The Information Content of the Term Structure of Risk-Neutral Skewness*

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Abstract

This study seeks to reconcile an ongoing debate about the price effect of risk-neutral skewness (RNS) on individual stocks by considering the maturity dimension. We document *positive* stock return predictability from short-term skewness, consistent with an informed trading/hedging demand, and *negative* predictability from long-term skewness, consistent with skewness preference. A term spread on RNS captures the different information sets from both the long- and short-term contract markets, resulting in even stronger predictability. The decile portfolio exhibiting the highest spread underperforms the decile portfolio with the lowest spread by 19.32% per year after controlling for common benchmarks. The term structure of RNS predicts firms' future earnings surprises and price crashes, consistent with informed trader demand for short-term options. This information difference between the short- and long-term options explains the difference in the pricing of their RNS, providing a potential resolution to the empirical debate.

Keywords: Risk-Neutral Skewness; Term Structure; Return Predictability; Hedging Demand; Informed Trading; Skewness Preference

JEL classification: G12, G13, G14

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1. Introduction

The behavioral and rational models of Brunnermeier, Gollier, and Parker (2007), Mitton and Vorkink (2007), and Barberis and Huang (2008), in which investors exhibit a preference for securities with positive skewness, have motivated a large empirical literature on whether positively skewed securities are overpriced and earn negative average excess returns. As the historical estimates of skewness provide poor forecasts of future skewness (Boyer, Mitton, and Vorkink, 2010), these studies commonly use option data to estimate investor expectations of risk-neutral skewness.

To date, these empirical studies have produced mixed evidence for whether option-implied risk-neutral skewness carries a positive or negative premium in the cross-section of equity returns. Consistent with the skewness preference theory, Bali and Murray (2013) and Conrad, Dittmar, and Ghysels (2013) find a negative relation between risk-neutral skewness (RNS) and future equity returns. These studies implicitly assume that option and stock markets reflect the same information and option-implied skewness proxies for the underlying skewness. Thus, positive option-implied skewness combined with skewness preference for the underlying leads to low expected returns.

This assumption is challenged by arbitrage opportunities and information differences between the option and equity markets. Ait-Sahalia, Wang, and Yared (2001) demonstrates that the risk-neutral density estimated from S&P 500 options is different from a density inferred from historical index returns, suggesting the option market includes a "peso problem" jump dynamic unobserved in the underlying asset. Consistent with an information difference between two markets, other studies contradict Bali and Murray (2013) and Conrad et al. (2013) by demonstrating that RNS can positively predict the cross-sectional future stock returns (Xing, Zhang, and Zhao, 2010; Stilger, Kostakis, and Poon, 2016).

Xing et al. (2010) suggest that informed option traders purchase out-of-the-money (OTM) put options before downward jumps in the underlying, which drives up the volatility of OTM puts and consequently leads to a steeper slope of the implied volatility function translating to a more negative RNS per Bakshi, Kapadia, and Madan (2003). Stilger et al. (2016) further find these trading activities mainly concentrate on stocks that are perceived as relatively overpriced by investors and costly to sell short. Therefore, hedging demand for underlying positions or speculation on pessimistic expectations causes informed investors to buy OTM puts or sell OTM calls, also pushing down RNS. As the mispricing information is transmitted to the stock market over time, these relatively overpriced stocks with low RNS subsequently underperform, producing a positive relation between RNS and future realized equity returns.

Our study contributes to this ongoing debate between two empirical views on RNS: the informed trading and hedging view that positive RNS predicts positive underlying returns because it reflects market beliefs, and the skewness-preference view that positive RNS predicts negative underlying returns because it encourages overbidding. We accomplish this by examining the relation between the term structure of RNS and subsequent monthly equity returns. Prior empirical investigations aggregate options with maturities over a certain relatively wide range to compute RNS, implicitly assuming a flat term structure. We hypothesize that investor types may have inherent maturity preferences,[1] and therefore the RNS across different maturity horizons may contain information particular to these types.

To do this, we use the OptionMetrics Volatility Surface file from 1996 to 2015 to calculate monthly RNS at the 1, 3, 6, 9, and 12 month maturities for a large sample of U.S. stocks. We estimate RNS for each security at each time horizon using the model-free method of (Bakshi et al., 2003) and analyze the cross-sectional predictive relationship between the RNS at different maturities with subsequent monthly underlying returns. The results indicate this relationship exhibits a monotonic pattern, which is significantly positive for the short-term (1 month), insignificant for the middle-term (6 month), and significantly negative for the long-term (12 month). In particular, a strategy long the equal-weighted (value-weighted) decile portfolio with the highest 1-month RNS and short the equal-weighted (value-weighted) decile

[1] Such as short-term speculation versus long-term hedging needs.

portfolio with the lowest 1-month RNS yields a risk-adjusted[2] alpha of 1.12% per month with t-statistic of 5.49 (0.95% per month with t-statistic of 3.76), while the same strategy based on 12-month RNS produces a corresponding alpha of -0.88% per month with t-statistic of -3.49 (-0.56% per month with t-statistic of -1.79). The positive predictability of future equity returns from short-term RNS is consistent with the informed trading (Xing et al., 2010) and hedging (Stilger et al., 2016) views, while the negative predictability from the long-term RNS is consistent with skewness preference (Bali and Murray, 2013; Conrad et al., 2013).

Since the short-term RNS predicts returns positively while long-term RNS does the opposite, we capture the different information sets between the two ends of the RNS term structure by constructing a new variable, the term spread of RNS. This is defined as 12-month RNS minus 1-month RNS. We then demonstrate that it effectively combines these two information sources resulting in even stronger negative predictability using the portfolio sorting approach. A trading strategy long equal-weighted (value-weighted) decile portfolio with the highest term spread and short equal-weighted (value-weighted) decile portfolio with the lowest term spread yields a FFCP5 alpha of -1.61% per month with t-statistic of -8.89 (-1.26% per month with t-statistic of -4.95). We check these results with a cross-sectional Fama-MacBeth (1973) regression, which is consistent.

To further explore the extent of the information impounded in the term structure of RNS, we examine whether short- and long-term RNS have differing predictive power for firms' standardized unexpected earnings (SUE) using a Fama-MacBeth (1973) regression. We find the short-term RNS is a positive predictor of SUE, suggesting that it captures option traders' superior information about earnings. Simultaneously, we find that long-term RNS is a negative predictor of SUE, which is consistent with skewness preference. As a robustness check for the information content of RNS across different maturities, we also test its ability to predict future stock price crashes. Consistent with the previous results, we find

[2]Using the FFCP5 benchmark model combining the Fama and French (1993) beta, size, and book-to-market factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor. Alternative benchmarks produce similar results.

a significantly negative (positive) relationship between the short-term (long-term) RNS and future price crashes. Notably, this predictability persists for at least 6 months. Furthermore, consistent with Stilger et al. (2016), we demonstrate that the positive predictability of future equity returns from short-term RNS is strongest for overpriced and short-sale constrained underlying stocks, indicating that the short-term RNS reflects hedging demand.

This paper contributes to the literature that empirically examines the connection between RNS and future stock returns. We reconcile the ongoing debate between the informed trading/hedging demand and skewness by demonstrating a term structure of RNS and its differential information content across option maturities. We find evidence consistent with informed trader preference for hedging underlying stock positions or speculating by trading short-term options. This interpretation is intuitive for several reasons: First, mispricing in the stock market can be corrected over a short time horizon. Second, short-term options are more sensitive to the variation of the underlying stock's price, thus they can provide more protection to hedgers or a more leveraged position to speculators. Third, the short-term option market is usually more liquid and thus imposes lower trading costs.

Thus, the RNS implied by short-term options deviates away from the expected skewness of the underlying stock by impounding informed trades in the short-term option market and therefore leads to positive predictability for future equity returns. As the option term increases, informed traders have monotonically decreasing hedging/speculating demand for the corresponding option contracts due to increasingly unfavorable timing, exposure, and liquidity characteristics. Thus these options more closely mirror the distribution of the underlying stock because they are less affected by informed trading. As a consequence, the skewness implied by the long-term options tends to reflect the equity market's expected skewness of the underlying stock and carries a negative risk premium. These patterns are consistent with Holowczak, Simaan, and Wu (2006), who find that the informativeness of option prices increases when option trading activity generates net sell or buy pressure on the underlying stock and even more so when the pressure coincides with deviations between the stock and options prices. Thus, the price effect of RNS across its term structure is determined by a combination of informed option traders' hedging/speculative demand and the equity market's expected skewness of the underlying stock.

This paper is closely linked to three strands of literature. The first of these is comprised of theoretical and empirical studies about skewness preference. The asset pricing models in Arditti (1967), Rubinstein (1973), Kraus and Litzenberger (1976), Kane (1982), and Harvey and Siddique (2000) indicate that assets with higher systematic skewness are more desirable and thus bear a negative risk premium. Brunnermeier et al. (2007), Mitton and Vorkink (2007), and Barberis and Huang (2008) propose models in which investors exhibit skewness preference. These models have been tested using historical (Boyer et al., 2010; Bali, Cakici, and Whitelaw, 2011) and option-based (Bali and Murray, 2013; Conrad et al., 2013) skewness measures.

A second investigates information diffusion from the option market to the stock market. A large body of work provides empirical evidence that both option volumes (see, e.g., Easley, O'hara, and Srinivas, 1998; Chan, Chung, and Fong, 2002; Cao, Chen, and Griffin, 2005; Pan and Poteshman, 2006) and option prices (Chakravarty, Gulen, and Mayhew, 2004; Ofek, Richardson, and Whitelaw, 2004) convey price information to the equity market. In particular, several studies confirm that the slope of the implied volatility function is positively related to price crash risk in both index and stock options (Bates, 1991; Pan, 2002; Xing et al., 2010). More broadly, An, Ang, Bali, and Cakici (2014) and Stilger et al. (2016) find recent evidence further confirming information transmission from the option to the equity market.

The third strand of related literature concerns the demand-based pricing option pricing theory. Bollen and Whaley (2004) provide evidence that net buying pressure affects the shape of the implied volatility function for both index and individual stock options. Garleanu, Pedersen, and Poteshman (2009) develop a demand-based option pricing model to explain these empirical findings and argue that the investors possessing an information advantage could drive higher demand for certain options and push up their implied volatility. Empirical studies by Holowczak et al. (2006) and Stilger et al. (2016) are consistent with this demand-based framework. This framework has since been applied to other asset classes such as futures (Hong and Yogo (2012)), bonds (Greenwood and Vayanos (2014) and Vayanos and Vila (2009)) and equities (Koijen and Yogo (2016)) in both theoretical and empirical studies.

The remainder of this paper is organized as follows. Section 2 describes the data and variable construction. Section 3 documents the differing explanatory power of the short- and long-term RNS on the cross-section of equity returns. Section 4 illustrates a novel anomaly, the term spread of RNS, that captures the difference in the information content of RNS at different maturities. Section 5 examines the information content in the term structure of RNS by relating it to earning surprises, price crashes, and investors' hedging demands. Section 6 concludes.

2. Data and Variable Construction

We first describe the data and the methods used to compute risk-neutral skewness across different maturities, as well as other firm characteristics for each individual stock. The sample is from January 1996 to December 2015.

2.1. Risk-Neutral Skewness

On the last trading day of each month, the firm i's option-implied skewness for a given maturity is calculated using the model-free methodology of Bakshi et al. (2003). The authors demonstrate that, using OTM call and put options prices with time to maturity τ, the risk-neutral skewness (RNS) of the distribution of the rate of return realized on the underlying stock over the following τ period is

$$Skew^Q = \frac{e^{r\tau}W(\tau) - 3\mu(\tau)e^{r\tau}V(\tau) + 2\mu(\tau)^3}{[e^{r\tau}V(\tau) - \mu(\tau)^2]^{3/2}} \tag{1}$$

where the risk-neutral expectation of log return of the underlying stock over the next τ period, $\mu(\tau)$, is given by

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

Here, r represents the τ-maturity annualized risk free rate. $V(\tau)$, $W(\tau)$, and $X(\tau)$ are the spot prices of τ-maturity quadratic, cubic, and quartic contracts, respectively, representing the fair value of the payoffs equal to the second, third, and the fourth power of the underlying stock's risk neutral log returns. Their expressions are given in A.1 in Appendix A.

To compute $V(\tau)$, $W(\tau)$, and $X(\tau)$, OTM call and put options with continuous strikes expiring in τ period would be required. However, traded options are available only at irregular strikes and maturities. In the real world, option-implied skewness pertaining to a constant τ are unlikely to be observed since option maturities decay daily and contracts are issued at monthly frequency at most. To deal with this data issue, studies using risk-neutral moments (see, e.g., Bakshi et al., 2003, Conrad et al., 2013, and Stilger et al., 2016) aggregate daily options data that falls in a window of time to maturity τ, computing RNS for a horizon equal to the mean of maturities within the group. For example, Stilger et al. (2016) use daily prices for all OTM options with τ between 10 and 180 days to calculate option-implied skewness with an average maturity across different stocks of 86.56 trading days. If more than one contract with different τs are available for options with a specific strike price, the authors choose the option with the smallest τ. We denote this method as "maturity bin" method.

One drawback of the "maturity bin" method is that options with different moneyness have different maturities within each bin, which cause the implied risk-neutral density with an average τ to actually contain information for horizons different from τ. For instance, suppose the spot price is \$100, and of contracts falling in the τ bin from 10 to 180 days, the shortest available maturity for an OTM put option with strike price \$80 is 30 days, while that for OTM call option with strike price \$120 is 150 days. By using the "maturity bin" method, information impounded in the one-month put and five-month call options would be reflected in the option-implied risk-neutral density with an average τ close to 3 months. Since the main purpose of this paper is to explicitly investigate information differences across the term structure of RNS, this method prevents a clean decomposition by maturity.

To mitigate this issue, we instead use standardized option implied volatilities in the Volatility Surface file from OptionMetrics. The file contains the interpolated volatility surface for each security on each day, obtained using a kernel smoothing algorithm. The Volatility Surface file encompasses information on standardized call and put options with maturity of 30, 60, 91, 122, 152, 182, 273, 365, 547, and 730 calendar days, at deltas of 0.20, 0.25, 0.30, 0.35, ..., 0.75, and 0.80 (with similar but negative deltas for puts). A standardized option is included only if enough traded option prices are available on that date to accurately interpolate the required values. The traded options data is first organized by maturity and moneyness and then interpolated by a kernel smoother to generate an implied volatility value at each of the specified interpolation grid points. In addition to option price information such as implied volatility, option premium, and strikes, a measure of the accuracy of the implied volatility calculation, denoted as dispersion, is also provided for each security/maturity/moneyness combination. A larger dispersion indicates a less accurate interpolation.

We use all standardized OTM options maturing in 30, 91, 152, 273, and 365 days to calculate RNS for 1, 3, 6, 9, and 12 months respectively, denoted as RNS1M, RNS3M, RNS6M, RNS9M and RNS12M. The OTM call (put) options are options with deltas of 0.45 (-0.45), 0.40 (-0.40), 0.35 (-0.35), 0.30 (-0.30), 0.25 (-0.25), and 0.20 (-0.20). To optimally execute the tradeoff between excluding less accurate data while keeping the sample as large as possible, we filter out stocks of which at least one implied volatility for a moneyness/maturity combination has a dispersion measure that is larger than 0.2. In unreported robustness checks, we have examined filtering rules with different dispersion thresholds and found that both stricter and looser rules produce results similar to those reported in the subsequent analysis. In addition, we only keep securities that have traded options with non-missing trading volume and non-zero open interests from the OptionMetrics price data file. Finally, we compute the integrals that appear in the formulae of $V(\tau)$, $W(\tau)$, and $X(\tau)$ by a trapezoidal rule detailed in equation A.2 in Appendix A.

Of the five resulting maturities, we define the 1-month and 12-month to be the short-term and long-term RNS, respectively. To integrate the different information contained in these two variables we also define the term spread of RNS (RNSTS) as the difference between the long-term and short-term RNS.

2.2. Other Firm Characteristics

To compute portfolio returns and stocks' idiosyncratic volatilities, we collect daily and monthly stock returns, market values and trading volumes from the Center for Research in Security Prices (CRSP). We calculate market value (MV) as the log of the closing share price times the number of shares outstanding. We obtain the annual book value of the firm from COMPUSTAT and then compute the book-to-market ratio (BM) as the log of the ratio between book value and market value. We also compute a series of control variables such as stock illiquidity (ILLIQ) proxied by Amihud (2002)'s price impact ratio , stock return momentum (MOM) and reversal (REV).

To test the firm-specific information impounded into the RNS at different maturities, we construct two variables representing significant firm-specific events. One is the standardized earnings surprise variable (SUE), which is defined as the actual earning minus analysts' forecast scaled by end-of-quarter price following Livnat and Mendenhall (2006). The other is the monthly price crash indicator (CRASH), which equals one for a firm-year that experience one or more crash days during the month, and zero otherwise. A crash is defined as a 3-σ negative daily return relative to daily historical volatility based on Hutton, Marcus, and Tehranian (2009), Kim, Li, and Zhang (2011a) and Kim, Li, and Zhang (2011b) and detailed in Appendix B.

To control for option liquidity and price pressure issues, we also collect data on option volume and open interests from the option price file in IvyDB's OptionMetrics. To proxy for the hedging demand of the short-term options we construct three measures: the put-to-all option volume ratio (PAOV), the aggregate open interest ratio (AOI), and the Zmijewski (1984) Z-score, following Stilger et al. (2016). In addition, we use the maximum daily return (MAX) and idiosyncratic volatility (IVOL) relative to the Fama and French (1993) model as proxies for stock overvaluation and short-selling constraint respectively.

The details of the construction of firm characteristics and option measures are detailed in Appendix B.

2.3. Summary Statistics

Table I presents summary statistics for the RNS of different maturities, the term spread of RNS, option volume and open interests, as well as all firm-specific characteristics. We report the number of firm/month observations, means, medians, standard deviations as well as 5th and 95th percentiles across stocks during the sample period.

Carr and Wu (2003) and Foresi and Wu (2005) observe that the risk-neutral distribution of index returns becomes more negatively skewed as option maturity increases. We find this pattern also exists for individual stocks. Table I shows that the mean and median of RNS becomes more negative with maturity. To the extent the RNS reflects investor beliefs, this is consistent with expectations of higher probability of disaster or crash events in individual equities. One possible reason is that as the time horizon increases, risk-averse investors require larger compensation for bearing crash risk. Since the risk-neutral density is the product of the risk premium and physical density adjusted by risk-free rate, the long term risk-neutral density becomes more negative than short term risk-neutral density does. An alternative explanation is that the short-term density contains different information than the long-term.

Table II shows the correlation between our main variables. The lower triangular of the correlation matrix presents Pearson correlations between each pair, while the upper triangular of the correlation matrix reports the non-parametric Spearman correlation matrix. As maturity increases, the corresponding RNS has less correlation with 1-month RNS. For example, as maturity increases from 3 month to 12 month, the Pearson (Spearman) correlation between the corresponding skewness and RNS1M decreases from 0.50 (0.55) to 0.27 (0.34). This is consistent with a divergence between the information contents in the short-term and long-term risk-neutral skewness.

3. RNS Term Structure and Return Predictability

We now test whether RNS of different maturities has differential predictive power for future returns of the underlying asset. We then consider how this difference in predictabilities matches the contradictory results in the empirical literature, advancing a potential way to reconcile the negative predictability consistent with skewness preference (Conrad et al., 2013; Bali and Murray, 2013) with the positive predictability consistent with informed trading (Xing et al., 2010) and hedging demand (Stilger et al., 2016).

We document different predictabilities of short- vs long-term RNS using the portfolio sorting approach. Each month, we rank all sample firms in ascending order according to their RNS estimates on the last trading day and assign them to decile portfolios. This sorting procedure results in 10 portfolios per RNS measure. We construct both value- and equal-weighted portfolio returns over the subsequent month to isolate the influence of small firms in the sample. Since we have five observations in the RNS term structure, we obtain a total of

100 portfolios, 50 equal- and 50 value-weighted, with returns sampled at monthly frequency over the period February 1996 through December 2015. We fit common benchmark models to the portfolios to test for abnormal performance indicative of predictive power across the RNS term structure. The t-values in the estimations are computed using Newey-West standard errors with five lags to account for autocorrelation.

Table III, we present the results of abnormal portfolio returns relative to our benchmarks for value- and equal-weighted portfolios across the RNS term structure. Panel A, B, C, D, and E report abnormal returns over the subsequent month of the portfolios sorted by 1-, 3-, 6-, 9-, and 12-month RNS, respectively. We use five standard asset pricing models as benchmarks: the Capital Asset Pricing Model (CAPM), the Fama and French 3-factor model (FF3) (Fama and French, 1992; Fama and French, 1993), the Fama and French 5-factor (FF5) model (Fama and French, 2015), the Carhart 4-factor model (Carhart, 1997), and the Fama and French 3-factor, Carhart momentum factor, and Pastor and Stambaugh (2003) liquidity factor (FFCP5) model.

Panel A of Table III reports the performance of portfolios sorted by 1-month RNS (RNS1M). Both value- and equal-weighted portfolio returns illustrate the strong positive relation between 1-month RNS and future stock returns over the subsequent month. A zero-cost trading strategy long the highest decile and short the lowest decile portfolio exhibits significant positive alphas relative to the CAPM, FF3, FF5, FFC4 and FFCP5 models at 1% level. In particular, the zero-cost high-low strategy for the value-weighted portfolio has significantly positive monthly alpha relative to all benchmark models ranging from 0.71% (8.52% annualized) relative to FF5 model to 0.96% (11.52% annualized) relative to CAPM model. The same strategy for equal-weighted portfolio has overall higher monthly alpha ranging from 0.98% (11.76% annualized) relative to FF3 model to 1.12% (13.44% annualized) relative to FFCP5 model. In addition, as we move from the lowest to highest RNS1M decile portfolio, we find there is a monotonic increase in abnormal performance. These results provide preliminary evidence that RNS calculated using the short-term 1-month standardized options has the same predictability as the skewness measure documented in Xing et al. (2010) and Stilger et al. (2016). The positive predictive power for future abnormal returns suggests that our 1-month RNS might contain informed option investors' speculative or hedging demand.

Panel B of Table III reports the performance of portfolios sorted by 3-month RNS (RNS3M). Both value- and equal-weighted portfolio returns have a weak positive relation between 3-month RNS and future stock returns over the subsequent month. While the zero-cost trading strategy long the highest decile and short the lowest decile portfolio exhibits positive and significant alphas for some models, it is insignificant for others. For the value-weighted portfolios the zero-cost hedging strategy results in a significant alpha at the 10% or lower level for all models except the FF5, while for equal-weighted portfolios the same strategy result in significant alpha at 10% only for FFC4 and FFCP5 models. In addition, the scale of alphas is much lower than that of alphas produced by 1-month RNS. These results show that as option maturity increases, the positive relation between RNS and future stock returns starts to become weaker.

Panel C of Table III reports the performance of portfolios sorted by 6-month RNS (RNS6M). The value- and equal-weighted portfolio returns exhibit a mixed and insignificant relation between 6-month RNS and future stock returns over the subsequent month. Indeed, for value-weighted portfolios, the zero-cost hedging strategy results in insignificant alphas for all benchmark models, while for equal-weighted portfolios, the same strategy result in insignificant alphas for all models except the FF3. Thus, as the option maturity increases to 6 months, the positive relation between RNS and future stock returns disappears.

A notable reversal occurs in Panel D of Table III. Here we report the performance of portfolios sorted by 9-month RNS (RNS9M). The value- and equal-weighted portfolio returns show a negative relation between 9-month RNS and future stock returns. The zero-cost strategy long the highest decile and short the lowest decile portfolio exhibits negative alphas, significant for some cases while insignificant for others. In particular, for value-weighted portfolios, the zero-cost trading strategy that long highest decile and short lowest decile portfolio results in insignificant alphas for all models except FF3 model, while for equal-weighted portfolios, the same strategy result in significantly negative alphas at 1% for all models. These results show that as term increases to 9 months, the relation between RNS and future stock returns begins to become negative.

Finally, Panel E of Table III reports the performance of portfolios sorted by 12-month RNS (RNS12M). Both value- and equal-weighted portfolio returns illustrate the strong negative relation between 12-month RNS and future stock returns over the subsequent month. The zero-cost trading strategy long the highest and short the lowest decile portfolio exhibits significantly negative alphas for most benchmark models. Notably, the zero-cost hedging strategy for the value-weighted portfolio has a significantly negative monthly alpha relative to all models except the FF5, ranging from -0.56% (-6.72% annualized) at the 10% significance level relative to FFCP model to -0.94% (-11.28% annualized) at the 1% significance level relative to FF3 model, while the same strategy for equal-weighted portfolio has overall larger monthly alpha ranging from -0.81% (-9.72% annualized) at the significance level 1% relative to the FF5 model to -1.24% (-14.88% annualized) at the significance level 1% relative to the FF3 model.

This significantnegative predictability is a sharp reversal from the positive predictability at the short end of the term structure of RNS and the insignificant predictability at its middle. Its significance is proof that these results are not driven by data quality issues potentially introduced by the illiquidity of long-term option contracts. If the data were simply becoming less reliable for high option maturities, we would expect to see a continuation of insignificant predictive power at the long end of the term structure. These results also provide preliminary evidence that RNS calculated from 12-month standardized options is consistent with skewness preference.

Taken altogether, we find short-term RNS positively predicts future stock returns, which is consistent with the prior empirical findings on skewness proxying for informed trading

(Xing et al., 2010) and hedging demand (Stilger et al., 2016), while long-term RNS predicts negative future stock returns which matches the empirical findings on skewness preference (Conrad et al., 2013; Bali and Murray, 2013). The variability of the results one gets depending on the maturity of options one uses points to a potential resolution of the contradiction between these two sets of empirical findings. One potential explanation for this phenomenon is that investors use short-term options to hedge or speculate based on their information advantage. We will investigate the validity of this explanation in section 5.

4. The Term Spread of RNS

Section 3 documents the differing predictive direction of long- and short-term RNS for future stock returns. To capture these different sources of information from both long- and short-term RNS, we construct a new variable, the term spread of RNS (RNSTS), which is defined as 12-month RNS minus 1-month RNS. As shown in Table II, RNSTS is positively related with RNS12M and negatively related with RNS1M by construction. Combining the negative predictive power of RNS12M and the opposite of the positive predictive power of RNS1M for future returns as shown in Section 3, RNSTS should borrow information from both ends of the term structure and serve as a significantly negative predictor of future returns. In this section, we use both portfolio sorting and Fama-MacBeth regression methodologies to show that the term spread possesses much stronger predictive power for future equity returns than either the short-term or long-term RNS in isolation.

4.1. Portfolio Sorts

In this subsection, we test the ability of the term spread of RNS (RNSTS) to integrate information from both ends of the RNS term structure using the portfolio sorting approach. In particular, each month, we rank all sample firms in ascending order according to their RNSTS measured on the last trading day, and assign them into RNSTS deciles. We then employ the ranking to construct both value- and equal-weighted portfolios for each decile over the subsequent month, forming 10 equal- and 10 value-weighted portfolios with returns sampled at the monthly frequency over the period February 1996 through December 2015. We fit the CAPM, FF3, FF5, FFC4, and FFCP5 benchmarks and compute alpha t-values using Newey-West standard errors with five lags to control for autocorrelation in returns.

In Table IV, we present the value- and equal-weighted portfolio performance of monthly decile portfolio based on RNSTS, the long-short term spread on RNS. From the table, both value- and equal-weighted portfolio returns illustrate the strong negative relation between the term spread and future portfolio returns over the subsequent month. The zero-cost trading strategy long the highest decile and short the lowest decile portfolio exhibits negative alphas relative to all five models significant at the 1% level. The zero-cost strategy for value-weighted portfolio has significantly negative monthly alphas ranging from -0.94% (-11.28% annualized) relative to FF5 model to -1.38% (-16.56% annualized) relative to CAPM model, while the same zero-cost strategy for the equal-weighted portfolio has overall greater monthly alphas ranging from -1.47% (17.64% annualized) relative to FF5 model to -1.72% (-20.64% annualized) relative to CAPM model. As we move from the lowest to highest RNSTM decile portfolio, we find there is a monotonic decrease in performance. These results support our conjecture that the term spread of RNS combines price-relevant information from the short- and long-term RNS resulting in improved negative predictability on future stock returns. Consistent with this, the scale of the abnormal returns produced by this new anomaly variable are greater than that of 1-month RNS and 12-month RNS individually. Notably, they are also greater than most existing anomalies in the general asset pricing literature.

4.2. Fama-MacBeth Regression

Next, we conduct the Fama and MacBeth (1973) cross-sectional regressions to confirm the return predictability of RNSTS, the term spread of RNS, while controlling for other confounding variables including market beta, firm size, book-to-market ratio, momentum, reversal, idiosyncratic volatility and illiquidity. We also control for characteristics of the underlying stock, its lagged price per share and return, as well as option liquidity characteristics, its volume and open interest. Table V reports the Fama-MacBeth coefficients of cross-sections of monthly excess stock returns on lagged term spread of RNS and a set of firm characteristics during the period 1996-2015.

Model (1) regresses the cross-section of monthly returns only on the term spread of RNS, RNSTS. Consistent with prior results, the term spread has a cross-sectional coefficient of -0.0101 significant at the 1% level, confirming the previously observed negative predictability. To control for RNSTS incorporating the effects of other known predictive variables, model (2) controls for market beta, firm size, book-to-market ratio, momentum, reversal and the Amihud (2002) illiquidity measure. The magnitude of the coefficient on the RNSTS term spread becomes smaller at -0.0072 but still remains significant at the 1% level. The known predictive variables have no significant additional explanatory power for the cross-section of future stock returns with the exception of firm size, which has a negative coefficient significant at the 10% level. This result further confirms the unique information content of the term spread of RNS in predicting stock returns relative to known predictive variables.

Model (3) further controls for trading characteristics of the underlying, its lagged price per share, return and idiosyncratic volatility. Model (4) controls for option liquidity by including option volume and open interest over the past month. The magnitudes of the coefficients of the term spread RNSTS become somewhat smaller still at -0.0066, but remain significant at the 1% level.

To summarize, both the portfolio sorting and Fama-MacBeth regression strategies demonstrate the robust negative predictability of returns from the term spread of RNS. Furthermore, this predictive effect is much stronger than that of using only short- or long-term RNS, indicating that the divergent information in two RNS measures is integrated by the term spread. In the next section, we further examine the firm-specific information that drives these patterns.

5. The Information Content of the RNS Term Structure for Firm-Specific Events

Given the opposite directions of return predictability stemming from short- and long-term risk neutral skewness, we next consider how this predictability may come about. In this section we examine the relationship between these two RNS measures and firms' earning surprises, likelihood of price crashes, and investors hedging demand. These results, taken with those in Section 3 and Section 4, help to complete the explanation we advance for the difference in return predictability across the RNS term structure. Specifically, these results all point to it being caused by differences in information sets of customers that drive demand for options at different points of the maturity continuum, resulting in differential return predictability across the RNS term structure.

5.1. Earnings Surprises and the Term Structure of RNS

The predictability of stock returns from short-term RNS is consistent with the informed trading argument in Xing et al. (2010). We explore whether option traders' superior information about firm fundamentals becomes impounded into the short-term RNS and thereby causes the positive predictive relationship between short-term RNS and firm performance. To do this, we follow Xing et al. (2010) and conduct a Fama-MacBeth cross-sectional regressions to test whether short-term RNS is a reliable predictor of earnings surprises, since this is a common and frequent source of news about the firm.

We use standardized unexpected earnings (SUE) to measure earnings surprises. SUE is defined as actual earnings minus the most recent analysts' forecast all scaled by stock price following Livnat and Mendenhall (2006). Since the earnings data usually becomes available within the next quarter, at each month, we regress the cross-section of next quarter's SUEs on short-term RNS after controlling for long-term RNS and other variables. We then aggregate all firm-specific coefficients of each month following the Fama-MacBeth procedure and compute Newey-West standard errors with five lags.

Table VI reports the Fama-MacBeth coefficients for short-term RNS in explaining the cross-section of SUEs over the next quarter, controlling for long-term RNS and a set of firm characteristics, during the period 1996-2015. Model (1) regresses quarterly SUE on long- and short-term RNS without controls. Consistent with Xing et al. (2010), the short-term RNS has a positive cross-sectional coefficient of 0.0006 at the 1% significance level. To isolate the potential effects of other predictive variables, model (2) adds market beta, firm size, book-to-market ratio, momentum, reversal and the Amihud (2002) illiquidity measure as controls. The coefficient on short-term RNS remains the same in both magnitude and significance. Model (3) and Model (4) add stock and option trading characteristics respectively. For both models, the coefficients of the short-term of RNS remain unchanged and significant at 1% level. This positive predictive relationship suggests that option informed traders with private information about an upcoming negative SUE hedge this downside risk (Stilger et al., 2016) or speculate (Xing et al., 2010) by buying short-term OTM puts or selling short-term OTM calls. This increases the slope of the implied volatility function, and therefore decreases the short-term RNS causing a positive relationship with SUEs.

In addition, Table VI shows that coefficients of long-term RNS for all regression models are significantly negative, which suggests that negative long-term skewness predicts higher future SUEs. This predictability is similar in direction to that of future stock returns from long-term RNS, consistent with the skewness preference theory that implies a negative risk premium for positive skewness. The long-term RNS's similar predictabilities on both future stock returns and earnings surprises is consistent with comovement in these two quantities. In other words, it is evidence that the negative risk premium theorized by skewness preference is driven by firm fundamentals.

5.2. *Future Price Crash and the Term Structure of RNS*

We next examine the different information sets in long- and short-term RNS by considering their ability to predict the probability of a price crash. To do this we construct a monthly price crash dummy for each firm, an indicator variable that equals one for a firm-month that contains one or more crash days, and zero otherwise. Following Hutton et al. (2009), Kim et al. (2011a) and Kim et al. (2011b), we define crash days as those in which the firm experiences daily returns that are 3.09 (0.1% for normal distribution) standard deviations below the mean daily return over the prior year.[3]

We again use the Fama-MacBeth approach by first conducting a monthly logistic regression of the future monthly price crash dummy on current short- and long-term RNS. We then aggregate coefficients across all months and compute the Newey-West standard errors with five lags for each coefficient. In Table VII, Column (1) reports the Fama-MacBeth coefficients of cross-sections of next month's price crash indicator on current month short- and long-term RNS.

Consistent with prior results, the coefficient of short-term RNS is significantly negative at the 1% level. This suggests that expectations of more negative news by informed traders impounded in a more negative short-term RNS predicts that future price crashes happen with greater probability. In addition, the coefficient of long-term RNS is significantly positive at the 1% level. This is consistent with skewness preference, according to which investors require lower return for holding stocks with higher skewness. Given the mechanical relationship of lower returns with higher probability of price crashes, the positive relation between long-term RNS and future price crashes is as expected.

To examine how long these predictabilities on price crash will hold, we perform the Fama-MacBeth (1973) regression of price crash indicator variables two through six month ahead on short- and long-term RNS in the current month in Columns (2) through (6) respectively.

[3]See Appendix B for details.

Among all these regressions, the coefficients of short-term RNS remain significantly negative, indicating that the predictive power of short-term RNS for price crashes persists for at least 6 months. While the coefficients of long-term RNS become insignificant, suggesting the positive predictive power of long-term RNS, caused by skewness preference theory, only persists for one month.

5.3. Hedging Demand and the Term Structure of RNS

The prior results demonstrate that short-term RNS contains unique information about future firms' stock and fundamental performance, which suggests that informed traders express their beliefs about underlying stocks primarily in the short-term option market. In this section, following Stilger et al. (2016), we provide direct evidence that investors' hedging demand for short-term options is reflected in the short-term RNS. This isolates hedging demand as one of the drivers of the positive predictability of stock returns from short-term RNS.

Following Bollen and Whaley (2004) and Garleanu et al. (2009), Stilger et al. (2016) conjecture a mechanism by which hedging demand for options results in the positive relationship between their RNS estimate and future stock returns. They provide some tests for the validity of this channel, the first of which is to consider whether stocks characterized by higher hedging demand exhibit a more negative RNS value. The intuition is that higher hedging demand for downside risk pushes up the price of the OTM put option (Garleanu et al., 2009), which results in a more negatively skewed risk-neutral density. The second test is whether the underperformance of the portfolio with the lowest RNS stocks is driven by stocks that are relatively overpriced, which would be another driver of hedging or speculative demand. The third test is whether the the underperformance of the portfolio with the lowest RNS stocks is driven by stocks that are too hard to sell short, also driving demand for options as an alternative to shorting. In this section, we conduct these tests for our short-term RNS measure.

Table VIII tests whether stocks characterized by higher hedging demand exhibit more negative RNS values. Following Stilger et al. (2016), three measures are used as hedging demand proxies: the ratio between aggregate put option volume and total option volume (PAOV) (Taylor, Yadav, Zhang, et al., 2009), the aggregate open interest across all options (AOI) (Hong and Yogo, 2012), and the Z-score of Zmijewski (1984) (ZD) capturing default risk. For the calculation of PAOV and AOI, only traded options with maturity from 10 to 45 days are used in order to match the 1-month maturity. Table VIII reports the time-series average of the RNS for quintile portfolios sorted by investor hedging demand. As each of the three the hedging demand measures increase, the short-term RNS decreases monotonically. This pattern is statistically significant, as the average RNS in highest hedging demand quintile is lower than that in lowest quintile at the 1% significance level. This confirms that short-term options with higher hedging demand have more negative RNS values as suggested by Stilger et al. (2016).

Panel A of Table IX presents the results for whether the underperformance of the portfolio with the lowest 1-month RNS (RNS1M) stocks is driven by stocks that are relatively overpriced. It reports the performance of double sorted portfolios by 1-month RNS and a proxy for overvaluation for the sample period from 1996 to 2015. We use the maximum daily stock returns over the last month (MAX) (Bali et al., 2011) as the proxy for overvaluation. At the end of each month, we sort all stocks into tercile portfolios in ascending order by RNS1M. Within each RNS1M tercile portfolio, we create another set of tercile portfolios in ascending order based on the MAX overvaluation proxy. We find that among three portfolios of stocks with the lowest 1-month RNS, the portfolio with highest MAX underperforms the portfolio with lowest maximum return by 1.0012% per month at the 1% significance level. This indicates the underperformance of the portfolio with the lowest 1-month RNS stocks is driven by the stocks exhibiting the highest degree of overpricing.

Panel B of Table IX presents the results for the test whether the underperformance of the portfolio with the lowest 1-month RNS stocks is driven by stocks that are relatively hard to short. It reports the performance of double sorted portfolios by 1-month RNS and a proxy for short-selling constraint for the sample period from 1996 to 2015. The short-selling constraint is proxied by idiosyncratic volatility (IVOL) following Wurgler and Zhuravskaya (2002). At the end of each month, we sort stocks into tercile portfolios in ascending order by RNS1M. Within each RNS1M tercile portfolio, we further sort the constituents into tercile portfolios in ascending order based on the short-selling constraint. We find that among three portfolios of stocks with the lowest 1-month RNS, the portfolio with highest short-selling constraint underperforms the portfolio with lowest maximum return by 0.9498% per month at significance level 1%. This indicates the underperformance of the portfolio with the lowest 1-month RNS stocks is also driven by stocks that are hard to short.

The results of these three tests in Tables IX and VIII show that hedging demand is a driver of the short-term RNS. Combined with the findings in previous two subsections, we have established evidence that short-term RNS contains both predictive information about the performance of the firm, and is positively related to hedging demand. This supports the conclusion that informed traders use short-term options to hedge downside risks or speculate on underlying stocks that are relatively overpriced and hard to short.

The hedging demand story implies the positive relation between RNS and future stocks' return, thus the negative relation between long-term RNS and future stock returns indicates the hedging demand hypothesis doesn't hold for long-term RNS. This indicates that investors rarely use long-term options to hedge risk, which is consistent with long-term options being inappropriate hedging or speculative instruments if overpricing is corrected in the short term. Another possible reason for hedgers' reluctance in using long-term options is that long-term options have lower delta than short-term options do, which make them provide less downside protection to hedgers and less exposure to the underlying for speculators. Finally, investors face more trading costs when hedging through long-term options, which are usually less liquid than the their short-term counterparts.

5.4. Discussions about Skewness Preference

If there were no information difference between the option and stock market, in the absence of informed speculators and hedgers, both the short-term and long-term RNS would reflect the equity market participants' expected risk-neutral skewness for the stock. The RNS across all maturities would thus bear the negative risk premium implied by skewness preference. Conversely, the activities of informed hedgers and speculators active in the short-term option market impounds new information in the short-term RNS resulting in different information sets and risk premia across the RNS term structure.

The results in Panel E of Table III, Table VI and Table VII all indicate the negative risk premium of long-term RNS, which are consistent with skewness preference. This evidence provides indirect evidence that long-term RNS is a good proxy of the underlying stocks' expected skewness. However, the claim that long-term RNS is close to the expected stock skewness is difficult to falsify because of a lack of a readily available expected stock skewness measure. Historical data is an unreliable proxy for the expectations of market participants: Conrad et al. (2013) find that while there is an association between risk-neutral and physical skewness measures, they are far from perfectly related.

6. Conclusion

This paper contributes to the ongoing debate in the literature about the direction of the relationship between individual stocks' risk-neutral skewness and the cross-section of future equity returns. We make our contribution by investigating the difference in information content across the term structure of RNS.

Using a large sample of stocks and options data from 1996 to 2015, we document positive predictability of future stock returns from short-term RNS consistent with the informed trading and hedging demand literature (Xing et al., 2010; Stilger et al., 2016; Bollen and Whaley, 2004; Garleanu et al., 2009), combined with negative predictability of returns using long-term RNS which supports the skewness preference theory (Brunnermeier et al., 2007; Mitton and Vorkink, 2007; Barberis and Huang, 2008; Bali and Murray, 2013; Conrad et al., 2013).

Using this information we create a new abnormal return predictor, the term spread of RNS, which we define as the long-term RNS minus short-term RNS. It is constructed to capture information sets at both ends of the RNS term structure. The decile portfolio with the highest spread underperforms the decile portfolio with the lowest spread by 19.32% per year after controlling for common risk factors. The magnitude and robustness of this anomalous return suggests that the RNS term spread serves its designed purpose of integrating information distributed across the RNS term structure.

We further test the information differences across the RNS term structure by providing evidence that the short-term RNS is a positive predictor of future firms' earnings surprise and a negative predictor of future stock price crashes. The long-term RNS reverses the direction of predictability.

Additionally, we find the positive predictability of equity returns from the short-term RNS is strongest for stocks that have high hedging or speculative demand from informed option traders consistent with Stilger et al. (2016). This evidence suggests that these informed traders mainly employ short-term options to trade, which produces the different (similar) information sets between the short-term (long-term) skewness expectations in the option and the equity market. As a result, the short-term RNS impounds more informed trades and thereby positively predicts stock returns, while the long-term RNS carries the negative risk premium associated with the equity market's expected skewness of the underlying as implied by skewness preference.

We thereby offer a possible way to reconcile the ongoing debate between two strands of the literature: one documenting the positive relationship between risk-neutral skewness and future stock returns following the informed trading and hedging literature, and the other documenting a negative relationship following skewness preference theory. Our results confirm the validity of both of them, under the proper conditions for each.

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Appendix A.

The spot prices of τ-maturity quadratic, cubic, and quartic contracts, $V(\tau)$, $W(\tau)$, and $X(\tau)$, have the following analytic formulas provided in equations (7)-(9) in Bakshi et al. (2003),

$$
\begin{aligned}
V(\tau) &= \int_S^\infty \frac{2\left(1-\ln\frac{K}{S}\right)}{K^2} C(\tau,K)dK + \int_0^S \frac{2\left(1+\ln\frac{S}{K}\right)}{K^2} P(\tau,K)dK \\
W(\tau) &= \int_S^\infty \frac{6\ln\frac{K}{S}-3\left(\ln\frac{K}{S}\right)^2}{K^2} C(\tau,K)dK - \int_0^S \frac{6\ln\frac{S}{K}+3\left(\ln\frac{S}{K}\right)^2}{K^2} P(\tau,K)dK \\
X(\tau) &= \int_S^\infty \frac{12\left(\ln\frac{K}{S}\right)^2-4\left(\ln\frac{K}{S}\right)^3}{K^2} C(\tau,K)dK + \int_0^S \frac{12\left(\ln\frac{S}{K}\right)^2+4\left(\ln\frac{S}{K}\right)^3}{K^2} P(\tau,K)dK
\end{aligned}
\tag{A.1}
$$

where S is the spot price and K is the strike price. $C(\tau,K)$ ($P(\tau,K)$) denotes the price of the call (put) with strike price K and τ period time to maturity.

To compute $V(\tau)$, $W(\tau)$, and $X(\tau)$ with OTM call and put options with discrete strikes expiring in τ period, we follow Bali and Murray (2013) to use the trapazoidal rule in calculating integrals, i.e.,

$$
\begin{aligned}
V(\tau) &= \sum_{i=1}^{n^C} \frac{2\left(1-\ln\frac{K_i^C}{S}\right)}{(K_i^C)^2} C(\tau,K_i^C)\Delta K_i^C + \sum_{i=1}^{n^P} \frac{2\left(1+\ln\frac{S}{K_i^P}\right)}{(K_i^P)^2} P(\tau,K_i^P)\Delta K_i^P \\
W(\tau) &= \sum_{i=1}^{n^C} \frac{6\ln\frac{K_i^C}{S}-3\left(\ln\frac{K_i^C}{S}\right)^2}{(K_i^C)^2} C(\tau,K_i^C)\Delta K_i^C - \sum_{i=1}^{n^P} \frac{6\ln\frac{S}{K_i^P}+3\left(\ln\frac{S}{K_i^P}\right)^2}{(K_i^P)^2} P(\tau,K_i^P)\Delta K_i^P \\
X(\tau) &= \sum_{i=1}^{n^C} \frac{12\left(\ln\frac{K_i^C}{S}\right)^2-4\left(\ln\frac{K_i^C}{S}\right)^3}{(K_i^C)^2} C(\tau,K_i^C)\Delta K_i^C + \sum_{i=1}^{n^P} \frac{12\left(\ln\frac{S}{K_i^P}\right)^2+4\left(\ln\frac{S}{K_i^P}\right)^3}{(K_i^P)^2} P(\tau,K_i^P)\Delta K_i^P
\end{aligned}
\tag{A.2}
$$

where K_i^C (K_i^P) are strikes that are ordered in increasing (decreasing) order, and $n^C(n^P)$ is the number of OTM calls (puts). We set $\Delta K_i^P = K_{i-1}^P - K_i^P$ for $2 \le i \le n^P$ and $\Delta K_1^P = S - K_1^P$. And $\Delta K_i^C = K_i^C - K_{i-1}^C$ for $2 \le i \le n^C$ and $\Delta K_1^C = K_1^C - S$.

Appendix B.

The definitions of the variables are detailed as follows. The corresponding summary statistics are presented in Table I.

BKM1M
: Risk-neutral (option-implied) skewness with 1 month to expiration. With standardized OTM options maturing in 30 days, BKM1M is estimated using the model-free methodology of Bakshi et al. (2003) and the trapezoidal rule (see section III.A in Bali and Murray, 2013).

BKM3M
: Risk-neutral (option-implied) skewness with 3 month to expiration. With standardized OTM options maturing in 91 days, BKM1M is estimated using the model-free methodology of Bakshi et al. (2003) and the trapezoidal rule (see section III.A in Bali and Murray, 2013).

BKM6M
: Risk-neutral (option-implied) skewness with 6 month to expiration. With standardized OTM options maturing in 152 days, BKM1M is estimated using the model-free methodology of Bakshi et al. (2003) and the trapezoidal rule (see section III.A in Bali and Murray, 2013).

BKM9M
: Risk-neutral (option-implied) skewness with 9 month to expiration. With standardized OTM options maturing in 273 days, BKM1M is estimated using the model-free methodology of Bakshi et al. (2003) and the trapezoidal rule (see section III.A in Bali and Murray, 2013).

BKM12M
: Risk-neutral (option-implied) skewness with 12 month to expiration. With standardized OTM options maturing in 365 days, BKM1M is estimated using the model-free methodology of Bakshi et al. (2003) and the trapezoidal rule (see section III.A in Bali and Murray, 2013).

BKMTS
: The term spread of risk-neutral skewness, which is defined as the difference between long-term skewness (BKM12M) and short-term skewness (BKM1M)

BETA
: The coefficient on market risk premium from the regression of excess monthly stock returns on market risk premium over last 60 months.

MV
: The natural log of market cap. The market cap is computed as the closing share price times the number of shares outstanding.

BM
: The natural log of book to market ratio. Here the annual book value of the latest available is employed.

MOM
: Momentum for firm i is calculated as its cumulative stock return from month $t-12$ to month $t-1$.

REV
: Reversal for firm i is calculated as its monthly return over the previous month $t-1$.

IVOL

Idiosyncratic volatility is defined as the standard deviation of residuals of daily firm-level residuals of the Fama and French (1993) three-factor model regression over the past 60 months.

SUE

The standardized earnings surprise variable, SUE, is defined actual earning minus analysts' forecast, scaled by stock price, based on Livnat and Mendenhall (2006).

CRASH

The monthly price crash measure is defined as the indicator variable that equals one for a firm-year that experience one or more crash days during the month, and zero otherwise. Based on Hutton et al. (2009), Kim et al. (2011a) and Kim et al. (2011b), crash days in a given month are days in which the firm experiences firm-specific daily returns 3.09 (0.1% for normal distribution) standard deviation below the mean firm-specific daily returns over the entire year. Here the firm-specific daily return is defined as the natural log of one plus the residual return from the regression, $r_{i,t} = a_i + b_{1i}r_{m,t-2} + b_{2i}r_{m,t-1} + b_{3i}r_{m,t} + b_{4i}r_{m,t+1} + b_{5i}r_{m,t+2} + \varepsilon_{i,t}$, where $r_{i,t}$ is the return on stock i on day t and $r_{m,t}$ is the return on the CRSP value-weighted market index on day t.

MAX

Maximum Daily Return for firm i is the highest daily stock return during the previous month $t-1$.

OPVOL

The total volumes of traded options for the underlying firm i on the last trading day of month t.

OPEN

The total open interests of traded options for the underlying firm i on the last trading day of month t.

PAOV

The put-to-all option volume ratio on a given trading day is the ratio of the total volume across all put options for a given maturity divided by the total volume across all options for a given maturity. We use 1-month PAOV to proxy hedging demand for short-term options. Here traded options with maturity from 10 to 45 days are classified as the 1-month options.

AOI

The aggregate open interest ratio of firm i on a given trading day is the ratio of the sum of open interests across all firm i's options for a given maturity divided by the sum of open interest across all firms with the same maturity on that day. We use 1-month AOI to proxy hedging demand for short-term options. Here traded options with maturity from 10 to 45 days are classified as the 1-month options.

ZD

Zmijewski (1984) Z-score, which measure the default risk of firm i, is computed as $Z = -4.3 - 4.5\frac{\text{Net Income}}{\text{Total Asset}} + 5.7\frac{\text{Total Debt}}{\text{Total Asset}} - 0.004\frac{\text{Current Asset}}{\text{Current Liability}}$. ZD is used as one proxy of hedging demand for short-term options.

Table I: Descriptive Statistics. This table provides the descriptive statistics of risk-neutral skewness with different maturities, the term spread of risk-neutral skewness, as well as of the firm-specific variables that are used in subsequent analysis. The sample consists of 358,974 firm-month combinations based on the information in OptionMetrics, Compustat and CRSP from Jan 1996 through Dec 2015. The definitions for these variables are introduced in the Appendix B.

Variables	N	P5	P50	P95	Mean	STD
RNS_1M	358,974	-0.7279	-0.3357	0.1951	-0.3119	0.2784
RNS_3M	358,974	-0.7796	-0.4461	-0.1381	-0.4512	0.1915
RNS_6M	358,974	-0.8905	-0.4955	-0.2443	-0.5232	0.1937
RNS_9M	358,974	-1.0040	-0.5210	-0.2380	-0.5599	0.2299
RNS_12M	358,974	-1.1137	-0.5381	-0.2064	-0.5878	0.2720
RNS_TS	358,974	-0.9063	-0.2269	0.2339	-0.2759	0.3475
BETA	288,608	0.2609	1.1410	2.6878	1.2612	0.7189
ME	358,974	164,348	1,342,040	26,650,991	6,908,145	14,789,417
BTM	284,960	0.0718	0.3737	1.2991	0.5041	0.4020
MOM	349,259	-0.5031	0.0949	1.1231	0.1858	0.5019
REV	284,748	-0.6250	0.4621	4.5214	1.0741	1.8103
IVOL	358,818	0.0119	0.0258	0.0518	0.0282	0.0121
SUE	105,877	-0.0070	0.0005	0.0078	0.0002	0.0056
CRASH	114,882	0.0000	0.0000	1.0000	0.0695	0.2543
MAX	358,843	0.0171	0.0467	0.1389	0.0589	0.0387
OPVOL	358,974	0	66	7,026	1,739	4,395
OPEN	358,974	126	3,740	173,144	39,760	87,269
PAOV	287,135	0.0000	0.2593	1.0000	0.3283	0.2561
AOI	358,637	0.0000	0.0000	0.0015	0.0004	0.0008
ZD	282,978	-3.9591	-1.6712	0.7976	-1.6251	1.4710

Table II: In-Sample Cross-sectional Correlations. This table reports the time-series average of cross-section correlation coefficients between risk-neutral skewness for different maturities, the term spread of risk-neutral skewness, and some selected firm-specific variables that are used in my analysis. The lower triangular matrix presents the Pearson correlation matrix; the upper triangular matrix presents the non-parametric Spearman correlation matrix. The sample consists of 358,974 firm-month combinations from Jan 1996 through December 2015 using data from OptionMetrics, Compustat and CRSP. The definitions for these variables are introduced in the Appendix B.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)RNS1M	1.00	0.55	0.44	0.38	0.34	-0.65	0.12	-0.29	0.10	-0.08	-0.06	0.24	-0.15	-0.18
(2)RNS3M	0.50	1.00	0.80	0.70	0.64	-0.04	0.24	-0.44	0.09	-0.10	-0.06	0.43	-0.17	-0.21
(3)RNS6M	0.37	0.79	1.00	0.95	0.89	0.21	0.34	-0.54	0.06	-0.10	-0.05	0.58	-0.16	-0.21
(4)RNS9M	0.31	0.70	0.95	1.00	0.97	0.32	0.39	-0.58	0.06	-0.11	-0.05	0.65	-0.15	-0.20
(5)RNS12M	0.27	0.63	0.88	0.97	1.00	0.38	0.42	-0.60	0.06	-0.12	-0.06	0.69	-0.14	-0.19
(6)RNSTS	-0.68	0.03	0.32	0.42	0.49	1.00	0.20	-0.16	-0.05	-0.00	0.03	0.27	0.04	0.02
(7)BETA	0.08	0.20	0.27	0.31	0.33	0.16	1.00	-0.28	0.01	-0.06	-0.05	0.57	0.05	0.04
(8)MV	-0.12	-0.17	-0.21	-0.21	-0.21	-0.04	-0.12	1.00	-0.27	0.17	0.19	-0.64	0.58	0.65
(9)BM	0.10	0.09	0.07	0.08	0.08	-0.03	0.01	-0.12	1.00	-0.35	-0.35	-0.06	-0.27	-0.25
(10)MOM	-0.05	-0.05	-0.03	-0.03	-0.03	0.02	-0.00	0.02	-0.29	1.00	-0.06	-0.04	0.06	0.03
(11)REV	-0.03	0.00	0.03	0.04	0.04	0.06	0.04	0.02	-0.21	-0.05	1.00	-0.03	0.14	0.10
(12)IVOL	0.16	0.32	0.42	0.47	0.50	0.21	0.57	-0.26	-0.02	0.09	0.14	1.00	-0.07	-0.10
(13)OPVOL	-0.04	-0.05	-0.05	-0.05	-0.04	0.01	0.03	0.57	-0.07	0.02	0.09	-0.06	1.00	0.84
(14)OPEN	-0.07	-0.08	-0.09	-0.09	-0.08	0.01	0.01	0.71	-0.06	-0.00	0.06	-0.11	0.78	1.00

Table III: Descriptive Statistics: Portfolios Formed on Risk-Neutral Skewness of Different Maturities. Panel A, B, C, D and E present abnormal return over the following month of decile portfolios sorted by 1-, 3-, 6-, 9-, and 12-month risk neutral skewness, respectively. 5 standard asset pricing models are used as benchmarks, which include Capital Asset Pricing Model (CAPM), Fama and French (1993) 3-factor model (FF3), Fama and French (2015) 5-factor model (FF5), Fama and French (1993) 3 factors plus Carhart (1997) momentum factor 4-factors model (FFC4) and Fama and French (1993) 3 factors, Carhart (1997) momentum factor plus Pastor and Stambaugh (2003) liquidity factor 5-factor model (FFCP5). In each panel, alphas of both value-weighted and equal-weighted portfolios are reported. All returns are monthly based estimates without annualization. T-statistics computed using Newey-West standard errors with five lags are in parentheses. ***, ** and * indicate 1%, 5%, and 10% significance levels, respectively.

Panel A: Alpha of Portfolios Sorted by 1-month RNS

A-1. Value-Weighted Portfolios

Decile	CAPM Alpha	FF3 Alpha	FF5 Alpha	FFC4 Alpha	FFCP5 Alpha
Low	-0.20	-0.18	-0.23	-0.19	-0.19
2	-0.02	0.01	-0.03	0.01	0.01
3	0.02	0.02	-0.09	0.04	0.03
4	0.03	0.06	0.00	0.05	0.05
5	0.30	0.32	0.23	0.33	0.33
6	0.21	0.24	0.26	0.36	0.37
7	0.24	0.23	0.09	0.28	0.28
8	0.27	0.25	0.03	0.27	0.27
9	0.41	0.37	0.28	0.53	0.53
High	0.76	0.65	0.48	0.76	0.76
High-Low	0.96***	0.83***	0.71***	0.95***	0.95***
t-stat.	(3.05)	(3.20)	(2.67)	(3.71)	(3.76)

A-2. Equally-Weighted Portfolios

Decile	CAPM Alpha	FF3 Alpha	FF5 Alpha	FFC4 Alpha	FFCP5 Alpha
Low	-0.35	-0.50	-0.68	-0.44	-0.44
2	-0.30	-0.43	-0.55	-0.35	-0.35
3	-0.19	-0.31	-0.40	-0.23	-0.23
4	-0.20	-0.31	-0.40	-0.23	-0.23
5	-0.02	-0.13	-0.20	-0.05	-0.05
6	0.02	-0.09	-0.19	0.02	0.02
7	-0.00	-0.13	-0.23	-0.02	-0.01
8	0.13	-0.02	-0.12	0.10	0.10
9	0.42	0.26	0.16	0.43	0.43
High	0.67	0.49	0.31	0.68	0.68
High-Low	1.02***	0.98***	0.99***	1.12***	1.12***
t-stat.	(4.88)	(5.15)	(4.68)	(5.49)	(5.49)

Panel B: Alpha of Portfolios Sorted by 3-month RNS

B-1. Value-Weighted Portfolios

Decile	CAPM Alpha	FF3 Alpha	FF5 Alpha	FFC4 Alpha	FFCP5 Alpha
Low	-0.02	0.01	-0.09	-0.01	-0.01
2	-0.02	-0.00	-0.15	0.01	0.00
3	0.11	0.10	-0.03	0.09	0.09
4	0.03	0.05	0.00	0.11	0.11
5	-0.04	0.00	0.02	0.02	0.02
6	0.30	0.33	0.34	0.47	0.47
7	-0.00	0.01	-0.05	0.08	0.08
8	0.29	0.31	0.28	0.30	0.30
9	0.44	0.38	0.34	0.56	0.56
High	0.60	0.49	0.24	0.67	0.67
High-Low	0.62*	0.47*	0.33	0.68***	0.68***
t-stat.	(1.95)	(1.91)	(1.26)	(2.67)	(2.68)

B-2. Equally-Weighted Portfolios

Decile	CAPM Alpha	FF3 Alpha	FF5 Alpha	FFC4 Alpha	FFCP5 Alpha
Low	0.07	-0.03	-0.22	-0.02	-0.02
2	-0.08	-0.20	-0.39	-0.17	-0.16
3	-0.08	-0.21	-0.37	-0.13	-0.13
4	-0.03	-0.16	-0.31	-0.08	-0.08
5	-0.14	-0.25	-0.33	-0.17	-0.17
6	-0.07	-0.20	-0.26	-0.09	-0.09
7	-0.05	-0.17	-0.22	-0.04	-0.04
8	0.00	-0.14	-0.21	-0.02	-0.02
9	0.22	0.05	-0.04	0.25	0.25
High	0.33	0.14	0.05	0.37	0.37
High-Low	0.25	0.17	0.26	0.39*	0.39*
t-stat.	(1.02)	(0.81)	(1.23)	(1.83)	(1.84)

Panel C: Alpha of Portfolios Sorted by 6-month RNS

C-1. Value-Weighted Portfolios

Decile	CAPM Alpha	FF3 Alpha	FF5 Alpha	FFC4 Alpha	FFCP5 Alpha
Low	0.03	0.04	-0.11	0.05	0.05
2	0.09	0.10	-0.05	0.06	0.06
3	0.06	0.05	-0.10	0.08	0.08
4	0.09	0.12	0.07	0.19	0.19
5	-0.01	0.00	0.08	0.05	0.05
6	0.30	0.33	0.41	0.40	0.40
7	0.06	0.09	0.23	0.19	0.19
8	-0.08	-0.06	0.10	0.00	0.00
9	-0.07	-0.08	-0.07	0.10	0.10
High	0.27	0.18	0.26	0.46	0.46
High-Low	0.24	0.14	0.37	0.41	0.41
t-stat.	(0.80)	(0.54)	(1.37)	(1.48)	(1.48)

C-2. Equally-Weighted Portfolios

Decile	CAPM Alpha	FF3 Alpha	FF5 Alpha	FFC4 Alpha	FFCP5 Alpha
Low	0.15	0.06	-0.15	0.06	0.06
2	0.08	-0.05	-0.28	-0.02	-0.02
3	0.18	0.03	-0.20	0.10	0.10
4	0.06	-0.06	-0.27	0.00	0.00
5	0.04	-0.09	-0.23	-0.02	-0.02
6	0.05	-0.08	-0.20	0.01	0.02
7	0.04	-0.08	-0.09	0.05	0.05
8	-0.04	-0.16	-0.17	-0.04	-0.04
9	-0.14	-0.29	-0.27	-0.10	-0.10
High	-0.26	-0.45	-0.42	-0.14	-0.14
High-Low	-0.41	-0.51***	-0.27	-0.20	-0.20
t-stat.	(-1.46)	(-2.36)	(-1.18)	(-0.89)	(-0.89)

Panel D: Alpha of Portfolios Sorted by 9-month RNS

D-1. Value-Weighted Portfolios

Decile	CAPM Alpha	FF3 Alpha	FF5 Alpha	FFC4 Alpha	FFCP5 Alpha
Low	0.02	0.03	-0.18	0.02	0.02
2	0.12	0.12	0.01	0.10	0.10
3	0.10	0.09	-0.06	0.12	0.12
4	0.01	0.05	0.01	0.05	0.05
5	0.32	0.34	0.36	0.40	0.40
6	0.19	0.21	0.31	0.29	0.29
7	-0.06	-0.04	0.08	0.04	0.04
8	-0.09	-0.06	0.14	0.08	0.08
9	-0.16	-0.14	-0.00	0.04	0.03
High	-0.59	-0.67	-0.37	-0.28	-0.28
High-Low	-0.61	-0.69**	-0.20	-0.30	-0.30
t-stat.	(-1.60)	(-2.31)	(-0.68)	(-1.01)	(-1.03)

D-2. Equally-Weighted Portfolios

Decile	CAPM Alpha	FF3 Alpha	FF5 Alpha	FFC4 Alpha	FFCP5 Alpha
Low	0.20	0.11	-0.13	0.11	0.11
2	0.15	0.04	-0.19	0.06	0.07
3	0.18	0.04	-0.23	0.09	0.09
4	0.19	0.05	-0.18	0.09	0.09
5	0.19	0.05	-0.15	0.11	0.11
6	0.18	0.04	-0.05	0.13	0.13
7	-0.05	-0.19	-0.27	-0.09	-0.09
8	-0.00	-0.13	-0.13	0.03	0.03
9	-0.09	-0.22	-0.16	-0.00	-0.00
High	-0.79	-0.97	-0.81	-0.62	-0.62
High-Low	-0.99***	-1.08***	-0.68***	-0.73***	-0.73***
t-stat.	(-2.81)	(-4.38)	(-2.85)	(-3.06)	(-3.07)

Panel E: Alpha of Portfolios Sorted by 12-month RNS

E-1. Value-Weighted Portfolios

Decile	CAPM Alpha	FF3 Alpha	FF5 Alpha	FFC4 Alpha	FFCP5 Alpha
Low	0.04	0.05	-0.14	0.03	0.03
2	0.14	0.14	-0.05	0.11	0.11
3	0.20	0.22	0.13	0.24	0.24
4	0.02	0.03	-0.11	0.01	0.01
5	0.15	0.16	0.30	0.23	0.23
6	0.01	0.04	0.10	0.10	0.10
7	0.11	0.12	0.20	0.20	0.20
8	-0.42	-0.39	-0.18	-0.25	-0.25
9	-0.05	-0.02	0.34	0.25	0.24
High	-0.83	-0.89	-0.61	-0.53	-0.53
High-Low	-0.87**	-0.94***	-0.47	-0.56*	-0.56*
t-stat.	(-2.12)	(-2.86)	(-1.59)	(-1.79)	(-1.79)

E-2. Equally-Weighted Portfolios

Decile	CAPM Alpha	FF3 Alpha	FF5 Alpha	FFC4 Alpha	FFCP5 Alpha
Low	0.22	0.13	-0.12	0.12	0.12
2	0.22	0.11	-0.16	0.13	0.14
3	0.23	0.10	-0.16	0.13	0.13
4	0.23	0.09	-0.18	0.14	0.14
5	0.19	0.04	-0.13	0.09	0.09
6	0.25	0.10	-0.06	0.19	0.19
7	0.05	-0.09	-0.16	-0.01	-0.01
8	-0.03	-0.17	-0.16	-0.01	-0.01
9	-0.24	-0.38	-0.26	-0.10	-0.10
High	-0.95	-1.11	-0.92	-0.76	-0.76
High-Low	-1.16***	-1.24***	-0.81***	-0.88***	-0.88***
t-stat.	(-3.05)	(-4.50)	(-3.11)	(-3.48)	(-3.49)

Table IV: Descriptive Statistics: Portfolios Formed on the Term Spread of Risk-Neutral Skewness. Panel A, B, C, D and E present abnormal return over the following month of decile portfolios sorted by the difference between 12- and 1-month risk neutral skewness, respectively. 5 standard asset pricing models are used as benchmarks, which include Capital Asset Pricing Model (CAPM), Fama and French (1993) 3-factor model (FF3), Fama and French (2015) 5-factor model (FF5), Fama and French (1993) 3 factors plus Carhart (1997) momentum factor 4-factors model (FFC4) and Fama and French (1993) 3 factors, Carhart (1997) momentum factor plus Pastor and Stambaugh (2003) liquidity factor 5-factor model (FFCP5). In each panel, alphas of both value-weighted and equal-weighted portfolios are reported. All returns are monthly based estimate without annualization. T-statistics computed using Newey-West standard errors with five lags are in parentheses. ***, ** and * indicate 1%, 5%, and 10% significance levels, respectively.

Panel A. Alpha of Value/Equally Weighted Portfolio Sorted by Term Spread of RNS

A-1. Value-Weighted Portfolios

Decile	CAPM Alpha	FF3 Alpha	FF5 Alpha	FFC4 Alpha	FFCP5 Alpha
Low	0.49	0.44	0.22	0.50	0.50
2	0.27	0.25	0.03	0.24	0.24
3	0.33	0.34	0.14	0.29	0.29
4	0.21	0.22	-0.02	0.20	0.20
5	0.13	0.12	-0.05	0.13	0.13
6	-0.14	-0.11	-0.12	-0.11	-0.11
7	-0.12	-0.08	-0.06	-0.13	-0.13
8	-0.21	-0.19	-0.06	-0.14	-0.14
9	-0.15	-0.12	0.05	-0.04	-0.04
High	-0.91	-0.94	-0.72	-0.76	-0.76
High-Low	-1.40***	-1.38***	-0.94***	-1.26***	-1.26***
t-stat.	(-5.25)	(-5.72)	(-4.84)	(-4.96)	(-4.95)

A-2. Equally-Weighted Portfolios

Decile	CAPM Alpha	FF3 Alpha	FF5 Alpha	FFC4 Alpha	FFCP5 Alpha
Low	0.66	0.50	0.26	0.61	0.61
2	0.47	0.34	0.13	0.42	0.42
3	0.39	0.26	0.05	0.33	0.33
4	0.33	0.20	-0.01	0.26	0.26
5	0.24	0.11	-0.08	0.19	0.20
6	0.02	-0.10	-0.21	-0.03	-0.03
7	-0.17	-0.30	-0.37	-0.23	-0.23
8	-0.26	-0.38	-0.34	-0.25	-0.25
9	-0.44	-0.57	-0.54	-0.40	-0.40
High	-1.07	-1.24	-1.20	-1.00	-1.00
High-Low	-1.72***	-1.74***	-1.47***	-1.61***	-1.61***
t-stat.	(-7.93)	(-9.79)	(-9.29)	(-8.82)	(-8.89)

Table V: Fama-MacBeth Cross-Sectional Regressions. This table reports the Fama-MacBeth coefficients of cross-sections of monthly excess stock returns on lagged term spread of risk-neutral skewness (RNSTS) and a set of firm characteristics during the period 1996-2015. RNSTS is calculated as the difference between long-term (12-month) and short-term (1-month) risk-neutral skewness. Models (2) controls for firms' beta (BETA), market value (MV), book-to-market ratio (BM), momentum (MOM), one-month reversal (REV),stock illiquidity proxied by Amihud (2002) price impact ratio (ILLQ). Model (3) additionally controls for lagged stock's return (RET), price per share (PRICE), and idiosyncratic volatility (IVOL). Model (4) additionally controls for option trading volume(OPVOL) and open interest(OPEN). T-statistics computed using Newey-West standard errors with five lags are in parentheses. ***, ** and * indicate 1%, 5%, and 10% significance levels, respectively.

	1	2	3	4
INTERCEPT	0.0062	0.0236 **	0.0211 *	0.0244 **
	(1.41)	(2.30)	(1.75)	(2.12)
RNSTS	-0.0101***	-0.0072 ***	-0.0066 ***	-0.0066 ***
	(-3.76)	(-4.30)	(-4.31)	(-4.30)
BETA		0.0005	0.0004	0.0004
		(0.25)	(0.24)	(0.22)
MV		-0.0011 *	-0.0008	-0.0010 *
		(-1.86)	(-1.38)	(-1.81)
BM		0.0005	-0.0001	-0.0002
		(0.29)	(-0.09)	(-0.15)
MOM		0.0002	-0.0004	-0.0004
		(0.07)	(-0.17)	(-0.17)
REV		-0.0002	-0.0003	-0.0003
		(-0.81)	(-1.03)	(-1.04)
ILLIQ		-46.5838	-44.3686	-44.6263
		(-1.53)	(-1.49)	(-1.49)
RET			-0.0212 ***	-0.0211 ***
			(-4.22)	(-4.24)
PRICE			-0.0000	-0.0000
			(-1.38)	(-1.31)
IVOL			0.0061	-0.0078
			(0.05)	(-0.06)
OPVOL				-0.0000
				(-1.24)
OPEN				0.0000 **
				(2.09)
Observations	356,286	234,418	234,418	234,418

Table VI: Fama-MacBeth Cross-Sectional Regressions. This table reports the Fama-MacBeth coefficients of cross-sections of the quarterly standardized earnings surprise (SUE) on lagged short-term(1 month) risk-neutral skewness(RNS1M), long-term(12 month) risk-neutral skewness(RNS12M), and a set of firm characteristics during the period 1996-2015. RNSTS is calculated as the difference between long-term (12-month) and short-term (1-month) risk-neutral skewness. Models (2) controls for firms' beta (BETA), market value (MV), book-to-market ratio (BM), momentum (MOM), one-month reversal (REV),stock illiquidity proxied by Amihud (2002) price impact ratio (ILLQ). Model (3) additionally controls for lagged stock's return (RET), price per share (PRICE), and idiosyncratic volatility (IVOL). Model (4) additionally controls for option trading volume(OPVOL) and open interest(OPEN). T-statistics computed using Newey-West standard errors with five lags are in parentheses. ***, ** and * indicate 1%, 5%, and 10% significance levels, respectively.

	1	2	3	4
INTERCEPT	-0.0015***	0.0000	0.0013 ***	0.0013 ***
	(-4.02)	(0.18)	(3.78)	(3.61)
RNS1M	0.0006 ***	0.0007 ***	0.0007 ***	0.0007 ***
	(2.53)	(2.45)	(2.79)	(2.75)
RNS12M	-0.0033***	-0.0022***	-0.0017***	-0.0017***
	(-4.78)	(-3.53)	(-2.76)	(-2.72)
BETA		0.0001	0.0002	0.0002 *
		(0.50)	(1.56)	(1.74)
MV		-0.0000***	-0.0000***	-0.0000
		(-3.73)	(-4.05)	(-0.40)
BM		-0.0019***	-0.0019***	-0.0018***
		(-2.81)	(-2.74)	(-2.68)
MOM		0.0004 ***	0.0007 ***	0.0007 ***
		(2.59)	(4.41)	(3.97)
REV		-0.0000	-0.0000	-0.0000
		(-1.51)	(-0.17)	(-0.29)
ILLIQ		-6.0140	-3.4769	-2.9820
		(-0.91)	(-0.43)	(-0.48)
RET			0.0030 ***	0.0031 ***
			(5.41)	(5.48)
PRICE			-0.0000***	-0.0000***
			(-2.76)	(-2.72)
IVOL			-0.0399***	-0.0413***
			(-2.98)	(-2.79)
OPVOL				-0.0000
				(-1.24)
OPEN				-0.0000
				(-0.13)
Observations	313,571	210,213	210,213	209,330

Table VII: Fama-MacBeth Cross-Sectional Regressions. This table reports the Fama-MacBeth coefficients of cross-sections of monthly price crash on lagged 1 month risk-neutral skewness(RNS1M), 12 month risk-neutral skewness(RNS12M), and a set of firm characteristics during the period 1996-2015. RNSTS is calculated as the difference between long-term (18 month) and short-term (1 month) risk-neutral skewness. Model (1), (2), ..., and (6) regress 1-, 2-, ..., and 6-month ahead price crash dummy on independent variables, respectively. T-statistics computed using Newey-West standard errors with five lags are in parentheses. ***, ** and * indicate 1%, 5%, and 10% significance levels, respectively.

	1	2	3	4	5	6
INTERCEPT	0.1099 ***	0.1077 ***	0.1068 ***	0.1059 ***	0.1061 ***	0.1047 ***
	(26.42)	(27.39)	(30.13)	(28.25)	(30.37)	(28.01)
RNS_1M	-0.0087***	-0.0087***	-0.0096***	-0.0105***	-0.0087***	-0.0059***
	(-4.24)	(-3.55)	(-5.43)	(-4.18)	(-3.47)	(-2.40)
RNS_12M	0.0096 ***	0.0048	0.0046	0.0044	0.0041	-0.0012
	(2.52)	(1.29)	(1.28)	(1.18)	(0.99)	(-0.26)
Observations	355,632	353,134	350,556	347,690	344,953	341,837

Table VIII: Average 1-month Risk-Neutral Skewness of Quintile Portfolios Sorted by Hedging Demand. This table reports the time-series average of the average RNS for quintile portfolios sorted by investor hedging demand. Three measures are used as hedging demand proxies, including the ratio of aggregate put option volume to total option volume (PAOV), the aggregate open interest across all options (AOI), and the Z-score of Zmijewski (1984) (ZD) to capture default risk. In order to match 1 month maturity, only options with maturity from 10 to 45 days are used to calculate the first two measures. The difference in average RNS between highest and the lowest hedging demand quintile portfolios are presented in the second to last line. T-statistics computed using Newey-West standard errors with five lags are in parentheses. ***, ** and * indicate 1%, 5%, and 10% significance levels, respectively.

Decile	Put-to-all Volume Ratio	Aggregate Open Interest	Z score Default Risk
Low	-0.2861	-0.2305	-0.2874
2	-0.3279	-0.2881	-0.3033
3	-0.3457	-0.3181	-0.3190
4	-0.3626	-0.3462	-0.3306
High	-0.3432	-0.3750	-0.3233
Q5-Q1	-0.0571***	-0.1445***	-0.0359***
T	(-26.17)	(-25.85)	(-14.21)

Table IX: In this table, panel A (B) reports the performance of double sorted portfolios by 1-month Risk-Neutral Skewness and the overvaluation (short-selling constraint) proxy for the sample period from 1996 to 2015. The stock overvaluation is proxied by the maximum daily stock returns over the last month (MAX). The short-selling constraint is proxied by idiosyncratic volatlity (IVOL). In the end of each month, stocks are sorted into tercile portfolios in ascending order by RNS1M. Within each RNS1M tercile portfolio, stocks are further sorted to tercile portfolios in ascending order based on the overvaluation (short-selling constraint) proxy. T-statistics computed using Newey-West standard errors with five lags are in parentheses. ***, ** and * indicate 1%, 5%, and 10% significance levels, respectively.

Panel A: Stock Overvaluation

	MAX low	MAX medium	MAX high	Difference
RNS1M low	0.0265	-0.2370**	-0.9747***	-1.0012***
	(0.24)	(-1.96)	(-6.28)	(-5.54)
RNS1M medium	0.2063*	-0.0927	-0.6049***	-0.8112***
	(1.68)	(-0.63)	(-3.29)	(-4.10)
RNS1M high	0.6129***	0.2044	-0.1857	-0.7986***
	(4.14)	(1.18)	(-0.98)	(-4.65)
Difference	0.5864***	0.4414***	0.7890***	
	(5.14)	(3.10)	(5.14)	

Panel B: Short-selling Constraint

	IVOL low	IVOL medium	IVOL high	Difference
RNS1M low	0.0430	-0.3288***	-0.9068***	-0.9498***
	(0.42)	(-2.62)	(-5.49)	(-5.01)
RNS1M medium	0.2723**	-0.1077	-0.6559***	-0.9282***
	(2.33)	(-0.74)	(-3.51)	(-4.69)
RNS1M high	0.4527***	0.3098*	-0.1317	-0.5844***
	(3.33)	(1.83)	(-0.60)	(-2.84)
Difference	0.4098***	0.6387***	0.7751***	
	(3.99)	(4.70)	(4.50)	