Asymmetric Variance Premium, Skewness Premium, and the Cross-Section of Stock Returns

Tao Huang* Junye Li† Fei Wu‡

First Version: June 2017; This version: July 2018

Abstract

We find a positive relationship between the individual stocks' asymmetric variance premia, defined as the difference between the risk-neutral and physical expected variance asymmetries, and the future stock returns. The high-minus-low hedge portfolio earns the excess return of 72 basis points per month, the characteristic-adjusted return of 66 basis points per month, and the industry-adjusted return of 79 basis points per month. They are all economically substantial and statistically highly significant. We show that asymmetric variance premium is closely related to skewness premium. Such a positive relationship can not be explained by risk-based asset pricing models. We find that the predictive power of asymmetric variance premium is information-driven and reflects trading activity of informed traders who place more transactions on options.

Keywords: Asymmetric Variance Premium, Skewness Premium, Return Predictability, Informed Trading, Liquidity, Limits-to-Arbitrage, Corporate Events.

JEL Classification: G11, G12, G14

*International Business School Suzhou, Xi'an Jiaotong-Liverpool University, Suzhou, China. Email: tao.huang@xjtlu.edu.cn

†ESSEC Business School, Paris-Singapore, Singapore. Email: li@essec.edu

‡Shanghai Advanced Institute of Finance, Shanghai Jiaotong Univeristy, Shanghai, China. Email: fwu@saif.sjtu.edu.cn

1. Introduction

It is argued that semivariances or variance asymmetry (i.e., the difference between upside and downside semivariances) provide a complement to or maybe a better measure than variance in evaluating risk (Markowitz, 1959, 1991). A number of recent papers find that market variance premium can predict stock market returns (Bollerslev, Tauchen, and Zhou, 2009; Drechsler and Yaron, 2011; Bollerslev et al., 2014), and Han and Zhou (2011) provide some evidence of the positive relationship between individual stocks' variance premia and future stock returns. However, it is not clear how premium to semivariances or variance asymmetry is related to stock returns. In this paper, we implement a cross-sectional analysis and examine the relationship between individual stocks' asymmetric variance premia, defined as the difference between the risk-neutral and physical variance asymmetries, and future stock returns.

Equipped with individual stock option prices, we infer the risk-neutral variance asymmetry from the out-of-money call and put options following similar methods proposed by Bakshi and Madan (2000) and Bakshi, Kapadia, and Madan (2003), whereas the physical variance asymmetry is estimated using realized variance (Andersen et al., 2001; Barndorff-Nielsen and Shephard, 2004) and realized semivariances (Barndorff-Nielsen, Kinnebrock, and Shepard, 2010). Using all common stocks listed on NYSE, AMEX, and NASDAQ with valid options and high-frequency data, we find that individual asymmetric variance premium is negative in general. Economically, if stock variance responds more strongly to negative returns than to positive returns, the negative sign of asymmetric variance premium suggests that the risk-neutral return distribution has greater variance asymmetry than the physical distribution has.

To investigate predictive power of individual stocks' asymmetric variance premia for stock returns, we implement portfolio analysis in ways similar to Fama and French (1996). At the end of each month from January 1996 to December 2013, we sort all stocks into quintile portfolios based on asymmetric variance premium and construct a high-minus-low hedge portfolio that longs the top quintile portfolio and shorts the bottom quintile portfolio. We hold these portfolios over the next month and compute their equal-weighted excess returns, characteristic- and industry-adjusted returns. We find that all three types of returns for portfolios 1 to 5 monotonically increase with respect to asymmetric variance premium. Furthermore, the hedge portfolio earns economically substantial and statistically significant excess return, characteristic- and industry-adjusted returns. It earns the excess return of 0.72% (t = 3.68) per month, and earns the characteristic- and industry-adjusted returns of 0.66% (t = 4.95) and 0.79% (t = 5.29) per month, respectively. Similar results are also observed in two independent double portfolio sorts, in which individual stock variance and variance risk premium are taken as respective control variables.

The risk-adjusted portfolio returns have similar patterns and deliver exactly the same implications. In each of the four factor models, i.e., the Fama-French three-factor model (Fama and French, 1993), the Carhart four-factor model (Carhart, 1997), the q-factor model (Hou, Xue, and Zhang, 2015), and the mispricing factor model (Stambaugh and Yuan, 2017), alphas from portfolios 1 to 5 monotonically increase with respect to asymmetric variance premium, and the hedge portfolio's alpha is economically substantial and statistically highly significant. We also find that portfolios with low asymmetric variance premia significantly underperform. The above results suggest that there exists a positive relationship between individual stocks' asymmetric variance premia and future stock returns. However, we find that the positive relationship between individual stocks' variance risk premia and future stock returns is not as strong as Han and Zhou (2011) suggest.

In addition to portfolio analysis, we also conduct Fama-MacBeth cross-sectional regressions, which allow us for controlling for a large number of variables. We consider some standard variables used in literature such as beta (Sharpe, 1964; Lintner, 1965), size (Banz, 1981; Lakonishok and Shapiro, 1986; Fama and French, 1992, 1993), book-to-market ratio (Fama and French, 1992), and momentum (Jegadeesh and Titman, 1993). We also control for a number of stock-related variables and option-related variables. In spite of such extensive controls, the coefficient on asymmetric variance premium is always positive and statistically significant. This result provides further evidence in support of our finding that the higher asymmetric variance premium is, the larger the future returns should be.

We show that our variance asymmetry measures satisfy properties proposed by Groeneveld and Meeden (1984) that any reasonable skewness measure should have, suggesting that asymmetric variance premium is closely related to skewness premium. To check this point, using both option and high-frequency data, we construct standard skewness premium, which is defined as the difference between the risk-neutral and physical expected skewness for each individual stock. We find that the cross-sectional correlation between asymmetric variance premium and standard skewness premium remains high over time. The time-series average is about 0.75. The portfolio analysis and Fama-MacBeth regressions based on standard skewness premium reveals a positive relationship between standard skewness premium and future stock returns. Furthermore, we find that the time series of monthly returns of the hedge portfolios based on asymmetric variance premium and on standard skewness premium fluctuate in parallel. Put together, we have a general result that skewness premium positively predicts future stock returns.

Can such a positive relationship be explained by risk-based equilibrium asset-pricing models? A large number of works argue that investors are of aversion to skewness risk (Arditti, 1967, 1971; Kraus and Litzenberger, 1976; Simkowitz and Beedles, 1978; Scott and Horvath, 1980; Conine and Tamarkin, 1981; Kane, 1982; Harvey and Siddique, 2000; Mitton and Vorkink, 2007).[1] Therefore, given that the risk-neutral measure has already internalized such skewness-aversion, the more negative asymmetric variance premium is, the higher investors' skewness-aversion should be. This should predict a negative relationship between asymmetric variance premium and future stock returns.

[1] Arditti (1967, 1971) shows both theoretically and empirically that investors require a higher risk premium on an investment whose return distribution is negatively skewed. Kraus and Litzenberger (1976) introduces a three-moment capital asset pricing model, which shows that expected return depends both on systematic variance and systematic skewness. Simkowitz and Beedles (1978) and Conine and Tamarkin (1981) argue that in the circumstances of non-perfect diversification, idiosyncratic skewness is relevant to pricing securities. Scott and Horvath (1980) extend Arditti's work and introduce both skewness and other higher moments in asset pricing. Kane (1982) shows that investment in risky assets is also affected by portfolio skewness and argues that skewness preference may cause investors not to completely diversify. Harvey and Siddique (2000) introduce systematic skewness into the pricing of securities through a stochastic discount factor and find that co-skewness is a priced factor. Mitton and Vorkink (2007) propose a model in which heterogeneous skewness preference makes investors underdiversify and show that idiosyncratic skewness affects asset prices.

The inconsistency may reveal that the stock and options markets are not fully integrated. When some informed investors choose to trade in options before trading in the underly stocks, the positive relationship may reflect the trading activity of informed traders. Easley, O'Hara, and Srinivas (1998) propose a multimarket sequential trade model, which incorporates both options and stocks. They argue that there exists a pooling equilibrium, in which informed traders may choose to trade either in the stock market or in the options market based on profits available. When the trader is informed of a good news, he/she may buy calls or sell puts. Such a trade increases call prices relative to put prices and makes the risk-neutral variance asymmetry large, resulting in a positive relationship between asymmetric variance premium and future stock returns. The pooling equilibrium can be reached and informed traders choose to trade options when the leverage and liquidity in options is high relative to stocks, and/or the overall fraction of informed traders is high.

We therefore test whether return predictability by asymmetric variance premium is stronger among stocks whose liquidity is low relative to liquidity of options written on them, and is stronger among stocks with more concentration of informed traders. We find that no matter which option liquidity measure and how to compute option liquidity, there is more predictability when option liquidity is high relative to stock liquidity and less predictability when option liquidity is low relative to stock liquidity. Furthermore, Using the PIN variable proposed by Easley, Kiefer, and O'Hara (1997) and Easley, Hvidkjaer, and O'Hara (2002) as a measure of the prevalence of informed traders and information asymmetry, we find that the positive relation between skewness premium and future stock returns is stronger among high PIN stocks.

We implement event studies to check where informed traders' information advantage comes from. We find that asymmetric variance premium immediately before both anticipated and unanticipated events has dominant predictive power for event returns. Kim and Verrecchia (1991) suggest that both informed and uninformed traders have strong incentives to acquire private information before anticipated information events such as earnings announcements. Skinner (1997) argues that informed traders' information advantage may become large immediately before significant corporate disclosures. Hence, this finding indicates that the predictive ability of asymmetric variance premium is information-driven and may suggest that informed traders have access to private information and trade on such private information before information events. We further find that asymmetric variance premium immediately after both anticipated and unanticipated events has predictive power for future post-event excess returns and such predictive power is much stronger in the case of unanticipated information events. Consistent with what Kim and Verrecchia (1994) suggest, this finding implies that informed traders have superior ability to process public information and such superior ability is much stronger when processing information that is less anticipated and/or more difficult to interpret.

The effect of informed trading could become more pronounced when there are greater limits-to-arbitrage in the underlying stocks. We then test whether limits-to-arbitrage do contribute to underperformance (overperformance) of portfolios with low (high) asymmetric variance premium. We use institutional ownership, idiosyncratic volatility, and analyst forecast dispersion to proxy limits-to-arbitrage. Based on each of these three proxies and asymmetric variance premium, we implement dependent or conditional double portfolio sorts. We find that the positive relation between asymmetric variance premium and future stock returns is stronger among stocks with severe limits to arbitrage. Stocks that significantly underperform are mostly those that are difficult to arbitrage and have small skewness premium.

The rest of the paper is organized as follows. Section 2 introduces our measure of asymmetric variance premium. Section 3 introduces the data and provides summary statistics. Section 4 investigates asymmetric variance premium and return predictability using portfolio analysis and Fama-MacBeth cross-sectional analysis. Section 5 implements several robustness checks. Section 6 investigates the relation between asymmetric variance premium and skewness premium. Section 7 provides some possible explanations of our main findings. Section 8 concludes the paper.

2. Asymmetric Variance Premium: Theory and Measures

In this section, we develop our measure of asymmetric variance premium (AVP). Under a given probability space, $(\Omega, \mathbb{P}, \mathcal{F})$, and the complete filtration, $\{\mathcal{F}_t\}_{t\geq 0}$, the individual stock price, $S_{i,t}$, is defined. The corresponding continuously compounded return is given by $R_{i,t} = \log(\frac{S_{i,t}+D_{i,t}}{S_{i,t-1}})$, where $D_{i,t}$ is the dividend payment of stock i at time t. Furthermore, assume that there exists at least one almost surely positive process, K_t, with $K_0 = 1$, such that the discounted gain process associated with any admissible trading strategy is a martingale (Harrison and Kreps, 1979). The K_t process is the stochastic discount factor or pricing kernel, which defines the risk-neutral probability measure, $\mathbb{Q}$, under which any contingent claims can be priced using the risk-neutral valuation. In what follows, we first discuss how to measure the risk-neutral and physical measures of variance asymmetry in Subsections 2.1 and 2.2, respectively, and then define our asymmetric variance premium in Subsection 2.3.

2.1. Option-Implied Variance and Semivariances

We follow the methods proposed by Bakshi and Madan (2000) and Bakshi, Kapadia, and Madan (2003) to infer the risk-neutral variance from the cross-section of out-of-money options in a model-free approach for each individual stock. Specifically, Bakshi and Madan (2000) show that any payoff function with bounded expectation on a stock can be spanned by a continuum of out-of-money call and put prices on that stock. Bakshi, Kapadia, and Madan (2003) define the variance, cubic, and quartic contracts and show how to compute the risk-neutral variance, skewness, and kurtosis using these contracts.

Consider the time-t price of a variance contract on stock i that pays off the squared log return at time $t+1$:

$$IV_{i,t} \equiv e^{-r_t^f \tau} \mathbb{E}^{\mathbb{Q}} \Big[R_{i,t+1}^2 | \mathcal{F}_t \Big], \tag{1}$$

where r_t^f is the risk-free rate of interest, τ is the time to maturity in years from time t to time $t+1$, and $\mathbb{E}^{\mathbb{Q}}$ defines the expectation under the risk-neutral measure. $IV_{i,t}$ is then the forward-looking expected risk-neutral variance. Bakshi, Kapadia, and Madan

(2003) show that $IV_{i,t}$ can be extracted from the out-of-money call and put option prices as follows,

$$IV_{i,t} = \int_{S_{i,t}}^{\infty} \frac{2\Big(1 - \log(\frac{K_i}{S_{i,t}})\Big)}{K_i^2} C(t,\tau;K_i)dK_i + \int_{0}^{S_{i,t}} \frac{2\Big(1 + \log(\frac{S_{i,t}}{K_i})\Big)}{K_i^2} P(t,\tau;K_i)dK_i, \quad (2)$$

where $C(t,\tau;K_i)$ and $P(t,\tau;K_i)$ are the time-t prices of the out-of-money call and put options, respectively, with the time-to-maturity of τ and the strike of K_i.

Similar to the variance contract, we can define an upside semivariance contract that pays off the squared positive log return, and a downside semivariance contract that pays off the squared negative log return. Their time-t prices are given by

$$IV_{i,t}^{+} \equiv e^{-r_t^f \tau}\mathbb{E}^{\mathbb{Q}}\Big[R_{i,t+1}^2 1_{R_{i,t+1}>0}|\mathcal{F}_t\Big], \quad (3)$$

$$IV_{i,t}^{-} \equiv e^{-r_t^f \tau}\mathbb{E}^{\mathbb{Q}}\Big[R_{i,t+1}^2 1_{R_{i,t+1}\leq 0}|\mathcal{F}_t\Big]. \quad (4)$$

Following the same argument as that in Bakshi, Kapadia, and Madan (2003), we can obtain

$$IV_{i,t}^{+} = \int_{S_{i,t}}^{\infty} \frac{2\Big(1 - \log(\frac{K_i}{S_{i,t}})\Big)}{K_i^2} C(t,\tau;K_i)dK_i, \quad (5)$$

$$IV_{i,t}^{-} = \int_{0}^{S_{i,t}} \frac{2\Big(1 + \log(\frac{S_{i,t}}{K_i})\Big)}{K_i^2} P(t,\tau;K_i)dK_i. \quad (6)$$

From Equations (1) to (6), it is clear that $IV_{i,t} = IV_{i,t}^{+} + IV_{i,t}^{-}$ holds.

Given the total risk-neutral variance, $IV_{i,t}$, and its upside and downside semivariances, $IV_{i,t}^{+}$ and $IV_{i,t}^{-}$, we define the risk-neutral variance asymmetry for stock i as the difference between the upside and downside risk-neutral semivariances normalized by the total risk-neutral variance:

$$VAQ_{i,t} = \frac{IV_{i,t}^{+} - IV_{i,t}^{-}}{IV_{i,t}}, \quad (7)$$

where the normalization is taken because the risk-neutral variance may differ substantially across individual stocks.

2.2. Realized Variance and Semivariances

In addition to the risk-neutral measures of variance and its upside and downside components, we construct the corresponding realized measures using the high-frequency data. In accordance with Andersen et al. (2001, 2003) and Barndorff-Nielsen and Shephard (2004), the realized variance of any stock i for any period t is simply defined as the summation of the squared high-frequency log returns in this period,

$$RV_{i,t} = \sum_{j=1}^{n_t} R_{i,t,j}^2, \tag{8}$$

where n_t denotes the number of the high-frequency returns recorded in this period. It has been shown that realized variance converges to quadratic variation when n_t goes to infinity.

Barndorff-Nielsen, Kinnebrock, and Shepard (2010) show that realized variance can be decomposed into upside and downside semivariances such that

$$RV_{i,t} = RV_{i,t}^+ + RV_{i,t}^-, \tag{9}$$

where $RV_{i,t}^+$ and $RV_{i,t}^-$ are upside and downside realized variance, respectively, defined as

$$RV_{i,t}^+ = \sum_{j=1}^{n_t} R_{i,t,j}^2 1_{R_{i,t,j}>0}, \qquad RV_{i,t}^- = \sum_{j=1}^{n_t} R_{i,t,j}^2 1_{R_{i,t,j}\leq 0}. \tag{10}$$

Similar to the risk-neutral measures that are forward-looking expected values, we also construct the expected realized measures,

$$\widetilde{RV}_{i,t} \equiv \mathbb{E}^{\mathbb{P}}\Big[RV_{i,t+1}|\mathcal{F}_t\Big], \tag{11}$$

and

$$\widetilde{RV}_{i,t}^+ \equiv \mathbb{E}^{\mathbb{P}}\Big[RV_{i,t+1}^+|\mathcal{F}_t\Big], \qquad \widetilde{RV}_{i,t}^- \equiv \mathbb{E}^{\mathbb{P}}\Big[RV_{i,t+1}^-|\mathcal{F}_t\Big]. \tag{12}$$

To solve the $\mathbb{P}$-expectations in Equations (11) and (12), we consider the following two variance forecasting models:

- Random Walk Model: we assume that realized variance, $RV_{i,t}$, and realized semi-variances, $RV_{i,t}^{+}$ and $RV_{i,t}^{-}$, all follow random walks, indicating

$$\widetilde{RV}_{i,t} = RV_{i,t}, \qquad \widetilde{RV}_{i,t}^{+} = RV_{i,t}^{+}, \qquad \widetilde{RV}_{i,t}^{-} = RV_{i,t}^{-}. \tag{13}$$

- ARX(1) Model: we assume that realized variance, $RV_{i,t}$, follows the following dynamics,

$$RV_{i,t+1} = \alpha + \beta RV_{i,t} + \gamma IV_{i,t} + \epsilon_{i,t}, \tag{14}$$

  indicating $\widetilde{RV}_{i,t} = \hat{\alpha} + \hat{\beta} RV_{i,t} + \hat{\gamma} IV_{i,t}$. The same forecasting model is also assumed for both $RV_{i,t}^{+}$ and $RV_{i,t}^{-}$.

Based on the expected realized measures, $\widetilde{RV}_{i,t}$, $\widetilde{RV}_{i,t}^{+}$, and $\widetilde{RV}_{i,t}^{-}$, we define the physical variance asymmetry for stock i in the same fashion as Equation (7) as follows,

$$VAP_{i,t} = \frac{\widetilde{RV}_{i,t}^{+} - \widetilde{RV}_{i,t}^{-}}{\widetilde{RV}_{i,t}}. \tag{15}$$

2.3. Variance Risk Premium and Asymmetric Variance Premium

Formally, variance risk premium (VRP) is defined as the difference between the risk-neutral and physical expected quadratic variations (QV),

$$VRP_{i,t} = \mathbb{E}^{\mathbb{Q}}\Big[QV_{i,t+1}|\mathcal{F}_t\Big] - \mathbb{E}^{\mathbb{P}}\Big[QV_{i,t+1}|\mathcal{F}_t\Big]. \tag{16}$$

The $\mathbb{Q}$-expectation in Equation (16) can be well captured by $IV_{i,t}$, and the $\mathbb{P}$-expectation in Equation (16) can be approximated by $\widetilde{RV}_{i,t}$. This suggests that variance risk premium at each time t for stock i can be computed as

$$VRP_{i,t} = IV_{i,t} - \widetilde{RV}_{i,t}. \tag{17}$$

Following the same argument, we define asymmetric variance premium at each time

t for stock i as the difference between the risk-neutral and physical variance asymmetry,

$$\begin{aligned} AVP_{i,t} &= VAQ_{i,t} - VAP_{i,t} \\ &= \frac{IV_{i,t}^{+} - IV_{i,t}^{-}}{IV_{i,t}} - \frac{\widetilde{RV}_{i,t}^{+} - \widetilde{RV}_{i,t}^{-}}{\widetilde{RV}_{i,t}}, \end{aligned} \tag{18}$$

which is our key variable in the cross-sectional analysis.

3. Data and Summary Statistics

3.1. Data

The sample we use in this paper combines different data sources and covers the period ranging from January 4, 1996 to December 31, 2013. Individual stock options data are obtained from OptionMetrics. We download the volatility surface file, which contains the interpolated implied volatility on standardized options with respect to deltas (Δ) and maturities for each security on each day. A stock needs to have option data for more than 2 years in order to be included in our dataset. Based on these data, we compute daily option-implied variance and semivariances using out-of-money call options ($0 < \Delta < 0.50$) and out-of-money put options ($-0.50 < \Delta < 0$) with time-to-maturity of 30 days. The monthly option-implied variance and semivariances are those of the last trading day in each month. Option volume file and yield curve file are also downloaded to access information on option trading volume and open interest and to interpolate the 30-day risk-free interest rates, respectively.

For constructing the realized measures, we rely on intraday high-frequency data obtained from the Trade and Quote (TAQ) database. TAQ provides historical tick-by-tick price data for all individual stocks listed on NYSE, AMEX, and NASDAQ. We rely on the consolidated trade file to construct the five-minute and fifteen-minute log returns starting from 9:30am to 4.00pm in each day and then compute both the daily and monthly annualized realized variance and semivariances. A stock is excluded when its high-frequency data available in a month are less than 15 days.

We download daily and monthly stock returns, shares outstanding, and daily and monthly trading volumes for each individual stock from the Center for Research in Security Prices (CRSP). To avoid survivorship bias, we adjust the individual stock returns for delisting. The firm-specific accounting data such as book equity are downloaded from Compustat. All common stocks trading on the NYSE, AMEX, and NASDAQ with valid options and high-frequency data are included in the sample. In total, there are 4,388 stocks in our sample.

3.2. Summary Statistics

Panel A of Table 1 presents summary statistics of variance risk premium and asymmetric variance premium. We report the number of firms included in our sample and medians and (10, 90)% quantiles of VRPs and AVPs across individual stocks for each year. There are only 910 firms in our sample in 1996. However, this number increases and there are 2,331 firms in our sample in 2013. We see that different from stock index VRP, which is always positive (Carr and Wu, 2009), individual stock's VRP can be positive or negative, as the 10% quantile of individual VRPs is negative and the 90% quantile of individual VRPs is positive in each year. The VRP median is negative before 2012. It then become positive afterwards except the year of 2008. We also notice that the individual stock's AVP can be positive or negative as the 10% quantile of individual AVPs is always negative and the 90% quantile of individual AVPs is always positive in each year. However, we find that the AVP median is negative over years. If stock variance responds more strongly to negative returns than to positive returns, the negative sign of AVP indicates that the risk-neutral return distribution has greater variance asymmetry than the physical distribution does.

Panel B of Table 1 presents summary statistics across AVP-based quintile portfolios. We see that there is virtually no relation between AVP and beta, size, or momentum, as when AVP increases in the portfolio, there is no clear increasing or decreasing tendency in these variables. There is some evidence of correlation between AVP and B/M, idiosyncratic volatility (IVol), or illiquidity. However, we find strong relation between AVP and reversal (Rev), maximum/minimum daily returns in the previous month (Max/Min), or put-call volume ratio (PCR), as when AVP increases, reversal declines, Max/Min decreases, and PCR increases.

4. Asymmetric Variance Premium and Return Predictability

In this section, we implement monthly cross-sectional analysis and examine the relationship between individual stocks' asymmetric variance premia and future returns. Throughout the section, to compute the expected realized measures, we assume random walks for realized variance and semivariances. In the next section, we will conduct a robustness check by assuming the ARX(1) model for the three realized measures. We first implement portfolio sorts in Subsection 4.1, and then perform Fama-MacBeth cross-sectional regressions in Subsection 4.2.

4.1. Portfolio Analysis

4.1.1. Single-Sorted Portfolios

In this part, we implement two independent single portfolio sorts based on variance risk premium (VRP) and asymmetric variance premium (AVP), respectively. Similar to Fama and French (1996), we sort all firms on the basis of their respective VRPs and AVPs into quintiles at the end of each month from January 1996 to December 2013. We then hold these quintile portfolios over the next month and computer their equal-weighted monthly returns. A hedge portfolio that longs the high VRP/AVP portfolio and shorts the low VRP/AVP portfolio is also formed.

Panel A of Table 2 presents average monthly returns in excess of one-month Treasury bill rate for the quintile and hedge portfolios based on VRP. We see that the average monthly excess returns for portfolios 1 to 5 monotonically increase with respect to VRP. They are 0.25%, 0.55%, 0.69%, 0.83%, and 0.85%, respectively. Furthermore, the monthly average excess return of the high-minus-low hedge portfolio is about 0.60%, which is statistically significant ($t = 2.46$). These results indicate that there may exist a positive cross-sectional relation between variance risk premium and future stock returns. Similar relation has been found by Han and Zhou (2011). To make sure that this relationship is robust for firm characteristics and industry effects. We also compute the characteristic- and industry-adjusted portfolio returns. The characteristic-adjusted returns are computed following Daniel et al. (1997) as the difference between individual stock returns and 125 size/book-to-market/momentum benchmark portfolio returns, and the industry-adjusted returns are calculated as the difference between individual stock returns and the returns in the same industry according to Fama-French 17 industry classifications. We see that both characteristic- and industry-adjusted returns for portfolios 1 to 5 monotonically increase with respect to VRP. The hedge portfolio earns the characteristic-adjusted return of 0.34% ($t = 2.12$) per month, and earns the industry-adjusted return of 0.49% ($t = 2.96$) per month. Putting together, the results seem to be consistent to fundamental theoretical prediction that rational investors would like to pay a premium to hedge against variance risk.

We now move to Panel B of Table 2 that presents average monthly excess returns, characteristic- and industry-adjusted returns for quintile portfolios and the hedge portfolio based on AVP. First, all three types of returns for portfolios 1 to 5 monotonically increase with respect to AVP. For example, the average monthly excess returns monotonically increase from 0.26% for portfolio 1 to 0.98% for portfolio 5, the average monthly characteristic-adjusted returns monotonically increase from -0.42% for portfolio 1 to 0.24% for portfolio 5, and the average monthly industy-adjusted returns monotonically increase from -0.72% for portfolio 1 to 0.07% for portfolio 5. Second, more importantly, we find that the high-minus-low hedge portfolio earns economically substantial and highly statistically significant returns. Its average monthly excess return is 0.72% ($t = 3.68$), and its characteristic- and industry-adjusted returns are 0.66% ($t = 4.95$) and 0.79% ($t = 5.29$) per month, respectively. These results suggest that there exists a positive cross-sectional relation between individual stocks' asymmetric variance premia and future stock returns.

4.1.2. Double-Sorted Portfolios

The results from the standard single portfolio sort reveals a strong positive relationship between asymmetric variance premium and future stock returns. We further implement two independent double-sort portfolio analysis to make sure that this positive relationship is robust for controlling for variance, measured by realized variance, and variance risk premium, respectively. At the end of each month, we first sort all stocks into quintile portfolios based independently on AVP and on either variance or VRP. We then form 25 portfolios based on the intersection of the two types of portfolios. We hold these portfolios over the next month and report their average monthly equal-weighted excess returns. The high-minus-low hedge portfolio returns based on asymmetric variance premium and on either variance or variance risk premium are also reported.

Panel A of Table 3 present portfolio returns from independent double-sort based on variance and AVP. We observe that holding variance constant, AVP continues to be positively related to future stock returns: for all levels of variance, the average monthly excess returns for portfolios 1 to 5 have increasing patterns with respect to AVP, and the high-minus-low hedge portfolios remain to earn statistically significant positive returns. For example, for stocks with low variance, the AVP-based hedge portfolio earns a monthly excess return of 0.24% ($t = 2.32$), whereas for stocks with high variance, it earns a monthly excess return of 0.98% ($t = 3.35$). We also observe some evidence of the negative relationship between variance and future stock returns as for all levels of AVP, the variance-based high-minus-low hedge portfolios earn negative returns. However, such a relationship only holds in stocks with low and middle levels of AVP.

Panel B of Table 3 presents portfolio returns from independent double-sort based on VRP and AVP. Similar results have been observed. Holding VRP constant, the average monthly excess returns for portfolios 1 to 5 monotonically increase with respect to AVP, and the returns of the AVP-based hedge portfolios are positive and vary from 0.43% to 0.88%, all of which are statistically significant. However, we find that the positive relationship between variance risk premium and future stock returns is not as strong as Table 2 suggests. It occurs largely among stocks with middle levels of AVP.

4.1.3. Risk-Adjusted Portfolio Returns

We further examine whether excess returns of AVP-based portfolios can be explained by commonly used risk factors. For this purpose, We consider the Fama-French three-factor model (Fama and French, 1993),

$$R_i - r^f = \alpha_i + \beta_{i,MKT}MKT + \beta_{i,SMB}SMB + \beta_{i,HML}HML + e_i, \tag{19}$$

and the Carhart four-factor model (Carhart, 1997),

$$R_i - r^f = \alpha_i + \beta_{i,MKT}MKT + \beta_{i,SMB}SMB + \beta_{i,HML}HML + \beta_{i,MOM}MOM + e_i, \tag{20}$$

where $R_i - r^f$ denotes portfolio returns in excess of one-month T-bill rates, and MKT, SMB, HML, and MOM are the usually used factors of market, size, value, and momentum, respectively.

We also consider the two recently developed factor models. One is the the q-factor model (Hou, Xue, and Zhang, 2015),

$$R_i - r^f = \alpha_i + \beta_{i,MKT}MKT + \beta_{i,SMB}SMB + \beta_{i,I/A}I/A + \beta_{i,ROE}ROE + e_i, \tag{21}$$

where I/A is the investment factor, which is constructed as the difference between the return on a portfolio of low investment stocks and the return on a portfolio of high investment stocks, and ROE is the profitability factor constructed as the difference between the return on a portfolio of high profitability stocks and the return on a portfolio of low profitability stocks.

The other is the mispricing-factor model (Stambaugh and Yuan, 2017),

$$R_i - r^f = \alpha_i + \beta_{i,MKT}MKT + \beta_{i,SMB}SMB + \beta_{i,MGMT}MGMT + \beta_{i,PERF}PERF + e_i, \tag{22}$$

where $MGMT$ and $PERF$ are referred to as the mispricing factors, which aggregate information across 11 well-known anomalies by averaging rankings within two clusters exhibiting the greatest co-movement in long-short returns. The first cluster of anomalies represent quantities that firms' managements can affect directly, and the factor arising from it is MGMT. The second cluster is related more to performance and is less directly controlled by management, and the factor constructed from this cluster is PERF. There is evidence that both the q- and mispricing-factor models outperform the Fama-French three-factor model, the Carhart four-factor model, and the Fama-French five-factor model (Fama and French, 2015) in explaining most of anomalies (Hou, Xue, and Zhang, 2017a, 2017b; Stambaugh and Yuan, 2017).

Panels A, B, C, and D of Table 4 present alphas and factor loadings from regressing portfolio excess returns on the Fama-French three-factor model, on the Carhart four-factor model, on the q-factor model, and on the mispricing-factor model, respectively. The alpha estimates deliver the same implication as shown above. In each of the four factor models, the monthly alpha for portfolios 1 to 5 increases with respect to AVP, and the high-minus-low hedge portfolio's alpha is positive, economically substantial, and highly statistically significant. Specifically, the hedge portfolio's alpha is 0.69% ($t = 4.45$) per month in the Fama-French three-factor model, is 0.68% ($t = 4.12$) per month in the Carhart four-factor model, is 0.44% ($t = 2.48$) per month in the q-factor model, and is 0.56% ($t = 3.18$) per month in the mispricing-factor model. These findings indicate that even after controlling for commonly used risk factors, the positive cross-sectional relation between asymmetric variance premium and future stock returns remain be of existence. Furthermore, all the four factor models indicate that low AVP portfolios (portfolios 1 and 2) economically and statistically significantly underperform.

In explaining dynamics of the hedge portfolio's returns, the market and size factors are not statistically significant in all of the four factor models. However, the hedge portfolio loads positively and significantly on the value factor in the Fama-French three-factor model and in the Carhart four-factor model; it loads positively and statistically signifiant on both the investment and profitability factors in the q-factor model; and in the mispricing-factor model, it loads positively and statistically significant only on one of the mispricing factors. These results indicate that returns on the hedge portfolio do not covary with the market, size, and momentum factors, but the investment and profitability factors and a management-related factor can help explain to some extent variations of its returns.

4.2. Fama-MacBeth Cross-Sectional Analysis

In this section, we test the relationship between asymmetric variance premium and stock returns by employing monthly Fama-MacBeth cross-sectional regressions (Fama and MacBeth, 1973). Different from portfolio sorts, this analysis allows for extensive controls of variables that have been found to have predictive power for stock returns. An important variable is variance risk premium, which has been found to positively predict future stock returns. Furthermore, we consider some standard variables frequently used in literature such as beta (Sharpe, 1964; Lintner, 1965), size (Banz, 1981; Lakonishok and Shapiro, 1986; Fama and French, 1992, 1993), book-to-market ratio (Fama and French, 1992), and momentum (Jegadeesh and Titman, 1993). We also control for those stock-related variables: the short-term reversal (Jegadeesh, 1990; Lehmann, 1990), idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang, 2006), illiquidity (Amihud, 2002), and expected idiosyncratic skewness (Boyer, Mitton, and Vorkink, 2010). Finally, the following option-related variables are also taken into account: implied volatility level, implied-volatility spread (Bali and Hovakimian, 2009; Cremers and Weinbaum, 2010), and implied volatility skew (Xing, Zhang, and Zhao, 2010).

For each month in our sample, we regress monthly excess returns of individual stocks on the lagged asymmetric variance premium values and a series of control variables. Table 5 presents the regression results, which confirm our main finding: the higher asymmetric variance premium is, the larger future excess returns investors expect, as the coefficient on asymmetric variance premium in each regression we consider is positive and statistically significant. Model 1 considers a simple regression in which we exclude all control variables and take asymmetric variance premium as the only predictor. The coefficient on asymmetric variance premium is 0.95 and highly statistically significant (t = 3.50). The adjusted R^2 is about 7% and highly statistically significant (t = 22.6). We then introduce variance risk premium as the only control variable in Model 2. The coefficient on asymmetric variance premium is positive and statistically significant, 1.06 ($t = 3.72$). We find that the slope estimate on VRP is positive and statistically significant, 0.44 ($t = 2.24$). The adjusted R^2 is about 8% ($t = 19.6$).

We now introduce the above-mentioned standard control variables, namely beta, size, book-to-market, and momentum, and the stock-related control variables one-by-one in Models 3-6, in addition to VRP. In Model 3, the standard variables, VRP, and the short-term reversal (Rev) are controlled. The slope estimate on asymmetric variance premium remains positive and highly statistically significant, 0.49 ($t = 3.19$). Consistent with Jegadeesh (1990) and Lehmann (1990), the coefficient on reversal is negative and statistically significant, -0.02 ($t = -2.58$). Coefficients on other variables are hardly significant. The adjusted R^2 increases to 12% ($t = 21.0$). In Model 4, we use the same control variables as in Model 3 except that the short-term reversal is replaced by idiosyncratic volatility (IVol), which is found to have a strong negative cross-sectional relation between idiosyncratic volatility and future stock returns (Ang et al., 2006). We find that the coefficient on asymmetric variance premium is 0.93 and remains highly statistically significant ($t = 4.01$). Consistent with Ang et al. (2006), the coefficient on idiosyncratic volatility is negative and statistically significant. The adjusted R^2 resulted from Model 4 is about 12% ($t = 20.6$). We introduce stock illiquidity (Amihud, 2002) in Model 5. The coefficient on asymmetric variance premium is 1.05 ($t = 4.24$) and the coefficient on illiquidity is not significant. The adjusted R^2 is 11% ($t = 21.4$). Boyer, Mitton, and Vorkink (2010) show that expected idiosyncratic skewness (EISkew), computed based on firm-specific characteristics, has a strong negative relation with future stock returns. Therefore, in Model 6, we control this variable as well. The coefficient on asymmetric variance premium is positive and highly significant, 0.99 ($t = 4.15$). The coefficient on EISkew is negative but marginally statistically significant. The adjusted R^2 is 12% ($t = 21.0$). In Models 3-6, though it is positive, the coefficient on VRP is statistically insignificant, except Model 5.

In Models 7-9, except VRP and the standard control variables, we add some option-related variables one-by-one: implied volatility level (IVLevel), implied volatility spread (IVSpread), and implied volatility skew (IVSkew). IVLevel is computed as the average of implied volatilities of the at-the-money call and at-the-money put. IVSpread is defined as the difference between implied volatilities of the at-the-money call and the implied volatility of the at-the-money put. Both Bali and Hovokimian (2009) and Cremers and Weinbaum (2010) find a strong positive relation between IVSpread and future stock returns. IVSkew is defined as the difference between the implied volatility of out-of-money put and the implied volatility of at-the-money call. IVSkew measures negative risk-neutral skewness. Xing, Zhang, and Zhao (2010) find that IVSkew negatively predicts future stock returns. We find that the coefficients on asymmetric variance premium are positive and highly statistically significant in these three models, and among these three option-related variables, only IVSpread is positive and statistically significant. In the last regression, Model 10, we include all control variables together. We still find positive and highly statistically significant coefficient on asymmetric variance premium, 0.38 ($t = 3.12$). The coefficient on VRP is insignificant. The adjusted R^2 is about 13% ($t = 20.6$).

5. Robustness Checks

In this section, we implement two robustness checks to test whether our main results found in Section 4 (i) are robust to realized measures constructed using different high-frequency stock returns in Subsection 5.1, and (ii) are robust to realized measures expected using the variance forecasting model of Equation (14) in Subsection 5.2. We only present portfolio returns and alphas. The Fama-MacBeth regressions deliver exactly the same implications and are not reported here.

5.1. 15-Minute High-Frequency Stock Returns

In Section 4, we construct realized measures using the 5-minute intraday high-frequency returns in each month. In this Subsection, we use the 15-minute high-frequency returns to construct realized variance and semivariances that are assumed to follow random walks.

Then following the same idea as in Section 2, we construct our asymmetric variance premium measure.

As before, at the end of each month, all stocks are sorted into quintile portfolios based on AVP and a high-minus-low hedge portfolio is formed. We then hold these portfolios over the next month and compute their excess returns, characteristic- and industry-adjusted returns, and alphas from the four factor models introduced in Section 4. Panel A of Table 6 presents portfolio returns and alphas. We see that all three types of portfolio returns and four alphas monotonically increase with respect to AVP. For example, the average monthly excess returns for portfolios 1 to 5 are 0.33%, 0.44%, 0.69%, 0.88%, and 0.89%, respectively, and the Carhart alpha increases from -0.39% for portfolio 1 to 0.11% for portfolio 5. Furthermore, the hedge portfolio earns economically substantial and statistically significant returns and alphas per month. Its average monthly excess return is about 0.55% (t = 2.95); its characteristic- and industry-adjusted returns are 0.54% (t = 3.89) and 0.67% (t = 4.69), respectively; alphas from the four factor models are 0.50% (t = 3.22), 0.51% (t = 3.16), 0.41% (t = 2.51), and 0.49% (t = 2.80) per month, respectively. The above results indicate that we still detect positive relationship between asymmetric variance premium and future stock returns when using 15-minute high-frequency returns.

5.2. Forecasted Variance and Semivariances

In the previous section, we assume that realized variance and semivariances follow random walks. As a result, the expected realized measures are the same as the current ones. This assumption may be too strong. In this Subsection, we adopt Equation (14) as our variance forecasting model. At each month starting from January 1997, for each individual stock, we first run the forecasting regression of Equation (14) for each of the three realized measures using all available data of that measure up to the current time, then compute the one-month-ahead expected realized variance and semivariances using the estimated parameters in Equation (14), and finally construct asymmetric variance premium using these expected realized measures in Equation (18).

Panel B of Table 6 presents portfolio returns and alphas based on such asymmetric variance premium. We find that all returns and alphas increase almost monotonically with respect to AVP. More importantly, the monthly returns and alphas earned by the high-minus-low hedge portfolio are positive and highly statistically significant. Specifically, the hedge portfolio's average monthly excess return is about 0.44% ($t = 3.99$); its average monthly characteristic- and industry-adjusted returns are 0.41% ($t = 3.85$) and 0.46% ($t = 4.56$), respectively; and its monthly alphas from the four factor models are 0.46% ($t = 4.01$), 0.46% ($t = 3.93$), 0.41% ($t = 3.40$), and 0.39% ($t = 3.18$), respectively. These results suggest that the positive relationship between asymmetric variance premium and future stock returns still holds when using expected realized measures.

6. Asymmetric Variance Premium and Skewness Premium

6.1. Relation to Skewness Premium

For a random variable, X, define its variance as $\sigma^2 \equiv Var(X)$, its upside semivariance as $\sigma_u^2 \equiv Var(X|X > m)$, and its downside semivariance as $\sigma_d^2 \equiv Var(X|X \leq m)$, for some threshold m. It can be shown that $\gamma = \frac{\sigma_u^2 - \sigma_d^2}{\sigma^2}$ is a proper measure of skewness in the sense that γ satisfies properties proposed by Groeneveld and Meeden (1984) that any reasonable skewness measure should have (see a proof by Feunou, Jahan-Parvar, and Tedongap (2016)). This suggests that our measure of asymmetric variance premium in Equation (18) should be closely related to skewness premium.

Formally, standard skewness premium (SSP) is defined as the difference between the risk-neutral and physical expectations of skewness, i.e.,

$$SSP_{i,t} = \mathbb{E}^{\mathbb{Q}}\Big[Skew_{i,t+1}|\mathcal{F}_t\Big] - \mathbb{E}^{\mathbb{P}}\Big[Skew_{i,t+1}|\mathcal{F}_t\Big], \tag{23}$$

where $Skew_{i,t}$ denotes skewness of an individual return distribution. If we can solve the risk-neutral and physical expectations in Equation (23), the relationship between standard skewness premium and asymmetric variance premium can be checked.

Define a cubic contract whose payoff at time $t + 1$ is $R_{i,t+1}^3$. Then its time-t price is given by $IW_t \equiv e^{-r_t^f \tau} \mathbb{E}^{\mathbb{Q}}\left[R_{i,t+1}^3 | \mathcal{F}_t\right]$. Bakshi, Kapadia, and Madan (2003) show that IW_t can be recovered from prices of out-of-money call and put options,

$$\begin{aligned} IW_{i,t} &= \int_{S_{i,t}}^{\infty} \frac{6\log(\frac{K_i}{S_{i,t}}) - 3(\log(\frac{K_i}{S_{i,t}}))^2}{K_i^2} C(t,\tau;K_i) dK_i \\ &\quad - \int_{0}^{S_{i,t}} \frac{6\log(\frac{K_i}{S_{i,t}}) + 3(\log(\frac{K_i}{S_{i,t}}))^2}{K_i^2} P(t,\tau;K_i) dK_i. \end{aligned} \tag{24}$$

Using $IW_{i,t}$ in Equation (24) together with $IV_{i,t}$ in Equation (2), the risk-neutral expectation of skewness can be obtained as follows,

$$\mathbb{E}^{\mathbb{Q}}\left[Skew_{i,t+1} | \mathcal{F}_t\right] = \frac{e^{r_t^f \tau} IW_{i,t} - 3\mu_{i,t} e^{r_t^f \tau} IV_{i,t} + 2\mu_{i,t}^3}{\left[e^{r_t^f \tau} IV_{i,t} - \mu_{i,t}^2\right]^{3/2}}, \tag{25}$$

where $\mu_{i,t}$ is the expected mean return of an individual stock (see Bakshi, Kapadia, and Madan (2003) for the exact formula of $\mu_{i,t}$), and out-of-money options have maturity of 30 days.

We can approximate the physical expectation of skewness using the realized skewness, which, following Neuberger (2012) and Amaya et al. (2015), is computed for each month, t, as follows,

$$RS_{i,t} = \frac{1}{21} \sum_{j=1}^{21} RDS_{i,t,j}, \tag{26}$$

where $RDS_{i,t,j}$ is the jth-day realized skewness computed using 5-minute intraday stock returns, $RDS_{i,t,j} = \frac{\sqrt{n_j} \sum_{k=1}^{n_j} R_{j,k}^3}{RV_j^{3/2}}$, in which n_j is the number of 5-minute high-frequency returns, $R_{j,k}$, available in the jth day, and RV_j is the jth-day realized variance.

Figure 1 plots the cross-sectional correlation between standard skewness premium, computed using the above approach, and asymmetric variance premium, constructed in Sections 2 and 4. We see that these two measures are highly correlated. The time-series average is large and highly statistically significant, 0.75 ($t = 263$).

6.2. Standard Skewness Premium and Return Predictability

In this part, we redo what we have done in Section 4 by substituting asymmetric variance premium with standard skewness premium and check whether similar positive relationship between standard skewness premium and future stock returns can be found. We first implement portfolio sorts and then conduct the Fama-MacBeth cross-sectional regressions.

6.2.1. Portfolio Analysis

As before, at the end of each month from January 1996 to December 2013, we first sort all firms on the basis of their SSP's into quintile portfolios and then hold these quintile portfolios over the next month and computer their equal-weighted monthly returns. A hedge portfolio that longs the high SSP portfolio and shorts the low SSP portfolio is also formed.

Panel A of Table 7 presents average monthly portfolio returns and alphas from the four factor models. First, all three types of portfolio returns and four alphas monotonically increase with respect to SSP. For example, the average monthly characteristic-adjusted returns for portfolios 1 to 5 are -0.35%, -0.20%, -0.12%, 0.02%, and 0.24%, respectively, and the Carhart alpha increases monotonically from -0.30% for portfolio 1 to 0.27% for portfolio 5. Second, the hedge portfolio earns positive and statistically significant returns and alphas. For example, its monthly excess return is about 0.57% (t = 3.35), and its monthly characteristic- and industry-adjusted returns are 0.58% (t = 4.63) and 0.74% (t = 5.16), respectively; alphas from the Fama-French three-factor model, the Carhart four-factor model, the q-factor model, and the mispricing factor model are 0.48% (t = 3.04), 0.57% (t = 3.42), 0.47% (t = 2.49), and 0.69% (t = 3.99) per month, respectively.

Panels B and C of Table 7 presents portfolio returns from two independent double-sorts based on SSP and either variance or VRP. We find very similar results to those in Table 3. For each level of variance, the average monthly excess returns for portfolios 1 to 5 increase almost monotonically with respect to SSP, and the hedge portfolio remains to earn statistically significant positive excess return, which ranges from 0.36% ($t = 2.88$) per month for the low level of variance to 0.94% ($t = 4.13$) per month for the middle level of variance. Some evidence of the negative relationship between variance and future stock returns is observed. For each level of variance risk premium, the average monthly excess returns for portfolios 1 to 5 also increase almost monotonically with respect to SSP, and the hedge portfolio's return is positive and varies from 0.47% to 0.82%, all of which are statistically significant. We also find that the positive relationship between variance risk premium and future stock returns observed in Panel A of Table 2 occurs largely among firms with middle and high levels of SSP.

Figure 2 plots the time series of monthly returns of the hedge portfolios based on asymmetric variance premium (solid line) and on standard skewness premium (dashed line). We see that the dynamics of both time series of returns are quite similar. The AVP-based hedge portfolio has a mean return of 0.72% and a standard deviation of 2.72%, whereas the SSP-based hedge portfolio's mean return is 0.57% and its standard deviation is 2.53%. When we take a look at excess returns of the market factor for the same period, its mean return is smaller (0.56%) and its standard deviation is larger (4.69%).

All in all, given that both asymmetric variance premium and standard skewness premium capture skewness premium of an individual stock. The results we have found by now suggest a positive relationship between skewness premium and future stock returns: the higher skewness premium is, the higher future stock returns investors expect.

6.2.2. Fama-MacBeth Regressions

We further implement the Fama-MacBeth cross-sectional regressions to detect the relationship between standard skewness premium and future stock returns. We employ the same control variables and the same regression models as those used in Subsection 4.2. Table 8 presents the regression results. We find very similar results to those in Table 5. No matter which model is used, the coefficient on standard skewness premium is always positive and highly statistically significant. For example, in Model 1 where SSP is the only predictor, the coefficient on SSP is 0.37 ($t = 3.70$); when we put all control variables together in Model 10, the coefficient on SSP becomes smaller, but still positive and highly statistically significant, 0.27 ($t = 4.26$) and the coefficient on VRP is insignificant. The adjusted R^2's range from 7% in Model 1 to 13% in Model 10.

7. Possible Explanations

We have found that asymmetric variance premium, a measure of skewness premium, positively predicts future stock returns. Can such a relationship be explained by risk-based equilibrium asset-pricing models? A large number of works argue that investors are of aversion to skewness risk (Arditti, 1967, 1971; Kraus and Litzenberger, 1976; Simkowitz and Beedles, 1978; Scott and Horvath, 1980; Conine and Tamarkin, 1981; Kane, 1982; Harvey and Siddique, 2000; Mitton and Vorkink, 2007). Therefore, given that the risk-neutral measure has already internalized such skewness-aversion, asymmetric variance premium defined in Equation (18) should be negative in general, and the more negative asymmetric variance premium is, the higher expected stock returns should be, suggesting a negative relationship between asymmetric variance premium and future stock returns.

The inconsistency between our empirical finding and risk-based theories may reveal that the stock and options markets are not fully integrated and options are not redundant. Where informed traders choose to profit from their information advantage has important effect on stock price movements. When some informed investors choose to trade in options before trading in the underlying stocks, the positive relationship we have found may reflect the trading activity of informed traders. Furthermore, rational investors/arbitrageurs may be limited in various ways in trading the underlying stocks, and could be not as aggressive in forcing stock prices to fundamentals as the standard financial models suggest (Shleifer and Vishny, 1997).

7.1. Asymmetric Information and Informed Trading

Easley, O'Hara, and Srinivas (1998) propose a multimarket sequential trade model, which incorporates both options and stocks and distinguishes two types of traders: uninformed traders who trade in both stock and option markets for liquidity reasons, and informed traders who have information advantage and can choose to trade either in stock market or in options market or in both markets based on profits available. The model has two equilibria: a separating equilibrium in which no informed traders use options, and a pooling equilibrium in which some informed traders choose to trade in the options market.

In the pooling equilibrium, when a trader is informed of a good news, he/she could choose to buy calls or sell puts. Such a trade increases call prices relative to put prices and makes the risk-neutral skewness large, resulting in a positive relationship between asymmetric variance premium and future stock returns. Easley, O'Hara, and Srinivas (1998) show that the pooling equilibrium can be reached and informed traders choose to trade options when the leverage and liquidity in options is high relative to stocks, and/or the overall fraction of informed traders is high.

We first test whether the predictive power of asymmetric variance premium is greater in stocks whose liquidity is low relative to liquidity of options written on them. To measure stock liquidity, we use Amihud illiquidity ratio (Amihud, 2002), and to measure option liquidity, we use option volume and option open interest. Then similar to Cremers and Weinbaum (2010), we construct two dummy variables that capture the relative liquidity of stock and option. The first one is high option liquidity and low stock liquidity dummy (HOLSD), and the other is low option liquidity and high stock liquidity dummy (LOHSD). HOLSD is equal to one for stocks that belong to the top 33% of option liquidity and the bottom 33% of stock liquidity; similarly, LOHSD is equal to one for stocks that belong to the bottom 33% of option liquidity and the top 33% of stock liquidity.

We run monthly Fama-MacBeth cross-sectional regressions of stock returns on the lagged AVP and products of AVP and the two dummy variables. We also introduce VRP, beta, size, B/M, and momentum as control variables in each regression. Table 9 presents the results from the cross-sectional regressions. To compute option volume and option open interest, we either use the total trading volume and open interest in each month or use the trading volume and open interest in the last trading day of each month. We see that no matter which option liquidity measure and how to compute option liquidity, the coefficient on AVP is always positive and highly statistically significant. More importantly, we find that the coefficient on the product of AVP and HOLSD is always positive and highly statistically significant, whereas the coefficient on the product of AVP and LOHSD is always negative and statistically significant except one case. For example, when we use monthly option volume as the measure of option liquidity, the coefficient on AVP is 1.19 ($t = 4.75$), the coefficient on AVP×HOLSD is 1.33 ($t = 3.68$), and the coefficient on AVP×LOHSD is -0.71 ($t = -2.03$). These results indicate that there is more predictability when option liquidity is high relative to stock liquidity and less predictability when option liquidity is low relative to stock liquidity. We further see that the F-tests reject null hypothesis of equal coefficients on two dummy-related variables.

Next, we test whether the return predictability by asymmetric variance premium is stronger in stocks that have more serious information asymmetry. The concentration of informed traders is a key variable in the model of Easley, O'Hara, and Srinivas (1998). We use the PIN variable proposed by Easley, Kiefer, and O'Hara (1997) and Easley, Hvidkjaer, and O'Hara (2002) as a measure of the prevalence of informed traders and information asymmetry. We then implement a dependent double portfolio sort based on PIN and AVP. At the end of each month, we first sort all stocks into tercile portfolios based on PIN, and then we sort stocks in each of these tercile portfolios into quintile portfolios and form a high-minus-low hedge portfolio on the basis of AVP. We hold these portfolios over the next month and compute their equal-weighted portfolio returns and alphas of the aforementioned four factor models.

Table 10 presents the portfolio returns and alphas. For brevity, we only report returns and alphas for those portfolios that combine the bottom and top tercile portfolios and odd quintile portfolios. The hedge portfolio's returns and alphas are economically substantial and highly statistically significant in high PIN stocks, whereas they become small and less significant in low PIN stocks. Specifically, among high PIN stocks, the monthly excess return, characteristic- and industry-adjusted returns of the hedge portfolio are 1.07% ($t = 4.07$), 1.04% ($t = 4.56$), and 1.14% ($t = 5.33$), respectively, and its monthly alphas from the four factor models are 1.04% (t = 4.08), 1.12% (t = 4.35), 0.89% (t = 2.98), and 1.07% (t = 3.78), respectively. In contrast, among low PIN stocks, both returns and alphas become small and alphas from the q-factor model and the mispricing factor are statistically insignificant. Underperformance of those stocks with low AVP and high PIN is much stronger than those stocks with low AVP and low PIN. Such results are consistent with those predicted by the sequential trade model of Easley, O'Hara, and Srinivas (1998).

7.2. Where Does Informed Traders' Information Advantage Come From?

We have shown that the positive relationship between asymmetric variance premium and future stock returns stems from information advantage possessed by informed traders who largely trade on options. Theoretical information-based models suggest that informed traders' information advantage may arise either from their pre-event acquisition of private information (Glosten and Milgrom, 1985; Kim and Verrecchia, 1991; Skinner, 1997), or from their superior ability to process the public disclosures (Kim and Verrecchia, 1994; Skinner, 1997), or from both. According to these models, when informed traders possess private information prior to corporate events, asymmetric variance premium immediately before these events should have strong predictive power for event returns; however, when informed traders have better information processing ability, asymmetric variance premium immediately after these events should have strong predictive power for post-event returns.

Therefore, in this part, we investigate how the predictive power of asymmetric variance premium change before and after important corporate information events, including both anticipated and unanticipated events. Similar to Jin, Livnat, and Zhang (2012), at any event day t, we define the event return as the excess return over days from $t-1$ to $t+1$, the base asymmetric variance premium as the average of daily asymmetric variance premiums over days from $t-50$ to $t-11$, the pre-event asymmetric variance premium as the average of daily asymmetric variance premiums over days from $t-10$ to $t-2$, the post-event asymmetric variance premium as the average of daily asymmetric variance premiums over days from $t+1$ to $t+5$, and the post-event return as the excess return over days from $t+6$ to $t+90$.

We first investigate the predictive power of asymmetric variance premium immediately before and after anticipated corporate events. We take earnings announcements to proxy anticipated corporate events. Earnings announcement data are obtained from Compustat for the period from the first quarter of 1996 to the fourth quarter of 2013. Panel A of Table 11 presents our main results from the quarterly Fama-MacBeth cross-sectional regressions. In Models 1-3, the dependent variable is the event returns, whereas in Model 4, the dependent variable is the post-event returns. When we use the base AVP as the only predictor in Model 1, its coefficient is about 0.012 and is highly significant ($t = 3.24$), suggesting that over the base window, informed traders are able to anticipate the subsequent returns around earnings announcements. We then use the pre-event AVP as the only predictor in Model 2, and find that its coefficient, 0.023 ($t = 6.48$), is much larger than that on base AVP in Model 1 and is highly statistically significant. When we include both base AVP and pre-event AVP in the regression in Model 3, the coefficient on base AVP becomes much smaller and statistically insignificant, 0.002 ($t = 0.51$), whereas the coefficient on pre-event AVP remains the same and highly statistically significant, 0.023 ($t = 6.48$). These results suggest that asymmetric variance premium immediately before corporate earnings announcement has dominant predictive power for event returns. In Model 4, we investigate whether the post-event AVP has any predictive power for the post-event returns. Except the post-event AVP, we also include base AVP, pre-event AVP, and the event returns in the regression for controlling for information available before and around information events. We find that the post-event AVP has a coefficient of 0.040 and highly statistically significant ($t = 3.32$); however, the other three variables are also statistically significant and have larger coefficients.

We then move to check the predictive power of asymmetric variance premium immediately before and after unanticipated corporate events. The unanticipated corporate events are proxied by extreme excess returns. At each day, similar to Jin, Livnat, and Zhang (2012), we calculate the three-day excess return, and if it is larger than 10% or smaller than -10%, we keep it in the extreme excess returns sample. We then implement monthly Fama-MacBeth cross-sectional regressions. Panel B of Table 11 presents the main regression results. Again as in Panel A, the dependent variable is the event return in Models 1-3 and it is the post-event return in Model 4. We find that both base AVP and pre-event AVP are positive and statistically highly significant when they are the sole predictors in Models 1 and 2, respectively. However, when they are both included in the regression in Model 3, the coefficient on base AVP becomes much smaller and statistically insignificant, whereas the coefficient on pre-event AVP is nearly the same as that in Model (2) and highly statistically significant. The regression result in Model 4 shows that the coefficient on the post-event AVP is positive and highly statistically significant, 0.033 ($t = 5.38$), whereas the coefficients on base AVP, pre-event AVP, and the event returns are all statistically insignificant, suggesting that only the post-event AVP has predictive power for the post-event excess returns in the case of unanticipated events.

To sum up, we find that asymmetric variance premium immediately before both anticipated and unanticipated events has dominant predictive power for event returns. Kim and Verrecchia (1991) suggest that both informed and uninformed traders have strong incentives to acquire private information before anticipated information events such as earnings announcements. Skinner (1997) argues that informed traders' information advantage may become large immediately before significant corporate disclosures. Hence, this finding indicates that the predictive ability of asymmetric variance premium is likely information-driven and may suggest that informed traders have access to private information and trade on such private information before information events. We further find that asymmetric variance premium immediately after both anticipated and unanticipated events has predictive power for future post-event excess returns and such predictive power is much stronger in the case of unanticipated information events. Consistent with what Kim and Verrecchia (1994) suggest, this finding implies that informed traders have superior ability to process public information and such superior ability is much stronger when processing information that is less anticipated and/or more difficult to interpret.

7.3. Limits to Arbitrage

The effect of informed trading should become more pronounced when there are greater limits-to-arbitrage in the underlying stocks, as informed investors would place more transactions on options. Hence, we test whether limits-to-arbitrage do also contribute to underperformance (overperformance) of portfolios with low (high) asymmetric variance premium. We use the following three proxies for limits-to-arbitrage. The first one is the institutional ownership (IO), which is measured as the percentage of shares outstanding held by institutions, obtained from the Thomson Financial Institutional Holdings (13F) database. Nagel (2005) and Campbell, Hilscher, and Szilagyi (2008) show that stocks with low institutional ownership may face serious short-sale constraints. Chen, Hong, and Stein (2002) and Asquith, Pathak, and Ritter (2005) argue that institutional ownership of a stock acts as a proxy for lendable supply. Amihud and Li (2006) show that firms with a higher degree of institutional ownership should be more fairly priced as institutional investors are generally better informed than retail investors. We therefore expect that the correction of mispricing should be more rapid in stocks with higher institutional ownership.

The second proxy is the idiosyncratic volatility of individual stocks (IVol). Shleifer and Vishny (1997) and Pontiff (2006) predict that high idiosyncratic volatility deters arbitrage activity. Ali, Hwang, and Trombley (2003), Mendenhall (2004), and Cao and Han (2016) employ idiosyncratic volatility to empirically characterize arbitrage risk. We measure idiosyncratic volatility using the standard deviation of the residuals resulted from regressing individual stock returns on the Cahart four-factor model.

The third is the analyst forecast dispersion (AFD). In line with Diether, Malloy, and Scherbina (2002), we compute analyst forecast dispersion by normalizing the standard deviation of I/B/E/S one-year earning per share forecasts by the average forecast level. High analyst forecast dispersion implies great information asymmetry, which makes arbitrage particularly risky and costly.

Based on each of these three proxies and asymmetric variance premium, we implement dependent double portfolio sorts. At the end of each month in our sample, we first sort all stocks into tercile portfolios based on each of the above proxies of limits-to-arbitrage, and then we sort stocks in each of these tercile portfolios into quintile portfolios and form a high-minus-low hedge portfolio on the basis of AVP. We hold these portfolios over the next month and compute their equal-weighted portfolio returns and alphas of the aforementioned four factor models.

Table 12 presents the average monthly excess returns, characteristic- and industry-adjusted returns, and alphas from the four factor models for those portfolios and the hedge portfolios. Panel A reports those results based on institutional ownership and asymmetric variance premium. First, the hedge portfolio's returns and alphas are economically substantial and statistically significant in stocks with the low level of institutional ownership, but they become small in stocks with the high level of institutional ownership. Specifically, among low IO stocks, the monthly excess return, characteristic- and industry-adjusted returns of the hedge portfolio are 0.86% ($t = 3.27$), 0.81% ($t = 4.35$), and 0.90% ($t = 4.70$), respectively, and its monthly alphas from the four factor models are 0.84% ($t = 4.51$), 0.83% ($t = 4.15$), 0.58% ($t = 2.64$), and 0.66% ($t = 3.43$), respectively. In contrast, among high IO stocks, both returns and alphas are small: the three returns are 0.48% ($t = 2.39$), 0.48% ($t = 3.22$), and 0.58% ($t = 3.29$) per month, respectively, and the four alphas are 0.44% ($t = 2.45$), 0.46% ($t = 2.56$), 0.30% ($t = 1.46$), and 0.48% ($t = 2.54$) per month, respectively. Second, the performance (alphas) of individual portfolios indicates that stocks that economically and statistically significantly underperform are mostly those that have the low level of institutional ownership and the low and middle levels of asymmetric variance premium.

When we use idiosyncratic volatility to proxy limits to arbitrage in Panel B, we find very similar results. The hedge portfolio's returns and alphas are all economically substantial and statistically significant in high IVol stocks, whereas these returns and alphas become small in low IVol stocks. Furthermore, those stocks that have the high level of idiosyncratic volatility and the low and middle levels of asymmetric variance premium significantly underperform. Whenever analyst forecast dispersion is used in Panel C, we still find that the hedge portfolio in high AFD stocks outperforms that in low AFD stocks. We find that stocks with the low level of asymmetric variance premium underperform in both low and high AFD stocks, but in the latter the underperformance is much stronger.

Put together, we have evidence that the positive relation between asymmetric variance premium and future stock returns is stronger among stocks with severe limits to arbitrage. Stocks that significantly underperform are mostly those that are difficult to arbitrage and have small asymmetric variance premium.

8. Conclusion

Semivariances or variance asymmetry provide a complement to or better measure than variance in evaluating risk (Markowitz, 1959, 1991). A number of recent papers find that market variance risk premium, defined as the difference between the risk-neutral and physical expected return variances, can predict stock market returns (Bollerslev, Tauchen, and Zhou, 2009; Drechsler and Yaron, 2011; Bollerslev et al., 2014). In this paper, we implement a cross-sectional analysis and examine the relationship between individual stocks' asymmetric variance premia and future stock returns. We define asymmetric variance premium as the difference between the risk-neutral and physical variance asymmetry, which are extracted from the out-of-money call and put options and from realized variance and semivariances, respectively. We find that individual asymmetric variance premium is negative in general, suggesting that the risk-neutral return distribution has greater variance asymmetry than the physical distribution does.

We find that there exists a positive relationship between the individual stocks' asymmetric variance premia and the future stock returns. The high-minus-low hedge portfolio earns the excess return of 72 basis points per month, the characteristic-adjusted return of 66 basis points per month, and the industry-adjusted return of 79 basis points per month. They are all economically substantial and statistically highly significant. Moreover, the hedge portfolio's alphas from the factor models are also economically substantial and statistically highly significant.

This positive relationship can not be explained by the standard risk-based asset pricing models. We show that asymmetric variance premium is closely related to skewness premium. We find evidence that the predictive power of asymmetric variance premium is information-driven and the positive relationship reflects the trading activity of informed traders trading in the options market. We further show that the positive relationship becomes stronger among stocks that are hard to arbitrage.

REFERENCES

Ali, A., Hwang, L.S., and Trombley, M.A. (2003). "Arbitrage Risk and the Book-to-Market Anomaly". *Journal of Financial Economics* 69, 355–373.

Amihud, Y. (2002). "Iliquidity and Stock Returns: Cross-Section and Time-Series Effects". *Journal of Financial Markets* 5, 31–56.

Amihud, Y., and Li, K. (2006). "The Declining Information Content of Dividend Announcements and the Effect of Institutional Holdings". *Journal of Financial and Quantitative Analysis* 41, 637–660.

Andersen, T.G., Bollerslev, T., Diebold, F.X., and Ebens, H. (2001). "The Distribution of Realized Stock Return Volatility". *Journal of Financial Economics* 61, 43–76.

Ang, A., Hodrick, R.J., Xing, Y., and Zhang, X. (2006). "The Cross-Section of Volatility and Expected Returns". *Journal of Finance* 61, 259–299.

Arditti, F.D. (1967). "Risk and Required Return on Equity". *Journal of Finance* 22, 9–36.

Arditti, F.D. (1971). "Another Look at Mutual Fund Performance". *Journal of Financial and Quantitative Analysis* 6, 909–912.

Asquith, P., Pathak, P.A., and Ritter, J.R. (2005). "Short interest, institutional ownership, and stock returns". *Journal of Financial Economics* 78, 243–276.

Bakshi, G., Kapadia, N., and Madan, D. (2003). "Stock Return Characteristics, Skew Laws, and the Differential Pricing of Individual Equity Options". *Review of Financial Studies* 16, 101–143.

Bakshi, G. and Madan, D. (2000). "Spanning and Derivative Security Valuation". *Journal of Financial Economics* 55, 205–238.

Bali, T., Cakici, N., and Whitelaw, R. (2011). "Maxing Out: Stocks as Lotteries and the Cross-Section of Expected Returns". *Journal of Financial Economics* 99, 427–446.

Bali, T. and Hovakimian, A. (2009). ‘Volatility Spreads and Expected Stock Returns”. *Management Science* 55, 1797–1812.

Banz, R.W. (1981). “The Relationship between Return and Market Value of Common Stocks”. *Journal of Financial Economics* 9, 3–18.

Barberis, N. and Huang, M. (2008). “Stocks as Lotteries: The Implications of Probability Weighting for Security Prices”. *American Economic Review* 98, 2066–2100.

Barndorff-Nielsen, O.E., Kinnebrock, S., and Shephard, N. (2010). “Measuring Downside Risk–Realized Seminvariance”. In: T. Bollerslev, J. Russell, and M. Watson (Eds), *Volatility and Time Series Econometrics: Essays in Honor of Robert Engle*, 117–136, Oxford University Press.

Barndorff-Nielsen, O.E. and Shephard, N. (2004). “Power and Bipower Variation with Stochastic Volatility and Jumps”. *Journal of Financial Econometrics* 2, 1–37.

Bollerslev, T., Marrone, J., Xu, L., and Zhou, H. (2014). “Stock Return Predictability and Variance Risk Premia: Statistical Inference and International Evidence”. *Journal of Financial and Quantitative Analysis* 49, 633–661.

Bollerslev, T., Tauchen, G., and Zhou, H. (2009). “Expected Stock Returns and Variance Risk Premia”. *Review of Financial Studies* 22, 4463–4492.

Boyer, B., Mitton, T., and Vorkink, K. (2010). “Expected Idiosyncratic Skewness”. *Review of Financial Studies* 23, 169–202.

Campbell, J., Hilscher, J., and Szilagyi, J. (2008). “In search of distress risk”. *Journal of Finance* 63, 2899–2939.

Cao, J., and Han, B. (2016). “Idiosyncratic Risk, Costly Arbitrage and the Cross-Section of Stock Returns”. *Journal of Banking and Finance* 73, 1–15.

Carhart, M. (1997). “On Persistence in Mutual Fund Performance”. *Journal of Finance* 52, 57–282.

Chen, J., Hong, H., and Stein, J. (2002). “Breadth of Ownership and Stock Returns”. *Journal of Financial Economics* 66, 171–205.

Conine, T.E and Tamarkin, M.J. (1981). “On Diversification Given Asymmetry in Returns”. *Journal of Finance* 36, 1143–1155.

Cremers, M. and Weinbaum, D. (2010). “Deviations from Put-Call Parity and Stock Return Predictability”. *Journal of Financial and Quantitative Analysis* 45, 335–367.

Daniel, K., Grinblatt, M., Titman, S., and Wermers, R. (1997). “Measuring Mutual Fund Performance with Characteristic-based Benchmarks”. *Journal of Finance* 52, 1035–1058.

Diether, K., Malloy, C.J., and Scherbina, A.D. (2002). “Differences of Opinion and the Cross-Section of Stock Returns”. *Journal of Finance* 57, 2113–2141.

Drechsler, I., and Yaron, A., (2011). “What's Vol Got to Do with It”. *Review of Financial Studies* 24, 1–45.

Easley, D., O'Hara, M., and Srinivas, P.S. (1998). “Option Volume and Stock Prices: Evidence on Where Informed Traders Trade”. *Journal of Finance* 53, 431–465.

Easley, D., Hvidkjaer, S., and O?Hara, M. (2002). “Is Information Risk a Determinant of Asset Returns?” *Journal of Finance* 57, 2185–2222.

Easley, D., Kiefer, N., and O?Hara, M. (1997). “One Day in the Life of a Very Common Stock”. *Review of Financial Studies* 10, 805–835.

Fama, E. and French, K. (1992). “The Cross-Section of Expected Stock Returns”. *Journal of Finance* 47, 427–465.

Fama, E. and French, K. (1993). “Common Risk Factors in the Returns on Stocks and Bonds”. *Journal of Financial Economics* 33, 3–56.

Fama, E. and French, K. (1996). “Multifactor Explanation of Asset Pricing Anomalies”. *Journal of Finance* 51, 55–84.

Fama, E. and French, K. (2015). “A Five-Factor Asset Pricing Model”. *Journal of Financial Economics* 116, 1–22.

Fama, E. and MacBeth, J. (1973). “Risk, Return, and Equilibrium: Empirical Tests”. *Journal of Political Economy* 71, 607–636.

Feunou, B., Jahan-Parvar, M.R., and Tedongap, R. (2016). “Which Parametric Model for Conditional Skewness?” *European Journal of Finance* 22, 1237–1271.

Glosten, L.R. and Milgrom, P.R. (1985). “Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders”. *Journal of Financial Economics* 14, 71–100.

Groeneveld, R.A. and Meeden, G. (1984). “Measuring Skewness and Kurtosis”. *Journal of the Royal Statistical Society: Series D* 33, 391–399.

Han, B. and Zhou, Y. (2011). “Variance Risk Premium and the Cross-Section of Stock Returns”. Working Paper, University of Toronto.

Harrison, M. and Kreps, D. (1979). “Martingales and Arbitrage in Multiperiod Securities Markets”. *Journal of Economic Theory* 20, 381–408.

Harvey, C. and Siddique, A. (2000). “Conditional Skewness in Asset Pricing Tests”. *Journal of Finance* 53, 1263–1295.

Hou, K., Xue, C., and Zhang, L. (2015). “Digesting Anomalies: An Investment Approach”. *Review of Financial Studies* 28, 650–705.

Hou, K., Xue, C., and Zhang, L. (2017a). “A Comparison of New Factor Models”. Working Paper, Ohio State University.

Hou, K., Xue, C., and Zhang, L. (2017b). “Replicating Anomalies”. Working Paper, Ohio State University.

Jegadeesh, N. (1990). “Evidence of Predictable Behavior of Security Returns”. *Journal of Finance* 45, 881–898.

Jegadeesh, N. and Titman, S. (1993). “Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency”. *Journal of Finance* 48, 65–91.

Kane, A. (1982). “Skewness Preference and Portfolio Choice”. *Journal of Financial and Quantitative Analysis* 17, 15–25.

Kim, O. and Verrecchia, R. (1991). “Market Reaction to Anticipated Announcements”. *Journal of Financial Economics* 30, 273–309.

Kim, O. and Verrecchia, R. (1994). “Market Liquidity and Volume around Earnings Announcements”. *Journal of Accounting and Economics* 17, 41–67.

Kraus, A. and Litzenberger, R.H. (1976). “Skewness Preference and the Valuation of Risk Assets”. *Journal of Finance* 31, 1085–1100.

Lakonishok, J. and Shapiro, A. (1986). “Systematic Risk, Total Risk, and Size as Determinants of Stock Market Returns”. *Journal of Banking and Finance* 10, 115–132.

Lakonishok, J., Shleifer, A., and Vishny, R. (1994). “Contrarian Investment, Extrapolation, and Risk”. *Journal of Finance* 49, 1541–1578.

Lehmann, B.N. (1990). “Fads, Martingales, and Market Efficiency”. *Quarterly Journal of Economics* 105, 1–28.

Lintner, J. (1965). "Security Prices, Risk, and Maximal Gains from Diversification". *Journal of Finance* 20, 587–615.

Markowitz, H. (1959) *Portfolio Selection: Efficient Diversification of Investment.* New York: John Wiley & Sons; 2nd Ed. (1991), Cambridge: Basil Blackwell.

Mendenhall, R.R. (2004). "Arbitrage Risk and Post-Earnings-Announcement Drift". *Journal of Business* 77, 875–894.

Mitton, T. and Vorkink, K. (2007). "Equilibrium Underdiversification and the Preference for Skewness". *Review of Financial Studies* 20, 1255–1288.

Nagel, S. (2005). "Short Sales, Institutional Investors and the Cross-Section of Stock Returns". *Journal of Financial Economics* 78, 277–309.

Neuberger, A. (2012). "Realized Skewness". *Review of Financial Studies* 28, 3423–3455.

Pontiff, J. (2006). "Costly arbitrage and the myth of idiosyncratic risk". *Journal of Accounting and Economics* 42, 35–52.

Scott, R.C. and Horvath, P.A. (1980). "On the Direction of Preference of Moments of Higher Order Than the Variance". *Journal of Finance* 35, 915–919.

Sharpe, W. (1964). "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk". *Journal of Finance* 19, 425–442.

Shleifer, A. and Vishny, R. (1997). "Limits of Arbitrage". *Journal of Finance* 52, 35–55.

Simkowitz, M.A. and Beedles, W.L. (1978). "Diversification in a Three-Moment World". *Journal of Financial and Quantitative Analysis* 13, 927–941.

Skinner, J.D. (1997). "Do Option Markets Improve Informational Efficiency?" *Contemporary Accounting Research* 14, 193-201.

Stambaugh, R. and Yuan, Y. (2017). "Mispricing Factors." *Review of Financial Studies* 30, 1270–1315.

Xing, Y., Zhang, X., and Zhao, R. (2010). "What Does the Individual Option Volatility Smirk Tell Us about Future Equity Returns?" *Journal of Financial and Quantitative Analysis* 45, 641–662.

Table 1: **Summary Statistics**

Panel A reports the number of firms (N.Firm) in our sample and medians and (10, 90)% quantiles of VRPs and AVPs across individual stocks for each year. VRPs and AVPs are computed using Equations (17) and (18), in which the risk-neutral measures are recovered from prices of out-of-money call and put options with maturity of 30 days, and the realized measures are constructed using the 5-minute intraday high-frequency stock returns. Option data and high-frequency data are obtained from OptionMetrics and TAQ, respectively. All common stocks trading on the NYSE, AMEX, and NASDAQ with valid option and high-frequency data are included in the sample. Panel B reports the average values of some selected firm-specific variables, including beta, log market equity (LnME), book-to-market ratio (B/M), momentum (MOM), short-term reversal (Rev), idiosyncratic volatility (IVOL), Amihud illiquidity (Illiq), the maximium (Max) and minimum (Min) daily returns of the previous month, and the put-call volume ratio (PCR) for the AVP-based quintile portfolios.

Panel A: Summary Statistics of VRP and AVP over Years

		VRP			AVP		
Year	N.Firm	Q10	Q50	Q90	Q10	Q50	Q90
1996	910	-1.316	-0.119	0.001	-0.429	-0.170	0.121
1997	1257	-0.958	-0.081	0.025	-0.387	-0.158	0.106
1998	1621	-0.847	-0.079	0.049	-0.398	-0.170	0.112
1999	1789	-0.723	-0.052	0.088	-0.404	-0.200	0.038
2000	1865	-0.950	-0.075	0.113	-0.411	-0.201	0.028
2001	1816	-0.573	-0.009	0.128	-0.420	-0.201	0.039
2002	1869	-0.441	-0.012	0.114	-0.453	-0.219	0.047
2003	1851	-0.188	0.014	0.107	-0.515	-0.225	0.070
2004	1993	-0.169	0.008	0.086	-0.503	-0.189	0.167
2005	2043	-0.108	0.010	0.106	-0.520	-0.199	0.138
2006	2174	-0.127	0.007	0.096	-0.513	-0.181	0.161
2007	2223	-0.147	0.007	0.099	-0.468	-0.170	0.143
2008	2183	-0.585	-0.052	0.103	-0.499	-0.222	0.087
2009	2053	-0.200	0.020	0.162	-0.544	-0.247	0.050
2010	2163	-0.145	0.023	0.141	-0.584	-0.235	0.115
2011	2221	-0.297	0.006	0.170	-0.493	-0.185	0.183
2012	2248	-0.087	0.026	0.225	-0.550	-0.195	0.200
2013	2331	-0.096	0.011	0.157	-0.521	-0.167	0.226

Panel B: Summary Statistics across AVP Portfolios

AVP	Beta	LnME	B/M	MOM	Rev	IVol	Illiq	Max	Min	PCR
1	1.03	14.25	0.41	8.76	8.50	2.17	2.10	6.51	-3.74	0.48
2	1.07	14.32	0.41	10.35	3.93	1.80	2.16	4.97	-3.86	0.50
3	1.06	14.34	0.41	10.61	1.21	1.69	2.23	4.42	-3.92	0.51
4	1.03	14.37	0.42	10.67	-1.44	1.65	2.28	4.03	-4.06	0.53
5	0.96	14.32	0.45	9.19	-5.18	1.85	2.28	3.76	-4.96	0.58

Table 2: **Asymmetric Variance Premium and Single-Sorted Portfolios**

This table presents average monthly portfolio returns (in %) based either on VRP (Panel A) or on AVP (Panel B). We sort all firms on the basis of their VRPs or AVPs into quintiles at the end of each month from January 1996 to December 2013. We then hold these quintile portfolios over the next month and computer their equal-weighted monthly returns. A hedge portfolio that longs the high VRP (AVP) portfolio and shorts the low VRP (AVP) portfolio is also formed. Excess returns, characteristic-adjusted returns, and industry-adjusted returns are reported. Excess return is the difference between portfolio returns and the one-month Treasury bill rate. Characteristic-adjusted returns are computed by adjusting returns using 125 ($5 \times 5 \times 5$) size/book-to-market/momentum portfolios (Daniel et al., 1997), and industry-adjusted returns are computed by adjusting returns using 17 industry portfolios (Fama and French, 1997). The Newey-West t-statistics with six lags are reported in brackets.

	Panel A: Variance Premium					
	1	2	3	4	5	5–1
Excess Ret	0.25 (0.50)	0.55 (1.27)	0.69 (1.92)	0.83 (2.22)	0.85 (2.00)	0.60 (2.46)
Char-Adj Ret	-0.31 (-2.55)	-0.07 (-0.67)	-0.04 (-0.36)	-0.01 (-0.09)	0.03 (-0.36)	0.34 (2.12)
Ind-Adj Ret	-0.64 (-2.89)	-0.33 (-1.52)	-0.26 (-1.09)	-0.18 (-0.76)	-0.15 (-0.66)	0.49 (2.96)
	Panel B: Asymmetric Variance Premium					
	1	2	3	4	5	5–1
Excess Ret	0.26 (0.62)	0.44 (1.04)	0.65 (1.57)	0.87 (2.15)	0.98 (2.42)	0.72 (3.68)
Char-Adj Ret	-0.42 (-4.03)	-0.24 (-2.90)	-0.06 (-0.67)	0.10 (0.92)	0.24 (2.07)	0.66 (4.95)
Ind-Adj Ret	-0.72 (-3.04)	-0.55 (-2.53)	-0.30 (-1.42)	-0.04 (-0.19)	0.07 (0.30)	0.79 (5.29)

Table 3: **Asymmetric Variance Premium and Double-Sorted Portfolios**

This table presents average monthly returns (in %) of the two independent double-sort portfolios. At the end of each month, we first sort all stocks into quintile portfolios based independently on AVP and on either variance (Panel A) or VRP (Panel B). We then form 25 portfolios based on the intersection of the two types of portfolios. We hold these portfolios over the next month and report their average monthly equal-weighted excess returns. The high-minus-low hedge portfolio returns based on asymmetric variance premium and on either variance or variance risk premium are also reported. The Newey-West t-statistics with six lags are reported in brackets.

	Panel A: Asymmetric Variance Premium					
Variance	1	2	3	4	5	5–1
1	0.68 (2.47)	0.74 (2.51)	0.89 (3.02)	0.92 (2.97)	0.92 (3.26)	0.24 (2.32)
2	0.68 (2.00)	0.63 (1.77)	0.82 (2.31)	1.07 (2.86)	0.99 (2.45)	0.31 (2.18)
3	0.41 (0.94)	0.67 (1.58)	0.87 (1.96)	1.19 (2.94)	1.25 (3.09)	0.84 (3.52)
4	0.17 (0.33)	0.33 (0.60)	0.68 (1.35)	0.71 (1.44)	1.08 (2.14)	0.91 (3.65)
5	-0.31 (-0.56)	-0.11 (-0.18)	-0.14 (-0.24)	0.33 (0.61)	0.67 (1.29)	0.98 (3.35)
5–1	-1.00 (-2.08)	-0.84 (-1.66)	-1.03 (-2.14)	-0.60 (-1.43)	-0.24 (-0.64)	——
Variance	Panel B: Asymmetric Variance Premium					
Premium	1	2	3	4	5	5–1
1	-0.12 (-0.23)	0.07 (0.12)	0.11 (0.22)	0.53 (1.08)	0.76 (1.65)	0.88 (2.67)
2	0.23 (0.51)	0.32 (0.71)	0.58 (1.33)	0.62 (1.56)	0.99 (2.41)	0.76 (3.27)
3	0.19 (0.50)	0.46 (1.21)	0.76 (2.21)	0.94 (2.61)	1.00 (2.71)	0.81 (4.21)
4	0.57 (1.47)	0.69 (1.86)	0.81 (2.15)	0.94 (2.48)	1.01 (2.63)	0.43 (2.04)
5	0.40 (0.93)	0.66 (1.46)	0.88 (1.97)	1.25 (2.90)	1.24 (2.87)	0.84 (3.28)
5–1	0.52 (1.73)	0.59 (2.01)	0.76 (2.64)	0.73 (2.53)	0.48 (1.73)	——

Table 4: **Asymmetric Variance Premium and Risk-Adjusted Portfolio Returns**

This table presents the alphas and factor loadings from regressing portfolio excess returns on the Fama-French three factors (Fama and French, 1993), on the Carhart four factors (Carhart, 1997), on the q factors (Hou, Xue, and Zhang, 2015), and on the mispricing factors (Stambaugh and Yuan, 2017), respectively. The portfolios are equally weighted and are rebalanced each month. The Neway-West t-statistics are reported in brackets. Data cover the period from January 1996 to December 2013.

Panel A: The Fama-French Three-Factor Model						
	1	2	3	4	5	5–1
Alpha	-0.47 (-4.04)	-0.31 (-2.92)	-0.11 (-0.88)	0.10 (0.77)	0.22 (1.37)	0.69 (4.45)
MKT	1.04 (37.5)	1.10 (36.7)	1.09 (31.0)	1.06 (21.9)	1.04 (20.7)	-0.01 (-0.12)
SMB	0.39 (7.75)	0.36 (5.59)	0.33 (3.82)	0.29 (2.45)	0.21 (1.67)	-0.17 (-1.64)
HML	0.11 (2.10)	0.15 (2.59)	0.23 (3.72)	0.35 (4.75)	0.45 (5.24)	0.33 (5.00)
Panel B: The Carhart Four-Factor Model						
	1	2	3	4	5	5–1
Alpha	-0.40 (-3.38)	-0.27 (-2.60)	-0.08 (-0.65)	0.15 (1.09)	0.28 (1.77)	0.68 (4.12)
MKT	1.00 (28.0)	1.07 (31.5)	1.07 (30.9)	1.03 (24.3)	1.00 (22.7)	-0.00 (-0.04)
SMB	0.41 (10.0)	0.37 (6.70)	0.34 (4.23)	0.30 (2.75)	0.23 (1.96)	-0.18 (-1.62)
HML	0.08 (1.71)	0.13 (2.34)	0.22 3.46)	0.33 (4.67)	0.41 (5.33)	0.33 (5.40)
MOM	-0.10 (-2.42)	-0.06 (-1.88)	-0.04 (-1.18)	-0.07 (-1.67)	-0.09 (-1.80)	0.01 (0.20)
Panel C: The q-Factor Model						
	1	2	3	4	5	5–1
Alpha	-0.42 (-3.25)	-0.30 (-2.83)	-0.16 (-1.33)	-0.03 (-0.18)	0.02 (0.09)	0.44 (2.48)
MKT	1.01 (35.5)	1.09 (31.4)	1.10 (25.0)	1.10 (18.5)	1.11 (16.5)	0.10 (1.39)
SMB	0.34 (6.35)	0.34 (4.89)	0.34 (3.59)	0.31 (2.41)	0.25 (1.75)	-0.09 (-0.83)
I/A	0.07 (0.92)	0.06 (0.87)	0.15 (2.11)	0.28 (3.77)	0.41 (4.72)	0.34 (4.59)
ROE	-0.11 (-2.07)	-0.03 (-0.62)	0.05 (0.79)	0.14 (1.80)	0.21 (2.13)	0.32 (3.46)
Panel D: The Mispricing-Factor Model						
	1	2	3	4	5	5–1
Alpha	-0.39 (-3.39)	-0.25 (-2.44)	-0.10 (-0.88)	0.09 (0.64)	0.17 (0.99)	0.56 (3.18)
MKT	0.99 (26.1)	1.05 (34.1)	1.06 (35.8)	1.03 (29.5)	1.02 (24.1)	0.02 (0.40)
SMB	0.41 (9.17)	0.40 (6.28)	0.38 (3.85)	0.37 (2.49)	0.31 (1.76)	-0.11 (-0.68)
MGMT	-0.05 (-0.83)	-0.05 (-0.79)	0.04 (0.52)	0.15 (1.77)	0.26 (3.07)	0.31 (4.86)
PERF	-0.09 (-2.51)	-0.06 (-2.05)	-0.04 (-1.21)	-0.06 (-1.54)	-0.07 (-1.48)	0.01 (0.37)

Table 5: **Asymmetric Variance Premium and Fama-MacBeth Regressions**

This table presents monthly Fama-MacBeth (1973) regressions of individual stock returns on AVP. We consider some standard variables used in literature such as beta, size, book-to-market ratio, and momentum. We also control for some stock-related variables such as variance, the short-term reversal, the maximum daily returns in the previous month, the minimum daily returns in the previous month, idiosyncratic volatility, and illiquidity. The following option-related variables are also taken into account: implied volatility skew, implied variance, implied-volatility spread, and put-call volume ratio. The sample period is from January 1996 to December 2013. The Newey-West t-statistics are in parenthesis.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	0.78	0.90	-0.05	0.50	-0.43	1.74	1.06	-0.21	-0.31	2.57
	(2.04)	(2.46)	(-0.04)	(0.50)	(-0.38)	(1.18)	(0.92)	(-0.19)	(-0.27)	(1.67)
AVP	0.95	1.06	0.49	0.93	1.05	0.99	0.93	0.97	1.04	0.38
	(3.50)	(3.72)	(3.19)	(4.01)	(4.24)	(4.15)	(4.32)	(3.86)	(4.19)	(3.12)
VRP		0.44	0.19	0.02	0.32	0.17	0.22	0.34	0.32	0.03
		(2.24)	(1.29)	(0.12)	(1.97)	(1.10)	(1.56)	(2.16)	(2.04)	(0.17)
Beta			-0.14	-0.13	-0.14	-0.13	-0.10	-0.14	-0.14	-0.09
			(-1.69)	(-1.67)	(-1.62)	(-1.62)	(-1.56)	(-1.70)	(-1.70)	(-1.30)
LnME			0.07	0.05	0.10	-0.00	0.03	0.08	0.08	-0.07
			(1.03)	(0.81)	(1.63)	(-0.04)	(0.41)	(1.23)	(1.32)	(-0.87)
B/M			-0.17	-0.21	-0.15	-0.19	-0.21	-0.17	-0.17	-0.21
			(-0.89)	(-1.15)	(-0.80)	(-1.02)	(-1.26)	(-0.89)	(-0.89)	(-1.33)
MOM			0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.00
			(0.07)	(0.38)	(0.19)	(0.43)	(0.40)	(0.27)	(0.31)	(-0.32)
Rev			-0.02							-0.02
			(-2.58)							(-3.57)
IVol				-0.15						-0.06
				(-2.16)						(-0.66)
Amihud					-0.04					-0.06
					(-1.45)					(-2.92)
EISkew						-3.84				1.83
						(-1.82)				(0.54)
IVLevel							-1.23			-1.38
							(-1.80)			(-1.76)
IVSpread								3.06		2.92
								(3.40)		(3.61)
IVSkew									0.13	0.82
									(0.48)	(1.93)
Adj R^2	0.07	0.08	0.12	0.12	0.11	0.12	0.12	0.11	0.11	0.13
	(22.6)	(19.6)	(21.0)	(20.6)	(21.4)	(21.0)	(19.7)	(21.4)	(21.2)	(20.6)

Table 6: **Robustness Checks**

This table presents portfolio returns and alphas (in %) from the four factor models for the three robustness checks. Portfolios are constructed using the same approach as in Section 2. In Panel A, we use the 15-minute high-frequency returns to construct realized measures, with which asymmetric variance premium is computed, and in Panel B, we use expected realized measures from the variance forecasting model of Equation (14) to construct asymmetric variance premium. The sample period is from January 1996 to December 2013. The Newey-West t-statistics are in parenthesis.

Panel A: Using 15-Min High-Frequency Returns						
	1	2	3	4	5	5–1
Excess Ret	0.33 (0.80)	0.44 (1.06)	0.69 (1.68)	0.88 (2.14)	0.89 (2.15)	0.55 (2.95)
Char-Adj Ret	-0.37 (-3.29)	-0.25 (-2.80)	-0.03 (-0.34)	0.11 (1.03)	0.17 (1.48)	0.54 (3.89)
Ind-Adj Ret	-0.66 (-2.79)	-0.57 (-2.51)	-0.27 (-1.28)	-0.03 (-0.14)	0.01 (0.05)	0.67 (4.69)
FF3F Alpha	-0.39 (-3.34)	-0.30 (-2.53)	-0.06 (-0.58)	0.11 (0.82)	0.11 (0.70)	0.50 (3.22)
Carhart Alpha	-0.33 (-2.95)	-0.26 (-2.16)	-0.03 (-0.26)	0.14 (1.04)	0.18 (1.16)	0.51 (3.16)
q-Alpha	-0.37 (-2.65)	-0.34 (-2.39)	-0.09 (-0.75)	-0.06 (-0.40)	0.04 (-0.21)	0.41 (2.51)
M-Alpha	-0.37 (-3.06)	-0.28 (-2.45)	-0.05 (-0.46)	0.10 (0.72)	0.11 (0.70)	0.49 (2.80)
Panel B: Using Forecasted Variance and Semivariances						
	1	2	3	4	5	5–1
Excess Ret	0.42 (0.98)	0.59 (1.36)	0.57 (1.31)	0.64 (1.51)	0.90 (2.12)	0.44 (3.99)
Char-Adj Ret	-0.23 (-2.17)	-0.10 (-1.28)	-0.13 (-1.60)	-0.02 (-0.17)	0.19 (1.86)	0.41 (3.85)
Ind-Adj Ret	-0.48 (-2.07)	-0.34 (-1.55)	-0.37 (-1.67)	-0.31 (-1.30)	-0.03 (-0.14)	0.46 (4.56)
FF3F Alpha	-0.27 (-2.29)	-0.10 (-0.89)	-0.12 (-0.96)	-0.07 (-0.47)	0.20 (1.52)	0.46 (4.01)
Carhart Alpha	-0.20 (-1.89)	-0.05 (-0.44)	-0.08 (-0.61)	-0.01 (-0.06)	0.26 (2.08)	0.46 (3.93)
q-Alpha	-0.26 (-1.92)	-0.12 (-1.07)	-0.21 (-1.68)	-0.18 (-1.26)	0.15 (1.08)	0.41 (3.40)
M-Alpha	-0.18 (-1.52)	-0.07 (-0.60)	-0.12 (-0.95)	-0.10 (-0.69)	0.23 (1.73)	0.39 (3.18)

Table 7: **Standard Skewness Premium and Portfolio Returns**

Panel A presents average monthly portfolio returns and alphas (in %) from the four factor models based on standard skewness premium. We sort all firms on the basis of their SSPs into quintiles at the end of each month from January 1996 to December 2013. We then hold these quintile portfolios over the next month and computer their equal-weighted monthly returns. A hedge portfolio that longs the high SSP portfolio and shorts the low SSP portfolio is also formed. Excess returns, characteristic-adjusted returns, and industry-adjusted returns are reported. Panels B and C present average monthly returns (in %) of the two independent double-sort portfolios. At the end of each month, we first sort all stocks into quintile portfolios based independently on SSP and on either variance or VRP. We then form 25 portfolios based on the intersection of the two types of portfolios. We hold these portfolios over the next month and report their average monthly equal-weighted excess returns. The high-minus-low hedge portfolio returns based on asymmetric variance premium and on either variance or variance risk premium are also reported. The Newey-West t-statistics with six lags are reported in brackets.

	Panel A: Standard Skewness Premium					
	1	2	3	4	5	5–1
Excess Ret	0.39 (1.06)	0.50 (1.22)	0.62 (1.45)	0.70 (1.65)	0.96 (2.22)	0.57 (3.35)
Char-Adj Ret	-0.35 (-3.20)	-0.20 (-2.06)	-0.12 (-1.53)	0.02 (0.17)	0.24 (2.16)	0.58 (4.63)
Ind-Adj Ret	-0.64 (-2.69)	-0.48 (-2.15)	-0.36 (-1.73)	-0.18 (-0.83)	0.09 (0.44)	0.74 (5.16)
FF3F Alpha	-0.31 (-2.86)	-0.24 (-2.20)	-0.15 (-1.40)	-0.08 (-0.55)	0.17 (1.06)	0.48 (3.04)
Carhart Alpha	-0.30 (-2.67)	-0.22 (-1.94)	-0.11 (-1.05)	-0.01 (-0.04)	0.27 (1.75)	0.57 (3.42)
q-Alpha	-0.37 (-3.17)	-0.30 (-2.73)	-0.20 (-1.79)	-0.15 (-0.92)	0.10 (0.51)	0.47 (2.49)
M-Alpha	-0.40 (-3.57)	-0.25 (-2.12)	-0.11 (-1.03)	-0.04 (-0.31)	0.29 (1.81)	0.69 (3.99)
	Panel B: Standard Skewness Premium					
Variance	1	2	3	4	5	5–1
1	0.68 (2.37)	0.81 (2.76)	0.94 (3.08)	0.87 (2.74)	1.04 (3.56)	0.36 (2.88)
2	0.69 (2.11)	0.73 (2.00)	0.88 (2.37)	1.01 (2.76)	1.07 (2.67)	0.37 (2.07)
3	0.38 (0.91)	0.79 (1.81)	0.92 (2.15)	0.91 (2.21)	1.32 (3.18)	0.94 (4.13)
4	0.30 (0.61)	0.34 (0.64)	0.43 (0.78)	0.60 (1.28)	1.04 (2.10)	0.75 (2.83)
5	-0.31 (-0.50)	-0.08 (-0.15)	-0.09 (-0.15)	0.15 (0.27)	0.44 (0.83)	0.75 (2.65)
5-1	-0.99 (-1.78)	-0.90(-1.90)	-1.03 (-2.19)	-0.72 (-1.84)	-0.59 (-1.36)	——
Variance	Panel C: Standard Skewness Premium					
Premium	1	2	3	4	5	5–1
1	0.02 (0.05)	0.11 (0.21)	0.03 (0.05)	0.38 (0.82)	0.60 (1.22)	0.58 (2.11)
2	0.42 (1.00)	0.28 (0.64)	0.49 (1.13)	0.63 (1.49)	0.93 (2.22)	0.51 (2.57)
3	0.34 (1.03)	0.57 (1.68)	0.82 (2.17)	0.63 (1.70)	1.16 (3.00)	0.82 (4.46)
4	0.55 (1.63)	0.81 (2.19)	0.92 (2.43)	0.87 (2.12)	1.02 (2.59)	0.47 (2.37)
5	0.51 (1.29)	0.74 (1.63)	0.82 (1.76)	0.96 (2.14)	1.23 (2.80)	0.72 (3.02)
5-1	0.48 (1.45)	0.63 (1.87)	0.79 (2.60)	0.58 (2.07)	0.62 (2.15)	——

Table 8: **Standard Skewness Premium and Fama-MacBeth Regressions**

This table presents monthly Fama-MacBeth (1973) regressions of individual stock returns on SSP. We consider some standard variables used in literature such as beta, size, book-to-market ratio, and momentum. We also control for some stock-related variables such as variance, the short-term reversal, the maximum daily returns in the previous month, the minimum daily returns in the previous month, idiosyncratic volatility, and illiquidity. The following option-related variables are also taken into account: implied volatility skew, implied variance, implied-volatility spread, and put-call volume ratio. The sample period is from January 1996 to December 2013. The Newey-West t-statistics are in parenthesis.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	0.72	0.82	-0.35	0.14	-0.95	1.46	0.97	-0.66	-0.81	2.56
	(1.80)	(2.16)	(-0.30)	(0.13)	(-0.84)	(0.99)	(0.83)	(-0.58)	(-0.71)	(1.68)
SSP	0.37	0.39	0.30	0.45	0.47	0.45	0.47	0.44	0.47	0.27
	(3.70)	(4.01)	(4.09)	(5.11)	(5.36)	(5.13)	(5.26)	(4.91)	(5.37)	(4.26)
VRP		0.42	0.20	-0.01	0.27	0.10	0.18	0.29	0.27	0.07
		(2.55)	(1.61)	(-0.03)	(2.00)	(0.72)	(1.45)	(2.16)	(2.03)	(0.50)
Beta			-0.14	-0.14	-0.16	-0.15	-0.11	-0.15	-0.16	-0.09
			(-1.78)	(-1.90)	(-1.86)	(-1.84)	(-1.74)	(-1.92)	(-1.93)	(-1.36)
LnME			0.09	0.07	0.13	0.02	0.04	0.11	0.11	-0.05
			(1.31)	(1.19)	(2.09)	(0.22)	(0.62)	(1.61)	(1.75)	(-0.68)
B/M			-0.17	-0.22	-0.15	-0.20	-0.24	-0.17	-0.17	-0.23
			(-0.90)	(-1.18)	(-0.78)	(-1.08)	(-1.38)	(-0.87)	(-0.87)	(-1.44)
MOM			0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.00
			(0.06)	(0.38)	(0.19)	(0.17)	(0.41)	(0.25)	(0.31)	(-0.44)
Rev			-0.02							-0.02
			(-2.55)							(-3.57)
IVol				-0.16						-0.02
				(-2.34)						(-0.23)
Amihud					-0.03					-0.06
					(-1.28)					(-2.81)
EISkew						-4.33				0.91
						(-2.11)				(0.27)
IVLevel							-1.50			-1.65
							(-2.16)			(-2.08)
IVSpread								3.31		2.93
								(3.50)		(3.51)
IVSkew									0.20	0.99
									(0.68)	(2.30)
Adj R^2	0.07	0.08	0.12	0.12	0.11	0.11	0.12	0.11	0.11	0.13
	(23.2)	(20.5)	(21.2)	(20.9)	(21.8)	(21.4)	(19.8)	(21.8)	(21.7)	(20.5)

Table 9: **Liquidity and Predictive Power of AVP**

The table presents the Fama-MacBeth cross-sectional regressions of stock returns on the lagged AVP and the relative liquidity of stocks and options. To measure stock liquidity, we use Amihud illiquidity ratio (Amihud, 2002), and to measure option liquidity, we use option volume and option open interest. To compute option volume and option open interest, we either use the total trading volume and open interest in each month under (1) or use the trading volume and open interest in the last trading day of each month under (2). Two dummy variables are constructed: the first one is high option liquidity and low stock liquidity dummy (HOLSD), and the other is low option liquidity and high stock liquidity dummy (LOHSD). HOLSD is equal to one for stocks that belong to the top 33% of option liquidity and the bottom 33% of stock liquidity; similarly, LOHSD is equal to one for stocks that belong to the bottom 33% of option liquidity and the top 33% of stock liquidity. The regressions are also controlled for these variables: VRP, beta, size, B/M, and Momentum. F-test is for testing equal coefficients on two dummy-related variables. The sample period is from January 1996 to December 2013. The Newey-West t-statistics with six lags are reported in parenthesis.

	Option Volume		Option Open Interest	
	(1)	(2)	(1)	(2)
Intercept	-0.68	-0.67	-0.71	-0.69
	(-0.58)	(-0.57)	(-0.61)	(-0.59)
AVP	1.19	1.22	1.20	1.20
	(4.75)	(4.70)	(4.60)	(4.63)
VRP	0.22	0.23	0.23	0.23
	(1.52)	(1.54)	(1.54)	(1.53)
AVP×HOLSD	1.33	0.79	1.26	1.03
	(3.68)	(2.24)	(3.87)	(2.80)
AVP×LOHSD	-0.71	-0.57	-0.60	-0.49
	(-2.03)	(-1.91)	(-2.13)	(-1.59)
Control Variables	Yes	Yes	Yes	Yes
Adj R^2	0.10	0.10	0.10	0.10
	(20.3)	(20.2)	(20.3)	(20.2)
F-test (p-value)	0.00	0.00	0.00	0.00

Table 10: **Information Asymmetry and Predictive Power of AVP**

This table presents monthly double-sort portfolio returns and alphas (in %) from the four factor models based on PIN and AVP. At the end of each month, we first sort all stocks into tercile portfolios based on PIN, and then we sort stocks in each of these tercile portfolios into quintile portfolios and form a high-minus-low hedge portfolio on the basis of AVP. We hold these portfolios over the next month and compute their equal-weighted portfolio returns and alphas of the four factor models. We only report returns and alphas for those portfolios that combine the bottom and top tercile portfolios and odd quintile portfolios. Excess return is the difference between portfolio returns and the one-month Treasury bill rate. Characteristic-adjusted returns are computed by adjusting returns using 125 ($5 \times 5 \times 5$) size/book-to-market/momentum portfolios (Daniel et al., 1997), and industry-adjusted returns are computed by adjusting returns using the Fama-French 17 industry portfolios (Fama and French, 1997). The three-factor (Fama and French, 1993), four-factor (Carhart, 1997), q-factor (Hou, Xue, and Zhang, 2015), and M-factor (Stambaugh and Yuan, 2016) alphas are also reported. The sample period is from January 1996 to December 2013. The Newey-West t-statistics are in parenthesis.

		Excess and Adjusted Returns			Alphas from Factor Models			
		Excess	Char-Adj	Ind-Adj	FF3F	Carhart	q-	M-
PIN	AVP	Ret	Ret	Ret	Alpha	Alpha	Alpha	Alpha
Low	1	0.28	-0.28	-0.66	-0.40	-0.31	-0.20	-0.17
		(0.56)	(-2.11)	(-2.36)	(-2.75)	(-2.34)	(-1.33)	(-1.03)
	3	0.62	0.03	-0.38	-0.07	-0.03	-0.04	0.08
		(1.47)	(0.30)	(-1.55)	(-0.53)	(-0.18)	(-0.30)	(0.55)
	5	0.81	0.17	-0.05	0.09	0.15	-0.04	0.06
		(2.10)	(1.58)	(-0.22)	(0.70)	(1.08)	(-0.22)	(0.38)
	5-1	0.54	0.45	0.60	0.49	0.46	0.16	0.22
		(1.95)	(2.47)	(2.75)	(2.90)	(2.62)	(0.82)	(1.06)
High	1	0.25	-0.55	-0.81	-0.58	-0.56	-0.63	-0.64
		(0.58)	(-3.04)	(-2.84)	(-4.08)	(-3.79)	(-3.99)	(-3.53)
	3	0.69	-0.19	-0.31	-0.16	-0.13	-0.24	-0.20
		(1.54)	(-1.32)	(-1.25)	(-0.92)	(-0.74)	(-1.39)	(-1.30)
	5	1.31	0.49	0.33	0.46	0.56	0.26	0.43
		(3.03)	(2.06)	(1.10)	(1.80)	(2.39)	(0.87)	(1.80)
	5-1	1.07	1.04	1.14	1.04	1.12	0.89	1.07
		(4.07)	(4.56)	(5.33)	(4.08)	(4.35)	(2.98)	(3.78)

Table 11: **Predictive Power of AVP and Corporate Events**

This table presents Fama-MacBeth (1973) cross-sectional regressions of individual event returns (Models 1-3) and post-event returns (Model 4) on event-related AVP measures. At any event day t, the event return (ERet) is defined as the excess return over days from $t-1$ to $t+1$ and the post-even return (PostERet) is defined as the excess return over days from $t+6$ to $t+90$. The explanatory variables include: the base asymmetric variance premium (AVP-Base), defined as the average of daily asymmetric variance premiums over days from $t-50$ to $t-11$, the pre-event asymmetric variance premium (AVP-PreE), defined as the average of daily asymmetric variance premiums over days from $t-10$ to $t-2$, and the post-event asymmetric variance premium (AVP-PostE), defined as the average of daily asymmetric variance premiums over days from $t+1$ to $t+5$. Earnings announcement data are obtained from Compustat for the period from the first quarter of 1996 to the fourth quarter of 2013. As for extreme events, we calculate the three-day excess return at each day and if it is larger than 10% or smaller than -10%, we keep it in the extreme events sample. The Newey-West $t-$statistics are reported in parenthesis.

	Panel A: Earnings Announcement				Panel B: Extreme Events			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Intercept	0.004	0.006	0.006	0.031	0.032	0.037	0.039	0.010
	(4.32)	(5.86)	(5.86)	(2.23)	(14.9)	(19.3)	(17.50)	(1.56)
AVP-Base	0.012		0.002	0.181	0.041		0.006	0.036
	(3.24)		(0.51)	(4.26)	(6.91)		(1.01)	(1.15)
AVP-PreE		0.023	0.023	0.044		0.070	0.069	0.019
		(6.48)	(6.48)	(2.38)		(17.3)	(16.8)	(1.69)
AVP-PostE				0.040				0.033
				(3.32)				(5.38)
ERet				0.138				0.008
				(5.19)				(0.57)
Adj R^2	0.001	0.003	0.004	0.017	0.005	0.009	0.013	0.019

Table 12: **Limits-to-Arbitrage and Predictive Power of AVP**

This table presents monthly double-sort portfolio returns and alphas (in %) from the four factor models based on proxies of limits-to-arbitrage and AVP. We use the institutional ownership (IO), idiosyncratic volatility (IVol), and analyst forecast dispersion (AFD) to proxy limits-to-arbitrage. At the end of each month in our sample, we first sort all stocks into tercile portfolios based on each of the above proxies of limits-to- arbitrage, and then we sort stocks in each of these tercile portfolios into quintile portfolios and form a high-minus-low hedge portfolio. We hold these portfolios over the next month and compute their equal-weighted portfolio returns and alphas of the aforementioned four factor models. We only report returns and alphas for those portfolios that combine the bottom and top tercile portfolios and odd quintile portfolios. Excess return is the difference between portfolio returns and the one-month Treasury bill rate. Characteristic-adjusted returns are computed by adjusting returns using 125 ($5 \times 5 \times 5$) size/book-to-market/momentum portfolios (Daniel et al., 1997), and industry-adjusted returns are computed by adjusting returns using the Fama-French 17 industry portfolios (Fama and French, 1997). The three-factor (Fama and French, 1993), four-factor (Carhart, 1997), q-factor (Hou, Xue, and Zhang, 2015), and M-factor (Stambaugh and Yuan, 2016) alphas are also reported. The sample period is from January 1996 to December 2013. The Newey-West t-statistics are in parenthesis.

Panel A: Predictive Power of AVP and Institutional Ownership								
		Excess and Adjusted Returns			Alphas from Factor Models			
		Excess	Char-Adj	Ind-Adj	FF3F	Carhart	q-	M-
IO	AVP	Ret	Ret	Ret	Alpha	Alpha	Alpha	Alpha
Low	1	-0.02	-0.67	-0.95	-0.74	-0.67	-0.63	-0.58
		(-0.05)	(-5.04)	(-4.06)	(-5.20)	(-4.85)	(-4.40)	(-4.10)
	3	0.37	-0.31	-0.55	-0.37	-0.35	-0.34	-0.33
		(0.91)	(-2.95)	(-2.73)	(-2.92)	(-2.75)	(-2.63)	(-2.66)
	5	0.84	0.14	-0.05	0.10	0.16	-0.06	0.08
		(2.23)	(1.01)	(-0.24)	(0.75)	(1.07)	(-0.32)	(0.51)
	5-1	0.86	0.81	0.90	0.84	0.83	0.58	0.66
		(3.27)	(4.35)	(4.70)	(4.51)	(4.15)	(2.64)	(3.43)
High	1	0.58	-0.21	-0.46	-0.20	-0.16	-0.31	-0.31
		(1.37)	(-1.59)	(-1.78)	(-1.61)	(-1.45)	(-2.42)	(-2.78)
	3	0.90	0.07	-0.16	0.10	0.13	-0.09	0.01
		(2.16)	(0.53)	(-0.70)	(0.56)	(0.70)	(-0.44)	(0.07)
	5	1.06	0.26	0.12	0.24	0.29	-0.01	0.17
		(2.40)	(1.65)	(0.39)	(1.26)	(1.59)	(-0.03)	(0.86)
	5-1	0.48	0.48	0.58	0.44	0.46	0.30	0.48
		(2.39)	(3.22)	(3.29)	(2.45)	(2.56)	(1.46)	(2.54)

Panel B: Predictive Power of AVP and Idiosyncratic Volatility								
		Excess and Adjusted Returns			Alphas from Factor Models			
		Excess	Char-Adj	Ind-Adj	FF3F	Carhart	*q*-	*M*-
IVol	AVP	Ret	Ret	Ret	Alpha	Alpha	Alpha	Alpha
Low	1	0.67	-0.09	-0.36	0.04	0.05	-0.18	-0.12
		(2.28)	(-0.61)	(-1.35)	(0.32)	(0.40)	(-1.15)	(-0.75)
	3	0.91	0.10	-0.04	0.26	0.25	-0.03	0.04
		(2.89)	(0.69)	(-0.15)	(1.90)	(1.75)	(-0.18)	(0.26)
	5	1.03	0.25	0.08	0.38	0.41	0.07	0.20
		(3.10)	(1.41)	(0.29)	(2.90)	(3.17)	(0.37)	(1.29)
	5-1	0.37	0.34	0.44	0.34	0.36	0.25	0.32
		(2.63)	(2.77)	(3.28)	(2.64)	(2.49)	(1.76)	(2.18)
High	1	0.04	-0.51	-0.94	-0.72	-0.62	-0.47	-0.51
		(0.09)	(-3.20)	(-3.50)	(-3.94)	(-3.72)	(-2.08)	(-2.49)
	3	0.07	-0.55	-0.84	-0.77	-0.70	-0.53	-0.50
		(0.12)	(-3.75)	(-3.52)	(-4.32)	(-4.34)	(-2.69)	(-2.80)
	5	0.72	0.13	-0.15	-0.13	-0.00	-0.10	0.08
		(1.49)	(0.80)	(-0.66)	(-0.59)	(-0.01)	(-0.37)	(0.38)
	5-1	0.68	0.64	0.79	0.59	0.62	0.37	0.59
		(2.65)	(3.14)	(3.44)	(2.75)	(2.64)	(1.46)	(2.38)

Panel C: Predictive Power of AVP and Analyst Forecast Dispersion								
		Excess and Adjusted Returns			Alphas from Factor Models			
		Excess	Char-Adj	Ind-Adj	FF3F	Carhart	*q*-	*M*-
AFD	AVP	Ret	Ret	Ret	Alpha	Alpha	Alpha	Alpha
Low	1	0.42	-0.28	-0.59	-0.31	-0.24	-0.27	-0.28
		(1.06)	(-2.67)	(-2.43)	(-2.80)	(-2.35)	(-2.15)	(-2.42)
	3	0.60	-0.09	-0.36	-0.15	-0.12	-0.24	-0.20
		(1.52)	(-0.94)	(-1.72)	(-1.14)	(-0.96)	(-1.74)	(-1.57)
	5	0.99	0.28	0.08	0.24	0.29	0.00	0.14
		(2.62)	(2.07)	(0.30)	(1.41)	(1.77)	(0.00)	(0.80)
	5-1	0.57	0.56	0.67	0.55	0.53	0.27	0.41
		(2.70)	(4.59)	(4.25)	(3.73)	(3.47)	(1.59)	(2.53)
High	1	0.09	-0.65	-0.88	-0.64	-0.58	-0.61	-0.49
		(0.21)	(-3.79)	(-3.45)	(-3.69)	(-3.57)	(-2.99)	(-2.68)
	3	0.70	-0.10	-0.21	-0.11	-0.08	-0.10	0.03
		(1.56)	(-0.70)	(-1.05)	(-0.68)	(-0.51)	(-0.54)	(0.16)
	5	0.88	0.15	0.02	0.06	0.14	-0.08	0.13
		(1.93)	(0.90)	(0.09)	(0.32)	(0.69)	(-0.30)	(0.61)
	5-1	0.79	0.80	0.90	0.70	0.72	0.53	0.63
		(2.87)	(3.35)	(3.87)	(2.83)	(2.69)	(1.76)	(2.19)

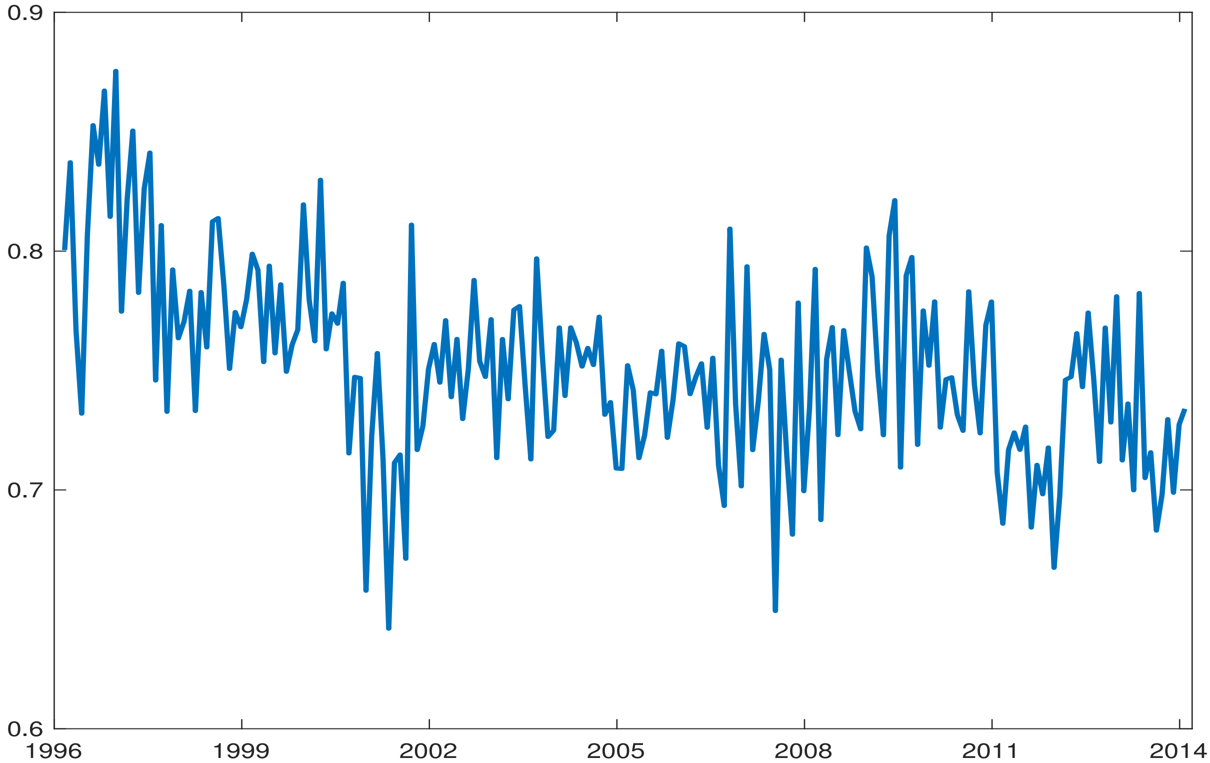

Figure 1: **Cross-Sectional Correlations between AVP and SSP**

The figure plots the cross-sectional correlation between asymmetric variance premium (AVP) and standard skewness premium (SSP). AVP is computed using Equation (18) and SSP is computed using Equation (23). In both equations, the risk-neutral measures are recovered from prices of out-of-money call and put options with maturity of 30 days, and the realized measures are constructed using the 5-minute intraday high-frequency individual stock returns and are assumed to follow random walks. The sample period is from January 1996 to December 2013.

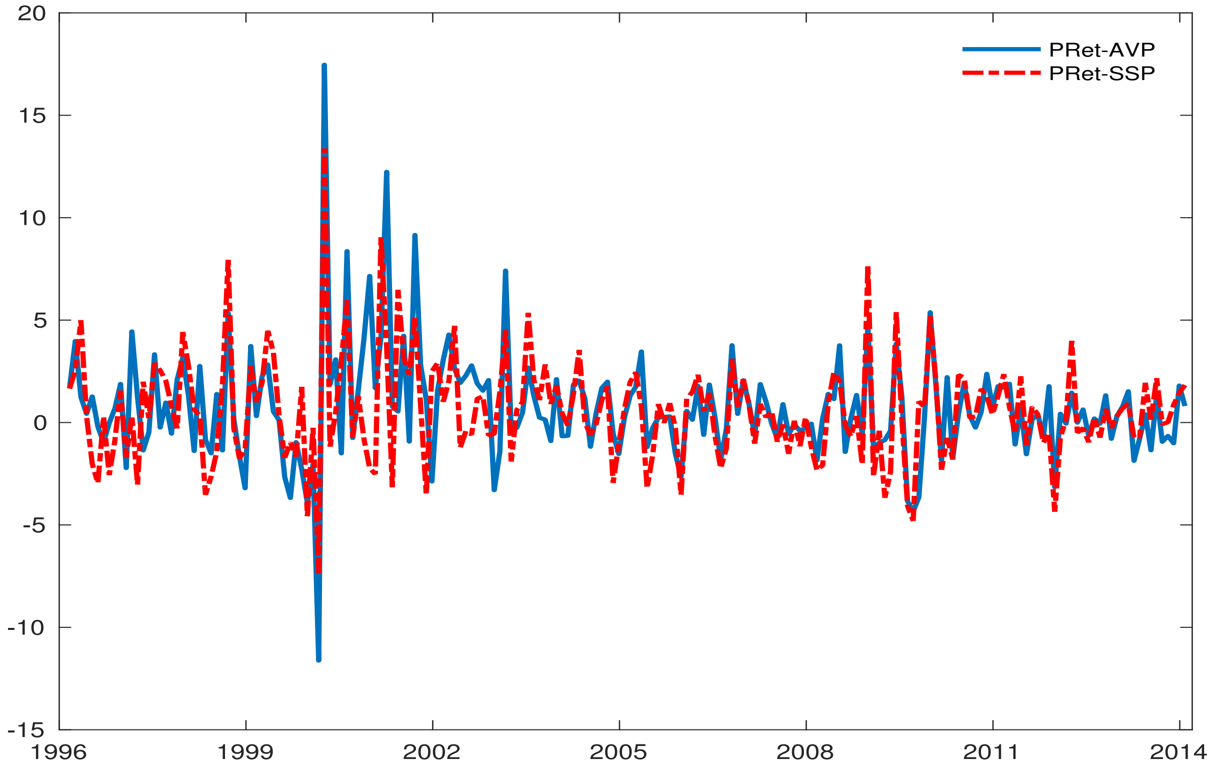

Figure 2: **Monthly Excess Returns of the Hedge Portfolios based on AVP and SSP** The figure plots the time series of monthly returns of the hedge portfolios based on asymmetric variance premium (AVP, solid line) and on standard skewness premium (SSP, dashed line). At the end of each month, we sort all firms on the basis of their AVPs (SSPs) into quintiles. A hedge portfolio that longs the high AVP (SSP) portfolio and shorts the low AVP (SSP) portfolio is then formed. We hold these portfolios over the next month and computer their equal-weighted monthly returns. AVP is computed using Equation (18) and SSP is computed using Equation (23). In both equations, the risk-neutral measures are recovered from prices of out-of-money call and put options with maturity of 30 days, and the realized measures are constructed using the 5-minute intraday high-frequency individual stock returns and are assumed to follow random walks. The sample period is from January 1996 to December 2013.