-MacBeth cross-sectional regressions.

This chapter contributes to existing literature in several aspects. First, this chapter decomposes the aggregate skewness by using a different approach compared with what has been done in Albuquerque (2012). The method used in this chapter links the aggregate skewness to systematic skewness risk of each individual asset, which is captured by gamma in Kraus and Litzenberger (1976). This helps readers to better understand why systematic skewness is important for asset returns.

Second, based on Kraus and Litzenberger (1976), this chapter calculates pricing factors, beta and gamma, by incorporating forward-looking information extracted from options. Compared with historical data, option-implied information performs better in predicting future market conditions (as discussed in Subsection 2.5.2 and Section 2.7). Thus, beta and gamma calculated by using option-implied information are expected to capture more relevant information about future asset returns.

The remaining of this chapter is organized as follows. Section 6.2 reviews relevant literature. Section 6.3 discusses data used in this chapter, and Section 6.4 presents methodology in detail. Section 6.5 documents results for portfolio level analysis obtained by using historical data, while Section 6.6 presents results for portfolio level analysis obtained by using option-implied information. Section 6.7 discusses empirical results for quintile portfolio level analysis. The following section, Section 6.8, focuses on the portfolio level analysis by double sorting to control for the effect of the other pricing factor. Section 6.9 shows results for cross-sectional regressions. The final section, Section 6.10, offers some concluding remarks.

## 6.2 Related Literature

The CAPM is derived based on the mean-variance approach and the assumption of quadratic utility functions, so it focuses on the relationship between mean and standard deviation.

Kraus and Litzenberger (1976) claim that investors' utility functions could be cubic, and such utility functions result in a preference for positive skewness. By focusing on first three moments of return distribution, they derive a two-factor model. In such a model, two pricing factors are systematic standard deviation (i.e., market beta) and systematic skewness (i.e., market gamma). The empirical results confirm theoretical predictions. Stocks with higher market betas tend to have higher returns, while stocks with higher market gammas tend to have lower returns. Furthermore, by using this two-factor model, the zero intercept for the security market line is not rejected. So, compared to the CAPM, the two-factor model proposed by Kraus and Litzenberger (1976) can better explain variation in asset returns.

Scott and Horvath (1980) analyze investors’ preference for skewness from the theoretical perspective. By looking at the utility function, they confirm the findings of Kraus and Litzenberger (1976). They find that investors have positive (negative) preference for positive (negative) skewness.

Friend and Westerfield (1980) test the model proposed by Kraus and Litzenberger (1976). In their analysis, they include bonds into the portfolio. However, they cannot find the existence of risk premium related to skewness. In addition, they claim that the significance of risk premium on systematic skewness risk is sensitive to different market indices and testing and estimation procedures.

Sears and Wei (1985) claim that mixed results about the risk premium on systematic skewness risk may result from the nonlinearity in the market risk premium. This theoretical paper maintains that economic prices of systematic skewness risk can be decomposed into two parts, the market risk premium and an elasticity coefficient that is proportional to the marginal rate of substitution between skewness and expected return. Sears and Wei (1988) carry out empirical analysis based on the theoretical framework. The empirical results provide evidence about the preference for positive skewness.

Fang and Lai (1997) propose a three-factor model incorporating systematic standard deviation risk, systematic skewness risk, and systematic kurtosis risk. The results show that investors are willing to accept lower returns on assets with positive systematic skewness, while they require that stocks with higher systematic standard deviation or systematic kurtosis should have higher returns.

Harvey and Siddique (2000) also confirm that investors require higher returns on assets with negative systematic skewness. Furthermore, the empirical results show that systematic skewness could help to explain the momentum effect.

Hung, Shackleton and Xu (2004) investigate systematic skewness and systematic kurtosis in the UK market. Empirical results provide limited evidence about the predictive power of higher co-moments due to data limitation.

Recently, after realizing the outperformance of option-implied information in predicting future volatility (see Subsection 2.7.1), some studies start incorporating forward-looking information in their empirical analysis.

For example, Ang, Hodrick, Xing and Zhang (2006) and Chang, Christoffersen and Jacobs (2013) use daily innovations in aggregate volatility index (VXO index and VIX index, respectively) to measure the second moment of market returns. So the model has two pricing factors, the market beta and sensitivity to innovations in aggregate volatility risk. The results show a negative relationship between an asset's sensitivity to innovations in aggregate volatility index and its return.

Some studies also investigate how option-implied information performs in context of portfolio selection. For example, Kostakis, Panigirtzoglou and Skiadopoulos (2011) extract implied distribution from option prices and compare the performance of forward-looking approach and backward-looking one in asset allocation. Rather than focusing on particular moments of return distribution (what this chapter does), their study extracts option-implied probability density function of the S&P500 index. Empirical findings show that, compared to historical distribution, the risk-adjusted implied distribution makes investors better off. DeMiguel, Plyakha, Uppal and Vilkov (2013) concentrate on how option-implied information (i.e., volatility, correlation and skewness) helps to improve portfolio selection (in terms of portfolio volatility, Sharpe ratio, and turnover).[57] Empirical results confirm that using option-implied information does improve the portfolio performance. Kempf, Korn and Sassning (2015) develop a family of fully-implied estimators of the covariance matrix from current prices of plain-vanilla options. By applying this forward-looking method to 30 stocks included in the Dow Jones Industrial Average, they find that fully-implied strategies outperform historical strategies, partially-implied strategies, and strategies based on combinations of historical and implied estimators.

These three studies concentrate on how to use option-implied information (e.g., option-implied information, volatility, correlation, skewness, and covariance matrix) to construct investment strategies and portfolios with superior performance, which is out of the scope of this chapter. Following three studies, which focus on how option-implied information explains stock returns, are more relevant.

Rehman and Vilkov (2012) and Stilger, Kostakis, and Poon (2016) focus on the predictive power of individual stocks' model-free implied skewness, which is calculated by using the method derived in Bakshi, Kapadia and Madan (2003). The empirical results show that model-free implied skewness calculated using option data at the end of each calendar month is positively related future one-month ahead stock returns. However, the positive relationship between model-free implied skewness and future stock returns conflicts with the findings in Conrad, Dittmar and Ghysels (2013), who documents a negative relationship between model-free implied skewness and future stock returns. Such a difference could be due to two reasons: (1) Conrad, Dittmar and Ghysels (2013) use a time series average of skewness over the last three months and (2) the investment horizon tested in Conrad, Dittmar and Ghysels (2013)

[57] DeMiguel, Plyakha, Uppal and Vilkov (2013) estimate option implied volatility and skewness by using the method derived in Bakshi, Kapadia and Madan (2003). Option-implied correlations are calculated by using the approach derived in Buss and Vilkov (2012).

is three-month period. Different from these previous studies, this chapter focuses on how the systematic part of standard deviation and skewness risk, not the total model-free implied volatility and skewness, can help to explain stock returns.

From previous literature, there is empirical evidence about the explanatory power of systematic skewness risk in asset pricing. Furthermore, previous literature confirms the outperformance of option-implied information in predicting future market conditions. So, to be distinguished from previous literature, rather than investigating option-implied volatility and skewness of each individual stock, this chapter focuses on the systematic standard deviation and skewness risk, which are calculated based on the model proposed in Kraus and Litzenberger (1976) and incorporating option-implied information into the analysis.

## 6.3 Data

This chapter uses the information about the S&P500 index. The S&P500 index is a capitalization-weighted index of 500 stocks. Among constituents of the S&P500 index, this chapter tests the relationship between asset returns and systematic standard deviation risk (i.e., beta) or systematic skewness risk (i.e., gamma).

In order to do such analysis, daily and monthly stock data are downloaded from CRSP. The information about constituents of the S&P500 index is available from Compustat. Option data for the S&P500 index are downloaded from "Volatility Surface" file in OptionMetrics. OptionMetrics provides data starting from the beginning of 1996. So, the sample period of our analysis starts from January 1996 to December 2012.

The S&P500 index includes 500 leading companies and captures approximately 80% coverage of available market capitalization in the US market. Constituents of the

S&P500 index change every year. The number of such changes in each year varies during the sample period. Details are presented in Table 6.1. During the sample period from 1996 to 2012, there are 968 firms in total as constituents of the S&P500 index. However, among these firms, only 903 firms have available stock and option data, which are required for the beta and gamma calculation. That is, this chapter includes 903 firms in the empirical analysis.

## 6.4 Methodology

### 6.4.1 A Two-Factor Model in Kraus and Litzenberger (1976)

From Kraus and Litzenberger (1976), in addition to systematic standard deviation risk, systematic skewness risk is another pricing factor, which should be taken into consideration by investors.

$$E\left[r_i\right]-r_f = b_1\beta_i + b_2\gamma_i \tag{6.1}$$

where $r_i$ is the return on asset $i$, $\beta_i = \sigma_{im}/\sigma_m^2$ measures systematic standard deviation risk of asset $i$, $\gamma_i = m_{imm}/m_m^3$ measures systematic skewness risk of asset $i$ (with $\sigma_m = \left[E\left[\left(r_{m,t}-E\left[r_{m,t}\right]\right)^2\right]\right]^{1/2}$ and $m_m = \left[E\left[\left(r_{m,t}-E\left[r_{m,t}\right]\right)^3\right]\right]^{1/3}$ ), $b_1 = \left(d\overline{W}/d\sigma_W\right)\sigma_m$, and $b_2 = \left(d\overline{W}/dm_W\right)m_m$. $b_1$ can be interpreted as the risk premium on beta, and $b_2$ can be interpreted as the risk premium on gamma. Kraus and Litzenberger (1976) calculate beta and gamma for an asset $i$ by using historical daily return data on individual stocks and the market index:

$$\beta_i = \frac{\sum_{t=1}^{T}\left(r_{m,t}-E\left[r_{m,t}\right]\right)\left(r_{i,t}-E\left[r_{i,t}\right]\right)}{\sum_{t=1}^{T}\left(r_{m,t}-E\left[r_{m,t}\right]\right)^2} \tag{6.2}$$

**Table 6.1: Changes in the S&P500 Index Constituents**

| Year | The number of changes in constituents in each year |
|---|---|
| 1996 | 20 |
| 1997 | 29 |
| 1998 | 37 |
| 1999 | 43 |
| 2000 | 53 |
| 2001 | 30 |
| 2002 | 24 |
| 2003 | 9 |
| 2004 | 20 |
| 2005 | 16 |
| 2006 | 32 |
| 2007 | 38 |
| 2008 | 35 |
| 2009 | 29 |
| 2010 | 16 |
| 2011 | 19 |
| 2012 | 18 |

$$\gamma_i = \frac{\sum_{t=1}^{T}\left(r_{m,t} - E\left[r_{m,t}\right]\right)^2\left(r_{i,t} - E\left[r_{i,t}\right]\right)}{\sum_{t=1}^{T}\left(r_{m,t} - E\left[r_{m,t}\right]\right)^3} \tag{6.3}$$

where $r_{m,t}$ is the return on the market portfolio. Later analysis uses daily stock return during previous one-year (i.e., 252 trading days) period for historical beta and gamma calculation. Then, next subsection discusses how systematic skewness risk links with aggregate skewness.

### 6.4.2 Decomposition of Aggregate Skewness

In Albuquerque (2012), under the assumption that the portfolio is constructed by using an equally-weighted scheme, the non-standardized skewness (i.e., the central third moment, $m_P^3$) of the portfolio is decomposed into three components: firm skewness, $co-vol$ (comovements of an asset's return with the return variance of other firms in the portfolio), and $co-cov$ (comovements of an asset's return with the covariance between any other two assets' returns):

$$\begin{aligned}
m_P^3 &= E\left[\left(r_{P,t} - E\left[r_{P,t}\right]\right)^3\right] \\
&= \frac{1}{N^3}\sum_{i=1}^{N}\frac{1}{T}\sum_{t}\left(r_{i,t} - E\left[r_{i,t}\right]\right)^3 \\
&+ \frac{3}{TN^3}\sum_{t}\sum_{i=1}^{N}\left(r_{i,t} - E\left[r_{i,t}\right]\right)\sum_{i'\neq i}^{N}\left(r_{i',t} - E\left[r_{i',t}\right]\right)^2 \\
&+ \frac{6}{TN^3}\sum_{t}\sum_{i=1}^{N}\left(r_{i,t} - E\left[r_{i,t}\right]\right)\sum_{i'>i}^{N}\sum_{l>i'}^{N}\left(r_{i',t} - E\left[r_{i',t}\right]\right)\left(r_{l,t} - E\left[r_{l,t}\right]\right)
\end{aligned} \tag{6.4}$$

Rather than using the decomposition method in Albuquerque (2012), this chapter decomposes non-standardized skewness of a portfolio (i.e., $m_P^3$) as follows:

$$
\begin{aligned}
m_P^3 &= E\left[\left(r_{P,t} - E\left[r_{P,t}\right]\right)^3\right] = E\left[\left(r_{P,t} - E\left[r_{P,t}\right]\right)\left(r_{P,t} - E\left[r_{P,t}\right]\right)^2\right] \\
&= E\left[\left[\sum_{i=1}^{n} w_i \left(r_{i,t} - E\left[r_{i,t}\right]\right)\right]\left(r_{P,t} - E\left[r_{P,t}\right]\right)^2\right] \\
&= \sum_{i=1}^{N} w_i E\left[\left(r_{i,t} - E\left[r_{i,t}\right]\right)\left(r_{P,t} - E\left[r_{P,t}\right]\right)^2\right]
\end{aligned}
\tag{6.5}
$$

where $r_{P,t}$ is the return on the portfolio $P$, $r_{i,t}$ is the return on an individual asset $i$ that is a constituent of the portfolio $P$, and $w_i$ is the weight for an individual asset $i$. From equation (6.5), it is obvious that the non-standardized aggregate skewness is the weighted average of co-movements of an asset's return with the return variance of the portfolio. Decomposing the non-standardized skewness of a portfolio in this way helps us to better understand the relationship between aggregate skewness and systematic skewness risk.

$$
\frac{m_P^3}{m_P^3} = \frac{\sum_{i=1}^{N} w_i E\left[\left(r_{i,t} - E\left[r_{i,t}\right]\right)\left(r_{P,t} - E\left[r_{P,t}\right]\right)^2\right]}{E\left[\left(r_{P,t} - E\left[r_{P,t}\right]\right)^3\right]} = \sum_{i=1}^{N} w_i \gamma_{iP} = 1 \tag{6.6}
$$

where $\gamma_{iP}$ is defined in the same way as in Kraus and Litzenberger (1976) and it measures the systematic skewness risk of an asset $i$. From this equation, gamma of the portfolio, which is equal to one, is the weighted-average of gammas on all constituents in that portfolio. That is, gamma is a linearly additive pricing factor as beta. On the basis of the decomposition, this chapter examines whether the predictive power of the aggregate skewness could be due to the gamma factor, which is a proxy for systematic skewness risk. So, this chapter investigates the relationship between asset returns and systematic skewness risk (i.e., market gamma) rather than that between asset returns and aggregate skewness.

### 6.4.3 Beta and Gamma Calculation by Using Option Data

In addition to beta and gamma calculation shown in equations (6.2) and (6.3), Kraus and Litzenberger (1976) propose another way to estimate beta and gamma. In the first step, excess return of an individual asset is regressed on market excess return and the squared deviation of the market excess return from its expected value:

$$r_{i,t} - r_{f,t} = c_{0i} + c_{1i}\left(r_{m,t} - r_{f,t}\right) + c_{2i}\left(r_{m,t} - E\left[r_{m,t}\right]\right)^2 + \varepsilon_{i,t} \tag{6.7}$$

After obtaining coefficients (i.e., $c_{1i}$ and $c_{2i}$) from time-series regressions by using historical data, the market beta and gamma for each individual stock could be calculated by using the following two equations:

$$\beta_i = c_{1i} + c_{2i}\left(m_m^3 / \sigma_m^2\right) \tag{6.8}$$

$$\gamma_i = c_{1i} + c_{2i}\left\{\left[k_m^4 - \left(\sigma_m^2\right)^2\right] \Big/ m_m^3\right\} \tag{6.9}$$

where $\sigma_m^2$ is the variance of the market portfolio ($\sigma_m^2 = E\left[\left(r_{m,t} - E\left[r_{m,t}\right]\right)^2\right]$, $m_m^3$ is the central third moment of the market portfolio ($m_m^3 = E\left[\left(r_{m,t} - E\left[r_{m,t}\right]\right)^3\right]$), and $k_m^4$ is the central fourth moment of the market portfolio ($k_m^4 = E\left[\left(r_{m,t} - E\left[r_{m,t}\right]\right)^4\right]$).

Previous empirical studies (French, Groth and Kolari, 1983; Buss and Vilkov, 2012; Chang, Christoffersen, Jacobs and Vainberg, 2012) support that option-implied data incorporate forward-looking information and they are more efficient in reflecting future market conditions. Thus, in addition to calculating beta and gamma by using historical data (as shown in equation (6.2) and (6.3)), this chapter calculates beta and gamma under the risk-neutral measure by using option-implied information. Based on equation (6.8) and (6.9), in order to incorporate forward-looking information, this chapter estimates model-free central moments (i.e., $\sigma_m^2$, $m_m^3$, and $k_m^4$) by using option data.

### 6.4.4 Central Moments Calculation under Risk-Neutral Measure

In order to calculate $\sigma_m^2$, $m_m^3$, and $k_m^4$ under risk-neutral measure, this chapter applies the method derived in Bakshi, Kapadia and Madan (2003). This chapter first calculates prices for the volatility, the cubic and the quartic contracts (i.e., $V(t,\tau)$, $W(t,\tau)$, and $X(t,\tau)$, respectively) by using out-of-the-money options.

$$V(t,\tau)=\int_{S_t}^{\infty}\frac{2\left(1-\ln\left[\frac{K}{S_t}\right]\right)}{K^2}C\left(t,\tau;K\right)dK+\int_0^{S_t}\frac{2\left(1+\ln\left[\frac{S_t}{K}\right]\right)}{K^2}P\left(t,\tau;K\right)dK \quad (6.10)$$

$$\begin{aligned}W(t,\tau)=&\int_{S_t}^{\infty}\frac{6\left(\ln\left[\frac{K}{S_t}\right]\right)-3\left(\ln\left[\frac{K}{S_t}\right]\right)^2}{K^2}C\left(t,\tau;K\right)dK\\&-\int_0^{S_t}\frac{6\left(\ln\left[\frac{S_t}{K}\right]\right)+3\left(\ln\left[\frac{S_t}{K}\right]\right)^2}{K^2}P\left(t,\tau;K\right)dK\end{aligned} \quad (6.11)$$

$$\begin{aligned}X(t,\tau)=&\int_{S_t}^{\infty}\frac{12\left(\ln\left[\frac{K}{S_t}\right]\right)^2-4\left(\ln\left[\frac{K}{S_t}\right]\right)^3}{K^2}C\left(t,\tau;K\right)dK\\&+\int_0^{S_t}\frac{12\left(\ln\left[\frac{S_t}{K}\right]\right)^2+4\left(\ln\left[\frac{S_t}{K}\right]\right)^3}{K^2}P\left(t,\tau;K\right)dK\end{aligned} \quad (6.12)$$

where $C\left(t,\tau;K\right)/P\left(t,\tau;K\right)$ is the price for the out-of-the-money call/put option on the S&P500 index with strike price of $K$ and time-to-expiration of $\tau$ at time $t$, and $S_t$ is the price of the underlying asset at time $t$. Then, by using $V(t,\tau)$, $W(t,\tau)$, and $X(t,\tau)$, this chapter calculates model-free central moments.

$$\left(\sigma_m^2\right)^Q=e^{r\tau}V(t,\tau)-\mu\left(t,\tau\right)^2 \quad (6.13)$$

$$\left(m_m^3\right)^Q = e^{r\tau}W\left(t,\tau\right) - 3e^{r\tau}\mu\left(t,\tau\right)V\left(t,\tau\right) + 2\mu\left(t,\tau\right)^3 \tag{6.14}$$

$$\left(k_m^4\right)^Q = e^{r\tau}X\left(t,\tau\right) - 4e^{r\tau}\mu\left(t,\tau\right)W\left(t,\tau\right) + 6e^{r\tau}\mu\left(t,\tau\right)^2 V\left(t,\tau\right) - 3\mu\left(t,\tau\right)^4 \tag{6.15}$$

where

$$\mu\left(t,\tau\right) = e^{r\tau} - 1 - \frac{e^{r\tau}V\left(t,\tau\right)}{2} - \frac{e^{r\tau}W\left(t,\tau\right)}{6} - \frac{e^{r\tau}X\left(t,\tau\right)}{24} \tag{6.16}$$

Thus, option-implied beta and gamma can be calculated by using the following two equations:

$$\beta_i^Q = c_{1i} + c_{2i}\left[\left(m_m^3\right)^Q \Big/ \left(\sigma_m^2\right)^Q\right] \tag{6.17}$$

$$\gamma_i^Q = c_{1i} + c_{2i}\left\{\left[\left(k_m^4\right)^Q - \left(\left(\sigma_m^2\right)^Q\right)^2\right] \Big/ \left(m_m^3\right)^Q\right\} \tag{6.18}$$

Then, option-implied beta and gamma for each individual stock ($\beta_i^Q$ and $\gamma_i^Q$) are used in empirical analysis. From these equations, it is clear that, rather than using model-free volatility and skewness (which is investigated in Rehman and Vilkov (2012), Conrad, Dittmar and Ghysels (2013), and Stilger, Kostakis, and Poon (2016)), this chapter focuses on systematic standard deviation and skewness risk (i.e., $\beta_i^Q$ and $\gamma_i^Q$), which combine historical and option-implied information.

### 6.4.5 Discussion on Option-Implied Gamma

As discussed in the introduction section 6.1, some previous studies also incorporate option-implied information to calculate beta and gamma from a different perspective. Ang, Hodrick, Xing and Zhang (2006) use the daily innovation in VXO index as a proxy for the second moment of market returns:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i\left(r_{m,t} - r_{f,t}\right) + \gamma_i \Delta VXO_t + \varepsilon_{i,t} \tag{6.19}$$

where $\gamma_i$ captures the comovement of an asset's excess return with the innovation in aggregate volatility index. Thus, $\gamma$ is a proxy for systematic skewness risk. Chang, Christoffersen and Jacobs (2013) use a similar way to incorporate forward-looking information by replacing the VXO index with the new VIX index:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i \left( r_{m,t} - r_{f,t} \right) + \gamma_i \Delta VIX_t + \varepsilon_{i,t} \tag{6.20}$$

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i \left( r_{m,t} - r_{f,t} \right) + \gamma_i \Delta VIX_t + \delta_i \Delta SKEW_t + \theta_i \Delta KURT_t + \varepsilon_{i,t} \tag{6.21}$$

Thus, the systematic skewness risk in these two studies can be written as:

$$\gamma_i = \frac{\operatorname{cov}\left( r_i - r_f , \Delta\sigma_m^Q \right)}{\operatorname{var}\left( \Delta\sigma_m^Q \right)} \tag{6.22}$$

Compared with previous literature, this chapter incorporates risk-neutral higher moments in a different way. Rather than changing the explanatory variables reflecting the second moment of the market portfolio return, this chapter sticks to the original model setting proposed by Kraus and Litzenberger (1976). In addition to risk-neutral variance, the method used in this chapter also includes risk-neutral skewness and kurtosis. Option-implied risk factors used in this chapter are expected to incorporate more useful information. Details about empirical results are presented in following sections.

## 6.5 Results for Portfolios Constructed by Using Historical Data

Previous literature provides supportive evidence that aggregate skewness is an important factor related to asset returns (Chang, Christoffersen and Jacobs, 2013; etc). This chapter investigates whether the effect of the aggregate skewness is due to the systematic skewness risk of each individual asset (i.e., whether gamma is an important pricing factor in addition to beta).

First, this section divides all available constituents of the S&P500 index into five quintiles based on each historical pricing factor (beta or gamma calculated by using equations (6.2) and (6.3), respectively). Within each quintile, equally-weighted or value-weighted portfolios are constructed. Then, a "5-1" long-short portfolio is constructed by holding a long position in portfolio with the highest factor and a short position in portfolio with the lowest factor. If the average return on the long-short portfolio is significantly non-zero, it indicates that the factor is significantly related to asset return. That is, the factor is important in explaining asset return, and it should be included in asset pricing models.

### 6.5.1 Quintile Portfolio Analysis on Historical Beta

First of all, this subsection presents results for quintile portfolios constructed among constituents of the S&P500 index based on historical beta, which is calculated by using previous 252-trading-day daily data at the end of each calendar month (as shown in Table 6.2). As shown in the table, after quintile portfolio construction, this chapter assumes that an investor's holding period varies from one month to 12 months. Portfolio 1 consists of stocks with the lowest historical beta, while portfolio 5 consists of stocks with the highest historical beta. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. Since quintile portfolios are constructed at the end of each calendar month, there are data overlaps for holding-period return calculation. In order to avoid potential serial autocorrelation issue, this chapter calculates p-values by using the Newey-West method.[58] Corresponding Newey-West p-values in Table 6.2 indicate that, there is no significant relationship between portfolio returns and historical beta no matter how long the investment horizon is.

[58] P-values presented in Table 6.2 to Table 6.14 are all calculated using the Newey-West method.

**Table 6.2: Results for Quintile Portfolio Analysis among Constituents of the S&P500 Index (Historical Beta)**

Notes: In order to form quintile portfolios among constituents of the S&P500 index, beta for each individual asset is calculated by using previous 252-day daily data.

$$\beta_i = \sum_{t=1}^{252}\left(r_{m,t} - E\left[r_{m,t}\right]\right)\left(r_{i,t} - E\left[r_{i,t}\right]\right) \Big/ \sum_{t=1}^{252}\left(r_{m,t} - E\left[r_{m,t}\right]\right)^2$$

After portfolio formation, the holding period varies from one-month to 12-month. "EW" means that the portfolio is constructed by equally weighting all constituents, while "VW" means that the portfolio is constructed by using value-weighted scheme. Portfolio 1 consists of stocks with the lowest historical beta, and portfolio 5 consists of stocks with the highest historical beta. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. The sample period is from January 1996 until December 2012.

| | 1 Month | | 2 Months | | 3 Months | | 4 Months | |
|---|---|---|---|---|---|---|---|---|
| | EW | VW | EW | VW | EW | VW | EW | VW |
| 1 | 0.0073 | 0.0063 | 0.0150 | 0.0132 | 0.0225 | 0.0201 | 0.0310 | 0.0279 |
| 2 | 0.0086 | 0.0068 | 0.0178 | 0.0152 | 0.0269 | 0.0228 | 0.0352 | 0.0298 |
| 3 | 0.0093 | 0.0064 | 0.0198 | 0.0124 | 0.0304 | 0.0201 | 0.0422 | 0.0288 |
| 4 | 0.0115 | 0.0075 | 0.0239 | 0.0150 | 0.0355 | 0.0216 | 0.0469 | 0.0294 |
| 5 | 0.0105 | 0.0072 | 0.0219 | 0.0147 | 0.0319 | 0.0217 | 0.0428 | 0.0287 |
| 5-1 | 0.0032 | 0.0009 | 0.0069 | 0.0015 | 0.0093 | 0.0016 | 0.0118 | 0.0008 |
| Newey-West P-value | (0.5872) | (0.8694) | (0.5383) | (0.8853) | (0.5604) | (0.9191) | (0. 5648) | (0.9690) |
| | 5 Months | | 6 Months | | 9 Months | | 12 Months | |
| | EW | VW | EW | VW | EW | VW | EW | VW |
| 1 | 0.0397 | 0.0358 | 0.0480 | 0.0435 | 0.0743 | 0.0667 | 0.1022 | 0.0893 |
| 2 | 0.0439 | 0.0373 | 0.0531 | 0.0443 | 0.0812 | 0.0684 | 0.1080 | 0.0919 |
| 3 | 0.0536 | 0.0370 | 0.0651 | 0.0454 | 0.0996 | 0.0688 | 0.1324 | 0.0924 |
| 4 | 0.0589 | 0.0368 | 0.0715 | 0.0451 | 0.1080 | 0.0721 | 0.1439 | 0.1019 |
| 5 | 0.0540 | 0.0363 | 0.0656 | 0.0449 | 0.1008 | 0.0710 | 0.1376 | 0.0980 |
| 5-1 | 0.0143 | 0.0004 | 0.0175 | 0.0014 | 0.0266 | 0.0044 | 0.0354 | 0.0087 |
| Newey-West P-value | (0.5590) | (0.9857) | (0.5295) | (0.9575) | (0.4565) | (0.8951) | (0.4080) | (0.8280) |

**Table 6.3: Results for Quintile Portfolio Analysis on Constituents of the S&P500 Index (Historical Gamma)**

Notes: In order to form quintile portfolios among constituents of the S&P500 index, gamma for each individual asset is calculated by using previous 252-day daily data.

$$\gamma_i = \sum_{t=1}^{252}\left(r_{m,t} - E\left[r_{m,t}\right]\right)^2\left(r_{i,t} - E\left[r_{i,t}\right]\right) \Big/ \sum_{t=1}^{252}\left(r_{m,t} - E\left[r_{m,t}\right]\right)^3$$

After portfolio formation, the holding period varies from one-month to 12-month. "EW" means that the portfolio is constructed by equally weighting all constituents, while "VW" means that the portfolio is constructed by using value-weighted scheme. Portfolio 1 consists of stocks with the lowest gamma, and portfolio 5 consists of stocks with the highest gamma. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. The sample period is from January 1996 until December 2012.

| | 1 Month | | 2 Months | | 3 Months | | 4 Months | |
|---|---|---|---|---|---|---|---|---|
| | EW | VW | EW | VW | EW | VW | EW | VW |
| 1 | 0.0057 | 0.0042 | 0.0145 | 0.0097 | 0.0218 | 0.0144 | 0.0308 | 0.0193 |
| 2 | 0.0093 | 0.0067 | 0.0197 | 0.0156 | 0.0287 | 0.0241 | 0.0391 | 0.0352 |
| 3 | 0.0098 | 0.0070 | 0.0203 | 0.0153 | 0.0312 | 0.0244 | 0.0422 | 0.0336 |
| 4 | 0.0101 | 0.0101 | 0.0219 | 0.0200 | 0.0334 | 0.0290 | 0.0444 | 0.0369 |
| 5 | 0.0122 | 0.0087 | 0.0218 | 0.0150 | 0.0321 | 0.0220 | 0.0417 | 0.0290 |
| 5-1 | 0.0065** | 0.0045 | 0.0073 | 0.0053 | 0.0103 | 0.0076 | 0.0109 | 0.0097 |
| Newey-West P-value | (0.0389) | (0.1956) | (0.1812) | (0.3711) | (0.1574) | (0.3308) | (0.2319) | (0.2895) |
| | 5 Months | | 6 Months | | 9 Months | | 12 Months | |
| | EW | VW | EW | VW | EW | VW | EW | VW |
| 1 | 0.0425 | 0.0265 | 0.0543 | 0.0360 | 0.0851 | 0.0596 | 0.1124 | 0.0771 |
| 2 | 0.0500 | 0.0459 | 0.0601 | 0.0562 | 0.0911 | 0.0796 | 0.1215 | 0.1050 |
| 3 | 0.0532 | 0.0434 | 0.0654 | 0.0540 | 0.0994 | 0.0855 | 0.1301 | 0.1149 |
| 4 | 0.0555 | 0.0446 | 0.0672 | 0.0527 | 0.1033 | 0.0809 | 0.1411 | 0.1090 |
| 5 | 0.0489 | 0.0338 | 0.0562 | 0.0383 | 0.0850 | 0.0598 | 0.1191 | 0.0869 |
| 5-1 | 0.0064 | 0.0073 | 0.0019 | 0.0023 | -0.0001 | 0.0002 | 0.0067 | 0.0098 |
| Newey-West P-value | (0.5583) | (0.4948) | (0.8848) | (0.8511) | (0.9948) | (0.9899) | (0.7716) | (0.6318) |

From portfolio level analysis, empirical results document no significant relationship between portfolio return and its historical beta. During previous years, beta is a well-documented pricing factor. There are lots of instruments that can be used to hedge the market risk. Previous studies also provide supportive evidence that historical beta cannot explain asset returns adequately.

### 6.5.2 Quintile Portfolio Analysis on Historical Gamma

This chapter also tests the relationship between an asset's return and its systematic skewness risk. Table 6.3 presents results for quintile portfolios constructed based on historical gamma, which is calculated by using previous 252-trading-day daily data at the end of each calendar month.

Looking at Table 6.3, there is no significant relationship between portfolio returns and historical gamma in 15 out of 16 cases. The only significant relationship between quintile portfolio returns and historical gamma can be found if quintile portfolios are constructed among constituents of the S&P500 index and investors hold the long-short portfolio for one month. There is a significant and positive mean return on "5-1" long-short portfolio for one-month predictive horizon (0.0065 per month with a p-value of 0.0389).

Overall, if beta and gamma for each individual stock are calculated by using historical data, it is difficult to detect a significant relationship between portfolio returns and beta or gamma no matter how long investors hold their long-short portfolios.

## 6.6 Results for Portfolios Constructed by Using Option Data

This section computes beta and gamma by using option-implied information following the process discussed in Subsections 6.4.3 and 6.4.4.

This chapter uses options with different day-to-maturities to calculate option-implied beta and gamma, and then assumes that the length of investors' holding periods should be the same as day-to-maturity of options used for beta and gamma calculation.[59] That is, time-to-expiration of options (i.e., the predictive period indicated by options) matches the length of investment horizon. This section then uses these option-implied beta and gamma in quintile portfolio level analysis to analyze the relationship between portfolio returns and option-implied beta or gamma.

### 6.6.1 Description of Model-Free Moments

In order to construct the proxy for systematic standard deviation risk ( $\beta_i^Q$ ) or systematic skewness risk ( $\gamma_i^Q$ ), second, third and fourth central moments of the S&P500 index (i.e., $\sigma_m^2$ , $m_m^3$ and $k_m^4$ ) are estimated under risk-neutral measure. Figure 6.1 plots risk-neutral central moments.

The first panel shows how risk-neutral variance performs during the sample period. It is clear that $\left(\sigma_m^2\right)^Q$ is higher during dot-com bubble around 1999 and financial crisis in 2008 and 2009. The second moment of the S&P500 index translates to risk. Thus, aggregate risk is always higher during crisis period. The second panel shows the variation of risk neutral third central moment. $\left(m_m^3\right)^Q$ is always negative, and it is more negative when the market is more volatile. During volatile period, the return distribution of the S&P500 index becomes more negatively skewed. In the third panel, risk-neutral fourth central moment (i.e., $\left(k_m^4\right)^Q$ ) becomes higher during the period of market crashes.

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[59] For example, if options with 91 day-to-maturity are used to calculate option-implied beta and gamma, the corresponding holding period will be three-month.

**Figure 6.1: Risk-Neutral Central Moments of The S&P500 Index**

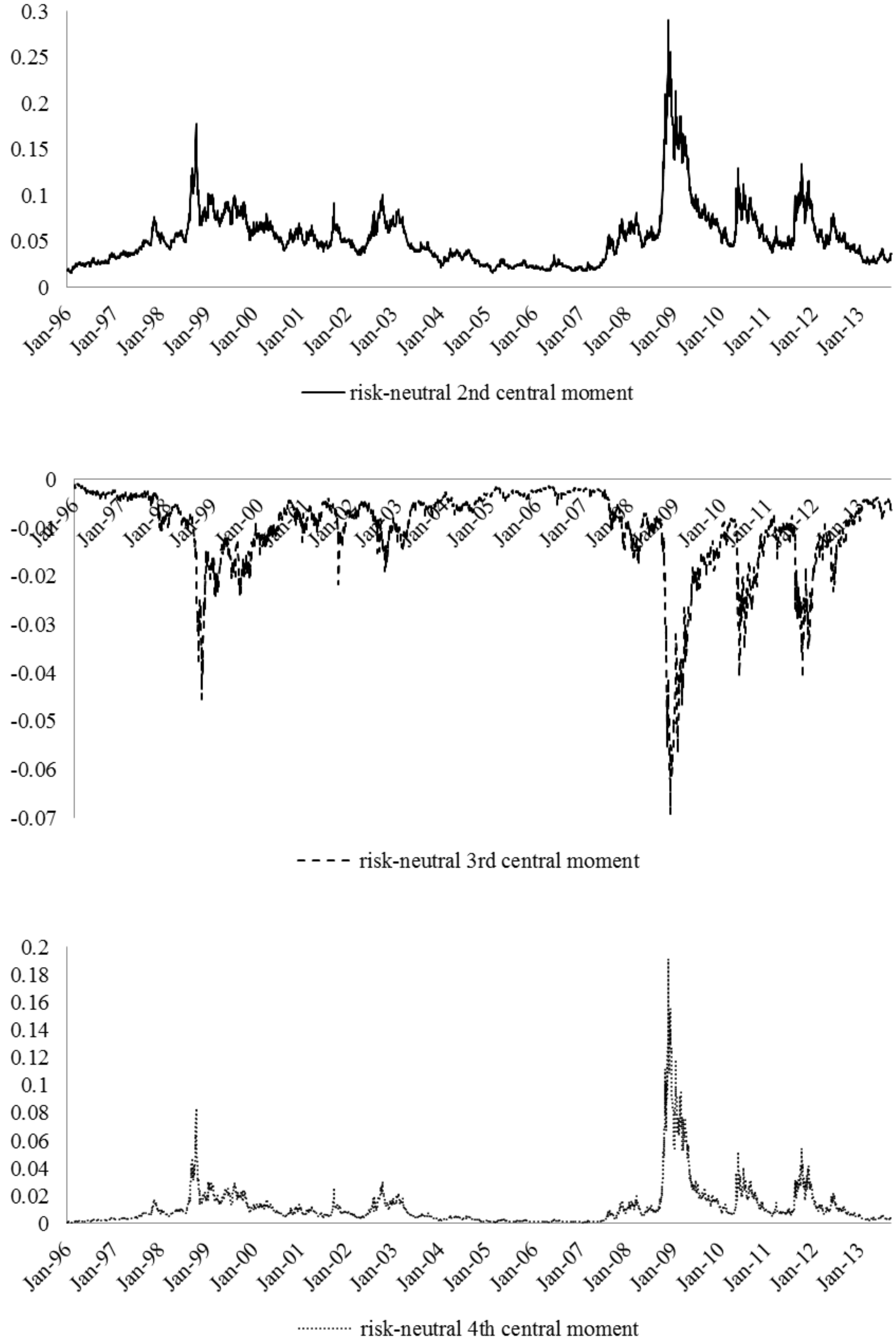

Figure 6.1 indicates that pair-wise correlations between any two of these three central moments are very high. By calculation, the correlation between $\left(\sigma_m^2\right)^Q$ and $\left(m_m^3\right)^Q$ is -0.9670, the correlation between $\left(\sigma_m^2\right)^Q$ and $\left(k_m^4\right)^Q$ is 0.9555, and the correlation between $\left(m_m^3\right)^Q$ and $\left(k_m^4\right)^Q$ is -0.9448. These three central moments are used for option-implied beta and gamma calculations.

### 6.6.2 Quintile Portfolio Analysis on Option-Implied Beta

This subsection presents results for quintile portfolios constructed on option-implied beta calculated by using options with different day-to-maturities. Results for quintile portfolio analysis using constituents of the S&P500 index are summarized in Table 6.4.

From Table 6.4, it is difficult to detect a significant relationship between option-implied beta and portfolio returns, since none of "5-1" long-short portfolios has a significant non-zero mean return.

Results in Table 6.4 provide no evidence about the outperformance of option-implied beta in explaining portfolio returns compared to historical beta. Again, it could be due to the fact that more and more instruments are available to hedge market risk which is captured by beta. It becomes difficult to explain stock returns only using beta.

### 6.6.3 Quintile Portfolio Analysis on Option-Implied Gamma

This chapter also calculates gamma by using option-implied information under risk-neutral measure. Quintile portfolios presented in Table 6.5 are constructed on option-implied gamma among constituents of the S&P500 index.

**Table 6.4: Results for Quintile Portfolio Analysis on Constituents of the S&P500 Index (Option-Implied Beta)**

Notes: In order to form quintile portfolios among constituents of the S&P500 index, this chapter first runs the following time-series regressions:

$$r_{i,t} - r_{f,t} = c_{0i} + c_{1i}\left(r_{m,t} - r_{f,t}\right) + c_{2i}\left(r_{m,t} - E\left[r_{m,t}\right]\right)^2 + \varepsilon_{i,t}$$

Then, this chapter uses $c_{1i}$ and $c_{2i}$ to calculate option-implied beta:

$$\beta_i^Q = c_{1i} + c_{2i}\left[\left(m_m^3\right)^Q \Big/ \left(\sigma_m^2\right)^Q\right]$$

where $\left(\sigma_m^2\right)^Q$ and $\left(m_m^3\right)^Q$ are calculated under risk-neutral measure by using the method derived in Bakshi, Kapadia and Madan (2003). To calculate model-free central moments, this chapter uses options with different day-to-maturity. After the portfolio formation, the holding period is the same as the day-to-maturity of options. "EW" means that the portfolio is constructed by equally weighting all constituents, while "VW" means that the portfolio is constructed by using value-weighted scheme. Portfolio 1 consists of stocks with the lowest option-implied beta, and portfolio 5 consists of stocks with the highest option-implied beta. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. The sample period is from January 1996 until December 2012.

| | 1 Month | | 2 Months | | 3 Months | | 4 Months | |
|---|---|---|---|---|---|---|---|---|
| | EW | VW | EW | VW | EW | VW | EW | VW |
| 1 | 0.0081 | 0.0068 | 0.0166 | 0.0142 | 0.0259 | 0.0225 | 0.0343 | 0.0301 |
| 2 | 0.0087 | 0.0066 | 0.0199 | 0.0172 | 0.0295 | 0.0267 | 0.0390 | 0.0375 |
| 3 | 0.0095 | 0.0083 | 0.0195 | 0.0175 | 0.0307 | 0.0264 | 0.0423 | 0.0346 |
| 4 | 0.0110 | 0.0085 | 0.0228 | 0.0175 | 0.0310 | 0.0243 | 0.0408 | 0.0327 |
| 5 | 0.0101 | 0.0053 | 0.0197 | 0.0104 | 0.0302 | 0.0174 | 0.0421 | 0.0253 |
| 5-1 | 0.0019 | -0.0015 | 0.0031 | -0.0038 | 0.0042 | -0.0050 | 0.0077 | -0.0048 |
| Newey-West P-value | (0.7290) | (0.7879) | (0.7584) | (0.7005) | (0.7456) | (0.6984) | (0.6151) | (0.7501) |
| | 5 Months | | 6 Months | | 9 Months | | 12 Months | |
| | EW | VW | EW | VW | EW | VW | EW | VW |
| 1 | 0.0425 | 0.0365 | 0.0518 | 0.0444 | 0.0768 | 0.0658 | 0.1046 | 0.0899 |
| 2 | 0.0491 | 0.0465 | 0.0585 | 0.0539 | 0.0914 | 0.0798 | 0.1203 | 0.1031 |
| 3 | 0.0534 | 0.0444 | 0.0642 | 0.0552 | 0.0945 | 0.0848 | 0.1268 | 0.1156 |
| 4 | 0.0496 | 0.0401 | 0.0631 | 0.0500 | 0.1029 | 0.0820 | 0.1377 | 0.1070 |
| 5 | 0.0558 | 0.0340 | 0.0659 | 0.0418 | 0.0988 | 0.0628 | 0.1351 | 0.0887 |
| 5-1 | 0.0132 | -0.0025 | 0.0140 | -0.0026 | 0.0220 | -0.0030 | 0.0304 | -0.0013 |
| Newey-West P-value | (0.4422) | (0.8788) | (0.4668) | (0.8864) | (0.3495) | (0.8891) | (0.2443) | (0.9584) |

**Table 6.5: Results for Quintile Portfolio Analysis on Constituents of the S&P500 Index (Option-Implied Gamma)**

Notes: In order to form quintile portfolios among constituents of the S&P500 index, this chapter first runs the following time-series regressions:

$$r_{i,t} - r_{f,t} = c_{0i} + c_{1i}\left(r_{m,t} - r_{f,t}\right) + c_{2i}\left(r_{m,t} - E\left[r_{m,t}\right]\right)^2 + \varepsilon_{i,t}$$

Then, this chapter uses $c_{1i}$ and $c_{2i}$ to calculate option-implied gamma:

$$\gamma_i^Q = c_{1i} + c_{2i}\left\{\left[\left(k_m^4\right)^Q - \left(\left(\sigma_m^2\right)^Q\right)^2\right] \Big/ \left(m_m^3\right)^Q\right\}$$

where $\left(\sigma_m^2\right)^Q$, $\left(m_m^3\right)^Q$ and $\left(k_m^4\right)^Q$ are calculated under risk-neutral measure by using the method derived in Bakshi, Kapadia and Madan (2003). To calculate model-free central moments, this chapter uses options with different day-to-maturity. After the portfolio formation, the holding period is the same as the day-to-maturity of options. "EW" means that the portfolio is constructed by equally weighting all constituents, while "VW" means that the portfolio is constructed by using value-weighted scheme. Portfolio 1 consists of stocks with the lowest option-implied beta, and portfolio 5 consists of stocks with the highest option-implied beta. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. The sample period is from January 1996 until December 2012.

| | 1 Month | | 2 Months | | 3 Months | | 4 Months | |
|---|---|---|---|---|---|---|---|---|
| | EW | VW | EW | VW | EW | VW | EW | VW |
| 1 | 0.0083 | 0.0065 | 0.0154 | 0.0097 | 0.0230 | 0.0152 | 0.0310 | 0.0210 |
| 2 | 0.0096 | 0.0083 | 0.0204 | 0.0182 | 0.0302 | 0.0271 | 0.0414 | 0.0367 |
| 3 | 0.0097 | 0.0071 | 0.0201 | 0.0165 | 0.0305 | 0.0251 | 0.0399 | 0.0325 |
| 4 | 0.0093 | 0.0085 | 0.0209 | 0.0166 | 0.0305 | 0.0230 | 0.0415 | 0.0324 |
| 5 | 0.0104 | 0.0058 | 0.0218 | 0.0135 | 0.0332 | 0.0218 | 0.0448 | 0.0290 |
| 5-1 | 0.0021 | -0.0008 | 0.0064 | 0.0038 | 0.0102 | 0.0066 | 0.0138 | 0.0079 |
| Newey-West P-value | (0.5253) | (0.8336) | (0.2534) | (0.5471) | (0.1776) | (0.4240) | (0.1222) | (0.4241) |
| | **5 Months** | | **6 Months** | | **9 Months** | | **12 Months** | |
| | EW | VW | EW | VW | EW | VW | EW | VW |
| 1 | 0.0400 | 0.0275 | 0.0482 | 0.0330 | 0.0769 | 0.0583 | 0.1082 | 0.0873 |
| 2 | 0.0509 | 0.0454 | 0.0622 | 0.0548 | 0.0926 | 0.0780 | 0.1221 | 0.1005 |
| 3 | 0.0497 | 0.0400 | 0.0604 | 0.0481 | 0.0962 | 0.0775 | 0.1304 | 0.1058 |
| 4 | 0.0519 | 0.0405 | 0.0632 | 0.0511 | 0.0957 | 0.0773 | 0.1265 | 0.1007 |
| 5 | 0.0578 | 0.0378 | 0.0696 | 0.0457 | 0.1030 | 0.0681 | 0.1373 | 0.0919 |
| 5-1 | 0.0178* | 0.0103 | 0.0214* | 0.0127 | 0.0261* | 0.0098 | 0.0291* | 0.0046 |
| Newey-West P-value | (0.0911) | (0.3587) | (0.0806) | (0.3320) | (0.0858) | (0.5628) | (0.0966) | (0.8169) |

This table presents that there is no significant relationship between value-weighted portfolio returns and option-implied gamma. Nevertheless, if investors construct equally-weighted "5-1" long-short portfolio and hold it for five months or longer, they can get marginally significant and positive profits. The profit on the equally-weighted long-short portfolio increases as investors extend their investment horizons.

Results presented in this section show that option-implied gamma is weakly and positively related to returns on equally-weighted portfolios.[60] So compared to historical gamma, option-implied gamma calculated in this chapter performs better in predicting asset returns for longer investment horizons (five months or longer).

## 6.7 Discussions

### 6.7.1 Discussions on Systematic Standard Deviation Risk

Sections 6.5 and 6.6 have some hints about the performance of historical beta/gamma and option-implied beta/gamma in predicting asset returns. No matter which method is used to calculate beta, it is difficult to detect a significant relationship between portfolio returns and beta.

Compared with previous literature, empirical results about beta are different. For example, Buss and Vilkov (2012) document a significant and positive relationship between option-implied beta and one-month future return. However, in this chapter, there is no significant relationship between beta and asset returns no matter how long the predictive period used in empirical analysis is. This chapter distinguishes from Buss and Vilkov (2012) since this chapter uses a two-factor model, while Buss and

[60] The findings here are inconsistent with results in previous literature. Details will be discussed in Subsection 6.7.2.

Vilkov (2012) only consider beta as a pricing factor. Thus, the setting of the model in our study is different.

In addition to systematic standard deviation risk, the model used in this chapter also takes the systematic skewness risk into consideration. The setting of the model used in this chapter is more close to real capital markets. From empirical results, after considering the systematic skewness risk, the predictive power of beta becomes less important.

### 6.7.2 Discussions on Systematic Skewness Risk

In addition to beta, gamma is another important and common-used pricing factor. From results for portfolio level analysis on gamma, if investors construct equally-weighted portfolios on historical gamma and hold them for a calendar month, they can get significant and positive return (0.65% with a Newey-West p-value of 0.0389). Nevertheless, the relationship between option-implied gamma and portfolio returns is marginally significant for longer investment horizons. If investors calculate gamma by using option-implied information, and hold equally-weighted “5-1” long-short portfolios for a longer period varying from five-month to 12-month, they get marginally significant profits.

The empirical analysis in this chapter does not provide supportive evidence about the predictive power of beta. However, it shows a weak and positive relationship between option-implied gamma and asset returns for investment horizons longer than five months.

It is known that beta has been widely tested during previous 50 years, and there are a lot of instruments, which can help to hedge the systematic standard deviation risk in capital markets. However, for gamma, it becomes more and more important in recent years. There are not too many instruments which can help to hedge the systematic skewness risk due to the limitation of capital markets. In addition to beta, gamma is an important pricing factor, which should be included into the asset pricing model and considered by investors to improve their trading strategies.

The relationship between option-implied gamma and future asset returns is marginally significant and positive. This conflicts with findings in previous studies (Ang, Hodrick, Xing and Zhang, 2006; and Chang, Christoffersen and Jacobs, 2013). This could be due to the fact that the setting of the model used in this chapter is different from what is used in previous literature. In addition, equations for beta and gamma calculation in Subsection 6.4.3 indicate that that beta and gamma are both calculated by using coefficients obtained from a regression model using historical daily data (i.e., $c_{1i}$ and $c_{2i}$). So, beta and gamma are highly correlated cross-sectionally. Portfolio level analysis in section 6.6 only considers one pricing factor at each time, and ignores the effect from the other factor. At the end of each calendar month, this chapter sorts stocks on only one factor among all stocks without eliminating the other effect. So results could be not robust.

### 6.7.3 Discussions on Size Effect

From Tables 6.2 to 6.5, it is easy to find that, in all cases, equally-weighted “5-1” long-short portfolios have higher average returns than value-weighted “5-1” long-short portfolios. This indicates that, in addition to beta measuring systematic volatility risk and gamma measuring systematic skewness risk, firm size is of importance. Thus, it would be interesting to test whether the size effect is more important compared to option-implied beta and gamma in explaining returns on constituents of the S&P500 index.

## 6.8 Results for Portfolio Level Analysis by Double Sorting

Since portfolio level analysis in Subsection 6.6 is not robust, this subsection controls for the effect of the other risk factor by constructing portfolios through double sorting. For example, to analyze the effect of option-implied beta on stock return with option-implied gamma controlled, this subsection first divides all stocks into five quintiles based on option-implied gamma. Within each gamma quintile, this subsection further forms five portfolios on the basis of option-implied beta. After constructing 25 portfolios, this subsection constructs new portfolios by equally weighting five portfolios with similar option-implied beta level across different option-implied gamma quintiles. Thus, each new portfolio has stocks with different option-implied gammas. This enables us to control for option-implied gamma when investigating the relationship between portfolio return and option-implied beta.

This subsection first presents results for relationship between option-implied beta and portfolio returns with option-implied gamma or firm size controlled. Then, this subsection discusses results for relationship between option-implied gamma and portfolio returns after controlling for option-implied beta or firm size. Finally, in order to make sure whether the size effect is more important, this subsection analyzes how firm size correlates with portfolio returns after controlling for option-implied beta or gamma.

### 6.8.1 Double-Sorting Portfolio Analysis on Option-implied Beta

In the double-sorting portfolio level analysis, to examine whether the significance of the relationship between portfolio returns and option-implied beta is sensitive to the length of holding period, this chapter assumes that investors can hold their portfolios for various periods. Table 6.6 presents results for portfolios

## Table 6.6: Results for Quintile Portfolios Constructed on Option-Implied Beta While Controlling for Option-Implied Gamma

Notes: In order to form quintile portfolios among constituents of the S&P500 index, this chapter first runs the following time-series regression:

$$r_{i,t} - r_{f,t} = c_{0i} + c_{1i}\left(r_{m,t} - r_{f,t}\right) + c_{2i}\left(r_{m,t} - E\left[r_{m,t}\right]\right)^2 + \varepsilon_{i,t}$$

Then, this chapter uses $c_{1i}$ and $c_{2i}$ to calculate option-implied beta and gamma:

$$\beta_i^Q = c_{1i} + c_{2i}\left[\left(m_m^3\right)^Q \Big/ \left(\sigma_m^2\right)^Q\right]$$

$$\gamma_i^Q = c_{1i} + c_{2i}\left\{\left[\left(k_m^4\right)^Q - \left(\left(\sigma_m^2\right)^Q\right)^2\right] \Big/ \left(m_m^3\right)^Q\right\}$$

$\left(\sigma_m^2\right)^Q$, $\left(m_m^3\right)^Q$ and $\left(k_m^4\right)^Q$ are calculated under risk-neutral measure by using the method derived in Bakshi, Kapadia and Madan (2003). To calculate model-free central moments, this chapter uses options with different day-to-maturities. First, this chapter divides all individual stocks into five quintiles based on option-implied gamma. Within each gamma quintiles, this chapter constructs 5 portfolios on option-implied beta. Then, this chapter averages returns on 5 portfolios with similar option-implied beta across option-implied gamma quintiles. After the portfolio formation, the holding period is the same as the day-to-maturity of options. "EW" means that the portfolio is constructed by equally weighting all constituents, while "VW" means that the portfolio is constructed by using value-weighted scheme. Portfolio 1 consists of stocks with the lowest option-implied beta while controlling for option-implied gamma, and portfolio 5 consists of stocks with the highest option-implied beta while controlling for option-implied gamma. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. The sample period is from January 1996 until December 2012.

| | | 1 | 2 | 3 | 4 | 5 | 5-1 | Newey-West P-value |
|---|---|---|---|---|---|---|---|---|
| 1 M | EW | 0.0081 | 0.0080 | 0.0096 | 0.0111 | 0.0105 | 0.0024 | (0.6324) |
| | VW | 0.0068 | 0.0058 | 0.0087 | 0.0073 | 0.0078 | 0.0010 | (0.8229) |
| 2 M | EW | 0.0173 | 0.0175 | 0.0188 | 0.0227 | 0.0222 | 0.0048 | (0.6111) |
| | VW | 0.0142 | 0.0149 | 0.0149 | 0.0161 | 0.0165 | 0.0023 | (0.7953) |
| 3 M | EW | 0.0256 | 0.0267 | 0.0287 | 0.0340 | 0.0322 | 0.0067 | (0.6142) |
| | VW | 0.0219 | 0.0233 | 0.0238 | 0.0255 | 0.0242 | 0.0024 | (0.8547) |
| 4 M | EW | 0.0342 | 0.0368 | 0.0393 | 0.0452 | 0.0428 | 0.0086 | (0.6017) |
| | VW | 0.0288 | 0.0299 | 0.0329 | 0.0351 | 0.0327 | 0.0039 | (0.8123) |
| 5 M | EW | 0.0430 | 0.0489 | 0.0489 | 0.0562 | 0.0531 | 0.0101 | (0.5870) |
| | VW | 0.0360 | 0.0403 | 0.0412 | 0.0438 | 0.0412 | 0.0052 | (0.7816) |
| 6 M | EW | 0.0527 | 0.0592 | 0.0590 | 0.0671 | 0.0652 | 0.0126 | (0.5463) |
| | VW | 0.0432 | 0.0493 | 0.0496 | 0.0534 | 0.0499 | 0.0067 | (0.7498) |
| 9 M | EW | 0.0816 | 0.0891 | 0.0899 | 0.1016 | 0.1015 | 0.0200 | (0.4519) |
| | VW | 0.0675 | 0.0718 | 0.0753 | 0.0818 | 0.0796 | 0.0121 | (0.6527) |
| 12 M | EW | 0.1089 | 0.1185 | 0.1236 | 0.1345 | 0.1384 | 0.0295 | (0.3331) |
| | VW | 0.0909 | 0.0992 | 0.1036 | 0.1036 | 0.1095 | 0.0186 | (0.5480) |

## Table 6.7: Results for Quintile Portfolios Constructed on Option-Implied Beta While Controlling for Firm Size

Notes: In order to form quintile portfolios among constituents of the S&P500 index, this chapter first runs the following time-series regressions

$$r_{i,t} - r_{f,t} = c_{0i} + c_{1i}\left(r_{m,t} - r_{f,t}\right) + c_{2i}\left(r_{m,t} - E\left[r_{m,t}\right]\right)^2 + \varepsilon_{i,t}$$

Then, this chapter uses $c_{1i}$ and $c_{2i}$ to calculate option-implied beta and gamma:

$$\beta_i^Q = c_{1i} + c_{2i}\left[\left(m_m^3\right)^Q \Big/ \left(\sigma_m^2\right)^Q\right]$$

$\left(\sigma_m^2\right)^Q$, $\left(m_m^3\right)^Q$ and $\left(k_m^4\right)^Q$ are calculated under risk-neutral measure by using the method derived in Bakshi, Kapadia and Madan (2003). To calculate model-free central moments, this chapter uses options with different day-to-maturities. First, this chapter divides all individual stocks into five quintiles based on firm size. Within each size quintiles, this chapter constructs 5 portfolios on option-implied beta. Then, this chapter averages returns on 5 portfolios with similar option-implied beta across size quintiles. After the portfolio formation, the holding period is the same as the day-to-maturity of options. "EW" means that the portfolio is constructed by equally weighting all constituents, while "VW" means that the portfolio is constructed by using value-weighted scheme. Portfolio 1 consists of stocks with the smallest option-implied beta while controlling for firm size, and portfolio 5 consists of stocks with the largest option-implied beta while controlling for firm size. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. The sample period is from January 1996 until December 2012.

| | | 1 | 2 | 3 | 4 | 5 | 5-1 | Newey-West P-value |
|---|---|---|---|---|---|---|---|---|
| 1 M | EW | 0.0085 | 0.0092 | 0.0094 | 0.0103 | 0.0099 | 0.0014 | (0.7813) |
| | VW | 0.0085 | 0.0092 | 0.0091 | 0.0098 | 0.0092 | 0.0007 | (0.8827) |
| 2 M | EW | 0.0179 | 0.0199 | 0.0211 | 0.0208 | 0.0187 | 0.0008 | (0.9247) |
| | VW | 0.0180 | 0.0196 | 0.0201 | 0.0203 | 0.0174 | -0.0006 | (0.9504) |
| 3 M | EW | 0.0275 | 0.0296 | 0.0324 | 0.0296 | 0.0281 | 0.0006 | (0.9556) |
| | VW | 0.0277 | 0.0291 | 0.0307 | 0.0292 | 0.0265 | -0.0013 | (0.9142) |
| 4 M | EW | 0.0361 | 0.0404 | 0.0430 | 0.0397 | 0.0391 | 0.0031 | (0.8141) |
| | VW | 0.0364 | 0.0399 | 0.0409 | 0.0380 | 0.0370 | 0.0005 | (0.9672) |
| 5 M | EW | 0.0456 | 0.0502 | 0.0521 | 0.0512 | 0.0512 | 0.0056 | (0.6932) |
| | VW | 0.0456 | 0.0498 | 0.0496 | 0.0486 | 0.0486 | 0.0030 | (0.8369) |
| 6 M | EW | 0.0547 | 0.0600 | 0.0638 | 0.0637 | 0.0612 | 0.0065 | (0.6730) |
| | VW | 0.0544 | 0.0590 | 0.0616 | 0.0603 | 0.0581 | 0.0037 | (0.8135) |
| 9 M | EW | 0.0810 | 0.0905 | 0.0974 | 0.1012 | 0.0940 | 0.0130 | (0.4789) |
| | VW | 0.0805 | 0.0889 | 0.0933 | 0.0972 | 0.0903 | 0.0098 | (0.6078) |
| 12 M | EW | 0.1097 | 0.1202 | 0.1291 | 0.1379 | 0.1272 | 0.0175 | (0.3746) |
| | VW | 0.1082 | 0.1175 | 0.1248 | 0.1321 | 0.1232 | 0.0150 | (0.4612) |

constructed on option-implied beta while controlling for option-implied gamma.

From Table 6.6, it is clear that, after controlling for option-implied gamma, average returns on "5-1" long-short portfolios are positive in all cases no matter how long the holding period is and no matter which weighting scheme is used for portfolio construction. However, there is no significant relationship between portfolio returns and option-implied beta. So results in Table 6.6 provide no evidence about the significant relationship between option-implied beta and portfolio returns after controlling for the effect of option-implied gamma.

Table 6.7 shows results for portfolios constructed on option-implied beta with firm size being controlled. Results in Table 6.7 indicate that, even though "5-1" long-short portfolios have positive mean return in most cases, it is difficult to find a significant relationship between option-implied beta and portfolio returns after controlling for firm size.

Results in this subsection indicate that it is difficult to detect a significant relationship between option-implied beta and portfolio returns after controlling for option-implied gamma or firm size.

### 6.8.2 Double-Sorting Portfolio Analysis on Option-implied Gamma

This subsection concentrates on the relationship between portfolio returns and option-implied gamma by taking into consideration the effect of option-implied beta or firm size.

Table 6.8 presents results for portfolios constructed on option-implied gamma after controlling for option-implied beta. No matter how long the investment horizon is, average returns on the "5-1" long-short portfolios are always negative. The change in sign of average returns on "5-1" long-short portfolios could be due to the high correlation between option-implied beta and gamma. However, the relationship

**Table 6.8: Results for Quintile Portfolios Constructed on Option-Implied Gamma While Controlling for Option-Implied Beta**

Notes: In order to form quintile portfolios among constituents of the S&P500 index, this chapter first runs the following time-series regressions

$$r_{i,t} - r_{f,t} = c_{0i} + c_{1i}\left(r_{m,t} - r_{f,t}\right) + c_{2i}\left(r_{m,t} - E\left[r_{m,t}\right]\right)^2 + \varepsilon_{i,t}$$

Then, this chapter uses $c_{1i}$ and $c_{2i}$ to calculate option-implied beta and gamma:

$$\beta_i^Q = c_{1i} + c_{2i}\left[\left(m_m^3\right)^Q \Big/ \left(\sigma_m^2\right)^Q\right]$$

$$\gamma_i^Q = c_{1i} + c_{2i}\left\{\left[\left(k_m^4\right)^Q - \left(\left(\sigma_m^2\right)^Q\right)^2\right] \Big/ \left(m_m^3\right)^Q\right\}$$

$\left(\sigma_m^2\right)^Q$, $\left(m_m^3\right)^Q$ and $\left(k_m^4\right)^Q$ are calculated under risk-neutral measure by using the method derived in Bakshi, Kapadia and Madan (2003). To calculate model-free central moments, this chapter uses options with different day-to-maturities. First, this chapter divides all individual stocks into five quintiles based on option-implied beta. Within each beta quintiles, this chapter constructs 5 portfolios on option-implied gamma. Then, this chapter averages returns on 5 portfolios with similar option-implied gamma across option-implied beta quintiles. After the portfolio formation, the holding period is the same as the day-to-maturity of options. "EW" means that the portfolio is constructed by equally weighting all constituents, while "VW" means that the portfolio is constructed by using value-weighted scheme. Portfolio 1 consists of stocks with the lowest option-implied gamma while controlling for option-implied beta, and portfolio 5 consists of stocks with the highest option-implied gamma while controlling for option-implied beta. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. The sample period is from January 1996 until December 2012.

| | | 1 | 2 | 3 | 4 | 5 | 5-1 | Newey-West P-value |
|---|---|---|---|---|---|---|---|---|
| 1 M | EW | 0.0116 | 0.0099 | 0.0101 | 0.0069 | 0.0088 | -0.0028 | (0.2538) |
| | VW | 0.0103 | 0.0065 | 0.0076 | 0.0048 | 0.0069 | -0.0034 | (0.1610) |
| 2 M | EW | 0.0235 | 0.0199 | 0.0189 | 0.0180 | 0.0182 | -0.0053 | (0.2955) |
| | VW | 0.0199 | 0.0139 | 0.0152 | 0.0135 | 0.0140 | -0.0058 | (0.2211) |
| 3 M | EW | 0.0338 | 0.0296 | 0.0285 | 0.0283 | 0.0271 | -0.0067 | (0.3979) |
| | VW | 0.0281 | 0.0197 | 0.0227 | 0.0231 | 0.0214 | -0.0067 | (0.3799) |
| 4 M | EW | 0.0440 | 0.0411 | 0.0379 | 0.0387 | 0.0366 | -0.0074 | (0.5044) |
| | VW | 0.0359 | 0.0310 | 0.0288 | 0.0312 | 0.0281 | -0.0078 | (0.4572) |
| 5 M | EW | 0.0524 | 0.0527 | 0.0486 | 0.0479 | 0.0484 | -0.0040 | (0.7602) |
| | VW | 0.0419 | 0.0420 | 0.0357 | 0.0385 | 0.0380 | -0.0039 | (0.7567) |
| 6 M | EW | 0.0623 | 0.0653 | 0.0598 | 0.0578 | 0.0580 | -0.0043 | (0.7770) |
| | VW | 0.0481 | 0.0541 | 0.0448 | 0.0456 | 0.0474 | -0.0007 | (0.9629) |
| 9 M | EW | 0.0974 | 0.0996 | 0.0942 | 0.0879 | 0.0848 | -0.0126 | (0.5132) |
| | VW | 0.0750 | 0.0817 | 0.0691 | 0.0724 | 0.0714 | -0.0036 | (0.8447) |
| 12 M | EW | 0.1355 | 0.1327 | 0.1243 | 0.1180 | 0.1134 | -0.0221 | (0.3408) |
| | VW | 0.1057 | 0.1099 | 0.0952 | 0.0932 | 0.0981 | -0.0077 | (0.7303) |

## Table 6.9: Results for Quintile Portfolios Constructed on Option-Implied Gamma While Controlling for Firm Size

Notes: In order to form quintile portfolios among constituents of the S&P500 index, this chapter first runs the following time-series regressions

$$r_{i,t} - r_{f,t} = c_{0i} + c_{1i}\left(r_{m,t} - r_{f,t}\right) + c_{2i}\left(r_{m,t} - E\left[r_{m,t}\right]\right)^2 + \varepsilon_{i,t}$$

Then, this chapter uses $c_{1i}$ and $c_{2i}$ to calculate option-implied beta and gamma:

$$\gamma_i^Q = c_{1i} + c_{2i}\left\{\left[\left(k_m^4\right)^Q - \left(\left(\sigma_m^2\right)^Q\right)^2\right] \Big/ \left(m_m^3\right)^Q\right\}$$

$\left(\sigma_m^2\right)^Q$, $\left(m_m^3\right)^Q$ and $\left(k_m^4\right)^Q$ are calculated under risk-neutral measure by using the method derived in Bakshi, Kapadia and Madan (2003). To calculate model-free central moments, this chapter uses options with different day-to-maturities. First, this chapter divides all individual stocks into five quintiles based on firm size. Within each size quintiles, this chapter constructs 5 portfolios on option-implied gamma. Then, this chapter averages returns on 5 portfolios with similar option-implied gamma across size quintiles. After the portfolio formation, the holding period is the same as the day-to-maturity of options. "EW" means that the portfolio is constructed by equally weighting all constituents, while "VW" means that the portfolio is constructed by using value-weighted scheme. Portfolio 1 consists of stocks with the smallest option-implied gamma while controlling for firm size, and portfolio 5 consists of stocks with the largest option-implied gamma while controlling for firm size. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. The sample period is from January 1996 until December 2012.

| | | 1 | 2 | 3 | 4 | 5 | 5-1 | Newey-West p-value |
|---|---|---|---|---|---|---|---|---|
| 1 M | EW | 0.0083 | 0.0100 | 0.0098 | 0.0096 | 0.0097 | 0.0014 | (0.6094) |
| | VW | 0.0080 | 0.0100 | 0.0096 | 0.0090 | 0.0091 | 0.0011 | (0.6886) |
| 2 M | EW | 0.0157 | 0.0210 | 0.0206 | 0.0206 | 0.0205 | 0.0049 | (0.2964) |
| | VW | 0.0149 | 0.0210 | 0.0198 | 0.0198 | 0.0194 | 0.0044 | (0.3573) |
| 3 M | EW | 0.0239 | 0.0306 | 0.0305 | 0.0310 | 0.0312 | 0.0073 | (0.2511) |
| | VW | 0.0229 | 0.0304 | 0.0295 | 0.0298 | 0.0295 | 0.0066 | (0.3114) |
| 4 M | EW | 0.0322 | 0.0406 | 0.0405 | 0.0428 | 0.0420 | 0.0098 | (0.1725) |
| | VW | 0.0310 | 0.0403 | 0.0388 | 0.0412 | 0.0397 | 0.0088 | (0.2368) |
| 5 M | EW | 0.0413 | 0.0500 | 0.0510 | 0.0537 | 0.0538 | 0.0124 | (0.1294) |
| | VW | 0.0399 | 0.0496 | 0.0485 | 0.0517 | 0.0512 | 0.0113 | (0.1859) |
| 6 M | EW | 0.0499 | 0.0605 | 0.0628 | 0.0652 | 0.0646 | 0.0146 | (0.1153) |
| | VW | 0.0480 | 0.0601 | 0.0596 | 0.0630 | 0.0612 | 0.0132 | (0.1721) |
| 9 M | EW | 0.0784 | 0.0907 | 0.0991 | 0.0999 | 0.0957 | 0.0173 | (0.1402) |
| | VW | 0.0766 | 0.0891 | 0.0943 | 0.0962 | 0.0920 | 0.0154 | (0.2133) |
| 12 M | EW | 0.1095 | 0.1214 | 0.1325 | 0.1330 | 0.1275 | 0.0179 | (0.1747) |
| | VW | 0.1066 | 0.1192 | 0.1259 | 0.1285 | 0.1230 | 0.0165 | (0.2309) |

between option-implied gamma and portfolio returns is not statistically significant after controlling for option-implied beta.

Next, this subsection investigates how option-implied gamma performs in explaining portfolio returns after controlling for firm size. Corresponding results are shown in Table 6.9. After controlling firm size, the relationship between option-implied gamma and portfolio returns is positive but not significant. In some cases, p-value is very close to 0.10. For example, if investor construct an equally-weighted “5-1” long-short portfolio and hold it for six months, the average return during six-month period is 1.46% with a p-value of 0.1153.

From the above analysis, after controlling for option-implied beta and firm size, there is very limited evidence about the relationship between option-implied gamma and portfolio returns.

### 6.8.3 Double-Sorting Portfolio Analysis on Firm Size

Due to different performances of equally-weighted and value-weighted portfolios documented in section 6.6, firm size could be an important pricing factor. This subsection presents results for double-sorting portfolio level analysis on firm size with option-implied beta or gamma controlled.

Table 6.10 presents results for portfolio level analysis on firm size with option-implied beta controlled. It is obvious that there is a significant and negative relationship between portfolio returns and firm size. The negative relationship is more significant for equally-weighted portfolios and for shorter (one-month and two-month periods) or longer holing horizons (nine-month or 12-month periods).

Controlling for effect of option-implied gamma gives us similar results as shown in Table 6.11. There is a negative relationship between portfolio returns and firm size.

## Table 6.10: Results for Quintile Portfolios Constructed on Firm Size While Controlling for Option-Implied Beta

Notes: In order to form quintile portfolios among constituents of the S&P500 index, this chapter first runs the following time-series regressions

$$r_{i,t} - r_{f,t} = c_{0i} + c_{1i}\left(r_{m,t} - r_{f,t}\right) + c_{2i}\left(r_{m,t} - E\left[r_{m,t}\right]\right)^2 + \varepsilon_{i,t}$$

Then, this chapter uses $c_{1i}$ and $c_{2i}$ to calculate option-implied beta and gamma:

$$\beta_i^Q = c_{1i} + c_{2i}\left[\left(m_m^3\right)^Q \Big/ \left(\sigma_m^2\right)^Q\right]$$

$\left(\sigma_m^2\right)^Q$, $\left(m_m^3\right)^Q$ and $\left(k_m^4\right)^Q$ are calculated under risk-neutral measure by using the method derived in Bakshi, Kapadia and Madan (2003). To calculate model-free central moments, this chapter uses options with different day-to-maturities. First, this chapter divides all individual stocks into five quintiles based on option-implied beta. Within each beta quintiles, this chapter constructs 5 portfolios on firm size. Then, this chapter averages returns on 5 portfolios with similar firm size across option-implied beta quintiles. After the portfolio formation, the holding period is the same as the day-to-maturity of options. "EW" means that the portfolio is constructed by equally weighting all constituents, while "VW" means that the portfolio is constructed by using value-weighted scheme. Portfolio 1 consists of stocks with the smallest firm size while controlling for option-implied beta, and portfolio 5 consists of stocks with the largest firm size while controlling for option-implied beta. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. The sample period is from January 1996 until December 2012.

| | | 1 | 2 | 3 | 4 | 5 | 5-1 | Newey-West p-value |
|---|---|---|---|---|---|---|---|---|
| 1 M | EW | 0.0126 | 0.0111 | 0.0088 | 0.0079 | 0.0070 | -0.0057* | (0.0543) |
| | VW | 0.0120 | 0.0111 | 0.0087 | 0.0080 | 0.0064 | -0.0057* | (0.0645) |
| 2 M | EW | 0.0268 | 0.0210 | 0.0198 | 0.0153 | 0.0156 | -0.0112* | (0.0637) |
| | VW | 0.0253 | 0.0209 | 0.0194 | 0.0154 | 0.0145 | -0.0109* | (0.0765) |
| 3 M | EW | 0.0389 | 0.0323 | 0.0288 | 0.0239 | 0.0232 | -0.0156* | (0.0782) |
| | VW | 0.0360 | 0.0325 | 0.0285 | 0.0242 | 0.0220 | -0.0140 | (0.1154) |
| 4 M | EW | 0.0520 | 0.0420 | 0.0396 | 0.0323 | 0.0324 | -0.0196* | (0.0860) |
| | VW | 0.0486 | 0.0421 | 0.0392 | 0.0327 | 0.0304 | -0.0182 | (0.1132) |
| 5 M | EW | 0.0643 | 0.0533 | 0.0499 | 0.0409 | 0.0417 | -0.0226 | (0.1088) |
| | VW | 0.0594 | 0.0530 | 0.0489 | 0.0412 | 0.0384 | -0.0210 | (0.1388) |
| 6 M | EW | 0.0777 | 0.0652 | 0.0586 | 0.0512 | 0.0506 | -0.0271* | (0.0968) |
| | VW | 0.0718 | 0.0652 | 0.0575 | 0.0511 | 0.0467 | -0.0251 | (0.1249) |
| 9 M | EW | 0.1177 | 0.0987 | 0.0903 | 0.0797 | 0.0776 | -0.0400* | (0.0682) |
| | VW | 0.1096 | 0.0988 | 0.0891 | 0.0789 | 0.0713 | -0.0384* | (0.0855) |
| 12 M | EW | 0.1578 | 0.1324 | 0.1203 | 0.1090 | 0.1047 | -0.0531* | (0.0544) |
| | VW | 0.1481 | 0.1327 | 0.1187 | 0.1079 | 0.0954 | -0.0527* | (0.0601) |

**Table 6.11: Results for Quintile Portfolios Constructed on Firm Size While Controlling for Option-Implied Gamma**

Notes: In order to form quintile portfolios among constituents of the S&P500 index, this chapter first runs the following time-series regressions

$$r_{i,t} - r_{f,t} = c_{0i} + c_{1i}\left(r_{m,t} - r_{f,t}\right) + c_{2i}\left(r_{m,t} - E\left[r_{m,t}\right]\right)^2 + \varepsilon_{i,t}$$

Then, this chapter uses $c_{1i}$ and $c_{2i}$ to calculate option-implied beta and gamma:

$$\gamma_i^Q = c_{1i} + c_{2i}\left\{\left[\left(k_m^4\right)^Q - \left(\left(\sigma_m^2\right)^Q\right)^2\right] \Big/ \left(m_m^3\right)^Q\right\}$$

$\left(\sigma_m^2\right)^Q$, $\left(m_m^3\right)^Q$ and $\left(k_m^4\right)^Q$ are calculated under risk-neutral measure by using the method derived in Bakshi, Kapadia and Madan (2003). To calculate model-free central moments, this chapter uses options with different day-to-maturities. First, this chapter divides all individual stocks into five quintiles based on option-implied gamma. Within each gamma quintiles, this chapter constructs 5 portfolios on firm size. Then, this chapter averages returns on 5 portfolios with similar firm size across option-implied gamma quintiles. After the portfolio formation, the holding period is the same as the day-to-maturity of options. "EW" means that the portfolio is constructed by equally weighting all constituents, while "VW" means that the portfolio is constructed by using value-weighted scheme. Portfolio 1 consists of stocks with the smallest firm size while controlling for option-implied gamma, and portfolio 5 consists of stocks with the largest firm size while controlling for option-implied gamma. The "5-1" long-short portfolio is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. The sample period is from January 1996 until December 2012.

| | | 1 | 2 | 3 | 4 | 5 | 5-1 | Newey-West p-value |
|---|---|---|---|---|---|---|---|---|
| 1 M | EW | 0.0132 | 0.0098 | 0.0090 | 0.0079 | 0.0074 | -0.0058* | (0.0913) |
| | VW | 0.0123 | 0.0098 | 0.0088 | 0.0077 | 0.0068 | -0.0055 | (0.1213) |
| 2 M | EW | 0.0275 | 0.0201 | 0.0197 | 0.0157 | 0.0153 | -0.0122* | (0.0785) |
| | VW | 0.0251 | 0.0201 | 0.0193 | 0.0151 | 0.0141 | -0.0110 | (0.1099) |
| 3 M | EW | 0.0403 | 0.0300 | 0.0301 | 0.0239 | 0.0229 | -0.0174* | (0.0743) |
| | VW | 0.0369 | 0.0300 | 0.0297 | 0.0233 | 0.0211 | -0.0158 | (0.1067) |
| 4 M | EW | 0.0532 | 0.0412 | 0.0400 | 0.0332 | 0.0307 | -0.0225* | (0.0681) |
| | VW | 0.0488 | 0.0412 | 0.0396 | 0.0328 | 0.0282 | -0.0206* | (0.0951) |
| 5 M | EW | 0.0657 | 0.0516 | 0.0517 | 0.0421 | 0.0389 | -0.0268* | (0.0759) |
| | VW | 0.0600 | 0.0515 | 0.0509 | 0.0415 | 0.0356 | -0.0243 | (0.1069) |
| 6 M | EW | 0.0795 | 0.0623 | 0.0628 | 0.0508 | 0.0479 | -0.0316* | (0.0741) |
| | VW | 0.0727 | 0.0621 | 0.0619 | 0.0500 | 0.0435 | -0.0292* | (0.0965) |
| 9 M | EW | 0.1196 | 0.0969 | 0.0950 | 0.0779 | 0.0744 | -0.0452* | (0.0549) |
| | VW | 0.1103 | 0.0969 | 0.0941 | 0.0763 | 0.0677 | -0.0425* | (0.0727) |
| 12 M | EW | 0.1601 | 0.1301 | 0.1277 | 0.1055 | 0.1007 | -0.0595** | (0.0415) |
| | VW | 0.1487 | 0.1301 | 0.1266 | 0.1034 | 0.0917 | -0.0570* | (0.0520) |

Such a negative relationship becomes stronger when extending the investment horizon. For example, by holding an equally-weighted “5-1” long-short portfolio for 12-month, investors can lose 5.95% p.a. with a p-value of 0.0415.

After controlling for option-implied beta or gamma, there is still a negative relationship between portfolio returns and firm size. This indicates that, for constituents of the S&P500 index, firm size is more important compared to option-implied beta and gamma constructed in this chapter during the period from 1996 and 2012.

## 6.9 Results for Cross-Sectional Regressions

To investigate whether option-implied beta and gamma are priced in cross-section of stock returns, this subsection runs cross-sectional regressions. In this chapter, option-implied beta and gamma are calculated for each individual constituent of the S&P500 index. So, this subsection uses firm-level cross-sectional regressions. Returns on individual stocks during holding periods of different length are regressed on option-implied beta, gamma and other firm-specific variables (i.e., size, book-to-market ratio, historical return during previous 12 to two month, historical return during previous one month, bid-ask spread, and stock trading volume during previous one month) at the end of each month. Then, this subsection tests whether the slope on each risk factor has a significantly non-zero mean. If the time-series mean of the slope is significant and positive (negative), it indicates a significant and positive (negative) relationship between asset returns and the corresponding pricing factor.

In addition, this subsection uses Fama-MacBeth two-step cross-sectional regressions to examine whether, in presence of other risk factors (e.g., $MKT$, $SMB$, $HML$ and $UMD$), option-implied components for beta and gamma calculation have significant risk premiums in explaining variation of asset returns (i.e., returns on 25 size portfolios or 25 book-to-market portfolios).

### 6.9.1 Results for Firm-Level Cross-Sectional Regressions

First, this subsection shows results for firm-level cross-sectional regressions (Table 6.12). Panel A presents results obtained by running firm-level cross-sectional regressions among constituents of the S&P500 index without control variables. These results indicate that it is difficult to detect a significant relationship between asset returns and option-implied beta or gamma.

Then, different firm-specific control variables are included into firm-level cross-sectional regressions to see whether the explanatory power of option-implied beta or gamma is significant when competing with other firm-specific effects. The corresponding results presented in Panel B of Table 6.12 show that there is no significant relationship between asset returns and option-implied beta even though the average slope on option-implied beta is always positive. The average slope on option-implied gamma is negative in all cases but not statistically significant. Some firm-specific control variables have significant average slopes. For example, Table 6.12 documents the value effect (stocks with low book-to-market ratios have lower returns). However, the momentum effect does not exist. Instead, the contrarian effect exists when comparing to previous one-month historical returns.

Thus, it is difficult to find evidence about the relationship between asset returns and option-implied beta or gamma in firm-level cross-sectional regressions. This is consistent with findings in portfolio level analysis. Some of firm-specific effects are statistically related to individual stock returns. This is consistent with pricing anomalies documented in previous studies (such as the value effect in Fama and French, 1992; the contrarian effect in De Bondt and Thaler, 1985 and 1987).

**Table 6.12: Firm-Level Cross-Sectional Regression Results**

Notes: During the sample period from January 1996 to December 2012, at the end of each calendar month, individual stocks' returns during holding period with different length are regressed on option-implied beta and gamma with and without the inclusion of different firm-specific factors at the end of each calendar month:

$$r_i = \alpha_i + b_\beta \beta_i + b_\gamma \gamma_i + \varepsilon_i$$

$$r_i = \alpha_i + b_\beta \beta_i + b_\gamma \gamma_i + b_{size} size_i + b_{B/M} \, B/M_i + b_{ret12to2M} ret12to2M_i + b_{ret1M} ret1M_i + b_{bid-askspread} bid\text{-}askspread_i + b_{vol} vol_i + \varepsilon_i$$

The length of the holding period is the same as the time-to-maturity of options used for beta and gamma calculation. Then, this chapter tests whether slopes on different factors have significantly non-zero mean through t-test.

| Panel A: Firm Level Cross-Sectional Regression Results without Control Variables | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 Month | 2 Months | 3 Months | 4 Months | 5 Months | 6 Months | 9 Months | 12 Months |
| *Intercept* | 0.0053 | 0.0110* | 0.0168* | 0.0222* | 0.0282* | 0.0338** | 0.0550** | 0.0744*** |
| p-value | (0.1134) | (0.0856) | (0.0718) | (0.0664) | (0.0556) | (0.0462) | (0.0140) | (0.0072) |
| $b_\beta$ | 0.0054 | 0.0119 | 0.0181 | 0.0248 | 0.0299 | 0.0355 | 0.0459 | 0.0564 |
| p-value | (0.3833) | (0.3424) | (0.3358) | (0.3126) | (0.3140) | (0.2942) | (0.2819) | (0.2660) |
| $b_\gamma$ | -0.0013 | -0.0036 | -0.0061 | -0.0085 | -0.0096 | -0.0109 | -0.0116 | -0.0109 |
| p-value | (0.3910) | (0.2669) | (0.2330) | (0.2179) | (0.2512) | (0.2362) | (0.2811) | (0.3657) |

(Continued)

| Panel B: Firm Level Cross-Sectional Regression Results with Control Variables | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 Month | 2 Months | 3 Months | 4 Months | 5 Months | 6 Months | 9 Months | 12 Months |
| *Intercept* | 0.0053* | 0.0105* | 0.0163** | 0.0212** | 0.0280** | 0.0356** | 0.0568*** | 0.0793*** |
| p-value | (0.0802) | (0.0655) | (0.0412) | (0.0416) | (0.0252) | (0.0134) | (0.0047) | (0.0016) |
| $b_{\beta}$ | 0.0024 | 0.0052 | 0.0085 | 0.0127 | 0.0135 | 0.0134 | 0.0143 | 0.0201 |
| p-value | (0.6487) | (0.6126) | (0.5680) | (0.5160) | (0.5620) | (0.6087) | (0.6666) | (0.6138) |
| $b_{\gamma}$ | -0.0011 | -0.0024 | -0.0041 | -0.0059 | -0.0058 | -0.0056 | -0.0041 | -0.0031 |
| p-value | (0.4332) | (0.3749) | (0.3277) | (0.3045) | (0.3939) | (0.4525) | (0.6426) | (0.7618) |
| $b_{size}$ | -0.0154 | -0.0301 | -0.0466 | -0.0622 | -0.0797 | -0.1036 | -0.1481 | -0.1818 |
| p-value | (0.4072) | (0.3781) | (0.3206) | (0.3102) | (0.2883) | (0.2358) | (0.2518) | (0.2713) |
| $b_{B/M}$ | 0.0037 | 0.0064 | 0.0090 | 0.0113 | 0.0130 | 0.0142 | 0.0254* | 0.0318* |
| p-value | (0.1053) | (0.1339) | (0.1431) | (0.1509) | (0.1621) | (0.1824) | (0.0735) | (0.0659) |
| $b_{ret12to2M}$ | -0.0046 | -0.0070 | -0.0105 | -0.0129 | -0.0167 | -0.0231 | -0.0313 | -0.0297 |
| p-value | (0.4180) | (0.5030) | (0.4547) | (0.4722) | (0.4493) | (0.3742) | (0.3331) | (0.4195) |
| $b_{ret1M}$ | -0.0164** | -0.0317** | -0.0244 | -0.0334* | -0.0257 | -0.0196 | -0.0134 | -0.0174 |
| p-value | (0.0374) | (0.0272) | (0.1860) | (0.0917) | (0.2981) | (0.5160) | (0.7401) | (0.7139) |
| $b_{bid-askspread}$ | -0.0059 | -0.0149 | -0.0202 | -0.0347 | -0.0398 | -0.0529 | -0.0939 | -0.1420 |
| p-value | (0.6541) | (0.5172) | (0.5191) | (0.3903) | (0.4118) | (0.3488) | (0.2681) | (0.2087) |
| $b_{vol}$ | 0.7825 | 1.4533 | 2.2430 | 2.4358 | 3.2695 | 4.6073 | 8.8461 | 11.5051 |
| p-value | (0.4488) | (0.4177) | (0.3320) | (0.3932) | (0.3329) | (0.2392) | (0.1370) | (0.1757) |

### 6.9.2 Results for Two-Stage Fama-MacBeth Cross-Sectional Regressions

Both beta and gamma calculations need to use option-implied central moments, as well as coefficients from regression using historical information. Then, this subsection tests whether option-implied components for beta and gamma calculation have significant risk premiums. This subsection uses $SMR$ to denote the option-implied component of beta (i.e., $\left(m_m^3\right)^Q \big/ \left(\sigma_m^2\right)^Q$), and $SSR$ to denote the option-implied component of gamma, (i.e., $\left[\left(k_m^4\right)^Q - \left(\left(\sigma_m^2\right)^Q\right)^2\right] \Big/ \left(m_m^3\right)^Q$). These two components are calculated at aggregate-level, so this subsection uses traditional two-stage Fama-MacBeth cross-sectional regressions. Instead of using individual stock returns, this subsection uses returns on 25 portfolios constructed on size or book-to-market among constituents of the S&P500 index. First, daily portfolio excess returns during previous one-month period are regressed on $SMR$ and $SSR$ calculated by using options with different day-to-maturities. In addition, the analysis also includes $MKT$, $SMB$, $HML$ and $UMD$ in the first-stage regressions. After obtaining beta coefficients on different factors, this subsection uses them as explanatory variables in the second-stage regressions to get the estimation of risk premiums. If the risk premium on one factor is significantly different from zero, it indicates that the pricing factor is priced in cross-section of stock returns.

Table 6.13 presents results for the second-stage of Fama-MacBeth cross-sectional regressions obtained by using 25 portfolios constructed on firm size. In Panel A of this table, $MKT$ has a significant and positive risk premium in 6 out of 8 cases (three-month holding period or longer). In addition, $SMR$ has a significant and positive risk premium in cross-section of asset returns if the holding period varies from two-month to six-month. $UMD$ has a marginally significant and negative risk premium in explaining asset returns for long-term holding period (i.e., nine-month or 12-month periods). If portfolios are constructed by using value-weighting scheme, Panel B documents similar results both in significance and in magnitude compared to those presented in Panel A. Thus, it is clear that $SMR$ gains a significant risk premium in explaining cross-section of returns on 25 size portfolios for investment horizons from two-month to six-month period (significant at a 5% significance level).

Table 6.14 shows results for 25 portfolios constructed on book-to-market ratio of individual firms. In Panel A of Table 6.14, it is clear that $SSR$ has a weakly significant and negative risk premium in only one case with two-month holding period (-0.0333 with p-value of 0.0752). $SMB$ has a marginally significant and negative risk premium in explaining returns on equally-weighted book-to-market portfolios in four cases (one-, three-, four- and five-month investment horizons). However, for value-weighted portfolios, there is no significant risk premium on $SMR$ or $SSR$. Thus, from Table 6.14, when explaining cross-section of returns on 25 book-to-market portfolios, there is weak evidence about the risk premium on $SSR$.

Through two-stage Fama-MacBeth cross-sectional regressions, this subsection provides empirical evidence about a positive risk premium on option-implied component for beta (i.e., $SMR$) in explaining cross-section of size portfolio returns over two- to six-month horizons, and very weak evidence about a negative risk premium on option-implied component of gamma (i.e., $SSR$) in explaining cross-section of book-to-market portfolio returns over two-month period. In addition to common-used risk factors ($MKT$, $SMB$, $HML$ and $UMD$), option-implied components ($SMR$ and $SSR$) used in this chapter, especially $SMR$ for beta calculation, should be taken into consideration when explaining cross-section of asset returns.

**Table 6.13: Two-Stage Fama-MacBeth Cross-Sectional Regression Results Using 25 Size Portfolios**

Notes: During the sample period from January 1996 to December 2012, at the end of each calendar month, this chapter forms 25 portfolios based on firm size and calculates equally-weighted and value-weighted returns on each trading day during previous one month, as well as returns in following months. In the first step of cross-sectional regressions, daily returns on each portfolio during previous one month are regressed on different market-based pricing factors to obtain factor loadings.

$$r_{p,t} - r_{f,t} = \alpha_p + \beta_p^{MKT} MKT_t + \beta_p^{SMR} SMR_t + \beta_p^{SSR} SSR_t + \beta_p^{SMB} SMB_t + \beta_p^{HML} HML_t + \beta_p^{UMD} UMD_t + \varepsilon_{p.t}$$

where $SMR = \left(m_m^3\right)^Q \Big/ \left(\sigma_m^2\right)^Q$ and $SSR = \left[\left(k_m^4\right)^Q - \left(\left(\sigma_m^2\right)^Q\right)^2\right] \Big/ \left(m_m^3\right)^Q$. Then, in the second step, holding period returns on 25 portfolios are regressed on factor loadings cross-sectionally.

$$r_p - r_f = \alpha_p + \lambda_{MKT}\beta_p^{MKT} + \lambda_{SMR}\beta_p^{SMR} + \lambda_{SSR}\beta_p^{SSR} + \lambda_{SMB}\beta_p^{SMB} + \lambda_{HML}\beta_p^{HML} + \lambda_{UMD}\beta_p^{UMD} + \varepsilon_p$$

Finally, this chapter uses hypothesis test to make sure whether different pricing factors have significant risk premiums in cross-section of stock returns. Results for the second step of Fama-MacBeth cross-sectional regressions are reported in this table.

| Panel A: Results for Fama-MacBeth Cross-Sectional Regressions Using Equally-Weighted Portfolios | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 Month | 2 Months | 3 Months | 4 Months | 5 Months | 6 Months | 9 Months | 12 Months |
| *Intercept* | 0.0046 | 0.0055 | 0.0044 | 0.0067 | 0.0075 | 0.0083 | 0.0199 | 0.0330 |
| p-value | (0.2478) | (0.3971) | (0.6157) | (0.5104) | (0.5186) | (0.5380) | (0.2947) | (0.1240) |
| $\lambda_{MKT}$ | 0.0036 | 0.0116 | 0.0216** | 0.0281** | 0.0361*** | 0.0438*** | 0.0596*** | 0.0746*** |
| p-value | (0.4037) | (0.1023) | (0.0157) | (0.0124) | (0.0086) | (0.0072) | (0.0085) | (0.0061) |
| $\lambda_{SMR}$ | 0.0053 | 0.0138** | 0.0164** | 0.0206*** | 0.0205** | 0.0220** | 0.0155 | 0.0180 |
| p-value | (0.1997) | (0.0109) | (0.0233) | (0.0060) | (0.0366) | (0.0296) | (0.2008) | (0.2402) |
| $\lambda_{SSR}$ | 0.0205 | -0.0102 | 0.0001 | 0.0003 | 0.0008 | -0.0009 | -0.0223 | -0.0935 |
| p-value | (0.6111) | (0.6630) | (0.9960) | (0.9914) | (0.9794) | (0.9806) | (0.7382) | (0.3720) |
| $\lambda_{SMB}$ | -0.0018 | 0.0021 | -0.0006 | -0.0009 | 0.0010 | -0.0009 | -0.0063 | -0.0081 |
| p-value | (0.3963) | (0.5338) | (0.8918) | (0.8791) | (0.8844) | (0.9063) | (0.5388) | (0.5155) |
| $\lambda_{HML}$ | 0.0008 | 0.0019 | 0.0043 | 0.0048 | 0.0069 | 0.0084 | 0.0125 | 0.0171 |
| p-value | (0.7462) | (0.6696) | (0.4864) | (0.5289) | (0.4546) | (0.4383) | (0.3591) | (0.3089) |
| $\lambda_{UMD}$ | -0.0009 | -0.0022 | -0.0067 | -0.0098 | -0.0144 | -0.0220 | -0.0422* | -0.0517* |
| p-value | (0.8008) | (0.7453) | (0.4629) | (0.3981) | (0.3180) | (0.2129) | (0.0707) | (0.0725) |

(Continued)

| Panel B: Results for Fama-MacBeth Cross-Sectional Regressions Using Value-Weighted Portfolios | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 Month | 2 Months | 3 Months | 4 Months | 5 Months | 6 Months | 9 Months | 12 Months |
| *Intercept* | 0.0044 | 0.0055 | 0.0044 | 0.0069 | 0.0078 | 0.0082 | 0.0198 | 0.0320 |
| p-value | (0.2700) | (0.4079) | (0.6260) | (0.4991) | (0.5070) | (0.5403) | (0.2867) | (0.1285) |
| $\lambda_{MKT}$ | 0.0036 | 0.0113 | 0.0213** | 0.0273** | 0.0351*** | 0.0434*** | 0.0593*** | 0.0748*** |
| p-value | (0.3907) | (0.1008) | (0.0139) | (0.0114) | (0.0089) | (0.0068) | (0.0074) | (0.0046) |
| $\lambda_{SMR}$ | 0.0054 | 0.0131** | 0.0145** | 0.0190** | 0.0202** | 0.0222** | 0.0193 | 0.0233 |
| p-value | (0.1872) | (0.0177) | (0.0487) | (0.0108) | (0.0313) | (0.0228) | (0.1102) | (0.1052) |
| $\lambda_{SSR}$ | 0.0108 | -0.0189 | -0.0054 | -0.0020 | -0.0036 | -0.0040 | -0.0231 | -0.0980 |
| p-value | (0.7820) | (0.4313) | (0.8291) | (0.9383) | (0.9074) | (0.9139) | (0.7326) | (0.3568) |
| $\lambda_{SMB}$ | -0.0021 | 0.0020 | -0.0006 | -0.0010 | 0.0006 | -0.0011 | -0.0059 | -0.0084 |
| p-value | (0.3200) | (0.5522) | (0.8948) | (0.8618) | (0.9293) | (0.8849) | (0.5636) | (0.4958) |
| $\lambda_{HML}$ | 0.0010 | 0.0018 | 0.0041 | 0.0050 | 0.0074 | 0.0082 | 0.0137 | 0.0184 |
| p-value | (0.6717) | (0.6794) | (0.4968) | (0.5027) | (0.4123) | (0.4308) | (0.3042) | (0.2596) |
| $\lambda_{UMD}$ | -0.0011 | -0.0018 | -0.0065 | -0.0097 | -0.0143 | -0.0212 | -0.0419* | -0.0520* |
| p-value | (0.7519) | (0.7808) | (0.4682) | (0.3921) | (0.3081) | (0.2116) | (0.0612) | (0.0631) |

**Table 6.14: Two-Stage Fama-MacBeth Cross-Sectional Regression Results Using 25 Book-to-Market Portfolios**

Notes: During the sample period from January 1996 to December 2012, at the end of each calendar month, this chapter forms 25 portfolios based on book-to-market ratio and calculates equally-weighted and value-weighted returns on each trading day during previous one month, as well as returns in following months. In the first step of cross-sectional regressions, daily returns on each portfolio during previous one month are regressed on different market-based pricing factors to obtain factor loadings.

$$r_{p,t} - r_{f,t} = \alpha_p + \beta_p^{MKT} MKT_t + \beta_p^{SMR} SMR_t + \beta_p^{SSR} SSR_t + \beta_p^{SMB} SMB_t + \beta_p^{HML} HML_t + \beta_p^{UMD} UMD_t + \varepsilon_{p.t}$$

where $SMR = \left(m_m^3\right)^Q \big/ \left(\sigma_m^2\right)^Q$ and $SSR = \left[\left(k_m^4\right)^Q - \left(\left(\sigma_m^2\right)^Q\right)^2\right] \big/ \left(m_m^3\right)^Q$ . Then, in the second step, holding period returns on 25 portfolios are regressed on factor loadings cross-sectionally.

$$r_p - r_f = \alpha_p + \lambda_{MKT}\beta_p^{MKT} + \lambda_{SMR}\beta_p^{SMR} + \lambda_{SSR}\beta_p^{SSR} + \lambda_{SMB}\beta_p^{SMB} + \lambda_{HML}\beta_p^{HML} + \lambda_{UMD}\beta_p^{UMD} + \varepsilon_p$$

Finally, this chapter uses the hypothesis test to make sure whether different pricing factors have significant risk premiums in cross-section of stock returns. Results for the second step of Fama-MacBeth cross-sectional regressions are reported in this table.

Panel A: Results for Fama-MacBeth Cross-Sectional Regressions Using Equally-Weighted Portfolios

| | 1 Month | 2 Months | 3 Months | 4 Months | 5 Months | 6 Months | 9 Months | 12 Months |
|---|---|---|---|---|---|---|---|---|
| *Intercept* | 0.0123*** | 0.0199*** | 0.0267*** | 0.0373*** | 0.0464*** | 0.0537*** | 0.0795*** | 0.1038*** |
| p-value | (0.0002) | (0.0005) | (0.0011) | (0.0002) | (0.0001) | (0.0001) | (0.0000) | (0.0000) |
| $\lambda_{MKT}$ | -0.0032 | -0.0014 | 0.0016 | 0.0007 | 0.0017 | 0.0040 | 0.0071 | 0.0129 |
| p-value | (0.4042) | (0.8358) | (0.8667) | (0.9532) | (0.9088) | (0.8195) | (0.7371) | (0.5899) |
| $\lambda_{SMR}$ | 0.0024 | 0.0053 | 0.0047 | -0.0044 | 0.0018 | 0.0031 | 0.0054 | 0.0123 |
| p-value | (0.5255) | (0.3062) | (0.4963) | (0.5044) | (0.8198) | (0.7032) | (0.6884) | (0.4212) |
| $\lambda_{SSR}$ | 0.0215 | -0.0333* | -0.0335 | -0.0272 | -0.0220 | -0.0133 | 0.0135 | 0.0114 |
| p-value | (0.2461) | (0.0752) | (0.1351) | (0.2263) | (0.4083) | (0.6097) | (0.8029) | (0.8666) |
| $\lambda_{SMB}$ | -0.0035* | -0.0053 | -0.0075* | -0.0110** | -0.0119* | -0.0106 | -0.0127 | -0.0167 |
| p-value | (0.0535) | (0.1324) | (0.0670) | (0.0482) | (0.0517) | (0.1222) | (0.1235) | (0.1122) |
| $\lambda_{HML}$ | 0.0008 | 0.0020 | 0.0029 | 0.0039 | 0.0051 | 0.0074 | 0.0124 | 0.0152 |
| p-value | (0.6857) | (0.5659) | (0.5708) | (0.5645) | (0.5349) | (0.4408) | (0.3143) | (0.3144) |
| $\lambda_{UMD}$ | -0.0014 | -0.0013 | -0.0032 | -0.0052 | -0.0055 | -0.0044 | -0.0116 | -0.0168 |
| p-value | (0.6384) | (0.8047) | (0.6704) | (0.6143) | (0.6597) | (0.7563) | (0.5074) | (0.4401) |

(Continued)

| Panel B: Results for Fama-MacBeth Cross-Sectional Regressions Using Value-Weighted Portfolios | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 Month | 2 Months | 3 Months | 4 Months | 5 Months | 6 Months | 9 Months | 12 Months |
| *Intercept* | 0.0158*** | 0.0194*** | 0.0250*** | 0.0302*** | 0.0358*** | 0.0420*** | 0.0702*** | 0.1002*** |
| p-value | (0.0000) | (0.0001) | (0.0007) | (0.0010) | (0.0022) | (0.0010) | (0.0000) | (0.0000) |
| $\lambda_{MKT}$ | -0.0086* | -0.0047 | -0.0018 | 0.0014 | 0.0045 | 0.0062 | 0.0041 | 0.0007 |
| p-value | (0.0512) | (0.5492) | (0.8575) | (0.9095) | (0.7601) | (0.6968) | (0.8369) | (0.9776) |
| $\lambda_{SMR}$ | -0.0009 | 0.0019 | 0.0068 | 0.0085 | 0.0135 | 0.0114 | 0.0074 | 0.0013 |
| p-value | (0.7869) | (0.7368) | (0.3545) | (0.3140) | (0.1566) | (0.3107) | (0.5496) | (0.9253) |
| $\lambda_{SSR}$ | 0.0064 | -0.0114 | -0.0048 | 0.0168 | 0.0271 | 0.0218 | 0.0308 | 0.0409 |
| p-value | (0.8454) | (0.6269) | (0.8583) | (0.5257) | (0.3304) | (0.4741) | (0.4459) | (0.5277) |
| $\lambda_{SMB}$ | -0.0004 | -0.0042 | -0.0039 | -0.0038 | -0.0029 | -0.0049 | -0.0065 | -0.0126 |
| p-value | (0.8153) | (0.1943) | (0.2674) | (0.4489) | (0.6165) | (0.4581) | (0.4379) | (0.2447) |
| $\lambda_{HML}$ | 0.0010 | 0.0016 | 0.0015 | 0.0018 | 0.0016 | 0.0032 | 0.0065 | 0.0109 |
| p-value | (0.6183) | (0.6765) | (0.7812) | (0.8010) | (0.8423) | (0.7391) | (0.5891) | (0.4643) |
| $\lambda_{UMD}$ | 0.0004 | 0.0006 | -0.0044 | -0.0056 | -0.0057 | -0.0024 | -0.0081 | -0.0130 |
| p-value | (0.8865) | (0.9099) | (0.5376) | (0.5496) | (0.5972) | (0.8488) | (0.6225) | (0.5241) |

## 6.10 Conclusions

Given the empirical evidence about the predictive power of higher moments shown in previous literature, it is expected that the mean-variance approach cannot fully describe capital markets. In addition to the systematic standard deviation risk, this chapter takes higher moments of asset returns into consideration, and focuses on the systematic skewness risk of individual stocks in addition to systematic standard deviation risk.

In addition to using historical data for pricing factors' calculation, this chapter incorporates forward-looking information. Empirical results show no evidence about the outperformance of option implied beta in explaining asset returns compared to historical beta. There are some evidence that option-implied gamma performs better than historical gamma in predicting asset returns over longer horizons (five-month or longer). The results reveal that, gamma is an important factor in asset pricing, and it gains marginally significant predictive power for long investment horizons. However, the predictive power of firm size is stronger than option-implied beta and gamma in explaining future returns of the S&P500 index constituents during the period from 1996 to 2012.

In order to make sure whether option-implied beta and gamma are priced in cross-section of asset returns, this chapter runs cross-sectional regressions. First, through firm-level cross-sectional regressions, it is difficult to find supportive evidence about the significant non-zero risk premiums on beta and gamma. This could be due to the high correlation between option-implied beta and gamma. Furthermore, this chapter also examines whether option-implied components used for beta and gamma calculation have significant risk premiums by using two-stage Fama-MacBeth cross-sectional regressions. The results confirm that option-implied component for beta calculation contains some useful information in explaining cross-section of size portfolio returns over two-month to six-month horizons, whereas option-implied component for gamma calculation has weak explanatory power in explaining book-to-market portfolio returns over two-month period.

Overall, this chapter provides weak empirical evidence that, in addition to systematic standard deviation risk, systematic skewness risk is of importance in explaining time-series and cross-section of stock returns. Furthermore, using option-implied information in asset pricing incorporates some useful information about future market conditions.

# Chapter 7 Conclusions

This thesis is motivated by the failure of the CAPM documented in empirical studies. Due to pricing anomalies found in previous literature, this thesis tries to figure out whether any other information could help with explanation or prediction of asset returns.

Previous literature tests the asset pricing model by using the historical information. In order to use historical data in asset pricing, the fragile assumption that historical information can reflect future market conditions is essential. However, this assumption does not hold in real markets. In addition, due to the development of financial markets, more and more instruments are available for trading. These derivatives are expected to capture more information about future financial markets. Theoretical studies enable us to extract useful information from different derivatives and provide more advanced methodology to construct asset pricing factors. Thus, in recently years, more and more studies use forward-looking information in asset pricing.

This thesis concentrates on how to use forward-looking information from different kinds of derivatives to explain or predict asset returns. This thesis consists of four independent chapters (presented in chapters 3, 4, 5 and 6). These chapters shed light on whether information contained in options or other derivatives is relevant to asset pricing, how to use forward-looking information more efficiently, and how to adjust investors' trading strategies in order to earn premiums.

First, chapter 3 tries to make sure whether option-implied information is related to asset returns. This chapter focuses on predictive power of different option-implied volatility measures at firm-level. This chapter constructs six volatility measures proposed in previous literature (i.e., call-put implied volatility spread, implied volatility skew, “above-minus-below”, “out-minus-at” of calls, “out-minus-at” of puts, and realized-implied volatility spread) for each individual firm. The empirical results for portfolio level analysis confirm that there is a positive relationship between stock returns and call-put implied volatility spread, whereas implied volatility skew is negatively related to stock returns. Also, “above-minus-below”, and realized-implied volatility spread are marginally and negatively related to stock returns. This chapter also compares the predictive power of these measures at firm-level. The results suggest that call-put implied volatility spread contains most relevant information for one-month ahead asset returns, while for longer investment horizons (two-month or three-month), the predictive power of “out-minus-at” of calls becomes more significant.

Chapter 4 constructs pricing factors by using implied volatilities extracted from at-the-money call and put options on individual stocks. The empirical results do not provide supportive evidence about significant risk premiums on volatility factors. That is, in most cases, volatility factors constructed in this chapter do not have significant risk premiums. Among all factors used in this chapter (implied volatility factor, market excess return, size factor, and book-to-market factor), size factor gains a significant risk premium in some cases. This indicates that risk related to firm size is relatively important. The insignificant results could be due to the short sample period and the data frequency used in the analysis, which are limitations of this chapter. This chapter uses stock return data at monthly frequency. So observations available in the analysis are fewer compared with other studies. If this chapter switches to use data at daily frequency, it is possible to get different results.

Previous studies document empirical evidence about the existence of market risk premium. Due to the negative relationship between market returns and aggregate volatility, Chapter 5 tests how sensitivities to aggregate volatility risk affect asset returns. Chapter 5 uses daily innovation in VIX index or VIX index futures as a proxy for the aggregate volatility risk. Different from findings in previous literature (Ang, Hodrick, Xing and Zhang, 2006), in Chapter 5, there is no significant evidence about the unconditional relationship between an asset's return and its sensitivity to aggregate volatility risk. Then, in order to make sure whether the aggregate volatility risk plays different roles in different scenarios, this chapter uses VIX futures basis to separate different market conditions. The empirical results confirm that the effect of the volatility risk is asymmetric. If investors only take into consideration the information during highly volatile period, stocks with higher sensitivities to volatility risk have significantly lower returns than those with lower sensitivities to volatility risk. Such a relationship does not exist if investors only consider the information during calm period. Furthermore, this chapter decomposes the VIX index into two parts, volatility calculated by using out-of-the-money call options and volatility calculated by using out-of-the-money put options. The results provide evidence that out-of-money put options contain more useful information about future volatility risk in explaining asset returns.

In order to improve the asset pricing model, Kraus and Litzenberger (1976) propose a two-factor model incorporating higher moments based on the CAPM. In addition to market beta, measuring the systematic standard deviation risk, there is another pricing factor, market gamma, measuring the systematic skewness risk. Chapter 6 investigates the systematic standard deviation and skewness risk, by incorporating forward-looking information. This chapter calculates an asset's systematic standard deviation risk and systematic skewness risk (i.e., market beta and market gamma) by using option-implied higher moments. The model used in this chapter is the same as the model-setting in Kraus and Litzenberger (1976). Empirical results show the outperformance of option-implied gamma compared to historical gamma over longer hozirons (five to 12 months). The results confirm that gamma is an important factor in asset pricing. The portfolio level analysis by double sorting reveals that firm size plays an important role in explaining stock returns. Then, the option-implied components in beta and gamma calculation gain significant risk premiums in traditional two-stage Fama-MacBeth cross-sectional regressions. This chapter provides investors another way to incorporate option-implied information.

In summary, this thesis shows different ways to extract useful information from financial derivatives and to construct significant pricing factors. This thesis provides empirical evidence about the importance of option-implied information in asset pricing. Investors could get some hints about how to adjust their trading strategies based on the length of investment horizons and different market conditions.

# Reference

Albuquerque, R., 2012, Skewness in Stock Returns: Reconciling the Evidence on Firm versus Aggregate Returns, The Review of Financial Studies, Vol. 25, pp. 1630-1673.

Ammann, M., and Buesser, R., 2013, Variance Risk Premiums in Foreign Exchange Markets, The Journal of Empirical Finance, Vol. 23, pp. 16–32.

An, B. J., Ang, A., Bali, T. G., and Cakici, N., 2014, The Joint Cross-Section of Stocks and Options, The Journal of Finance, Vol. 69, pp. 2279-2337.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Ebens, H., 2001, The Distribution of Realized Stock Return Volatility, The Journal of Financial Economics, Vol. 61, pp. 43–76.

Ang, A., Chen, J., Xing, Y., 2006, Downside Risk, The Review of Financial Studies, Vol. 19, pp. 1191-1239.

Ang, A., Hodrick, R. J., Xing, Y., and Zhang, X., 2006, The Cross-Section of Volatility and Expected Returns, The Journal of Finance, Vol. 61, pp. 259-299.

Arisoy, Y. E., 2014, Aggregate Volatility and Market Jump Risk: An Option-Based Explanation to Size and Value Premia, The Journal of Futures Markets, Vol. 34, pp. 34-55.

Arisoy, Y. E., Salih, A., and Akdeniz, L., 2007, Is Volatility Risk Priced in the Securities Market? Evidence from S&P 500 Index Options, Journal of Futures Markets, Vol. 27, pp. 617-642.

Bakshi, G., and Kapadia, N., 2003, Delta-Hedged Gains and the Negative Market Volatility Risk Premium, The Review of Financial Studies, Vol. 16, pp. 527-566.

Bakshi, G., Kapadia, N., and Madan, D., 2003, Stock Return Characteristics, Skew Laws, and the Differential Pricing of Individual Equity Options, The Review of Financial Studies, Vol. 16, pp. 101-143.

Bali, T. G., and Cakici, N., 2008, Idiosyncratic Volatility and the Cross Section of Expected Returns, The Journal of Financial and Quantitative Analysis, Vol. 43, pp. 29-58.

Bali, T. G., and Hovakimian, A., 2009, Volatility Spreads and Expected Stock Returns, Management Science, Vol. 55, pp. 1797-1812.

Baltussen, G., Grient, B. V. D., Groot, W. D., Hennink, E., and Zhou, W., 2012, Exploiting Option Information in the Equity Market, The Financial Analysts Journal, Vol. 68, pp. 56-72.

Banz, R. W., 1981, The Relationship between Return and Market Value of Common Stocks, The Journal of Financial Economics, Vol. 9, pp. 3-18.

Barndorff-Nielsen, O. E., and Shephard, N., 2004, Power and Bipower Variation with Stochastic Volatility and Jumps, The Journal of Financial Econometrics, Vol. 2, pp. 1-37.

Basu, S., 1977, Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis, The Journal of Finance, Vol. 32, pp. 663-682.

Bates, D. S., 2000, Post-’87 Crash Fears in the S&P 500 Futures Option Market, The Journal of Econometrics, Vol. 94, pp. 181-238.

Bawa, V. S., and Lindenberg, E. B., 1977, Capital Market Equilibrium in a Mean-Lower Partial Moment Framework, The Journal of Financial Economics, Vol. 5, pp. 189-200.

Berk, J. B., Green, R. C., and Naik, V., 1999, Optimal Investment, Growth Options, and Security Returns, The Journal of Finance, Vol. 54, pp. 1553-1607.

Black, F., and Scholes, M., 1973, The Pricing of Options and Corporate Liabilities, Journal of Political Economy, Vol. 81, pp. 637–654.

Blair, B. J., Poon, S., and Taylor, S. J., 2001, Forecasting S&P 100 volatility: the incremental information content of implied volatilities and high-frequency index returns, The Journal of Econometrics, Vol. 105, pp. 5–26.

Blume, M. E., 1970, Portfolio Theory: A Step toward Its Practical Application, The Journal of Business, Vol. 43, pp. 152-173.

Blume, M. E., and Friend, I., 1973, A New Look at the Capital Asset Pricing Model, The Journal of Finance, Vol. 28, pp. 19-34.

Bollerslev, T., 1986, Generalized Autoregressive Conditional Heteroskedasticity, The Journal of Econometrics, Vol. 31, pp. 307-327.

Bollerslev, T., Gibson, M., and Zhou, H., 2011, Dynamic Estimation of Volatility Risk Premia and Investor Risk Aversion from Option-Implied and Realized Volatilities, The Journal of Econometrics, Vol. 160, pp. 235-245.

Bollerslev, T., Tauchen, G., and Zhou, H., 2009, Expected Stock Returns and Variance Risk Premia, The Review of Financial Studies, Vol. 22, pp. 4463-4492.

Brennan, M. J., 1971, Capital Market Equilibrium with Divergent Borrowing and Lending Rates, The Journal of Financial and Quantitative Analysis, Vol. 6, pp. 1197-1205.

Britten-Jones, M., and Neuberger, A., 2000, Option Prices, Implied Price Processes, and Stochastic Volatility, The Journal of Finance, Vol. 55, pp. 839-866.

Buss, A., and Vilkov, G., 2012, Measuring Equity Risk with Option-Implied Correlations, The Review of Financial Studies, Vol. 25, pp. 3113-3140.

Buss, A., Schlag, C., and Vilkov, G., 2009, CAPM with Option-Implied Betas: Another Rescue Attempt, working paper.

Campbell, J. Y., 1993, Intertemporal Asset Pricing Without Consumption Data, American Economic Review, Vol. 83, pp. 487-512.

Campbell, J. Y., 1996, Understanding Risk and Return, The Journal of Political Economy, Vol. 104, pp. 298-345.

Campbell, R. A. J., Forbes, C. S., Koedijk, K. G., and Kofman, P., 2008, Increasing Correlations or Just Fat Tails? The Journal of Empirical Finance, Vol. 15, pp. 287-309.

Carhart, M. M., 1997, On Persistence in Mutual Fund Performance, The Journal of Finance, Vol. 52, pp. 57-82.

Carr, P., and Wu, L., 2009, Variance Risk Premiums, The Review of Financial Studies, Vol. 22, pp. 1311-1341.

Chang, B. Y., Christoffersen, P., and Jacobs, K., 2013, Market Skewness Risk and the Cross-Section of Stock Returns, The Journal of Financial Economics, Vol. 107, pp. 46-68.

Chang, B. Y., Christoffersen, P., Jacobs, K., and Vainberg, G., 2012, Option-Implied Measures of Equity Risk, The Review of Finance, Vol. 16, pp. 385-428.

Chen, J., 2003, Intertemporal CAPM and the Cross-Section of Stock Returns, EFA 2002 Berlin Meetings Discussion Paper, Available at SSRN: http://ssrn.com/abstract=301918.

Christensen, B. J., and Prabhala, N. R., 1998, The Relation between Implied and Realized Volatility, The Journal of Financial Economics, Vol. 50, pp. 125-150.

Christie-David, R., and Chaudhry, M., 2001, Coskewness and Cokurtosis in Futures Markets, The Journal of Empirical Finance, Vol. 8, pp. 55-81.

Conrad, J., Dittmar, R. F., and Ghysels, E., 2013, Ex Ante Skewness and Expected Stock Returns, The Journal of Finance, Vol. 68, pp. 85-124.

Cooper, M. J., Gulen, H., and Schill, M. J., 2008, Asset Growth and the Cross-Section of Stock Returns, The Journal of Finance, Vol. 63, pp. 1609-1651.

Cremers, M., and Weinbaum, D., 2010, Deviations from Put-Call Parity and Stock Returns Predictability, The Journal of Financial and Quantitative Analysis, Vol. 45, pp. 335-367.

Daniel, K., and Titman, S., 2006, Market Reactions to Tangible and Intangible Information, The Journal of Finance, Vol. 61, pp. 1605-1643.

De Bondt, W. F. M., and Thaler, R., 1985, Does the Stock Market Overreact? The Journal of Finance, Vol. 40, pp. 793-805.

De Bondt, W. F. M., and Thaler, R., 1987, Further Evidence on Investor Overreaction and Stock Market Seasonality, The Journal of Finance, Vol. 42, pp. 557-581.

DeLisle, R. J., Doran, J. S., and Peterson, D. R., 2011, Asymmetric Pricing of Implied Systematic Volatility in the Cross-Section of Expected Returns, The Journal of Futures Markets, Vol.31, pp. 34-54.

DeMiguel, V., Plyakha, Y., Uppal, R., and Vilkov, G., 2013, Improving Portfolio Selection Using Option-Implied Volatility and Skewness, The Journal of Financial and Quantitative Analysis, Vol. 48, pp. 1813–1845.

Diether, K. B., Malloy, C. J., and Scherbina, A., 2002, Difference of Opinion and the Cross-Section of Stock Returns, The Journal of Finance, Vol. 57, pp. 2113-2141.

Dittmar, R. F., 2002, Nonlinear Pricing Kernels, Kurtosis Preference, and Evidence from the Cross Section of Equity Returns, The Journal of Finance, Vol. 57, pp. 369-403.

Doran, J. S., and Krieger, K., 2010, Implications for Asset Returns in the Implied Volatility Skew, The Financial Analysts Journal, Vol. 66, pp. 65-76.

Doran, J. S., Peterson, D. R., and Tarrant, B. C., 2007, Is There Information in the Volatility Skew? The Journal of Futures Markets, Vol. 27, pp. 921-959.

Easley, D., O'Hara, M., and Srinivas, P.S., 1998, Option Volume and Stock Prices: Evidence on Where Informed Traders Trade, The Journal of Finance, Vol. 53, pp. 431–465.

Engle, R. F., 1982, Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation, Econometrica, Vol. 50, pp. 987-1007.

Fama, E. F., and French, K. R., 1992, The Cross-Section of Expected Stock Returns, The Journal of Finance, Vol. 47, pp. 427-465.

Fama, E. F., and French, K. R., 1993, Common Risk Factors in the Returns on Stocks and Bonds, The Journal of Financial Economics, Vol. 33, pp. 3-56.

Fama, E. F., and MacBeth, J. D., 1973, Risk, Return, and Equilibrium: Empirical Tests, The Journal of Political Economy, Vol. 81, pp. 607-636.

Fang, H., and Lai, T. Y., 1997, Co-Kurtosis and Capital Asset Pricing, The Financial Review, Vol. 32, pp. 293-307.

Farago, A., and Tédongap, R., 2015, Volatility Downside Risk, Working paper.

Ferson, W. E., and Harvey, C. R., 1991, The Variation of Economic Risk Premiums, The Journal of Political Economy, Vol. 99, pp. 385-415.

French, D. W., Groth, J. C., and Kolari, J. W., 1983, Current Investor Expectations and Better Betas, The Journal of Portfolio Management, Vol. 10, pp. 12-17.

French, K. R., 1980, Stock Returns and the Weekend Effect, The Journal of Financial Economics, Vol. 8, pp. 55-69.

Friend, I., and Westerfield, R., 1980, Co-Skewness and Capital Asset Pricing, The Journal of Finance, Vol. 35, pp. 897-913.

Gemmill, G., 1996, Did Option Traders Anticipate the Crash? Evidence from Volatility Smiles in the UK with US Comparisons, The Journal of Futures Markets, Vol. 16, pp. 881-897.

Hansen, L. P., 1982, Large Sample Properties of Generalized Method of Moments Estimators, Econometrica, Vol. 50, pp. 1029-1054.

Harvey, C. R., and Siddique, A., 2000, Conditional Skewness in Asset Pricing Tests, The Journal of Finance, Vol. 55, pp. 1263-1295.

Heston, S. L., 1993, A Closed-Form Solution for Options with Stochastic Volatility with Applications to Bond and Currency Options, The Review of Financial Studies, Vol. 6, pp. 327-343.

Huang, X., and Tauchen, G., 2005, The Relative Contribution of Jumps to Total Price Variance, The Journal of Financial Econometrics, Vol. 3, pp. 456–499.

Hull, J.C., 2012, Options, Futures, and Other Derivatives, 8th Edition, New York: Pearson.

Hung, D. C., Shackleton, M., and Xu, X., 2004, CAPM, Higher Co-moment and Factor Models of UK Stock Returns, Jounral of Business, Finance and Accounting, Vol. 31, pp. 87–112.

Huskaj, B., and Nossman, M., 2013, A Term Structure Model for VIX Futures, The Journal of Futures Markets, Vol. 33, pp. 421-442.

Jackwerth, J. C. and Vilkov, G., 2015, Asymmetric Volatility Risk: Evidence from Option Markets, Available at SSRN: http://ssrn.com/abstract=2325380.

Jagannathan, R., and Wang, Z., 1996, The Conditional CAPM and the Cross-Section of Expected Returns, The Journal of Finance, Vol. 51, pp. 3-53.

Jegadeesh, N., and Titman, S., 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, The Journal of Finance, Vol. 48, pp. 65-91.

Kang, B. J., Kim, T. S., and Yoon, S. J., 2010, Information Content of Volatility Spreads, The Journal of Futures Markets, Vol. 30, pp. 533-558.

Karagiannis, S., 2014, An Investigation of the Lead-Lag Relationship between the VIX Index and the VIX Futures on the S&P500, International Journal of Science, Innovation and New Technology, Vol. 1, pp. 43-56.

Keim, D. B., 1983, Size-Related Anomalies and Stock Return Seasonality: Further Empirical Evidence, The Journal of Financial Economics, Vol. 12, pp. 13-32.

Kempf, A., Korn, O., and Sassning, S., 2015, Portfolio Optimization Using Forward-Looking Information, The Review of Finance, Vol. 19, pp. 467–490.

Kostakis, A., Muhammad, K., and Siganos, A., 2012, Higher Co-Moments and Asset Pricing on London Stock Exchange, The Journal of Banking and Finance, Vol. 36, pp. 913-922.

Kostakis, A., Panigirtzoglou, N., and Skiadopoulos, G., 2011, Market Timing with Option-Implied Distributions: A Forward-Looking Approach, Management Science, Vol. 57, pp. 1231–1249.

Kraus, A., and Litzenberger, R. H., 1976, Skewness Preference and the Valuation of Risk Assets, The Journal of Finance, Vol. 31, pp. 1085-1100.

Lim, K. G., 1989, A New Test of the Three-Moment Capital Asset Pricing Model, The Journal of Financial and Quantitative Analysis, Vol. 24, pp. 205-216.

Lin, Y. N., 2007, Pricing VIX Futures: Evidence from Integrated Physical and Risk-Neutral Probability Measures, The Journal of Futures Markets, Vol. 27, pp. 1175-1217.

Lintner, J., 1965, The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets, The Review of Economics and Statistics, Vol. 47, pp. 13-37.

Loughran, T., and Ritter, Y. R., 1995, The New Issues Puzzle, The Journal of Finance, Vol. 50, pp. 23-51.

Lu, Z., and Zhu, Y., 2010, Volatility Components: The Term Structure Dynamics of VIX Futures, The Journal of Futures Markets, Vol. 30, pp. 230-256.

Lyandres, E., Sun, L., and Zhang, L., 2008, The New Issues Puzzle: Testing the Investment-Based Explanation, The Review of Financial Studies, Vol. 21, pp. 2825-2855.

Markowitz, H. M., 1959, Portfolio Selection: Efficient Diversification of Investments, New York: John Wiley & Sons.

Merton, R. C., 1973, An Intertemporal Capital Asset Pricing Model, Econometrica, Vol. 41, pp. 867-887.

Mo, H., and Wu, L., 2007, International Capital Asset Pricing: Evidence from Options, The Journal of Empirical Finance, Vol. 14, pp. 465-498.

Mossin, J., 1966, Equilibrium in a Capital Asset Market, Econometrica, Vol. 34, pp. 768-783.

Muzzioli, S., 2011, The Skew Pattern of Implied Volatility in the DAX Index Options Market, Frontiers in Finance and Economics, Vol. 8, pp. 43-68.

Pan, J., and Poteshman, A. M., 2006, The Information in Option Volume for Future Stock Prices, The Review of Financial Studies, Vol. 19, pp. 871-908.

Petkova, R., and Zhang, L., 2005, Is Value Riskier than Growth? The Journal of Financial Economics, Vol. 78, pp. 187-202.

Pong, S., Shackleton, M. B., Taylor. S. J., and Xu, X., 2004, Forecasting Currency Volatility: A Comparison of Implied Volatilities and AR(FI)MA Models, The Journal of Banking and Finance, Vol. 28, pp. 2541-2563.

Poon, S. H., and Granger, C., 2005, Practical Issues in Forecasting Volatility, The Financial Analysts Journal, Vol. 61, pp. 45-56.

Rehman, Z., and Vilkov, G., 2012, Risk-Neutral Skewness: Return Predictability and Its Sources, Working Paper.

Rosenberg, B., Reid, K., and Lanstein, R., 1985, Persuasive Evidence of Market Inefficiency, The Journal of Portfolio Management, Vol. 11, pp. 9-16.

Ross, S. A., 1976, The Arbitrage Theory of Capital Asset Pricing, The Journal of Economic Theory, Vol. 13, pp. 341-360.

Rozeff, M. S., and Kinney, W. R., 1976, Capital Market Seasonality: The Case of Stock Returns, The Journal of Financial Economics, Vol. 3, pp. 379-402.

Schwert, G. W., 2003, Chapter 15 Anomalies and Market Efficiency, Handbook of the Economics of Finance, Vol. 1, pp. 939-974.

Scott, R. C., and Horvath, P. A., 1980, On the Direction of Preference for Moments of Higher Order than the Variance, The Journal of Finance, Vol. 35, pp. 915-919.

Sears, R. S., and Wei, K. C. J., 1985, Asset Pricing, Higher Moments, and the Market Risk Premium: A Note, The Journal of Finance, Vol. 40, pp. 1251-1253.

Sears, R. S., and Wei, K. C. J., 1988, The Structure of Skewness Preferences in Asset Pricing Models with Higher Moments: An Empirical Test, The Financial Review, Vol. 23, pp. 25-38.

Sharpe, W. F., 1964, Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk, The Journal of Finance, Vol. 19, pp. 425-442.

Shu, J., and Zhang, J. E., 2012, Causality in the VIX Futures Market, The Journal of Futures Markets, Vol. 32, pp. 24-46.

Siegel, A. F., 1995, Measuring Systematic Risk Using Implicit Beta, Management Science, Vol. 41, pp. 124-128.

Stilger, P. S., Kostakis, A., and Poon, S., 2016, What Does Risk-Neutral Skewness Tell Us About Future Stock Returns? Management Science, Forthcoming.

Szakmary, A., Ors, E., Kim, J. K., and Davidson, W. N., 2003, The Predictive Power of Implied Volatility: Evidence from 35 Futures Markets, The Journal of Banking and Finance, Vol. 27, pp. 2151-2175.

Taylor, S. J., 1986, Modeling Financial Time Series, New York: John Wiley & Sons.

Taylor, S. J., 2005, Asset Price Dynamics, Volatility, and Prediction, Princeton: Princeton University Press.

Taylor, S. J., Yadav, P. K., Zhang, Y., 2010, The Information Content of Implied Volatilities and Model-Free Volatility Expectations: Evidence from Options Written on Individual Stocks, The Journal of Banking and Finance, Vol. 34, pp. 871-881.

Titman, S., Wei, K. C. J., and Xie, F., 2004, Capital Investments and Stock Returns, The Journal of Financial and Quantitative Analysis, Vol. 39, pp. 677-700.

Woerner, J. H. C., 2005, Estimation of Integrated Volatility in Stochastic Volatility Models, Applied Stochastic Models in Business and Industry, Vol. 21, pp. 27-44.

Xing, Y., Zhang, X., and Zhao, R., 2010, What Does the Individual Option Volatility Smirk Tell Us about Future Equity Returns? The Journal of Financial and Quantitative Analysis, Vol. 45, pp. 641-662.

Yu, W. W., Lui, E. C. K., and Wang, J. W., 2010, The Predictive Power of the Implied Volatility of Options Traded OTC and on Exchanges, The Journal of Banking and Finance, Vol. 34, pp. 1-11.

Zhang, J. E., and Zhu, Y., 2006, VIX Futures, The Journal of Futures Markets, Vol. 26, pp. 521-531.