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Risk-Neutral Skewness, Informed Trading, and the Cross-Section of Stock Returns

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Abstract

This paper uses the volatility surface data from options contracts to document a strong, robust, and positive cross-sectional relation between risk-neutral skewness (RNS) and subsequent stock returns. The differential return between high and low RNS stocks amounts to 0.17% per week. Pre-announcement RNS is positively related to earnings announcement returns, and the positive RNS-return relation is more pronounced for other non-scheduled news releases, suggesting that it is informed trading that drives the positive relation between RNS and subsequent stock returns. We also find that RNS contains incremental information beyond trading signals captured by option implied volatility and volume.

I. Introduction

Ex ante skewness predicts future stock returns. However, the sign and source of this predictability are still under debate. From a theoretical perspective, Brunnermeier, Gollier, and Parker (2007) and Barberis and Huang (2008) argue that investors face a trade-off between diversification and skewness. Investors hold more undiversified positions in positively skewed securities due to a preference for lottery-type stocks (Kumar (2009)). This preference leads to overpricing of the highly skewed securities and thus predicts a negative relation between skewness and expected returns. Mitton and Vorkink (2007) document that individual investors hold undiversified portfolios and accept lower Sharpe ratios for positive skewness. Conrad, Dittmar, and Ghysels (2013) find that risk-neutral skewness (RNS) is negatively related to the subsequent returns in the cross-section. However, both Rehman and Vilkov (2012) and Stilger, Kostakis, and Poon (2017) find a positive correlation between ex ante skewness and future stock returns and argue that their findings are consistent with overpricing of stocks with the most negative ex ante skewness. Our paper aims to shed light on this debate by providing new evidence and a novel channel for the relation between ex ante skewness and stock return.

Using RNS as a proxy for ex ante skewness, we find a strong, robust, and positive cross-sectional relation between RNS and subsequent week stock returns from Jan. 1996 to June

2015. An investment strategy that buys high RNS stocks and sells low RNS stocks produces raw returns of 17 basis points (bps) (t-statistic = 3.59) and risk-adjusted returns of 16 bps (t- statistic = 3.40) per week based on the Fama--French (2015) 5-factor model plus the momentum factor as in Carhart (1997). The Fama--Macbeth (1973) regressions yield similar results after controlling for both firm characteristics and existing option-based signals.[2]

We investigate two possible mechanisms for the positive relation between RNS and subsequent stock returns. First, we test whether this positive RNS-return relation is driven by mispricing. If high (low) RNS stocks are relatively undervalued (overvalued), then we would also observe such a positive RNS-return relation. However, using the anomaly-based firm-level mispricing index of Stambaugh, Yu, and Yuan (2015), we find the opposite pattern. The high RNS stocks are overvalued rather than undervalued, as compared to the low RNS stocks.[3] This finding suggests that the positive RNS-return relation is unlikely to be driven by mispricing based on the 11 well-known anomalies adopted by Stambaugh et al. (2015).

Second, we examine whether informed options trading accounts for the RNS-return relation. Black (1975) and Easley, O'Hara, and Srinivas (1998) suggest that informed traders may prefer trading in the options market because of the high embedded leverage and the circumvention of short-sale constraints. If informed traders are privy to forthcoming good (bad) news, then their trading will cause OTM call (put) prices to increase and result in a higher positive (negative) skewed risk-neutral density. As the new information arrives and gets incorporated into the stock price, a positive RNS-return relation would be observed.

[2] Firm characteristics include size, book-to-market ratio, past returns, idiosyncratic volatility, illiquidity, coskewness, asset growth, profitability, the abnormal trading volume, and the maximum daily return over the past month. Option-based signals include the risk-neutral volatility, implied volatility skew of Xing, Zhang, and Zhao (2010), implied volatility spread of Cremers and Weinbaum (2010), call-put volume ratio of Pan and Poteshman (2006), and the variance risk premium of Bali and Hovakimian (2009).

[3] As Stambaugh et al. (2015) explain, the firm-level index is a cross-sectional measure. A higher (lower) mispricing measure indicates that the stock is relatively overvalued (undervalued) in the cross-section.

To test this information mechanism, we first examine the RNS-return relation around earnings announcements. Then, we consider all corporate news releases including scheduled and non-scheduled news releases.[4] There is a positive relation between pre-announcement RNS and cumulative abnormal returns (CARs) on the earnings announcement days and the post-announcement returns. Further, the stock return predictability of RNS is much stronger prior to all news releases as well as non-scheduled news releases, suggesting that the positive RNS-return relation can be largely attributed to informed trading in the options market.

Since our findings point to an informed trading mechanism for the positive RNS-return relation, it is crucial that our results are not subsumed by the known informed option trading signals. To address the issue, we further control for the implied volatility skew (IV_Skew) of Xing et al. (2010), the implied volatility spread (IV_Spread) of Cremers and Weinbaum (2010), the call-put volume ratio (CP_Ratio) of Pan and Poteshman (2006), and the variance risk premium (RV-IV Spread) of Bali and Hovakimian (2009) in the Fama--MacBeth regressions. We find that the return predictability of RNS remains statistically significant and economically large, suggesting that RNS contains incremental information beyond the existing option trading signals. To examine the incremental information content of RNS, we independently sort stocks based on RNS and one of the existing option signals (i.e., IV_Skew, IV_Spread, CP_Ratio, or RV-IV Spread) into 5x5 portfolios. The positive RNS-return relation exists almost among all portfolios sorted by one of the existing option signals.

We conduct several additional robustness tests. (i) We first ask whether trading frictions and limits-to-arbitrage can account for the RNS-return relation. While the positive RNS-return relation is more pronounced for the stocks with higher idiosyncratic volatility (Ivol) and higher illiquidity (ILLIQ), the positive RNS-return relation remains significant for the stocks with low

[4] The firm specific news release data is obtained from the RavenPack database that has comprehensive coverage on real time corporate news, and tracks each news release with various metric, such as category, novelty, sentiment score etc.

Ivol and ILIIQ, suggesting that trading frictions and limits-to-arbitrage, while important, cannot fully explain the RNS-return relation. (ii) Non-linearities in illiquidity, coskewness, short interest, and risk-neutral volatility (RNV) do not explain the RNS-return relation. (iii) Informed traders with negative news about a firm can profit by short selling or by trading in the options market. The short interest evidence is consistent with informed trading in the options market. (iv) Last, we investigate the RNS-return relation for various formation and holding periods from 1 week to 13 weeks, for a total of 169 (13 formation and 13 holding weeks) strategies. This exercise helps reconcile the mixed results of the RNS-return relation in the literature based on different formation and holding periods.[5] We find that the return spread between high and low RNS portfolios decreases with the formation and holding periods.

Our paper contributes to the literature in two ways. First, we document new evidence and provide a mechanism for the positive RNS-return relation. While our mechanism is rooted in the informed options trading literature, the information content in the RNS is incremental to the existing trading signals based on implied volatility or volume.[6] Our findings are corroborated by Borochin, Chang, and Wu (2018) who study the information content of RNS term structure and find a positive (negative) relation between short-term (long-term) RNS and subsequent stock returns. However, our paper differs from Borochin et al. (2018) as we provide a direct test on the information mechanism that includes earnings announcements and the release of both scheduled and non-scheduled corporate news.

Second, the positive RNS-return relation is not driven by mispricing. This contrasts with the following papers. Rehman and Vilkov (2012) and Stilger et al. (2017) both argue that only the negative RNS predicts subsequent stock returns because of overpricing of stocks with

[5] Our main analysis is based on 1-week formation period and 1-week holding period. A strategy based on 4-week formation period and 4-week holding period resembles the setup in Rehman and Vilkov (2012) and Stilger et al. (2017). Meanwhile, a strategy based on non-overlapping, 13-week formation period and 13-week holding period resembles the setup in Conrad et al. (2013).

[6] See Easley et al. (1998), Pan and Poteshman (2006), Roll, Schwartz, and Subrahmanyam (2010), Johnson and So (2012), An et al (2014), and Ge, Lin, and Pearson (2016), among others.

the most negative RNS, while Gkionis, Kostakis, Skiadopoulos, and Stilger (2018) argue that the positive RNS additionally predicts subsequent week's stock returns due to underpricing of the stocks with the highest RNS. Borochin and Zhao (2019) argue that RNS predicts next-month returns due to higher returns of previously undervalued stocks. Our paper differs from these studies as we find that RNS positively predicts future earnings announcement returns, and this positive RNS-return relation also becomes more pronounced before non-scheduled news releases, suggesting that informed options trading seems to be the main driver of the positive RNS-return relation.

II. Risk-neutral higher moments

We follow the methodology developed by Bakshi and Madan (2000) and Bakshi, Kapadia, and Madan (2003) (BKM) to extract the estimates of RNS.[7] The BKM methodology assumes a continuum of option strikes that spans the underlying stock spot price. In reality, however, such a continuum of strikes is generally not available. Prior studies have used daily option closing quotes to select out-of-the-money (OTM) call and put options that have an approximately similar strike-to-spot price distance (Dennis and Mayhew (2002), Friesen, Zhang, and Zorn (2012), and Conrad et al. (2013)). However, the simulation results of Dennis and Mayhew (2002) show that an asymmetric strike-to-spot price distance for OTM put and call options may result in significant bias in the RNS estimates.

We avoid this asymmetric strike-to-spot price distance between OTM put and call options by using the OptionMetrics volatility surface database, which contains standard option contracts with a constant maturity and a matched delta. This data allows us to identify a collection of OTM put and call option pairs that have the same absolute values of delta.[8]

[7] Details are in Internet Appendix C.
[8] In Appendix 1, we show that put-call pairs with matched deltas have a symmetrical strike-to-spot price distance.

In addition, we control for the option contract terms (maturity and moneyness) to ensure that both the time-series and the cross-sectional variations in RNS are driven only by shifts in the risk-neutral density function. The volatility surface database contains standardized options contracts with constant maturities and a fixed interval of the delta. This ensures that (i) for a given firm, the time-series of RNS is extracted from options with identical maturity and moneyness and (ii) at a given point of time, the cross-section of RNS is also extracted from options with identical maturity and moneyness. Thus, the time-series and cross-sectional RNS variations, if any, are indeed caused by shifts in the underlying stocks risk-neutral density curve, and not by dissimilarities in the option contract terms.[9]

We follow Bakshi and Madan (2000) and BKM to extract risk-neutral moments from options prices, including risk-neutral variance (RNV), risk-neutral skewness (RNS), and risk-neutral kurtosis (RNK) each day. We require that at least two OTM call and put options exist on day *t*. An OTM call (put) option is defined as options with delta greater than 0.2 (−0.375) and less than 0.375 (−0.2). Second, the OTM call and put options must have the same absolute delta. This requirement ensures that delta-matched OTM call and put options have identical strike-to-spot price distances. Options that do not have matched counterpart contracts are excluded from the RNS calculation. Third, at least two delta-matched OTM put-call pairs are needed to proceed with the RNS calculation. We then follow Dennis and Mayhew (2000) and Conrad et al. (2013) and use a trapezoidal approximation for integral calculations stipulated in BKM.

III. Data

We obtain options data for 30-day maturity standardized options contracts from Ivy DBs OptionMetrics volatility surface dataset. The data provides several key option metrics for

[9] There is strong evidence that option contract terms have a significant impact on the option return distribution. See, for example, Coval and Shumway (2001), Ni (2008), and Boyer and Vorkink (2014).

standard options contracts with constant maturity. Using binomial tree models that adjust for early exercise and expected dividend payments over an options life, implied volatilities together with the corresponding implied strike prices and premiums are reported. Besides, for each maturity, options are listed by delta in fixed increments of 0.05, from 0.2 to 0.8 for call options and from −0.8 to −0.2 for put options. OptionMetrics only performs calculations and records data entries if sufficient option price data exists to implement accurate interpolations for the required values. Effectively, the volatility surface data allows for the entire range of strikes and moneyness to be used when computing RNS. The volatility surface data also allows us to obtain a large cross-sectional sample. Our sample coverage is similar to that in An, Ang, Bali, and Cakici (2014).

We merge the option data with stock price data from CRSP focusing only on common stocks (share codes 10 and 11) traded on U.S stock exchanges. Following Conrad et al. (2013), the risk-free rate is the continuously compounded yield computed from the 3-month Treasury rate on a bank discount basis. The sample period is from January of 1996, the earliest date in the OptionMetrics database, until June of 2015. After eliminating firm-days without at least two OTM call and put options, we are left with a comprehensive sample of 6,187 unique firms and 10,212,182 firm-day observations of RNS. The comprehensive cross-sectional coverage provides the power to reject the null of no cross-sectional relation between RNS and stocks returns.

[Table 1 about here]

Table 1 presents sample descriptive statistics by year for the risk-neutral moments. The sample coverage expands over time, increasing from 1,881 stocks in 1996 to 2,711 stocks in 2015. We report the 5th percentile, median, and 95th percentile for the RNS estimates of the sample. The risk-neutral distribution of stock returns is negatively skewed and fat-tailed. The median RNV and RNS in the full sample period are 0.23 and −0.51, respectively.[10] The median RNV and RNS are elevated (in absolute terms) in 2008 and 2009 during the recent financial crisis.

IV. The Relation Between RNS and the Cross-Section of Stock Returns

IV.A Portfolio Sorts

Table 2 presents the portfolio results. Panel A reports returns from weekly RNS sorts. At the close of trading each Tuesday, stocks are sorted into deciles based on the average daily RNS from the prior Wednesday to Tuesday. The Low (High) group contains stocks with the lowest (highest) average RNS. Since trading in the options and stock markets are not synchronized, we skip 1 day between the formation and the holding periods, i.e., the Wednesday of sorting week. Value-weighted portfolio holding period returns are computed from Thursday to the next Wednesday.

[Table 2 about here]

The average value-weighted raw return for the decile 1 (Low RNS) portfolio is 17 bps per week. The returns increase monotonically with RNS to 34 bps per week for the decile 10 (High RNS) portfolio. This pattern remains when we use the Fama--French (2015) factors and the momentum factor (FF5+Mom) for the risk adjustment. The alpha increases from 17 bps for the Low RNS portfolio to 33 bps for the High RNS portfolio. This pattern yields an economically significant long-short (High-Low) hedge portfolio alpha of 16 bps per week (t-statistic = 3.40). The results are similar when the risk adjustment is performed with the Hou, Xue, and Zhang (2015) q-factor model with or without the momentum factor. Note that all

[10] Note that while we use 30-day maturity options to compute the risk-neutral moments, we report RNV in annualized terms so as to make it comparable to the VIX index. RNV is higher than VIX because it is computed for individual stocks as opposed to a portfolio of stocks.

High-Low RNS value-weighted portfolio t-statistics exceed the threshold of three recommended by Harvey, Liu, and Zhu (2016).

In addition, we implement various alternative portfolio approaches, with different combinations on i) sort on the weekly average RNS vs. sort on a single day RNS on Tuesday, ii) skip 1 day vs. without skipping a day following portfolio formation, and iii) value-weighted returns vs. equally-weighted returns. The results are reported in Internet Appendix A Table IA.1.

The positive RNS-return relation is robust and stays economically large and statistically significant across all alternative portfolio settings. A few points are noteworthy. First, the value-weighted and the equal-weighted portfolios have similar results (raw hedge return of 17 bps for the value-weighted portfolio in Table 2 vs. 20 bps for the equal-weighted portfolio). This suggests that the positive RNS-return relation is not only driven by small stocks. Second, skipping a day or not between the holding and formation periods does not alter results, suggesting the positive RNS-return relation is unlikely to be explained by the price pressure effect documented by Goncalves-Pinto, Grundy, Hameed, Van der Heijden, and Zhu (2019). Third, sorting on a single day RNS provides similar results. This is likely due to the rich information content of RNS.

Table IA.2 presents the value-weighted raw returns as well as the alphas for decile portfolios sorted on RNS for three different sorting and holding periods. Panel A presents the weekly returns for a 4 week holding period with RNS sorted on the prior week. Panels B and C present monthly returns and alphas with sorting on RNS in the prior month and the last 5 days of the prior month, respectively. The High-Low RNS portfolio raw returns are 0.14% per week, 0.54% per month and 0.57% per month in Panels A, B, and C respectively. These results show that the positive RNS-return relation is quite robust in both weekly and monthly formation and holding periods.

IV.B Characteristics of RNS Portfolios

In this subsection, we provide average firm characteristics for the RNS sorted portfolios.

- Size: Natural logarithm of firm capitalization measured at the end of each month. The market capitalization is calculated as the stock price times the number of shares outstanding, and the units are in millions of dollars.
- Book-to-Market ratio (BM): Following Fama and French (1992), for each month from July of year *t* to June of year *t+1*, BM is calculated as the ratio of book value of common equity for the fiscal year ending in year *t−1* dividend by market value at the end of December in the year *t−1*.
- Illiquidity (ILLIQ): Following Amihud (2002), the illiquidity measure for firm *i* in month *t* is the average ratio of the absolute daily return to its daily dollar trading volume.

$$ILLIQ_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{itd}|}{DVOL_{itd}} * 10^6 ,$$

where D_{it} represents the number of days with non-zero trading volume in a month.

- CoSkew: Following Harvey and Siddique (2000), co-skewness in month *t* is the slope coefficient on the squared market excess return from a regression of the stock *i*'s excess return on the market excess return and the squared market excess return. The regression is estimated using daily data over the past 12 months.

$$R_{i,t} - RF_t = \alpha_i + \beta_i(R_{m,t} - RF_t) + CoSkew_{i,t}(R_{m,t} - RF_t)^2 + \varepsilon_{i,t} .$$

- AG: Following Cooper, Gulen, and Schill (2008), asset growth is the increase in total assets from the fiscal year-end in year *t−2* to year *t−1* divided by total assets at fiscal year-end in year *t−2.*

- IVOL: Idiosyncratic volatility for each stock is calculated from squared residuals obtained from regressions of daily excess return on the Fama and French (1993) factors over the past 12 months.
- AVOL: Following Gervais, Kaniel, and Mingelgrin (2001) the abnormal trading volume is the weekly trading volume relative to the average of the previous 9 weeks.
- Prof: Following Ball, Gerakos, Linnainmaa, and Nikolaev (2015), profitability is computed as gross profit minus selling, general, and administrative expenses (excluding research and development expenses) deflated by the book value of total assets.
- MAX: The maximum daily return over the prior month proposed by Bali, Cakici, and Whitelaw (2011) proxies for the lottery-type preferences of investors.
- Ret1: This is the return over the week when RNS is computed, as calculated from the prior week Wednesday to Tuesday (the sorting day).[11] The past weekly or monthly return proxies for reversals documented in Lehmann (1990) and Jegadeesh (1990).
- Ret(2, 12): This is the cumulative return over the past eleven months that skips the most recent past month proxies for momentum as in Jegadeesh and Titman (1993).
- RNV: This is risk-neutral volatility following BKM.

Panel B of Table 2 reports the time-series averages of the cross-sectional median firm characteristics for each of the decile RNS portfolios. There are no apparent differences in RNV across RNS portfolios. The exception is the Low RNS portfolio, for which RNV is higher (0.023). The higher RNS stocks tend to be smaller with a higher BM. The median BM ratio increases from 0.59 for the Low RNS portfolio to 0.71 for the High RNS portfolio. RNS is positively correlated with the Amihud (2002) illiquidity measure, with ILLIQ increasing from 0.01 for the Low RNS portfolio to 0.06 for the High RNS portfolio. Co-skewness decreases

[11] In unreported results, we find similar results when we define Ret1 as return over the prior month.

from a median of 0.23 for the Low RNS portfolio to −0.26 for the High RNS portfolio. MAX increases from 0.048 for the low RNS portfolio to 0.065 for the high RNS portfolio. AVOL is also positively correlated with RNS and increases from 1.044 for the low RNS to 1.099 for the High RNS portfolio. The past 1 week (eleven months, not including the past 1 month) return decreases from 0.80% (15.69%) for the Low RNS portfolio to −0.67% (3.31%) for the High RNS portfolio.

The results suggest that RNS is correlated with various firm characteristics that have been used in the literature to predict returns in the cross-section. For example, smaller, more illiquid stocks, and stocks with low past month returns have higher RNS. Hence, the positive RNS-return relation may result from its correlations with certain firm characteristics. To address this concern, we will control for these characteristics in Fama--MacBeth (1973) regressions.

IV.C Fama--MacBeth Cross-Sectional Regressions

We estimate the Fama--MacBeth (1973) cross-sectional regressions to examine the incremental impact of RNS on subsequent stock returns, while controlling for the known firm characteristics that predict stock returns. The following regression is performed using weekly returns:

$$R_{i,t+1} = \beta_{0,t} + \beta_{1,t} RNS_{i,t} + Controls_{i,t} + \varepsilon_{i,t+1} \, ,$$

$R_{i,t+1}$ is firm *i*'s weekly excess return or risk-adjusted return from Thursday of week *t* to Wednesday of week *t+1*. We follow Brennan, Chordia, and Subrahmanyam (1998) and use either the FF5+Mom or the q-factor+Mom factors to obtain the risk-adjusted returns. $RNS_{i,t}$ is firm *i*'s average daily RNS calculated from Wednesday of week *t−1* to Tuesday of week *t*. $Controls$ represents the firm characteristics that are known to predict returns.

In addition to the firm-level characteristics listed above, we also control for existing option-based variables that have been shown to predict cross-sectional stock returns. These variables include implied volatility skew (IV_Skew) of Xing et al. (2010), implied volatility spread (IV_Spread) of Cremers and Weinbaum (2010), call-put volume ratio (CP_Ratio) of Pan and Poteshman (2006), and the variance risk premium (RV-IV Spread) of Bali and Hovakimian (2009) computed as the difference between the realized and implied volatilities.[12] The gist is to test whether RNS has incremental return predictability and make sure that our documented RNS-return relation is not a reproduction of the existing option-based signals.[13] Table 3 reports the average slope coefficients and their corresponding Newey--West (1987) t-statistics with 12 lags (results are similar with 4, 8, and 16 lags) to account for potential autocorrelation and heteroscedasticity in the time-series of slope coefficients.

[Table 3 about here]

The average RNS slope coefficient in the univariate model that regresses stock excess returns on the intercept and the lagged RNS is 0.125 (t-statistic = 3.90), consistent with the positive cross-sectional relation between RNS and stock returns. In the multivariate regression of excess returns on RNS and all the control variables, the average RNS slope coefficient is 0.09 (t-statistic = 5.14).[14] The average adjusted R^2 increases from 0.2% in the univariate regressions to 9.0% in the multivariate regressions. With risk-adjusted returns, the coefficient on RNS remains highly significant. In terms of economic significance, a 1-standard-deviation increase in RNS is associated with a 6 bps increase in returns per week (3.12% per year).

[12] Note that the variance risk premium (VRP) is actually defined by Bollerslev, Tauchen, and Zhou (2009) as the difference between the implied and realized volatilies. We follow Bali and Hovakimian (2009) and Rehman and Vilkov (2012) and calculate VRP as the difference between realized volatility (over the prior 30 days) and average implied volatilities from at-the-money put and call options.

[13] The pairwise average cross-sectional correlation between RNS and the existing option-based signals are: −0.226 for IV_Skew, 0.127 for IV_Spread, 0.024 for CP_Ratio, and −0.001 for RV-IV Spread.

[14] The Panels A and B of Table IA.3 in Internet Appendix A present the univariate and bivariate results for RNS and the option-based predictors IV_Skew, IV_Spread, CP_Ratio, and RV-IV spread, respectively. The RNS coefficients remains significant in all specifications.

Regardless of the risk-adjustment or the inclusion of the control variables, the coefficient on RNS is always positive and highly significant. In all model specifications, the t-statistic exceeds the threshold of three as suggested by Harvey et al. (2016) as well as the higher threshold of 3.38 suggested by Chordia, Goyal, and Saretto (2020).

IV.D RNS and the Existing Option-Based Return Predictors

The average RNS coefficient is 0.098 across the multivariate regressions in Table 3. The coefficient of IV_Skew is statistically insignificant. Xing et al. (2010) argue that IV_Skew captures the slope of the implied volatility curve and is thus a proxy for RNS, which may explain the insignificant coefficient of IV_Skew in the presence of RNS. On the other hand, IV_Spread and RV-IV Spread have significant coefficients. But the economic significance of this return predictability is smaller than that of RNS. Specifically, a 1-standard-deviation increase (decrease) in IV_Spread (RV-IV Spread) is associated with a 4 bps increase in return per week, as compared with a 6 bps increase in return for RNS. Thus, RNS has the incremental information content that is not reflected in the existing option-based return predictors.

Table 4 presents the long-short returns for double sorted RNS portfolios. Each Tuesday, we independently sort stocks based on RNS and one of the existing option-based signals: IV_Skew, IV_Spread, CP_Ratio, and RV-IV Spread. Twenty-five portfolios are formed, and the returns are evaluated from Thursday to the next Wednesday. To calculate the RNS return premium between the high and low RNS stocks, we average returns across five intersecting portfolios of high (low) RNS and the option-based signal quintile portfolios and then calculate return difference between the high and low RNS portfolios. The reported raw returns and alphas are averages across the five IV_Skew portfolios, the five IV_Spread portfolios, the five CP_Ratio portfolios, and the five RV-IV Spread portfolios.[15]

[Table 4 about here]

The positive RNS-return relation remains statistically significant and economically large, after controlling for the existing option signals. For example, with Fama--French (2015) factors plus the momentum factor (FF5+Mom), the risk-adjusted alphas are 13 bps (t-statistic = 3.02), 14 bps (t-statistic = 3.63), 17 bps (t-statistic = 4.40), and 15 bps (t-statistic = 3.54) per week after controlling for IV_Skew, IV_Spread, CP_Ratio, and RV-IV Spread, respectively. The results are about the same for alphas for the q-factor model of Hou et al. (2015), and the Stambaugh and Yuan (2017) mispricing factors. These results suggest that RNS has incremental return predictability to the existing option-based signals. Therefore, the positive RNS-return relation is not a reflection of the results from these existing option-based signals.

While the above analysis shows that RNS contains incremental information relative to the existing option-based signals, it does not subsume all these signals. This can be seen by the fact that combining RNS with an existing signal further enhances return predictability in the cross-section. A strategy that takes long and short positions on the corresponding corner portfolios delivers higher returns, and all corner portfolios are sufficiently populated.[16] The results of corner portfolio performance are reported in Table IA.5 of Internet Appendix A. For example, a strategy that longs high RNS/IV_Spread and shorts low RNS/IV_Spread intersection portfolio results in a raw value-weighted return of 32 bps per week (t-statistic = 4.94), the corresponding risk-adjusted alpha using the FF5+Mom factors is 31 bps per week (t-statistic = 4.91).

[15] The full details of the returns for the 25 portfolios are presented in Table IA.4 of Internet Appendix A.
[16] The number of stocks in each corner portfolios are as follow: High RNS/Low IV_Skew: 45; Low RNS/High IV_Skew: 102; High RNS/High IV_Spread: 85; Low RNS/Low IV_Spread: 83; High RNS/High CP_Ratio: 62; Low RNS/Low CP_Ratio: 73; High RNS/Low RV-IV: 64; Low RNS/High RV-IV: 56.

V. What Drives the Relation Between RNS and the Cross-Section of Stock Returns

The finding of a robust and positive cross-sectional relation between the RNS and stock returns in the previous section is at odds with the theoretical models of Brunnermeier et al. (2007) and Barberis and Huang (2008). In this section, we investigate the potential mechanisms for this positive correlation. We explore two possible mechanisms that could lead to the positive RNS-return relation, namely mispricing and informed trading.

V.A Mispricing Channel

Could the High RNS portfolio stocks be undervalued and the Low RNS portfolio stocks be overvalued, which consequently leads to the positive RNS-return relation after the correction of mispricing? We use the Stambaugh et al. (2015) firm-level mispricing index, and compare the value-weighted average mispricing measure for stocks in the High and Low RNS-sorted decile portfolios. The firm-level mispricing index of Stambaugh et al. (2015) is a cross-sectional measure. A higher (lower) mispricing measure indicates that the stock is relatively overvalued (undervalued) in the cross-section. If high (low) RNS stocks are relatively undervalued (overvalued), then these stocks would have a relatively lower (higher) mispricing measure, which would result in the positive RNS-return relation.

Interestingly, we find the opposite pattern. Figure 1 tracks the mispricing index in the prior month, the following month, and the month of the sorting week. It shows clear evidence that the High RNS portfolio stocks are overpriced, compared with the Low RNS portfolio stocks. In unreported results, we find that the Low (High) RNS portfolio has a mispricing measure of 42.93 (48.33) in the month of the sorting week. The difference in the mispricing measure between the High and Low RNS portfolios is highly significant.

[Figure 1 about here]

If mispricing is the driver of our main finding, given the overvaluation, the return of the High RNS portfolio after the sorting week should be lower than that of the Low RNS portfolio. The price correction should lead to a negative relation between RNS and future stock returns. Therefore, the mispricing channel is not likely to explain the positive RNS-return relation. Moreover, our results are robust when using the mispricing factors to obtain alphas (Table 4), suggesting that the positive RNS-return relation is not due to the mispricing of the different RNS portfolios.

The fact that RNS is positively related to future stock returns even for the overvalued stocks, suggesting that RNS might contain valuable and novel information reflected in options trading. This is what motivates us to examine the information mechanism as the main explanation for the positive RNS-return relation that we explore in the next section.

V.B Information Channel

In this subsection, we propose and test whether the positive RNS-return relation is driven by informed trading in the options market such that new information is incorporated into options prices before being incorporated into stock prices. Black (1975) and Easley et al. (1998) have suggested that informed investors may prefer trading in the options markets because of the high embedded leverage in options contracts and to avoid the short-sale constraints.[17]

To examine this information channel, we conduct two tests. First, using firm-level quarterly earnings announcements as information events, we test whether pre-announcement RNS could predict cumulative abnormal returns (CARs) around the announcement days.

[17] Also see An et al (2014), Xing et al (2010), Pan and Poteshman (2006), Roll et al. (2010), Johnson and So (2012), Chan, Ge, and Lin (2015), Gharghori, Maberly, and Nguyen (2015), Hayunga and Lung (2014), Ge et al. (2016), Cremers, Fodor, Muravyev, and Weinbaum (2019), among others.

Second, using Dow Jones news archive corporate news release as information events, we examine whether the RNS return predictability is stronger before the release of the news.

For earnings announcement information event, we calculate the firm-level average RNS (*Pre_RNS*) during a 5-day window [−7, −3], where *t* is the earnings announcement day. We compute announcement day CARs over a 3-day window [−1, +1] around the announcement day, and various post-announcement windows. This is consistent with the prior setting that uses weekly average RNS to predict subsequent returns, skipping 1 day between RNS construction window and prediction window. CARs are calculated as the difference in the firm return and the equally-weighted market return. We then run quarterly Fama--MacBeth regressions with the same control variables as before:

$$CAR_{i,t+1} = \beta_{0,t} + \beta_1 Pre\_RNS_{it} + Controls_{it} + \varepsilon_{i,t+1} ,$$

Panel A of Table 5 reports the coefficient estimates on *Pre_RNS;* the coefficient estimates on control variables are not reported for brevity. The pre-announcement RNS is positively related to the CARs around the earnings announcements as well as the returns over the post-announcement periods. The *Pre_RNS* coefficients are 0.09 (t-statistic = 2.06), 0.07 (t-statistic = 2.21), 0.22 (t-statistic = 2.85), and 0.41 (t-statistic = 3.12) for the [−1, +1], [+2, +5], [+2, +10], and [+2, +60] return windows, respectively. This finding suggests that prior to earnings announcements, the option-based RNS starts to incorporate the information content of earnings announcements before the information gets reflected in stock prices.

[Table 5 about here]

Panel B of Table 5 documents the differential impact of RNS on returns around earnings announcements compared to periods that exclude the earnings announcements. The High-minus-Low RNS return spread and risk-adjusted alphas based on weekly sorted RNS portfolios are reported. Each Tuesday, firms are sorted into decile portfolios based on the average level of risk-neutral skewness from the previous Wednesday to Tuesday. Value-weighted portfolios are formed and held from Thursday to the next Wednesday. The return and alpha differentials are presented for firms that have no earnings announcements during the holding period or the skip day and for firms with an earnings announcement during the holding period or the skip day. The holding period raw return of High-Low RNS spread for the earnings announcement firms is almost three times as large as that for the non-earnings announcement firms (0.38% vs. 0.14%). The alpha differentials across the High and Low RNS decile portfolios with respect to FF5+Mom, q-factor, and q-factor+Mom are at least three times as large for the earnings announcement firms as compared to the non-earnings announcement firms. These results further support the idea that RNS captures informed options trading.

Next, we examine this information channel in a setting with richer information events that cover the arrival of all corporate news. We use corporate news release data from RavenPack that contains all news stories reported by Dow Jones Newswire and the Wall Street Journal.[18] This setup allows us to test whether RNS return predictability is associated with the arrival of forthcoming corporate news. The return predictability of RNS prior to corporate news releases should become stronger if the information channel is the main driver of RNS-return relation.

Following Dang, Moshirian, and Zhang (2015), Augustin, Brenner, Grass, and Subrahmanyam (2018), and Jiang, Li, and Wang (2018), we consider only news stories with both RavenPack relevance and novelty scores of 100 such that the news is not stale or outdated.[19] We estimate predictive weekly Fama--MacBeth cross-sectional regressions as follows:

$$R_{i,t+1} = \beta_{0,t} + \beta_{1,t} ND_{i,t+1} + \beta_{2,t} RNS_{i,t} + \beta_{3,t} RNS_{i,t} \times ND_{i,t+1} + Controls_{i,t} + \varepsilon_{i,t+1}$$

[18] RavenPack is a data service that provides real time sentiment, relevance, and novelty data obtained from various news feeds.
[19] Hafez (2009) shows that 80% of all news stories that are less relevant and non-novel simply add noise.

News release dummy ND_i equals 1, if firm *i* has news release in week *t+1*. The coefficient on the interaction term $RNS_{i,t} \times ND_{i,t+1}$ captures RNS incremental return predictability associated with the news release. The rest of the variables are the same as those in the previous section.

[Table 6 about here]

Table 6 reports the Fama--MacBeth coefficient estimates for (i) $ND_{i,t+1}$, (ii) $RNS_{i,t}$, and (iii) the interaction of $RNS_{i,t} \times ND_{i,t+1}$. The coefficient estimates of the control variables are not reported for brevity. In Panel A, we include all the firm-level news releases. In Panel B, we focus on the release of non-scheduled news, which excludes the news category of earnings announcements. In Panel C, we focus on a subset of important non-scheduled news releases such that $ND_{i,t+1}$ equals 1 if there is a non-scheduled news release in week *t+1* relating to mergers and acquisition, analyst rating, assets, bankruptcy, credit, credit ratings, dividends, equity actions, labor issues, price targets, products and services, and revenues. Hence, Panel A has a rich set of information events, consisting of 896,402 firm-week observations. Panel B contains 743,176 firm-week observations of non-scheduled news releases. Finally, Panel C includes 313,225 non-scheduled news releases that are relatively more important. We focus on the coefficient of the interaction term $RNS_{i,t} \times ND_{i,t+1}$. If it is the information mechanism that drives the positive RNS-return relation, then we anticipate a positive significant coefficient on the interaction term, indicating incremental return predictability of RNS_t prior to the news release in week *t+1*. That is, RNS-return relation becomes more salient before the corporate news release.

For each model in each Panel, the coefficient estimate on the interaction term $RNS_{i,t} \times ND_{i,t+1}$ is significantly positive and at least twice as large as that of RNS. The result confirms our expectation that the positive RNS-return relation is significantly larger during the weeks with relevant and novel news releases. RNS extracted from equity options contains new information on both scheduled earnings announcements as well as other non-scheduled corporate news releases.[20] Overall, the results in this section not only highlight the incremental RNS return predictability prior to the corporate news release but also provide concrete evidence to support our hypothesized channel that the positive RNS-return relation is mainly driven by informed trading in the options market.

VI. Robustness and Discussions

VI.A Robustness Checks

This section presents a summary of the robustness checks with details in Internet Appendix B. We first investigate whether trading frictions and limits-to-arbitrage impact the results, with the Amihud (2002) illiquidity measure (ILLIQ) and idiosyncratic volatility as the proxies. We find that the positive RNS-return relation is more pronounced for stocks with higher idiosyncratic volatility and higher illiquidity. However, the RNS-return relation remains significant for stocks with low limits-to-arbitrage and low illiquidity, indicating that the limits-to-arbitrage and illiquidity, while important, cannot fully account for the RNS-return relation.

Next, we test for potential non-linearities in the RNS-return relation by sorting stocks into portfolios by RNS and either ILLIQ, CoSkew, Ret1, or risk-neutral volatility (RNV). The results indicate that the positive RNS-return relation is not driven by ILLIQ, co-skewness, return reversals, and RNV.

[20] Moreover the internet appendix Table IA.6 shows that the interaction terms of IV_Skew, IV_Spread, CP_Ratio, and RV-IV Spread with $ND_{i,t+1}$ are all indistinguishable from zero. Only the interaction term $RNS_{i,t} \times ND_{i,t+1}$ is significant.

Another potential concern is that the positive RNS-return relation is driven by informed short selling rather than informed options trading.[21] We find that when the short interest increases the most from 1 month to the next, there is a lower RNS-related impact in the subsequent week possibly because a large fraction of the information might be already incorporated into stock prices. This is either due to the informed investors actively buying puts as well as going short in the underlying stocks or due to the put option market makers hedging their positions via shorting the underlying stocks. Nevertheless, we also find that the differential returns and alphas between the high and the low RNS portfolio remain economically large and statistically significant after controlling for short interest or change of short interest.

Finally, we examine 169 different strategies formed using different permutations of the formation and holding periods from 1 to 13 weeks. There is a strong and robust positive relation between RNS and the cross-section of stock returns at the weekly frequency. For the overall sample, the return predictability is present for all formation and holding periods up to 13 weeks. However, for the longer formation and holding periods, the RNS-return relation is not robust during the early subsample from Jan. 1996 to June 2005.

VI.B Discussions of Results

In this section, we discuss and review our results in the context of the related literature. Our finding of a positive cross-sectional RNS return relation is consistent with Stilger et al. (2017) and Gkionis et al. (2018). However, our explanation of this positive relation is fundamentally different. Stilger et al. (2017) argue that stocks with negative RNS are

[21] The existing studies show that equity lending and options markets are linked. See, e.g., Figlewski and Webb (1993) Lamont and Thaler (2003), Ofek, Richardson, and Whitelaw, (2004), Battalio and Schultz (2011) and Grundy, Lim, and Verwijmeren (2012), Lin and Lu (2016), Atmaz and Basak (2018), and Muravyev, Pearson, and Pollet (2018).

overvalued, and short-sale constraints hinder the price correction process, thereby leading to negative returns of the stocks with negative RNS. They use high expected idiosyncratic skewness (Boyer, Mitton, and Vorkink (2010)), the maximum past month return (Bali et al. (2011)), and the probability of a jackpot return (Conrad, Kapadia, and Xing (2014)) to proxy for overvaluation. The drawback of using these variables is that they capture the stock return skewness by construction, making their results difficult to interpret.

In contrast, Gkionis et al. (2018) argue that the positive RNS-return relation can also be driven by the stocks with the highest RNS that are undervalued. Borochin and Zhao (2019) argue that the positive RNS-return relation is driven by the higher returns of previously undervalued stocks. In Section 4.1, we use the mispricing measure proposed by Stambaugh et al. (2015) and show that the above overpricing or underpricing explanation is inconsistent with our results.

Moreover, we find that the positive RNS-return relation is robust across the entire RNS spectrum, rather than just stocks with high or low RNS. Specifically, in Table 7, we split the sample along various dimensions based on the lagged RNS. Panel A divides the sample into two by the median RNS value. Panels B, C, and D split the sample by the 90^{th}, 80^{th}, and 75^{th} percentile RNS values. Finally, Panel E splits the sample by the positive and negative RNS values. The RNS-return relation is robust to the different splits of the samples, suggesting that the positive relation is not driven by just the high or just the low RNS stocks as argued in Stilger et al. (2017) and Gkionis et al. (2018).

[Table 7 about here]

Meanwhile, our results in the previous section show that the positive RNS-return relation is mostly consistent with the informed options trading before corporate news releases, both scheduled and unscheduled. There is a large literature consistent with the view that informed traders prefer the options market, thereby leading to a lead-lag relation between options trading and stock returns (e.g., Xing et al. (2010), Cremers and Weinbaum (2010), Pan and Poteshman (2006), Roll et al. (2010), Johnson and So (2012), Ge et al. (2016)).

The literature also examines the information content of options trading with respect to various corporate events. For instance, Chan et al. (2015) focus on mergers and acquisitions; Gharghori et al. (2015) examine stock splits; Hayunga and Lung (2014) and Lin and Lu (2015) study analyst revisions; Xing et al. (2010), and Johnson and So (2012) analyze earnings announcements; and Cremers, Fodor, Muravyev, and Weinbaum (2019) focus on various news announcements. Our results provide evidence consistent with this stream of literature that informed options trading causes shifts in the risk-neutral density, which leads to the positive RNS-return predictability in the cross-section. Our results are also in line with Bali, Hu, and Murray (2019) who find that unsystematic components of ex ante skewness and kurtosis are related to the cross-section of expected stock returns based on analyst price targets.

Our results demonstrate that RNS has the unique information content that is not captured by the existing option-based return predictors. For example, Cremer and Weinbaum (2010) and Broadie, Chernov, and Johannes (2007) acknowledge that the implied volatility spread is a noisy measure of price pressure. By construction, the implied volatility spread reflects the deviation from put-call parity, which is fundamentally different from RNS based on the risk-neutral distribution of underlying returns. Implied volatility spread can thus be viewed as capturing a transitory effect of deviation from put-call parity relation due to price pressure, while RNS reflects the tail effect of the underlying return distribution. This explanation is consistent with our hypothesis that the incremental return predictability of RNS stems from option informed traders' private knowledge regarding firm-level information. Our earnings announcements and other corporate news releases results corroborate this explanation.

Besides, the results in Panel B of Table IA.3 and Table 3 show that the stock return predictability of implied volatility skew (IV_Skew) becomes much weaker in the horse race with RNS and other option based signals. IV_Skewis calculated using a subset of out-of-money (OTM) put options (moneyness ranges from 0.8 to 0.95) and at-the-money (ATM) call options (moneyness ranges from 0.95 to 1.05). Specifically, as described by Xing et al. (2010), IV_Skew is constructed with one OTM put with moneyness closest to 0.95, and one ATM call with moneyness closest to 1. Hence, it misses a large number of options trading outside these moneyness ranges.

In contrast, our estimation of RNS is based on pairs of OTM call and put contracts that are matched on moneyness, i.e., having the same absolute delta. OTM calls (puts) are defined as options with delta greater than 0.2 (–0.375) and less than 0.375 (–0.2). Moreover, since we are using the OptionMetrics volatility surface data, we do not use closing quotes from illiquid contracts, and our estimation is consistently performed using four pairs of same maturity OTM calls and puts (eight contracts). This requirement further ensures that both the time-series and the cross-sectional variations of RNS are less likely to be driven by the particular choice of option contracts and the differences in their characteristics, including time-to-maturity, moneyness, and illiquidity. Hence, the information content IV_Skew captures is, at best, a subset of RNS, thereby resulting in the loss of its explanatory power in the horse race.

VII. Conclusions

We document a strong, robust, and positive cross-sectional relation between RNS and subsequent stock returns. This positive RNS-return relation peaks at the weekly frequency and stays significant at the monthly and quarterly frequency. We provide evidence consistent with the idea that the positive RNS-return relation is driven by informed trading in the options market. Using scheduled quarterly earnings announcements and other non-scheduled news releases, we show that the pre-announcement RNS predicts future stock returns, and the predictability is much stronger for news release weeks. Overall, our results suggest that new information is reflected in options prices before being incorporated into stock prices, leading to the positive relation between RNS and subsequent stock returns.

Appendix 1

Proof that absolute delta matched put-call pairs provide the same strike-to-spot price distance

Under the Black-Scholes model, Call option delta: $\delta_c = N(d1)_c$, and Put option delta: $\delta_p = N(d1)_p - 1 = N(-d1)_p$, where

$$d1_c = \frac{Ln\left(\frac{S}{K_c}\right) + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}$$

and

$$d1_p = \frac{Ln\left(\frac{S}{K_p}\right) + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}$$

S is the current spot price, K_c and K_p are the strike prices for the call and put option respectively, r is the risk-free rate, σ is return volatility and T is time to maturity.

For a put-call OTM option pair that has the same absolute value of delta, i.e. $|\delta_c| = |\delta_p|$

$$|N(d1)_c| = |N(-d1)_p|$$

$$|d1_c| = |-d1_p|$$

$$\left|\frac{Ln\left(\frac{S}{K_c}\right) + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}\right| = \left|-\frac{Ln\left(\frac{S}{K_p}\right) + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}\right|$$

$$\left|Ln(\frac{S}{K_c})\right| = \left|Ln(\frac{S}{K_p})\right|$$

$$|Ln(S) - Ln(K_c)| = |Ln\ (S) - Ln(\ K_p)|$$

Therefore, for a pair of OTM put and call options, the same absolute value of delta implies identical strike-to-spot price distance.

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Table 1: Descriptive Statistics

Table 1 reports the average number of stocks and the number of daily risk-neutral skewness observations in each year from Jan. 1996 to June 2015. The 5th percentile, median, and 95th percentiles for daily risk-neutral volatility (annualized), RNS, and risk-neutral kurtosis are also reported. The last row reports values for the entire sample. The sample consists of a total of 10,212,182 stock/day RNS observations that are extracted for 6,187 unique firms during the sample period.

			Risk-Neutral Volatility			Risk-Neutral Skewness			Risk-Neutral Kurtosis		
Date	# of Firms	# of Obs.	P5	P50	P95	P5	P50	P95	P5	P50	P95
1996	1,881	405,194	0.10	0.20	0.39	–1.65	–0.35	1.17	5.46	6.84	9.11
1997	2,251	485,301	0.11	0.21	0.40	–1.30	–0.32	0.93	5.53	6.78	8.63
1998	2,481	544,712	0.12	0.24	0.46	–1.22	–0.30	0.99	5.27	6.67	8.71
1999	2,585	557,758	0.14	0.27	0.50	–1.15	–0.31	0.84	5.16	6.54	8.54
2000	2,510	498,341	0.17	0.33	0.64	–1.07	–0.31	0.70	4.75	6.34	8.37
2001	2,185	450,034	0.14	0.29	0.61	–1.23	–0.48	0.44	4.71	6.19	7.64
2002	2,068	458,224	0.13	0.26	0.51	–1.45	–0.66	0.47	4.75	6.12	7.62
2003	1,974	436,969	0.11	0.21	0.41	–1.54	–0.68	0.61	5.23	6.32	7.91
2004	2,086	464,374	0.10	0.19	0.37	–1.45	–0.56	0.75	5.51	6.49	8.07
2005	2,179	496,609	0.09	0.18	0.36	–1.52	–0.51	1.09	5.52	6.63	8.70
2006	2,323	517,198	0.09	0.18	0.36	–1.47	–0.52	0.90	5.60	6.70	8.55
2007	2,438	547,292	0.09	0.18	0.37	–1.46	–0.53	0.72	5.53	6.66	8.30
2008	2,444	541,714	0.14	0.28	0.60	–1.38	–0.62	0.60	4.14	6.14	8.05
2009	2,352	524,634	0.14	0.28	0.55	–1.43	–0.73	0.37	4.50	6.03	7.77
2010	2,406	550,896	0.11	0.21	0.42	–1.54	–0.70	0.78	5.21	6.34	8.49
2011	2,589	577,998	0.11	0.23	0.49	–1.60	–0.65	1.31	4.82	6.33	9.60
2012	2,602	579,176	0.10	0.21	0.48	–1.70	–0.61	1.48	5.00	6.43	10.21
2013	2,697	615,246	0.09	0.18	0.43	–1.68	–0.58	1.18	5.25	6.52	9.20
2014	2,775	643,261	0.09	0.21	0.49	–1.59	–0.39	1.69	5.04	6.56	10.29
2015	2,711	317,251	0.09	0.21	0.47	–1.66	–0.42	2.05	5.01	6.57	11.34
Overall	6,187	10,212,182	0.11	0.23	0.46	–1.47	–0.51	0.97	5.02	6.46	8.71

Table 2
Weekly Decile Portfolios Sorted on Risk-Neutral Skewness

Panel A of Table2 reports weekly value-weighted returns on portfolios sorted on risk-neutral skewness (RNS). Each Tuesday, firms are sorted into decile portfolios based on the average level of risk-neutral skewness from the previous Wednesday to Tuesday. Value-weighted portfolios are formed and held from Thursday to the next Wednesday. Alphas are estimated using (i) the Fama--French (2015) 5 factors and the momentum factor (FF5+Mom), (ii) the q-factor model of Hou et al. (2014) (q-factor), and (iii) the q-factor model plus the momentum factor (q-factor+Mom). Panel B reports firm characteristics for each decile portfolio. RNV is the monthly risk-neutral volatility. Size is log market capitalization in millions. BM is book-to-market ratio from July of year *t* to June of year *t+1* estimated using the *t-1* fiscal year-ends book value and the market value as of December of year *t-1*. AG is the growth in assets from fiscal year *t-2* to *t-1*, and Prof refers to cash profitability (excluding accruals) as in Ball et al (2016). ILLIQ is the Amihud (2002) illiquidity measure. CoSkew is co-skewness measure based on Harvey and Siddique (2000). Max is the maximum daily return over the past month. AVOL is the abnormal trading volume computed as in Gervais et al. (2001). Ret(2,12) represents the cumulative return over the past eleven months that skips the most recent past month, and Ret1 is the return over the week when RNS is computed. The time-series means of the cross-sectional median value are reported. Newey--West (1987) t- statistics are reported in parenthesis.

Panel A. Weekly Sort on Risk-Neutral Skewness

	Low	2	3	4	5	6	7	8	9	High	High-Low
Raw Return	0.17	0.24	0.26	0.27	0.30	0.28	0.28	0.27	0.34	0.34	0.17
	(2.39)	(3.00)	(3.03)	(3.00)	(3.19)	(2.97)	(3.08)	(2.87)	(3.83)	(4.22)	(3.59)
FF5+Mom	0.17	0.23	0.26	0.27	0.29	0.27	0.28	0.27	0.33	0.33	0.16
	(2.43)	(3.14)	(3.29)	(3.09)	(3.23)	(3.12)	(3.16)	(2.95)	(3.80)	(4.04)	(3.40)
q-factor	0.17	0.25	0.27	0.28	0.31	0.29	0.30	0.29	0.35	0.35	0.18
	(2.55)	(3.36)	(3.51)	(3.28)	(3.49)	(3.31)	(3.37)	(3.16)	(3.96)	(4.24)	(3.54)
q-factor+Mom	0.18	0.24	0.26	0.28	0.30	0.28	0.29	0.28	0.34	0.35	0.17
	(2.56)	(3.32)	(3.44)	(3.23)	(3.44)	(3.28)	(3.29)	(3.07)	(3.91)	(4.19)	(3.38)

Table 2 (continued)

Panel B. Descriptive Statistics for Risk-Neutral Skewness Decile Portfolios

	Low	2	3	4	5	6	7	8	9	High
RNS	–1.357	–0.868	–0.707	–0.590	–0.486	–0.381	–0.262	–0.110	0.129	1.706
RNV	0.023	0.013	0.010	0.008	0.007	0.006	0.006	0.006	0.007	0.010
Size	8.012	7.869	7.704	7.519	7.317	7.110	6.900	6.693	6.515	6.382
BM	0.592	0.545	0.530	0.530	0.536	0.550	0.573	0.607	0.645	0.714
AG	0.178	0.218	0.239	0.253	0.270	0.280	0.279	0.284	0.268	0.219
Prof	0.528	0.584	0.589	0.644	0.560	0.509	0.453	0.481	0.446	0.483
Ivol	0.018	0.021	0.023	0.025	0.026	0.028	0.029	0.029	0.029	0.027
ILLIQ	0.012	0.015	0.012	0.018	0.017	0.022	0.024	0.034	0.046	0.055
CoSkew	0.232	0.324	0.306	0.243	0.143	–0.001	–0.083	–0.147	–0.200	–0.256
Max	0.048	0.055	0.060	0.064	0.068	0.070	0.072	0.073	0.071	0.065
AVOL	1.044	1.035	1.037	1.044	1.047	1.054	1.067	1.079	1.089	1.099
Ret1 (%)	0.800	0.730	0.690	0.620	0.560	0.410	0.200	–0.100	–0.390	–0.670
Ret(2,12) (%)	15.690	19.930	24.330	27.060	27.520	26.330	21.290	15.060	8.580	3.310

Table 3
Fama--MacBeth Cross-Sectional Regressions

Table 3 presents the time-series average of the weekly cross-section regression coefficients. The individual stock excess or risk-adjusted return in week t+1 is regressed on the risk-neutral skewness (RNS) in week t. Firm characteristics and option based signals are used as controls. Option based signals include implied volatility skew (IV_Skew), implied volatility spread (IV_Spread), call-put volume ratio (CP_Ratio), and the difference between realized and implied volatility (RV-IV). Firm characteristics are described in Table 2. Newey--West (1987) t-statistics are reported in parenthesis. The average adjusted R^2 is reported for each model specification in the last row.

	Excess Return	Excess Return	FF5+Mom	q-factor+Mom
RNS	**0.125**	**0.093**	**0.101**	**0.100**
	(3.90)	**(5.14)**	**(5.62)**	**(5.65)**
IV_Skew		–0.184	–0.058	–0.228
		(–0.87)	(–0.28)	(–1.16)
IV_Spread		0.860	0.961	0.897
		(2.86)	(3.14)	(2.98)
RV-IV Spread		–0.243	–0.282	–0.293
		(–2.90)	(–3.44)	(–3.67)
CP_Ratio		0.000	0.000	0.000
		(–0.07)	(–0.19)	(0.03)
RNV		–0.611	–1.288	–1.317
		(–0.47)	(–1.53)	(–1.60)
Size		–0.013	–0.010	–0.010
		(–1.03)	(–0.99)	(–1.08)
BM		–0.010	–0.001	–0.013
		(–0.24)	(–0.03)	(–0.34)
Ivol		–0.983	–0.940	–0.756
		(–0.53)	(–0.46)	(–0.39)
ILLIQ		0.015	0.063	0.191
		(0.04)	(0.19)	(0.58)
Max		0.063	–0.011	0.165
		(0.15)	(–0.02)	(0.36)
Ret(2,12)		0.048	–0.006	0.006
		(1.00)	(–0.18)	(0.15)

Ret1		–0.366	–0.425	–0.355
		(–1.44)	(–1.73)	(–1.44)
CoSkew		0.013	0.017	0.015
		(2.49)	(3.22)	(2.88)
AG		–0.030	–0.025	–0.028
		(–2.22)	(–1.75)	(–2.09)
Prof		0.000	0.000	0.000
		(0.12)	(1.09)	(0.17)
AVOL		0.025	0.038	0.036
		(1.53)	(2.38)	(2.29)
Intercept	0.275	0.378	0.172	0.160
	(2.42)	(2.52)	(1.37)	(1.33)
Adj. R^2 (%)	0.002	0.090	0.046	0.048

Table 4
Double Sort on Risk-Neutral Skewness and Other Option Signals

Table 4 reports the portfolio returns formed by sorting on (i) RNS and implied volatility skew (IV_Skew) in Panel A, (ii) RNS and implied volatility spread (IV_Spread) in Panel B, and (iii) RNS and put-call volume ratio (CP_Ratio) in Panel C, and (iv) RNS and difference between realized and implied volatility (RV-IV). At the end of the trading day on each Tuesday, stocks are independently sorted into quintiles based on RNS, and IV_Skew or IV_Spread or CP_Ratio or RV-IV Spread. Portfolio returns are value-weighted, calculated from Thursday of the sorting week to the following Wednesday. Differential returns and alphas between high and low RNS portfolios (RNS quintile 5 minus RNS quintile 1) are reported. The RNS quintile 5 and quintile 1 returns are calculated as average returns across the five intersecting portfolios formed by sorting on the variables IV_Skew or IV_Spread or CP_Ratio or RV-IV Spread. Alphas are computed with respect to the Fama--French (2015) 5 factors plus a momentum factor, the Hue, Xue, and Zhang (2015) q-factors plus a momentum factor, and the mispricing factors of Stambaugh and Yuan (2017). Newey--West (1987) t-statistics are reported in parenthesis.

	Raw	Alpha FF5+ Mom	Alpha Q-Factors+Mom	Alpha Mispricing Factors
Panel A. RNS and IV_Skew				
High RNS-Low RNS	0.116	0.127	0.128	0.122
	(2.85)	(3.02)	(3.14)	(3.20)
Panel B. RNS and IV_Spread				
High RNS-Low RNS	0.153	0.143	0.138	0.150
	(3.75)	(3.63)	(3.80)	(3.87)
Panel C. RNS and CP_Ratio				
High RNS-Low RNS	0.173	0.173	0.179	0.181
	(4.50)	(4.40)	(4.69)	(4.98)
Panel D. RNS and RV-IV Spread				
High RNS-Low RNS	0.158	0.150	0.151	0.159
	(3.94)	(3.54)	(3.82)	(3.93)

Table 5
Risk-Neutral Skewness Return Predictability and Earnings Announcements

Panel A of Table 5 reports the coefficient estimates from quarterly Fama--MacBeth regressions of cumulative abnormal returns (CAR) on average RNS computed over the period *t-7* to *t-3* prior to earnings announcement day *t*. The CAR for each firm is its stock return in excess of the equally weighted market return. CAR[X,Y] refers to the period $t+X$ to $t+Y$. All firm characteristics from Table 3 are included. Only the coefficient estimate of RNS is reported. Newey--West (1987) t-statistics are in parenthesis. The average adjusted R^2 is the time-series average of the cross-sectional adjusted R^2s. Panel B reports the High-minus-Low RNS return spread and risk-adjusted alphas based on weekly sorted RNS portfolios. On each Tuesday, firms are sorted into decile portfolios based on the average level of risk-neutral skewness from the previous Wednesday to Tuesday. Value-weighted portfolios are formed and held from Thursday to the next Wednesday. Full sample refers to the overall sample. Earnings Announcement Sample includes firms whose announcement occurs during the holding period. The sample Excluding Earnings Announcement excludes firms if the announcement occurs during the holding period. Alphas are estimated using (i) the Fama--French (2015) 5 factors and the momentum factor (FF5+Mom), (ii) the q-factor model of Hou et al. (2014) (q-factor), and (iii) the q-factor model plus the momentum factor (q-factor+Mom). Newey--West (1987) t-statistics are reported in parenthesis.

Panel A. Fama—MacBeth Coefficient Estimates

	CAR[–1,+1]	CAR[+2,+5]	CAR[+2,+10]	CAR[+2,+20]	CAR[+2,+40]	CAR[2,+60]
RNS coefficient	0.087	0.067	0.217	0.465	0.493	0.0.413
	(2.06)	(2.21)	(2.85)	(3.67)	(3.47)	(3.12)
Average adj. R^2 (%)	1.82%	1.30%	1.47%	1.76%	2.43%	2.48%

Panel B. Return Spreads and Alphas

	Raw Return	Alpha_FF5+ Mom	Alpha q-factor	Alpha_ q-factor+Mom
Full sample	0.17%	0.16%	0.18%	0.16%
	(3.59)	(3.40)	(3.54)	(3.38)
Earnings announcement sample	0.38%	0.42%	0.43%	0.45%
	(2.32)	(2.12)	(2.25)	(2.29)
Excluding earnings announcements	0.14%	0.13%	0.14%	0.14%
	(2.97)	(2.66)	(2.91)	(2.87)

Table 6

Risk-Neutral Skewness Return Predictability and News Release

Table 6 presents coefficient estimates from weekly Fama--MacBeth cross-sectional regressions. Using the RavenPack news database, we introduce a news dummy (ND) variable to capture the arrival of the news release. ND for a firm equals 1 if there is at least one news release for that firm with RavenPack both relevance and novelty scores of 100 during week t+1. The stock return of week t+1 is regressed on the NewDummy in week t+1, risk-neutral skewness (RNS) in week t, and an interaction term of RNS and ND, after controlling for all firm characteristics as in Table 3. In Panel A, ND equals 1 if there is any eligible news release about the firm. In Panel B, ND equals 1 if a non-scheduled news release occurs in week t+1. All news other than earnings news is treated as non-scheduled news. In Panel C, ND equals 1 if a selected non-scheduled news release occurs in week t+1. The selected non-scheduled news includes thirteen types of news releases in RavenPack, that are 1) merger-acquisition, 2) analyst rating, 3) assets, 4) bankruptcy, 5) credit, 6) credit ratings, 7) dividends, 8) equity actions, 9) labor issues, 10) price targets, 11) products services, and 12) revenues. All control variables from Table 3 are included. The average adjusted R^2 is the time-series average of the cross-sectional adjusted R^2. Newey--West (1987) t-statistics are reported in parenthesis.

Panel A. All News Release	Excess Return	FF5+Mom	q-factor +Mom
ND	0.207	0.144	0.138
	(7.56)	(5.13)	(5.00)
RNS	0.062	0.042	0.045
	(2.05)	(2.01)	(2.06)
RNS * ND	**0.153**	**0.101**	**0.095**
	(5.91)	**(3.40)**	**(3.28)**
Total number of firm-week observations	1,717,679	1,717,679	1,717,679
Total number of firm-week with news	896,402	896,402	896,402
Average adjusted R^2 (%)	0.30%	5.30%	2.50%

Table 6 (continued)

Panel B. All Non-Scheduled News Release			
ND	0.302	0.183	0.179
	(10.73)	(6.65)	(6.43)
RNS	0.061	0.036	0.036
	(1.87)	(1.96)	(1.93)
RNS * ND	**0.217**	**0.145**	**0.138**
	(7.71)	**(4.63)**	**(4.48)**
Total no. of firm-week observations	1,717,679	1,717,679	1,717,679
Total no. of firm-week with non-scheduled news	743,176	743,176	743,176
Average adj. R^2 (%)	0.30%	5.40%	2.50%
Panel C. Selected Non-Scheduled News Release			
ND	0.411	0.309	0.307
	(13.94)	(8.93)	(9.14)
RNS	0.086	0.046	0.049
	(2.38)	(2.21)	(2.51)
RNS * ND	**0.263**	**0.219**	**0.208**
	(8.37)	**(5.72)**	**(5.62)**
Total no. of firm-week observations	1,717,679	1,717,679	1,717,679
Total no. of firm-week with non-earnings news	313,225	313,225	313,225
Average adj. R^2 (%)	0.30%	5.40%	2.60%

Table 7
Risk-Neutral Skewness Return Predictability in Split Samples

Table 7 reports the coefficient estimates from weekly Fama--MacBeth regressions. The overall sample is split into two groups based on different criteria. In Panel A, the sample is split based on the median RNS; in Panel B the sample is split based on the 90th RNS percentile; in Panel C the sample is split based on the 80th RNS percentile; in Panel D the sample is split based on the 75th RNS percentile, and in Panel E the sample is split based on whether RNS is positive or negative. Column (1) is the univariate model with weekly excess returns as the dependent variable. Columns (2), (3) and (4) are multivariate models that control for all firm characteristics as in Table 3. Column (2) uses weekly excess returns as the dependent variable. Columns (3) and (4) use risk-adjusted returns (with FF5+Mom, and q-factor+Mom as factor models) as the dependent variables. Newey--West (1987) adjusted t-statistics are in parenthesis.

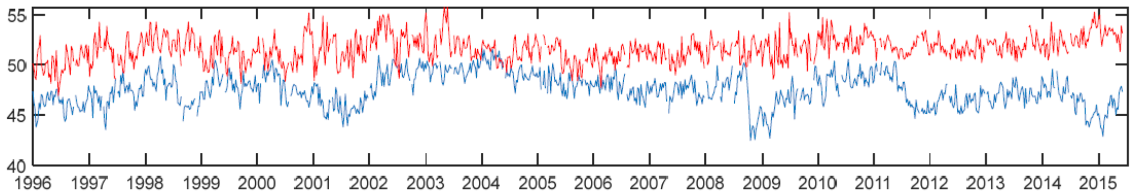
	Excess Return Univariate	Excess Return	FF5+Mom	Q-factor+Mom
Panel A. Above and Below the Median RNS				
RNS * Dummy (=1, if RNS ≥ B)	0.111	0.053	0.063	0.064
	(3.07)	(3.22)	(3.93)	(4.32)
RNS * Dummy (=1, if RNS < B)	0.143	0.118	0.114	0.112
	(3.16)	(8.03)	(8.78)	(8.98)
Panel B. Above and Below 90th RNS Percentile				
RNS * Dummy (=1, if RNS ≥ B)	0.084	0.035	0.045	0.047
	(1.89)	(1.67)	(2.31)	(2.52)
RNS * Dummy (=1, if RNS < B)	0.150	0.126	0.123	0.120
	(2.82)	(7.87)	(8.61)	(8.75)
Panel C. Above and Below 80th RNS Percentile				
RNS * Dummy (=1, if RNS ≥ B)	0.088	0.033	0.045	0.048
	(2.03)	(1.60)	(2.32)	(2.59)
RNS * Dummy (=1, if RNS < B)	0.154	0.132	0.127	0.124
	(2.92)	(7.86)	(8.71)	(8.88)
Panel D. Above and Below 75th RNS Percentile				
RNS * Dummy (=1, if RNS ≥ B)	0.081	0.035	0.048	0.052
	(1.97)	(1.80)	(2.65)	(2.98)
RNS * Dummy (=1, if RNS < B)	0.156	0.131	0.126	0.122
	(3.05)	(8.06)	(8.76)	(8.88)
Panel E. Positive and Negative RNS				
RNS * Dummy (=1, if RNS ≥ B)	0.076	0.029	0.042	0.044
	(1.58)	(1.30)	(2.03)	(2.24)
RNS * Dummy (=1, if RNS < B)	0.162	0.135	0.130	0.127
	(2.88)	(7.66)	(8.51)	(8.71)

Figure 1

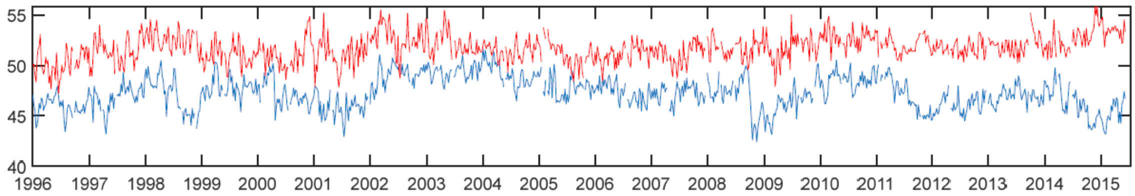
Time-Series Plot of Mispricing Index for the Low and High RNS Decile Portfolios

Figure 1 provides time-series plots of average mispricing index value (MISP) of Stambaugh et al. (2015) for the Low and High RNS portfolios. Graph A presents the MISP value in the month prior to the month of the sorting week. Graph B presents the MISP value for the month of the sorting week. Graph C presents MISP value for the month following the month of the sorting week. In each graph, the MISP value for the Low RNS portfolio is lower than that of the High RNS portfolio.

Graph A. Prior Month



Graph B. Current Month



Graph C. Subsequent Month