Risk-Neutral Systematic Risk and Asset Returns

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Abstract

Based on the mean-variance approach, Kraus and Litzenberger (1976) consider investors' preference for the third moment and propose a two-factor pricing model, which includes systematic variance risk and systematic skewness risk. To distinguish from previous studies, this study incorporates option-implied information to construct systematic variance risk and systematic skewness risk. Through portfolio level analysis, we find a positive relationship between asset return and systematic variance risk, and a negative relationship between asset return and systematic skewness risk. Finally, cross-sectional regression results confirm the existence of risk premiums on systematic variance risk and systematic skewness risk.

Keywords: systematic variance risk, systematic skewness risk, model-free moments

JEL Classification: G12

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1. Introduction

The Capital Asset Pricing Model (CAPM) is derived based on the mean-variance approach proposed by Markowitz (1959) and it establishes a linear relationship between an asset's return and its systematic risk. Based on the CAPM, there is only one pricing factor related to asset returns (i.e. beta, which measures the systematic market risk of an asset). That is, the CAPM assumes that investors only focus on the first two moments of return distribution and have no preference over higher moments. However, this assumption could conflict with asset price dynamics in capital markets.

Some studies take higher moments into consideration and distinguish the preference for the third moment (i.e. skewness) by analyzing investors' utility functions. Among these studies, Kraus and Litzenberger (1976) start with non-polynomial utility functions and derive a linear three moment asset pricing model on the basis of the CAPM. In their model, in addition to beta (which measures the systematic variance risk), there is another pricing factor gamma (which measures the systematic skewness risk). Gamma measures the co-movement between an individual asset's excess return and the second moment of the market portfolio.[1] The results show that the systematic skewness is negatively related to asset returns so that the systematic skewness is an important factor in pricing risky assets. Later studies also document supportive evidence of a positive skewness preference (Scott and Horvath, 1980; Sears and Wei, 1985 and 1988; Fang and Lai, 1997; Harvey and Siddique, 2000). That is, investors require higher returns on assets with negative systematic skewness.

[1] In Kraus and Litzenberger (1976), by using historical data, the second moment of the market portfolio is measured by $\left(R_{M,t} - E[R_{M,t}]\right)^2$.

After realizing the importance of systematic skewness in asset pricing, instead of using historical data, empirical studies try to incorporate forward-looking information to explain why systematic skewness is important and to shed light on the relationship between systematic skewness and asset return. Some studies use option-implied factors to measure the second moment of the market portfolio for gamma calculation. Ang, Hodrick, Xing and Zhang (2006) use daily innovations in VXO index as a proxy. The empirical results show that stocks with higher sensitivities to innovations in aggregate volatility have lower average returns. So, empirical findings in Ang, Hodrick, Xing and Zhang (2006) are consistent with the theoretical prediction. Chang, Christoffersen and Jacobs (2013) use daily innovations in VIX index to measure the second moment of the market portfolio. The empirical results show that the relationship between asset return and systematic skewness is sensitive to the length of horizon for gamma estimation. If systematic skewness risk is estimated during 1-month period, stocks with higher sensitivities to changes in VIX index have lower average returns. However, such a phenomenon cannot be observed if the systematic skewness risk is estimated during 6-month period.

Furthermore, Chang, Christoffersen and Jacobs (2013) also look at the relationship between an asset’s return and its sensitivity to aggregate skewness. Stocks with higher sensitivities have significantly lower future returns. Such a negative relationship is robust no matter whether the sensitivity to aggregate skewness is estimated during previous 1-month or 6-month period. So, aggregate skewness is important in asset pricing.

Albuquerque (2012) decomposes the aggregate skewness into three parts: individual firm's skewness, the co-movement between a firm's return and the return variance in other firms within the portfolio (i.e. $co - vol$), and co-movement between a firm's return and the covariance between any other two firms within the portfolio (i.e. $co - cov$). The empirical results show that cross-sectional heterogeneity in firm announcement events (i.e. $co - cov$) is the main driver of the aggregate skewness.

Based on previous literature, this study focuses on systematic variance risk (i.e. market beta) and systematic skewness risk (i.e. market gamma) of individual stocks. In the theoretical part, we decompose skewness of the portfolio in a different way compared with the method used in Albuquerque (2012). We stick to the two-factor model proposed by Kraus and Litzenberger (1976), and calculate beta and gamma by partially incorporating option-implied information.

Then, in the empirical part, we calculate option-implied beta and gamma for constituents of S&P 500 index, and investigate how beta and gamma relate to future asset returns. We study the relationship between asset return and beta or gamma through portfolio level analysis among constituents of S&P 500 index. We note that constructing portfolios on one factor does not allow us to control for effect of other risk factors. According to Kraus and Litzenberger (1976), beta and gamma are both calculated by using coefficients obtained from regressions using daily historical data (discussed in section 2.2.3). It is expected that option-implied beta and gamma should be highly correlated cross-sectionally. Thus, we control for the effect of gamma (beta) when investigating the relationship between option-implied beta (gamma) and asset return by using a double sorting method. In our analysis, we also look at different investment time horizons in order to see how predictive power of each pricing factor (i.e. beta or gamma) changes with time. Through portfolio level analysis, we can clearly see that beta and gamma are both important pricing factors with significant explanatory power.

After confirming the relationship between portfolio return and option-implied beta or gamma through portfolio level analysis, we run Fama-MacBeth cross-sectional regressions at firm level to see whether beta and gamma gain significant risk premiums in cross-section of individual stock returns. In such analysis, we also include firm-specific control variables, such as size, book-to-market ratio, historical return during previous 12 to 2 months, historical return during previous 1 month, bid-ask spread and trading volume in previous one month. The inclusion of control variables enables us to ensure whether the predictive power of option-implied beta or gamma still persists after considering firm-specific risk factors.

In addition, in order to make sure whether components of beta and gamma calculated by using option data have significant risk premiums, we use 25 portfolios constructed on size or book-to-market ratio to run two-stage Fama-MacBeth cross-sectional regressions.

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

Second, based on Kraus and Litzenberger (1976), we calculate pricing factors, beta and gamma, by incorporating forward-looking information. Compared to historical data, option-implied information performs better in predicting future market conditions.[2] Thus, beta and gamma calculated by using option data are expected to capture more relevant information about future asset returns.

The remaining of this paper is organized as follows. Section 2 discusses data and methodology used in this study. Section 3 focuses on the portfolio level analysis by using a double sorting method to control for the effect of the other pricing factor. Section 4 shows results for cross-sectional regressions. The final section, section 5, offers some concluding remarks.

2. Data and Methodology

2.1 Data

In this study, we focus on the S&P500 index. The S&P500 index is a capitalization-weighted index of 500 stocks. Among constituents of S&P500 index, we investigate the relationship between asset return and systematic variance risk, beta, or systematic skewness risk, gamma.

In order to do such analysis, daily and monthly stock data are downloaded from CRSP. The information about constituents of S&P500 index is available from Compustat. In addition, the option data for S&P500 index are downloaded from "Volatility Surface" file in OptionMetrics. The option data are available from the beginning of 1996. So, the sample

[2] For example, Christensen and Prabhala (1998), Blair, Poon and Taylor (2001), Poon and Granger (2005), and Taylor, Yadav and Zhang (2010) show the outperformance of option-implied information in forecasting future volatility. French, Groth and Kolari (1983), Chang, Christoffersen, Jacobs and Vainberg (2012), and Buss and Vilkov (2012) incorporate option-implied information in beta estimation. The empirical results show that option-implied beta performs better than historical beta in explaining the relationship between risk and return.

period of our analysis starts from January 1996 until December 2012.

2.2 Methodology

2.2.1 The Two-Factor Model in Kraus and Litzenberger (1976)

The CAPM is derived by assuming polynomial utility functions. Based on this assumption, the effect of higher moments could be ignored. However, such an assumption does not hold in real markets. Thus, one potential reason for the failure of the CAPM could be the omission of higher moments. If investors' utility functions are non-polynomial, the effect of higher moments should be considered. Starting from this point, Kraus and Litzenberger (1976) claim that, in addition to beta, gamma (i.e. systematic skewness risk) is another pricing factor, which should be taken into consideration by investors.

$$E[R_i] - R_f = b_1\beta_i + b_2\gamma_i \quad (1)$$

where R_i is the return on an asset i, $\beta_i = \sigma_{iM}/\sigma_M^2$ is the market beta or systematic standard deviation of an asset i, $\gamma_i = m_{iMM}/m_M^3$ is the market gamma or systematic skewness of an 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 $m_M = \left[E\left[\left(R_{M,t} - E\left[R_{M,t}\right]\right)^3\right]\right]^{1/3}$), $b_1 = (d\bar{W}/d\sigma_W)\sigma_M$, and $b_2 = (d\bar{W}/dm_W)m_M$. b_1 can be interpreted as the market price of beta, and b_2 can be interpreted as the market price of gamma. Kraus and Litzenberger (1976) calculate beta and gamma for an asset i by using historical daily return data on individual stocks and market portfolio:

$$\beta_i = \frac{\sum_{t=1}^{T}\left(R_{M,t} - E\left[R_{M,t}\right]\right)\left(R_{i,t} - E\left[R_{i,t}\right]\right)}{\sum_{t=1}^{T}\left(R_{M,t} - E\left[R_{M,t}\right]\right)^2} \quad (2)$$

$$\gamma_i = \frac{\sum_{t=1}^{T}\left(R_{M,t} - E[R_{M,t}]\right)^2\left(R_{i,t} - E[R_{i,t}]\right)}{\sum_{t=1}^{T}\left(R_{M,t} - E[R_{M,t}]\right)^3} \quad (3)$$

where $R_{M,t}$ is the return on the market portfolio. Then, next sub-section discusses how systematic skewness risk links with aggregate skewness.

2.2.2 Decomposition of Aggregate Skewness

In Albuquerque (2012), under the assumption that the portfolio is constructed by using equal-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 returns with the return variance of the other firms in the portfolio), and $co - cov$ (comovements of an asset's returns with the covariance between any other two assets' returns):

$$\begin{aligned} m_P^3 &= E\left[\left(R_{P,t} - E[R_{P,t}]\right)^3\right] \\ &= \frac{1}{N^3}\sum_{i=1}^{N}\frac{1}{T}\sum_{t}\left(R_{i,t} - E[R_{i,t}]\right)^3 \\ &+ \frac{3}{TN^3}\sum_{t}\sum_{i=1}^{N}\left(R_{i,t} - E[R_{i,t}]\right)\sum_{i'\neq i}\left(R_{i',t} - E[R_{i',t}\right)^2 \\ &+ \frac{6}{TN^3}\sum_{t}\sum_{i=1}^{N}\left(R_{i,t} - E[R_{i,t}]\right)\sum_{i'>i}^{N}\sum_{l>i'}^{N}\left(R_{i',t} - E[R_{i',t}\right)\left(R_{l,t} - E[R_{l,t}\right) \quad (4) \end{aligned}$$

Rather than using the decomposition method in Albuquerque (2012), in our study, we decompose skewness of the portfolio in another way. The non-standardized skewness of a portfolio can be decomposed as follows:

$$
\begin{aligned}
m_P^3 = E\left[\left(R_{P,t} - E[R_{P,t}]\right)^3\right] &= E\left[\left(R_{P,t} - E[R_{P,t}]\right)\left(R_{P,t} - E[R_{P,t}]\right)^2\right] \\
&= E\left[\left[\sum_{i=1}^{N} w_i\left(R_{i,t} - E[R_{i,t}]\right)\right]\left(R_{P,t} - E[R_{P,t}]\right)^2\right] \\
&= \sum_{i=1}^{N} w_i E\left[\left(R_{i,t} - E[R_{i,t}]\right)\left(R_{P,t} - E[R_{P,t}]\right)^2\right] \quad (5)
\end{aligned}
$$

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 (5), we can see that the non-standardized aggregate skewness is the weighted average of co-movements of an asset's returns with the variance of the portfolio return. 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.

$$
\frac{m_P^3}{m_P^3} = \frac{\sum_{i=1}^{N} w_i E\left[\left(R_{i,t} - E[R_{i,t}]\right)\left(R_{P,t} - E[R_{P,t}]\right)^2\right]}{E\left[\left(R_{P,t} - E[R_{P,t}]\right)^3\right]} = \sum_{i=1}^{N} w_i\, \gamma_{iP} = 1 \quad (6)
$$

where γ_{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, we can see that gamma of the portfolio, which is equal to one, is the weighted-average of gammas on all constituents in that portfolio. Therefore, gamma is a linearly additive pricing factor as beta. On the basis of our decomposition, we wonder whether the predictive power of aggregate skewness could be due to gamma, which is a proxy of systematic skewness risk. So, in our study, we investigate the relationship between asset return and systematic skewness risk (i.e. gamma) rather than that between asset return and aggregate skewness.

2.2.3 Beta and Gamma Calculation by Using Option Data

In addition to beta and gamma calculation shown in equations (2) and (3), Kraus and Litzenberger (1976) propose another way to estimate beta and gamma. In the first step, excess return of an individual asset should be regressed on market excess return and the squared deviation of the market excess return from its expected value:

$$R_{i,t} - R_{f,t} = c_{0i} + c_{1i}\left(R_{M,t} - R_{f,t}\right) + c_{2i}\left(R_{M,t} - E[R_{M,t}]\right)^2 \quad (7)$$

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 asset could be calculated by using the following two equations:

$$\beta_i = c_{1i} + c_{2i}(m_M^3/\sigma_M^2) \quad (8)$$

$$\gamma_i = c_{1i} + c_{2i}\{[k_M^4 - (\sigma_M^2)^2]/m_M^3\} \quad (9)$$

where σ_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 support that option-implied data incorporate forward-looking information and they are more efficient in reflecting future market conditions. Thus, rather than calculating beta and gamma by using historical data, we calculate beta and gamma under the risk-neutral measure by incorporating option-implied information. In order to do this, we estimate σ_M^2, m_M^3 and k_M^4 by using option data.

2.2.4 Central Moments Calculation under Risk-Neutral Measure

In order to calculate σ_M^2, $m_M^3$and k_M^4 under risk-neutral measure, we apply the method derived in Bakshi, Kapadia and Madan (2003). We first calculate 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 call and put options.

$$V(t,\tau) = \int_{S(t)}^{\infty} \frac{2\left(1 - ln\left[\frac{K}{S(t)}\right]\right)}{K^2} C(t,\tau;K)dK + \int_{0}^{S(t)} \frac{2\left(1 + ln\left[\frac{S(t)}{K}\right]\right)}{K^2} P(t,\tau;K)dK \quad (10)$$

$$W(t,\tau) = \int_{S(t)}^{\infty} \frac{6\,ln\left[\frac{K}{S(t)}\right] - 3\left(ln\left[\frac{K}{S(t)}\right]\right)^2}{K^2} C(t,\tau;K)dK$$

$$- \int_{0}^{S(t)} \frac{6\,ln\left[\frac{S(t)}{K}\right] + 3\left(ln\left[\frac{S(t)}{K}\right]\right)^2}{K^2} P(t,\tau;K)dK \quad (11)$$

$$X(t,\tau) = \int_{S(t)}^{\infty} \frac{12\left(ln\left[\frac{K}{S(t)}\right]\right)^2 - 4\left(ln\left[\frac{K}{S(t)}\right]\right)^3}{K^2} C(t,\tau;K)dK$$

$$+ \int_{0}^{S(t)} \frac{12\left(ln\left[\frac{S(t)}{K}\right]\right)^2 + 4\left(ln\left[\frac{S(t)}{K}\right]\right)^3}{K^2} P(t,\tau;K)dK \quad (12)$$

Then, by using $V(t,\tau)$, $W(t,\tau)$ and $X(t,\tau)$, we can calculate model-free central moments.

$$(\sigma_M^2)^Q = e^{r\tau}V_{i,t}(t,\tau) - \mu_{i,t}(\tau)^2 \quad (13)$$

$$(m_M^3)^Q = e^{r\tau}W_{i,t}(t,\tau) - 3\mu_{i,t}(\tau)e^{r\tau}V_{i,t}(t,\tau) + 2\mu_{i,t}(\tau)^3 \quad (14)$$

$$(k_M^4)^Q = e^{r\tau}X_{i,t}(t,\tau) - 4\mu_{i,t}(\tau)e^{r\tau}W_{i,t}(t,\tau) + 6e^{r\tau}\mu_{i,t}(\tau)^2V_{i,t}(t,\tau) - 3\mu_{i,t}(\tau)^4 \quad (15)$$

where

$$\mu_{i,t}(\tau) = e^{r\tau} - 1 - \frac{e^{r\tau}V_{i,t}(t,\tau)}{2} - \frac{e^{r\tau}W_{i,t}(t,\tau)}{6} - \frac{e^{r\tau}X_{i,t}(t,\tau)}{24} \quad (16)$$

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

$$\beta_i^Q = c_{1i} + c_{2i}\left[\frac{(m_M^3)^Q}{(\sigma_M^2)^Q}\right] \quad (17)$$

$$\gamma_i^Q = c_{1i} + c_{2i}\left\{\frac{[(k_M^4)^Q - ((\sigma_M^2)^Q)^2]}{(m_M^3)^Q}\right\} \quad (18)$$

We use the option-implied beta and gamma (β_i^Q and γ_i^Q) in our empirical analysis.

2.2.5 Discussion on Option-Implied Gamma

As discussed in the introduction section, some previous studies try to incorporate option-implied information to calculate beta and gamma. In Ang, Hodrick, Xing and Zhang (2006), the daily innovation in VXO index is a proxy of the second moment of market portfolio:

$$E[R_i] - R_f = \alpha + \beta_i(R_M - R_f) + \gamma_i \Delta VXO \quad (19)$$

where γ_i is actually a proxy of systematic skewness risk. Similarly, Chang, Christoffersen, and Jacobs (2013) use a similar way to incorporate forward-looking information by using the daily change in VIX index:

$$E[R_i] - R_f = \alpha + \beta_i(R_M - R_f) + \gamma_i \Delta VIX \quad (20)$$

$$E[R_i] - R_f = \alpha + \beta_i(R_M - R_f) + \gamma_i \Delta VIX + \delta_i \Delta SKEW + \theta_i \Delta KURT \quad (21)$$

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

$$\gamma_i = \frac{cov(E[R_i] - R_f, \Delta\sigma_M^Q)}{var(\Delta\sigma_M^Q)} \quad (22)$$

Compared to previous literature, this study incorporates model-free central higher moments in a different way. Rather than changing the explanatory variables reflecting the second moment of the market portfolio return, we stick to the original model setting proposed by Kraus and Litzenberger (1976). In addition to risk-neutral variance, the method used in this study also includes risk-neutral skewness and kurtosis. We believe that our option-implied risk factors incorporate more useful information. Details about empirical results are presented in the following section.

3. Results for Portfolio Level Analysis

Previous literature provides a vast of supportive evidence that the aggregate skewness is an important factor related to asset return (Chang, Christoffersen and Jacobs, 2013; etc). Based on our decomposition, we wonder whether the effect of the aggregate skewness is due to the systematic skewness risk of each individual asset. We test whether gamma is an important pricing factor in addition to beta.

We use options with different day-to-expiration to calculate option-implied beta and gamma, and assume that the length of investors' holding periods should be the same as the day-to-expiration of options used for beta and gamma calculation.[3] That is, time-to-expiration of options (i.e. the predictive period indicated by options) matches the length of investment horizons. We then use these option-implied beta and gamma in portfolio level analysis to analyze the relationship between portfolio return and option-implied beta or gamma.

In addition, results for portfolio level analysis discussed in this section are obtained by using a double-sorting method. By using such a method, we control for the effect of the other risk factor in our analysis. For example, if we want to analyze the effect of option-implied beta on stock return, we first divide all stocks in our sample into five quintiles based on option-implied gamma. Within each gamma quintile, we further form five portfolios on the basis of option-implied beta. After constructing 25 portfolios, we construct new portfolios by

[3] For example, if we use options with 91 day-to-maturity to calculate option-implied beta and gamma, the corresponding holding period will be 3-month.

equally weighting five portfolios with similar option-implied beta level across different option-implied gamma quintiles. Thus, in each new portfolio, we have stocks with different option-implied gammas. That is, we control for option-implied gamma when investigating the relationship between portfolio return and option-implied beta.

In this section, we first have a look at different model-free moments. Then, section 3.2 presents results for relationship between option-implied beta and portfolio return, and section 3.3 discuss results for relationship between option-implied gamma and portfolio return.

3.1 Description of Model-Free Moments

In order to construct the proxy of systematic variance risk (β_i^Q) or systematic skewness risk (γ_i^Q), we need to calculate central second, third and fourth moments for S&P500 index (i.e. σ_M^2, m_M^3 and k_M^4) under risk-neutral measure. We plot central moments in Figure 1

[Insert Figure1 here]

From the first panel, we can see how risk-neutral variance performs during the sample period. It is clear that $(\sigma_M^2)^Q$ 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 volatility risk is always higher during crisis period.

The second panel shows the variation of risk neutral third central moment. We can find that $(m_M^3)^Q$ is always negative and its magnitude increases when the market is more volatile. During volatile period, the return distribution of S&P500 index becomes more negatively skewed.

Then, in the third panel, we can find that risk-neutral fourth central moment (i.e. $(k_M^4)^Q$) becomes higher during the period of market crashes.

From Figure 1, we can find that the pairwise correlation between any two of these three central moments are very high. By calculation, we can find that the correlation between $(\sigma_M^2)^Q$ and $(m_M^3)^Q$ is -0.9670, the correlation between $(\sigma_M^2)^Q$ and $(k_M^4)^Q$ is 0.9555, and the correlation between $(m_M^3)^Q$ and $(k_M^4)^Q$ is -0.9448. These three central moments are used for option-implied beta and gamma calculations.

3.2 Double-Sorting Portfolio Analysis on Option-Implied Beta

In the double-sorting portfolio level analysis, in order to make sure whether the significance of the relationship between portfolio return and option-implied beta is sensitive to the length of holding period, we assume that investors can hold their portfolios for various periods. Table 1 presents results for portfolios constructed on option-implied beta while controlling for option-implied gamma.

[Insert Table 1 here]

From the table, it is clear that, after controlling for option-implied gamma, average returns on "5-1" arbitrage 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, we cannot find any significant relationship between portfolio returns and option-implied beta if the holding period varies from one month to nine months. If the holding period is extended to 12 months, we can find that the average return on the equally-weighted portfolio is statistically significant and positive (2.95% p.a. with a p-value of 0.0493). That is, for long investment horizons, there is a significant and positive relationship between portfolio return and option-implied beta after controlling for option-implied gamma.

3.3 Double-Sorting Portfolio Analysis on Option-Implied Gamma

This sub-section concentrates on the relationship between portfolio return and option-implied gamma by taking into consideration the effect of option-implied beta. The corresponding results are presented in Table 2.

[Insert Table 2 here]

In Table 2, we can easily find that, after considering the effect of option-implied beta, average returns on "5-1" arbitrage portfolios constructed on option-implied gamma are negative for all holding periods from one month to one year. However, in most cases, average returns are not statistically significant. Only for one-year investment horizon, if the arbitrage portfolio is constructed by using equally-weighted scheme, the average return on the arbitrage portfolio is -2.21% p.a. with a p-value of 0.0525. Thus, after controlling for option-implied beta, there is a significant and negative relationship between portfolio return and option-implied gamma for long-term investment horizons.

From the results presented in this section, we can see that, after taking the correlation between option-implied beta and gamma into consideration, for 1-year horizon, option-implied beta is positively related to asset returns, while option-implied gamma is negatively related to asset returns. Such results are consistent with what relevant theory predicts.

4. Results for Fama-MacBeth Cross-Sectional Regressions

4.1 Results for Firm-Level Cross-Sectional Regressions

To assure whether option-implied beta and gamma are priced in cross-section of stock returns, we run cross-sectional regressions. In above analysis, option-implied beta and gamma are calculated for each individual constituent of the S&P500 index. So, we use firm level cross-sectional regressions. We regress returns on individual stocks during holding periods of different length on option-implied beta, gamma and other firm-specific variables (i.e. size, book-to-market ratio, historical return during previous 12 to 2 month, historical return during previous 1 month, bid-ask spread, and stock trading volume during previous 1 month) at the end of each month. Then, we test whether the slope on each risk factor has 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.

Results for firm-level cross-sectional regressions are presented in Table 3.

[Insert Table 3 here]

If we run firm-level cross-sectional regressions among constituents of S&P500 without including control variables, we obtain results shown in Panel A. In this panel, both option-implied beta and gamma have significant average slopes. The average slope on option-implied beta is significant and positive in 5 out of 8 cases, while the average slope on option-implied gamma is significant and negative in 6 out of 8 cases.

Thus, without considering firm-specific control variables, we find that, for holding periods with intermediate length, option-implied beta is significantly and positively related to asset return, while option-implied gamma is significantly and negatively related to asset return.

Then, we include different firm-specific control variables into firm-level cross-sectional regressions to see whether the explanatory power of option-implied beta or gamma still persists. The corresponding results are presented in Panel B of Table 3. In this panel, there is no significant relationship between asset return and option-implied beta. For option-implied gamma, we can find a marginally significant and negative average slope in explaining stock returns for 4-month holding period (-0.0059 with a p-value of 0.0703). For firm-specific control variables, we can find some significant average slopes. Size is significantly and negatively related to asset returns (i.e. the size effect). We also find the existence of the Book-to-Market effect (stocks with low book-to-market ratios have lower returns). We can find the contrarian effect based on our analysis. Furthermore, there is a significant and negative relationship between bid-ask spread (i.e. a proxy of liquidity risk) and asset returns, and the relationship between trading volume and stock returns is significant and positive.

Thus, after including firm-specific control variables into cross-sectional regressions, the significance of the slope on option-implied beta or gamma is mitigated. Some of firm-specific effects are statistically related to individual stock returns. These results are consistent with the pricing anomalies documented in previous studies (such as the size effect in Banz, 1981; the book-to-market effect in Fama and French, 1992; the contrarian effect in De Bondt and

Thaler, 1985 and 1987). We can still find a marginally significant and negative average slope on option-implied gamma for 4-month predictive period. The cross-sectional regression results confirm the significance of risk premium on systematic skewness risk.

4.2 Results for Fama-MacBeth Two-Stage Cross-Sectional Regressions

We know that, for both beta and gamma calculation, we need to use option-implied central moments, as well as coefficients from regression by using historical information. In this section, we test whether the option-implied components for beta and gamma calculation have significant risk premiums. We use SMR to denote the option-implied component of beta, i.e. $SMR = (m_M^3)^Q/(\sigma_M^2)^Q$, and SSR to denote the option-implied component of gamma, i.e. $SSR = [(k_M^4)^Q - ((\sigma_M^2)^Q)^2]/(m_M^3)^Q$. These two components are calculated at aggregate level, so we use traditional two-stage Fama-MacBeth cross-sectional regressions. Instead of using individual stock return, we use returns on 25 portfolios constructed on size or book-to-market ratio among constituents of the S&P500 index. First, we regress daily portfolio excess returns during previous 1-month period on SMR and SSR calculated by using options with different day-to-expirations. In addition, we also include SMB, HML and UMD in the first-stage regressions. After obtaining beta coefficients on different factors, we use 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.

[Insert Table 4 here]

Table 4 presents results obtained by using 25 portfolios constructed on firm size. From Panel A of this table, we can find that MKT has significant and positive risk premium in 7 out of 8 cases (the only exception is for 1-month holding period). In addition, SMR has a significant and positive risk premium in cross-section of asset returns if the holding period varies from 2-month to 6-month. We can also find that UMD has significant and negative risk premium in explaining asset returns for mid- to long-term holding period. In Panel B, if portfolios are constructed by using value-weighting scheme, we can find similar results both in statistical significance and in magnitude. In addition, HML gains marginally significant and positive risk premium in explaining asset returns for period longer than 9 months.

[Insert Table 5 here]

In Table 5, we use 25 portfolios constructed on book-to-market ratio of individual firms. In Panel A of Table 5, it is clear that SSR has significant and negative risk premium in only one case with 2-month holding period (-0.0333 with p-value of 0.0888). SMB has significant and negative risk premium in explaining returns on book-to-market portfolios in all cases with different length of holding periods. HML gains marginally significant and positive risk premium in explaining asset returns for period longer than 9 months. However, if we construct value-weighted portfolios, we can find no significant risk premium on SMR or SSR.

From this subsection, through two-stage Fama-MacBeth cross-sectional regressions, we can find empirical evidence about positive risk premium on option-implied component for beta (i.e. SMR) in explaining cross-section of size portfolio return, and weak evidence about negative risk premium on option-implied component of gamma (i.e. SSR) in explaining cross-section of book-to-market portfolio return. That is, in addition to common-used risk factors (MKT, SMB, HML and UMD), option-implied components (SMR and SSR) used in our analysis have significant risk premiums in cross-section of asset returns. This indicates that the components used for option-implied beta and gamma calculation do incorporate useful information which cannot be captured by existing pricing factors.

5. Conclusion

Given the empirical evidence about the predictive power of higher moments shown in previous literature, we believe that the mean-variance approach cannot fully describe capital markets. In addition to the systematic variance risk, this study takes higher moments of asset returns into consideration, and focuses on the systematic skewness risk of individual stocks in addition to systematic variance risk.

In this study, we assume that the predictive power of aggregate skewness documented in previous studies is due to the systematic skewness risk, which is measured by gamma proposed in Kraus and Litzenberger (1976). Rather than using historical data for pricing factors' calculation, we incorporate forward-looking information. The results reveal that, in addition to beta, gamma is also an important factor in asset pricing. The empirical results for double-sorting portfolio level analysis in this study confirm that option-implied beta is positively related to asset return, while option-implied gamma is negatively related to asset return.

In order to make sure whether option-implied beta and gamma are priced in cross-section of asset returns, we run cross-sectional regressions. First, through firm-level cross-sectional regressions, we can verify that the relationship between asset return and option-implied beta is significant and positive, while the relationship between asset return and option-implied gamma is significant and negative. The significance of risk premium on option-implied gamma is even stronger than that of option-implied beta. Furthermore, we also examine 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 the importance of option-implied components used in calculating option-implied beta and gamma.

Overall, this study provide empirical evidence that, in addition to systematic variance risk, systematic skewness risk is of great importance in explaining time-series and cross-section of stock returns. Furthermore, using option-implied information in asset pricing incorporates useful information about future market conditions.

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Figure 1: Model-Free Central Moments of the S&P500 Index

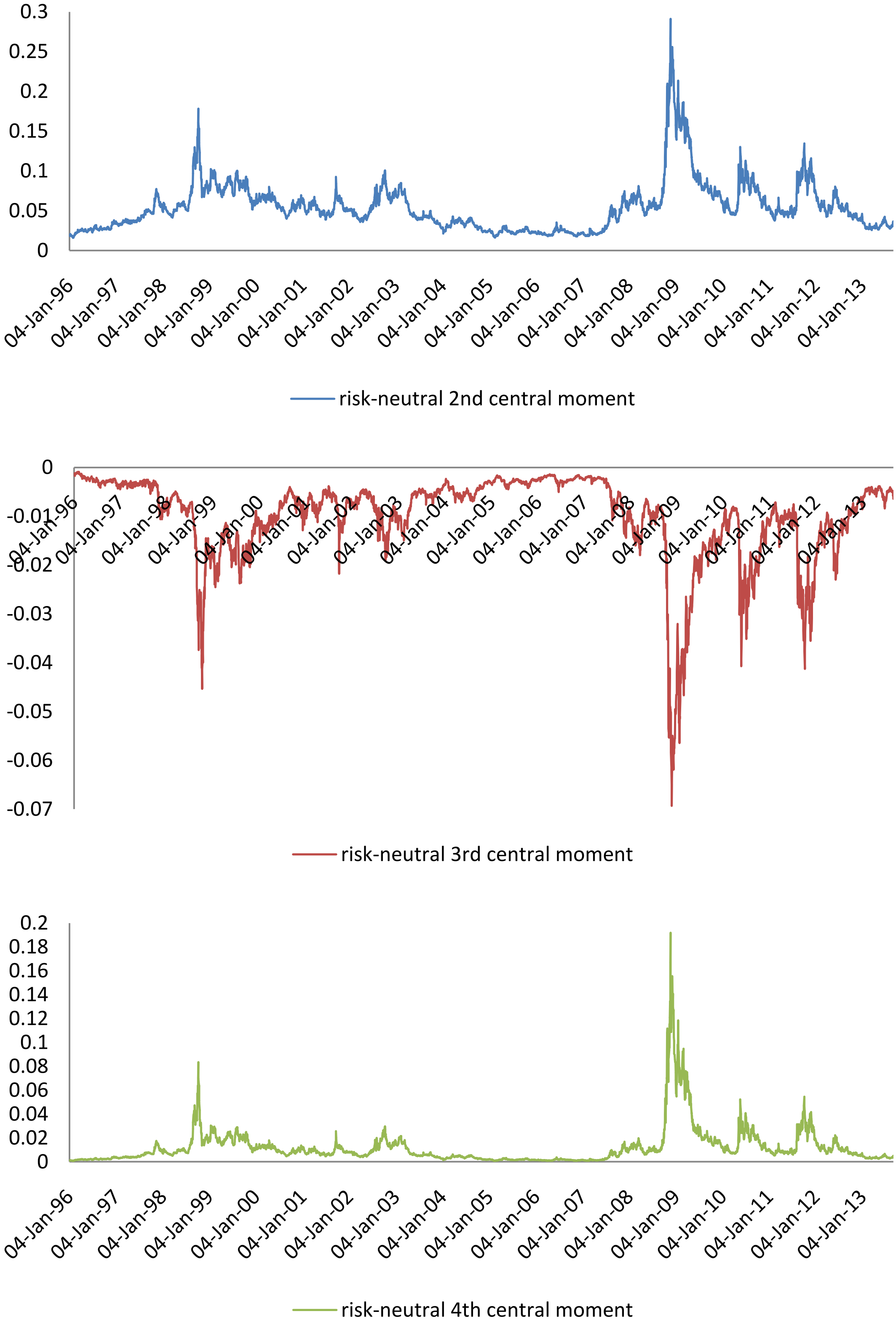

Table 1: Results for Quintile Portfolios Constructed on Option-Implied Beta While Controlling for Option-Implied Gamma

Note: In order to form quintile portfolios among constituents of the S&P500 index, we first run the following time-series regression:

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

Then, we use c_{1i} and c_{2i} to calculate option-implied beta and gamma:

$$\beta_i^Q = c_{1i} + c_{2i}[(m_M^3)^Q/(\sigma_M^2)^Q]$$

$$\gamma_i^Q = c_{1i} + c_{2i}\{[(k_M^4)^Q - ((\sigma_M^2)^Q)^2]/(m_M^3)^Q\}$$

$(\sigma_M^2)^Q$, $(m_M^3)^Q$ and $(k_M^4)^Q$ are calculated under risk-neutral measure by using the method derived in Bakshi, Kapadia and Madan (2003). To calculate model-free central moments, we use options with different day-to-maturity. First, we divide all individual stocks into five quintiles based on option-implied gamma. Within each gamma quintiles, we construct 5 portfolios on option-implied beta. Then, we average 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.

		1	2	3	4	5	5-1	p-value
1M	EW	0.0081	0.0080	0.0096	0.0111	0.0105	0.0024	(0.6253)
	VW	0.0068	0.0058	0.0087	0.0073	0.0078	0.0010	(0.8126)
2M	EW	0.0173	0.0175	0.0188	0.0227	0.0222	0.0048	(0.4879)
	VW	0.0142	0.0149	0.0149	0.0161	0.0165	0.0023	(0.7129)
3M	EW	0.0256	0.0267	0.0287	0.0340	0.0322	0.0067	(0.4098)
	VW	0.0219	0.0233	0.0238	0.0255	0.0242	0.0024	(0.7626)
4M	EW	0.0342	0.0368	0.0393	0.0452	0.0428	0.0086	(0.3571)
	VW	0.0288	0.0299	0.0329	0.0351	0.0327	0.0039	(0.6734)
5M	EW	0.0430	0.0489	0.0489	0.0562	0.0531	0.0101	(0.3140)
	VW	0.0360	0.0403	0.0412	0.0438	0.0412	0.0052	(0.6048)
6M	EW	0.0527	0.0592	0.0590	0.0671	0.0652	0.0126	(0.2526)
	VW	0.0432	0.0493	0.0496	0.0534	0.0499	0.0067	(0.5431)
9M	EW	0.0816	0.0891	0.0899	0.1016	0.1015	0.0200	(0.1300)
	VW	0.0675	0.0718	0.0753	0.0818	0.0796	0.0121	(0.3649)
12M	EW	0.1089	0.1185	0.1236	0.1345	0.1384	0.0295**	(0.0493)
	VW	0.0909	0.0992	0.1036	0.1036	0.1095	0.0186	(0.2271)

Table 2: Results for Quintile Portfolios Constructed on Option-Implied Gamma While Controlling for Option-Implied Beta

Note: In order to form quintile portfolios among constituents of the S&P500 index, we first run the following time-series regressions

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

Then, we use c_{1i} and c_{2i} to calculate option-implied beta and gamma:

$$\beta_i^Q = c_{1i} + c_{2i}[(m_M^3)^Q/(\sigma_M^2)^Q]$$

$$\gamma_i^Q = c_{1i} + c_{2i}\{[(k_M^4)^Q - ((\sigma_M^2)^Q)^2]/(m_M^3)^Q\}$$

$(\sigma_M^2)^Q$, $(m_M^3)^Q$ and $(k_M^4)^Q$ are calculated under risk-neutral measure by using the method derived in Bakshi, Kapadia and Madan (2003). To calculate model-free central moments, we use options with different day-to-maturity. First, we divide all individual stocks into five quintiles based on option-implied beta. Within each beta quintiles, we construct 5 portfolios on option-implied gamma. Then, we average 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.

		1	2	3	4	5	5-1	p-value
1M	EW	0.0116	0.0099	0.0101	0.0069	0.0088	-0.0028	(0.2898)
	VW	0.0103	0.0065	0.0076	0.0048	0.0069	-0.0034	(0.1839)
2M	EW	0.0235	0.0199	0.0189	0.0180	0.0182	-0.0053	(0.2342)
	VW	0.0199	0.0139	0.0152	0.0135	0.0140	-0.0058	(0.1469)
3M	EW	0.0338	0.0296	0.0285	0.0283	0.0271	-0.0067	(0.2075)
	VW	0.0281	0.0197	0.0227	0.0231	0.0214	-0.0067	(0.1911)
4M	EW	0.0440	0.0411	0.0379	0.0387	0.0366	-0.0074	(0.2633)
	VW	0.0359	0.0310	0.0288	0.0312	0.0281	-0.0078	(0.2059)
5M	EW	0.0524	0.0527	0.0486	0.0479	0.0484	-0.0040	(0.5874)
	VW	0.0419	0.0420	0.0357	0.0385	0.0380	-0.0039	(0.5820)
6M	EW	0.0623	0.0653	0.0598	0.0578	0.0580	-0.0043	(0.5986)
	VW	0.0481	0.0541	0.0448	0.0456	0.0474	-0.0007	(0.9316)
9M	EW	0.0974	0.0996	0.0942	0.0879	0.0848	-0.0126	(0.1940)
	VW	0.0750	0.0817	0.0691	0.0724	0.0714	-0.0036	(0.7038)
12M	EW	0.1355	0.1327	0.1243	0.1180	0.1134	-0.0221*	(0.0525)
	VW	0.1057	0.1099	0.0952	0.0932	0.0981	-0.0077	(0.4898)

Table 3: Firm-Level Cross-Sectional Regression Results

At the end of each calendar month, we regress individual stocks' returns during holding period with different length on option-implied beta and gamma with and without the inclusion of different firm-specific factors at the end of each calendar month:

$$R_i = a_i + b_\beta \beta_i + b_\gamma \gamma_i$$

$$R_i = a_i + b_\beta \beta_i + b_\gamma \gamma_i + b_{size}\, size_i + b_{B/M} B/M_i + b_{Ret12to2M} Ret12to2M_i + b_{Ret1M} Ret1M_i + b_{bid-askspread}\ bid-askspread_i + b_{vol}\, vol_i + \varepsilon_i$$

The length of the holding period is the same as the time-to-maturity of options used for beta and gamma calculation. Then, we test whether slopes on different factors have significantly non-zero mean through t-test.

Panel A: Firm Level Cross-Sectional Regression Results without Control Variables								
	1M	2M	3M	4M	5M	6M	9M	12M
Intercept	0.0053*	0.0110**	0.0168***	0.0222***	0.0282***	0.0338***	0.0550***	0.0744***
p-value	(0.0946)	(0.0174)	(0.0040)	(0.0013)	(0.0005)	(0.0002)	(0.0000)	(0.0000)
b_β	0.0054	0.0119	0.0181	0.0248*	0.0299*	0.0355**	0.0459**	0.0564**
p-value	(0.3466)	(0.1808)	(0.1137)	(0.0735)	(0.0633	(0.0479)	(0.0309)	(0.0241)
b_γ	-0.0013	-0.0036	-0.0061*	-0.0085**	-0.0096**	-0.0109**	-0.0116**	-0.0109*
p-value	(0.3508)	(0.1157)	(0.0500)	(0.0303)	(0.0372)	(0.0270)	(0.0327)	(0.0694)

(Continued)

Panel B: Firm Level Cross-Sectional Regression Results with Control Variables								
	1M	2M	3M	4M	5M	6M	9M	12M
Intercept	0.0053*	0.0105**	0.0163***	0.0212***	0.0280***	0.0356***	0.0568***	0.0793***
p-value	(0.0765)	(0.0137)	(0.0016)	(0.0005)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
b_{β}	0.0024	0.0052	0.0085	0.0127	0.0135	0.0134	0.0143	0.0201
p-value	(0.6246)	(0.4735)	(0.3415)	(0.2498)	(0.2826)	(0.3287)	(0.3841)	(0.3023)
b_{γ}	-0.0011	-0.0024	-0.0041	-0.0059*	-0.0058	-0.0056	-0.0041	-0.0031
p-value	(0.4100)	(0.2310)	(0.1079)	(0.0703)	(0.1202)	(0.1598)	(0.3544)	(0.5387)
b_{size}	-0.0154	-0.0301	-0.0466	-0.0622*	-0.0797*	-0.1036**	-0.1481**	-0.1818**
p-value	(0.3871)	(0.2508)	(0.1293)	(0.0885)	(0.0591)	(0.0255)	(0.0228)	(0.0264)
$b_{B/M}$	0.0037*	0.0064**	0.0090**	0.0113**	0.0130***	0.0142**	0.0254***	0.0318***
p-value	(0.0971)	(0.0304)	(0.0137)	(0.0102)	(0.0094)	(0.0104)	(0.0004)	(0.0002)
$b_{Ret\,12to2M}$	-0.0046	-0.0070	-0.0105	-0.0129	-0.0167	-0.0231*	-0.0313*	-0.0297
p-value	(0.3332)	(0.3199)	(0.2021)	(0.1877)	(0.1522)	(0.0890)	(0.0596)	(0.1181)
$b_{Ret\,1M}$	-0.0164**	-0.0317***	-0.0244*	-0.0334**	-0.0257	-0.0196	-0.0134	-0.0174
p-value	(0.0477)	(0.0085)	(0.0995)	(0.0351)	(0.1705)	(0.3716)	(0.6357)	(0.5953)
$b_{bid-askspread}$	-0.0059	-0.0149	-0.0202	-0.0347	-0.0398	-0.0529	-0.0939**	-0.1420**
p-value	(0.7016)	(0.4664)	(0.4107)	(0.1963)	(0.1649)	(0.1217)	(0.0477)	(0.0184)
b_{vol}	0.7825	1.4533	2.2430	2.4358	3.2695	4.6073*	8.8461**	11.5051**
p-value	(0.5033)	(0.3839)	(0.2199)	(0.2349)	(0.1607)	(0.0560)	(0.0142)	(0.0184)

Table 4: Two-Stage Fama-MacBeth Cross-Sectional Regression Results Using 25 Size Portfolios

Note: At the end of each calendar month, we form 25 portfolios based on firm size and calculate 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, we regress daily returns on each portfolio during previous one month on different market-based pricing factors to obtain factor loadings.

$$r_{p,t} - r_{f,t} = a_p + \beta_{p,MKT} MKT_t + \beta_{p,SMR} SMR_t + \beta_{p,SSR} SSR_t + \beta_{p,SMB} SMB_t + \beta_{p,HML} HML_t + \beta_{p,UMD} UMD_t$$

where $SMR = (m_M^3)^Q / (\sigma_M^2)^Q$ and $SSR = [(k_M^4)^Q - ((\sigma_M^2)^Q)^2]/(m_M^3)^Q$. Then, in the second step, we regress holding period returns on 25 portfolios on factor loadings cross-sectionally to obtain gamma.

$$r_p - r_f = a_p + \gamma_{MKT} \beta_{p,MKT} + \gamma_{SMR} \beta_{p,SMR} + \gamma_{SSR} \beta_{p,SSR} + \gamma_{SMB} \beta_{p,SMB} + \gamma_{HML} \beta_{p,HML} + \gamma_{UMD} \beta_{p,UMD}$$

Finally, we use the hypothesis test to make sure whether different pricing factors have significant risk premiums in cross-section of stock returns (i.e. whether mean of gamma is different from zero).

Panel A: Results for Fama-MacBeth Cross-Sectional Regressions Using Equally-Weighted Portfolios								
	30-Day	60-Day	91-Day	122-Day	152-Day	182-Day	273-Day	365-Day
intercept	0.0046	0.0055	0.0044	0.0067	0.0075	0.0083	0.0199	0.0330**
p-value	(0.2644)	(0.3335)	(0.5079)	(0.3702)	(0.3615)	(0.3743)	(0.1022)	(0.0197)
γ_{MKT}	0.0036	0.0116*	0.0216***	0.0281***	0.0361***	0.0438***	0.0596***	0.0746***
p-value	(0.4157)	(0.0541)	(0.0024)	(0.0006)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
γ_{SMR}	0.0053	0.0138***	0.0164**	0.0206***	0.0205**	0.0220**	0.0155	0.0180
p-value	(0.1377)	(0.0060)	(0.0194)	(0.0071)	(0.0299)	(0.0286)	(0.2022)	(0.1874)
γ_{SSR}	0.0205	-0.0102	0.0001	0.0003	0.0008	-0.0009	-0.0223	-0.0935
p-value	(0.5893)	(0.6000)	(0.9954)	(0.9901)	(0.9761)	(0.9768)	(0.6710)	(0.2596)
γ_{SMB}	-0.0018	0.0021	-0.0006	-0.0009	0.0010	-0.0009	-0.0063	-0.0081
p-value	(0.3997)	(0.5015)	(0.8649)	(0.8393)	(0.8367)	(0.8604)	(0.3498)	(0.3191)
γ_{HML}	0.0008	0.0019	0.0043	0.0048	0.0069	0.0084	0.0125	0.0171*
p-value	(0.7281)	(0.5759)	(0.2758)	(0.2935)	(0.2046)	(0.1833)	(0.1061)	(0.0706)
γ_{UMD}	-0.0009	-0.0022	-0.0067	-0.0098	-0.0144*	-0.0220**	-0.0422***	-0.0517***
p-value	(0.7927)	(0.6738)	(0.2475)	(0.1482)	(0.0740)	(0.0254)	(0.0006)	(0.0006)

(Continued)

Panel B: Results for Fama-MacBeth Cross-Sectional Regressions Using Value-Weighted Portfolios								
	30-Day	60-Day	91-Day	122-Day	152-Day	182-Day	273-Day	365-Day
intercept	0.0044	0.0055	0.0044	0.0069	0.0078	0.0082	0.0198*	0.0320**
p-value	(0.2846)	(0.3389)	(0.5128)	(0.3479)	(0.3401)	(0.3715)	(0.0967)	(0.0211)
γ_{MKT}	0.0036	0.0113*	0.0213***	0.0273***	0.0351***	0.0434***	0.0593***	0.0748***
p-value	(0.4089)	(0.0548)	(0.0024)	(0.0006)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
γ_{SMR}	0.0054	0.0131***	0.0145**	0.0190**	0.0202**	0.0222**	0.0193	0.0233*
p-value	(0.1218)	(0.0094)	(0.0407)	(0.0115)	(0.0271)	(0.0239)	(0.1153)	(0.0785)
γ_{SSR}	0.0108	-0.0189	-0.0054	-0.0020	-0.0036	-0.0040	-0.0231	-0.0980
p-value	(0.7653)	(0.3222)	(0.7993)	(0.9273)	(0.8915)	(0.8972)	(0.6495)	(0.2231)
γ_{SMB}	-0.0021	0.0020	-0.0006	-0.0010	0.0006	-0.0011	-0.0059	-0.0084
p-value	(0.3163)	(0.5103)	(0.8665)	(0.8146)	(0.8990)	(0.8262)	(0.3679)	(0.2833)
γ_{HML}	0.0010	0.0018	0.0041	0.0050	0.0074	0.0082	0.0137*	0.0184**
p-value	(0.6494)	(0.5903)	(0.2860)	(0.2645)	(0.1632)	(0.1709)	(0.0682)	(0.0444)
γ_{UMD}	-0.0011	-0.0018	-0.0065	-0.0097	-0.0143*	-0.0212**	-0. 0419***	-0.0520***
p-value	(0.7446)	(0.7224)	(0.2535)	(0.1453)	(0.0695)	(0.0253)	(0.0004)	(0.0004)

Table 5: Two-Stage Fama-MacBeth Cross-Sectional Regression Results Using 25 Book-to-Market Portfolios

Note: At the end of each calendar month, we form 25 portfolios based on book-to-market ratio and calculate 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, we regress daily returns on each portfolio during previous one month on different market-based pricing factors to obtain factor loadings.

$$r_{p,t} - r_{f,t} = a_p + \beta_{p,MKT} MKT_t + \beta_{p,SMR} SMR_t + \beta_{p,SSR} SSR_t + \beta_{p,SMB} SMB_t + \beta_{p,HML} HML_t + \beta_{p,UMD} UMD_t$$

where $SMR = (m_M^3)^Q/(\sigma_M^2)^Q$ and $SSR = [(k_M^4)^Q - ((\sigma_M^2)^Q)^2]/(m_M^3)^Q$. Then, in the second step, we regress holding period returns on 25 portfolios on factor loadings cross-sectionally to obtain gamma.

$$r_p - r_f = a_p + \gamma_{MKT}\beta_{p,MKT} + \gamma_{SMR}\beta_{p,SMR} + \gamma_{SSR}\beta_{p,SSR} + \gamma_{SMB}\beta_{p,SMB} + \gamma_{HML}\beta_{p,HML} + \gamma_{UMD}\beta_{p,UMD}$$

Finally, we use the hypothesis test to make sure whether different pricing factors have significant risk premiums in cross-section of stock returns (i.e. whether mean of gamma is different from zero).

Panel A: Results for Fama-MacBeth Cross-Sectional Regressions Using Equally-Weighted Portfolios

	30-Day	60-Day	91-Day	122-Day	152-Day	182-Day	273-Day	365-Day
intercept	0.0123***	0.0199***	0.0267***	0.0373***	0.0464***	0.0537***	0.0795***	0.1038***
p-value	(0.0010)	(0.0004)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ_{MKT}	-0.0032	-0.0014	0.0016	0.0007	0.0017	0.0040	0.0071	0.0129
p-value	(0.3698)	(0.8095)	(0.8221)	(0.9308)	(0.8640)	(0.7299)	(0.5750)	(0.3946)
γ_{SMR}	0.0024	0.0053	0.0047	-0.0044	0.0018	0.0031	0.0054	0.0123
p-value	(0.4969)	(0.2925)	(0.5167)	(0.5763)	(0.8480)	(0.7368)	(0.6444)	(0.4026)
γ_{SSR}	0.0215	-0.0333*	-0.0335	-0.0272	-0.0220	-0.0133	0.0135	0.0114
p-value	(0.2619)	(0.0888)	(0.1634)	(0.2841)	(0.4787)	(0.6945)	(0.8060)	(0.8849)
γ_{SMB}	-0.0035*	-0.0053*	-0.0075**	-0.0110**	-0.0119**	-0.0106*	-0.0127*	-0.0167**
p-value	(0.0792)	(0.0674)	(0.0348)	(0.0161)	(0.0184)	(0.0608)	(0.0558)	(0.0431)
γ_{HML}	0.0008	0.0020	0.0029	0.0039	0.0051	0.0074	0.0124*	0.0152*
p-value	(0.6903)	(0.4728)	(0.3938)	(0.3388)	(0.3014)	(0.1798)	(0.0599)	(0.0547)
γ_{UMD}	-0.0014	-0.0013	-0.0032	-0.0052	-0.0055	-0.0044	-0.0116	-0.0168
p-value	(0.6482)	(0.7696)	(0.5455)	(0.4111)	(0.4568)	(0.6022)	(0.2308)	(0.1588)

(Continued)

Panel B: Results for Fama-MacBeth Cross-Sectional Regressions Using Value-Weighted Portfolios								
	30-Day	60-Day	91-Day	122-Day	152-Day	182-Day	273-Day	365-Day
intercept	0.0158***	0.0194***	0.0250***	0.0302***	0.0358***	0.0420***	0.0702***	0.1002***
p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ_{MKT}	-0.0086**	-0.0047	-0.0018	0.0014	0.0045	0.0062	0.0041	0.0007
p-value	(0.0289)	(0.4039)	(0.7906)	(0.8573)	(0.6300)	(0.5433)	(0.7280)	(0.9628)
γ_{SMR}	-0.0009	0.0019	0.0068	0.0085	0.0135	0.0114	0.0074	0.0013
p-value	(0.7880)	(0.7184)	(0.3224)	(0.2760)	(0.1187)	(0.2436)	(0.5270)	(0.9232)
γ_{SSR}	0.0064	-0.0114	-0.0048	0.0168	0.0271	0.0218	0.0308	0.0409
p-value	(0.8368)	(0.5777)	(0.8373)	(0.4791)	(0.3180)	(0.4775)	(0.5059)	(0.5294)
γ_{SMB}	-0.0004	-0.0042	-0.0039	-0.0038	-0.0029	-0.0049	-0.0065	-0.0126*
p-value	(0.8412)	(0.1675)	(0.2538)	(0.3855)	(0.5302)	(0.3394)	(0.2955)	(0.0999)
γ_{HML}	0.0010	0.0016	0.0015	0.0018	0.0016	0.0032	0.0065	0.0109
p-value	(0.5800)	(0.5400)	(0.6389)	(0.6522)	(0.7158)	(0.5311)	(0.2924)	(0.1446)
γ_{UMD}	0.0004	0.0006	-0.0044	-0.0056	-0.0057	-0.0024	-0.0081	-0.0130
p-value	(0.8953)	(0.8900)	(0.3700)	(0.3145)	(0.3588)	(0.7398)	(0.3655)	(0.2357)