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The information content of the term structure of risk-neutral skewness[☆]

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ABSTRACT

We seek to reconcile the debate about the price effect of risk-neutral skewness (RNS) on stocks. We document positive predictability from short-term skewness, consistent with informed-trading demand, and negative predictability from long-term skewness, consistent with skewness preference. A term spread on RNS captures different information from long- and short-term contracts, resulting in stronger predictability. The quintile portfolio with the lowest spread outperforms that with highest spread by 14.64% annually. The term structure of RNS predicts earnings surprises and price crashes. We extract the slope factor from RNS term structure, estimate its risk premium, and explore its relation with several macroeconomic variables.

1. Introduction

The behavioral and rational models of Brunnermeier et al. (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 most historical estimates of skewness provide poor forecasts of future skewness (Boyer et al., 2010), empirical studies commonly use option data to estimate investor expectations of skewness.

To date, existing 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 skewness preference theory, Conrad et al. (2013) find a negative relation between risk-neutral skewness (RNS) and future equity returns. This approach implicitly assumes that option and stock markets reflect the same information and that option-implied skewness proxies for expected underlying skewness. Thus, positive option-implied skewness combined with skewness preference among investors in the underlying asset leads to low expected returns.

This assumption is challenged by findings of information differences between the option and equity markets. Ait-Sahalia et al. (2001) demonstrate that the risk-neutral density estimated from the S&P 500 options is different from a density inferred from historical index returns, suggesting that 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 (Conrad et al., 2013) by demonstrating that RNS can positively predict future stock returns (Xing et al., 2010; Bali and Murray, 2013; Stilger et al., 2017; Bali et al., 2019). While Bali and Murray (2013) focus on the returns of a hedged asset with skewness exposure, part of their analysis confirms a positive relationship between RNS and the underlying asset. Stilger et al. (2017) suggest that the difference

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between the (Conrad et al., 2013) results and others are driven by the aggregation of RNS across time periods. In this study, we consider the role of the option maturity horizon in defining the relationship of RNS with the cross-section of underlying returns.

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 et al., 2003). Furthermore, Stilger et al. (2017) find this trading activity mainly concentrates 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 information is transmitted from the option market to the stock market these relatively overpriced stocks with low RNS subsequently underperform, producing a positive relation between RNS and future realized equity returns. Bali et al. (2019) find that option-implied skewness is positively related to future expected returns from analyst forecasts and implied cost of capital calculations.

Our study contributes to this ongoing debate between two empirical views on RNS by considering its term structure: we find that short-term options have more informed traders consistent with the view that positive RNS predicts positive underlying returns because it reflects market beliefs. We also find that long-term options have more uninformed hedgers consistent with the skewness preference view that positive RNS predicts negative underlying returns because it results in overbidding. We build the intuition for the potential to reconcile informed trading and skewness preference using a multi-period equilibrium model where investors have heterogeneous skewness preferences and information sets, detailed in Appendix A.

Importantly, our theoretical results show that when there is a small proportion of informed investors, the risk premium for RNS is negative. In this case, RNS is predominantly determined by uninformed investors' expected skewness for assets. Uninformed investor preferences thus result in more demand and lower subsequent return for positively-skewed assets. Conversely, when the proportion of informed traders increases, the RNS risk premium turns positive. In this case, RNS reflects informed traders' superior information about the true skewness of assets. Thus for a stock with higher RNS, its true skewness should be higher than what uninformed investors expect. When the information becomes public afterwards, the demand for the stock increases, pushing up its price and generating a positive relation between RNS and subsequent return.

We empirically test whether the direction of RNS return predictability varies with the maturity of the options used to compute it. In other words, we test the predictability of the underlying returns across the term structure of RNS, as we hypothesize that the proportion of informed traders may vary across options with different maturities. If differently informed investor types have different maturity preferences and thereby produce market segmentation across option maturities, the resulting RNS estimated across different maturity horizons may contain distinct information sets. While we cannot directly map trades to investor types, we can conjecture that informed traders may prefer to use short-term options due to lower costs while hedgers may need longer-maturity contracts. Our findings confirm this conjecture.

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 that this relationship exhibits a monotonic pattern, which is significantly positive for the short-term (1 month), insignificant for the middle-term (6 months), and significantly negative for the long-term (12 months). In particular, a strategy that is long the equal-weighted quintile portfolio with the highest 1-month RNS and short the equal-weighted quintile portfolio with the lowest 1-month RNS yields a risk-adjusted[1] return (alpha) of 0.95% per month with a t-statistic of 5.78, while the same strategy based on 12-month RNS produces a corresponding alpha of −0.56% per month with a t-statistic of −2.52. The positive predictability of future equity returns from short-term RNS is consistent with informed trading (Xing et al., 2010) and hedging (Stilger et al., 2017) interpretations, 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 has positive predictive power for returns while long-term RNS has the opposite, we capture the different information sets on the two ends of the RNS term structure by constructing a term spread of RNS defined as 12-month RNS minus 1-month RNS. We demonstrate that this spread effectively combines the two information sources and yields even stronger negative return predictability for the underlying asset using a portfolio sorting approach. A trading strategy that is long the equal-weighted quintile portfolio with the highest term spread and short the equal-weighted quintile portfolio with the lowest term spread yields an alpha of −1.22% per month with a t-statistic of −6.61 after controlling for the Fama and French 3 factors, Carhart momentum factor, and Pastor and Stambaugh (2003) liquidity factor. We confirm these results with a (Fama and MacBeth, 1973) cross-sectional regression.

To further explore the extent of the information impounded in the term structure of RNS, we test whether short- and long-term RNS have differing predictive power for firms' standardized unexpected earnings (SUE) using a (Fama and MacBeth, 1973) regression. We find that 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, consistent with overvaluation due to 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 a significantly negative (positive) relationship between the short-term (long-term) RNS and future price crashes. Notably, the predictive power of short-term RNS persists for at least 6 months. Furthermore, consistent with Stilger et al. (2017), we demonstrate that the positive predictability of

[1] We use the FFCP5 benchmark model that combines 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.

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. In addition, we provide some direct evidence showing that the long-term RNS reflects skewness preference. We compare long-term RNS with two recent well-known physical skewness measures exhibiting negative predictive power for equity returns consistent with the skewness preference literature, maximum daily return over the previous month (MAX) (Bali et al., 2011) and expected idiosyncratic skewness (EIS) (Boyer et al., 2010). We find that our long-term RNS measure not only has strong positive correlation with these physical skewness proxies, but also complements them in identifying low expected return stocks with lottery-like payoffs.

We find that the term structure of RNS is largely explained by two principal factors, a level and a slope, similar to findings for the yield term structure by Nelson and Siegel (1987), Litterman and Scheinkman (1991) and Christensen et al. (2011). The RNS term structure slope factor, which is most significantly related to both cross-sectional and time-series stock returns, is significantly related to the (Welch and Goyal, 2008) macroeconomic state variables for the equity premium in vector autoregressive models.

We help to reconcile the ongoing debate about the direction of the skewness anomaly by demonstrating the existence of 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 (Bali et al., 2011). Second, short-term options are more sensitive to the variation of the underlying stock's price, thus providing 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.

The RNS implied by short-term options deviates away from the expected skewness of the underlying stock due to informed trading. 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. Being increasingly less affected by informed trading, these longer-term options more closely mirror the distribution of the underlying stock. 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 et al. (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 expectations about the skewness of the underlying stock.

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 identifies an RNS term structure similar to that of interest rates, and finds that the "slope" factor has a significant relation with macroeconomic variables related to expected equity returns. Section 7 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. Our sample is from January 1996 to December 2015.

2.1. Risk-neutral skewness

On the last trading day of each month, firm i's option-implied skewness for a given maturity is calculated using the model-free methodology of Bakshi et al. (2003). To compute the RNS τ periods ahead, we need to use the authors' method to compute the τ-period value of payoffs to the second, third, and fourth power of the underlying stock's risk neutral log returns. To implement this approach in practice, OTM call and put options with continuous strikes expiring in τ periods would be required. However, traded options are available only at irregular strikes and maturities, and thus option-implied risk-neutral skewness measures at a constant maturity are unlikely to be observed since option maturities decay daily but contracts are issued at weekly 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., 2017) 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. (2017) 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 that 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.[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 use the trapezoidal rule to compute the integrals to evaluate the quadratic, cubic, and quartic contracts following Bakshi et al. (2003).

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 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 ratio between book value and market value. We also compute a series of control variables such as stock illiquidity (ILLIQ) proxied by Amihud's (2002) 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 earnings 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 experiences 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 et al. (2009), and Kim et al. (2011a,b) 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 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., 2017). In addition, we use the maximum daily return over the last month (MAX) and expected idiosyncratic skewness (EIS) as proxies for stock overvaluation and lottery-like payoffs, and idiosyncratic volatility (IVOL) relative to the (Fama and French, 1993) model as a proxy for short-sale constraint. The construction of firm characteristics and option measures is detailed in Appendix B.

2.3. Summary statistics

Table 1 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 1 shows that the mean and median of RNS become more negative with maturity. To the extent that 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 2 shows the correlation among 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 months to 12 months, the Pearson (Spearman) correlation between the corresponding skewness and RNS1M decreases from 0.50 (0.54) to 0.25 (0.30). This is consistent with a divergence between the information contents in the short-term and long-term risk-neutral skewness.

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[2] The mean (95% quantile) for the dispersions of implied volatility for 1, 3, 6, 9, and 12 months are 0.0320 (0.1250), 0.0196 (0.0706), 0.0162 (0.0556), 0.0138 (0.0486) and 0.0132 (0.0463) respectively.

Table 1
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 December 2015. The definitions for these variables are introduced in 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	288,446	0.2611	1.1412	2.6880	1.2614	0.7190
MV	358,974	164,348	1,342,039	26,650,990	6,908,144	14,789,417
BM	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	106,045	−0.0070	0.0005	0.0078	0.0001	0.0057
CRASH	354,986	0.0000	0.0000	1.0000	0.1004	0.3005
MAX	358,843	0.0171	0.0467	0.1389	0.0589	0.0387
EIS	270,289	−0.3331	0.2803	1.2306	0.3363	0.4610
OPVOL	358,974	0	66	7,026	1,738	3,975
OPEN	358,974	126	3,740	173,143	39,759	87,253
ZD	282,978	−3.9591	−1.6712	0.7976	−1.6251	1.4717

Table 2
In-sample cross-sectional correlations. This table reports the time-series average of cross-sectional 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 Appendix B.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)RNS1M	1.00	0.54	0.42	0.35	0.30	−0.65	0.12	−0.28	0.10	−0.09	−0.07	0.22	0.13	0.18
(2)RNS3M	0.50	1.00	0.78	0.67	0.61	−0.04	0.24	−0.43	0.08	−0.12	−0.07	0.41	0.29	0.31
(3)RNS6M	0.36	0.78	1.00	0.94	0.88	0.23	0.34	−0.54	0.04	−0.12	−0.07	0.57	0.42	0.39
(4)RNS9M	0.29	0.68	0.95	1.00	0.97	0.35	0.39	−0.58	0.03	−0.12	−0.07	0.65	0.48	0.43
(5)RNS12M	0.25	0.61	0.88	0.96	1.00	0.41	0.42	−0.61	0.02	−0.13	−0.08	0.70	0.52	0.46
(6)RNSTS	−0.66	0.03	0.34	0.46	0.53	1.00	0.20	−0.19	−0.08	−0.01	0.02	0.30	0.27	0.15
(7)BETA	0.08	0.19	0.27	0.31	0.32	0.17	1.00	−0.27	0.01	−0.07	−0.06	0.57	0.39	0.31
(8)MV	−0.11	−0.17	−0.20	−0.21	−0.20	−0.05	−0.12	1.00	−0.24	0.20	0.20	−0.64	−0.38	−0.56
(9)BM	0.09	0.08	0.06	0.06	0.06	−0.03	0.01	−0.10	1.00	−0.35	−0.35	−0.10	−0.06	0.12
(10)MOM	−0.05	−0.06	−0.03	−0.03	−0.03	0.02	−0.00	0.02	−0.27	1.00	−0.06	−0.05	−0.09	−0.27
(11)REV	−0.03	−0.00	0.02	0.03	0.03	0.05	0.05	0.03	−0.21	−0.05	1.00	−0.05	−0.04	−0.07
(12)IVOL	0.14	0.29	0.41	0.47	0.50	0.24	0.55	−0.24	−0.05	0.10	0.12	1.00	0.57	0.57
(13)MAX	0.05	0.15	0.22	0.26	0.28	0.16	0.28	−0.12	0.01	−0.02	0.04	0.42	1.00	0.33
(14)EIS	0.14	0.25	0.30	0.33	0.35	0.12	0.29	−0.17	0.14	−0.24	0.03	0.60	0.27	1.00

3. RNS term structure and return predictability

We demonstrate that the RNS of different maturities has differential predictive power for future returns of the underlying asset. We then consider how this difference in predictability 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., 2017).

We document the differential predictive power of short- vs long-term RNS using a 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 quintile portfolios. This sorting procedure results in 5 equal-weighted portfolios per RNS measure. Since we have five observations in the RNS term structure, we obtain a total of 25 portfolios, 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 possible autocorrelation and conditional heteroscedasticity.

In Table 3, we present the results of abnormal portfolio returns relative to our benchmarks for equal-weighted portfolios across the RNS term structure. Panels 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.

Table 3
Portfolios formed on risk-neutral skewness of different maturities. Panels A, B, C, D and E present abnormal return over the following month of quintile 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 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.

Quintile	CAPM Alpha	FF3 Alpha	FF5 Alpha	FFC4 Alpha	FFCP5 Alpha
Panel A: Alpha of portfolios sorted by 1-month RNS					
Low	−0.33	−0.46	−0.61	−0.40	−0.40
2	−0.20	−0.31	−0.40	−0.23	−0.23
3	−0.00	−0.11	−0.19	−0.02	−0.01
4	0.06	−0.08	−0.18	0.04	0.04
High	0.54	0.37	0.23	0.55	0.55
High-Low	0.87***	0.83***	0.85***	0.95***	0.95***
t-stat.	(5.03)	(5.32)	(4.86)	(5.79)	(5.78)
Panel B: Alpha of portfolios sorted by 3-month RNS					
Low	−0.00	−0.12	−0.30	−0.09	−0.09
2	−0.06	−0.19	−0.34	−0.10	−0.10
3	−0.11	−0.22	−0.30	−0.13	−0.13
4	−0.03	−0.15	−0.22	−0.03	−0.03
High	0.27	0.09	0.00	0.31	0.31
High-Low	0.27	0.21	0.31*	0.40**	0.40**
t-stat.	(1.29)	(1.23)	(1.67)	(2.30)	(2.31)
Panel C: Alpha of portfolios sorted by 6-month RNS					
Low	0.11	0.00	−0.22	0.02	0.02
2	0.12	−0.02	−0.24	0.05	0.05
3	0.05	−0.09	−0.21	−0.00	−0.00
4	0.00	−0.12	−0.13	0.01	0.01
High	−0.20	−0.37	−0.35	−0.12	−0.12
High-Low	−0.32	−0.37**	−0.13	−0.14	−0.14
t-stat.	(−1.25)	(−2.09)	(−0.70)	(−0.74)	(−0.75)
Panel D: Alpha of portfolios sorted by 9-month RNS					
Low	0.18	0.07	−0.16	0.09	0.09
2	0.18	0.05	−0.20	0.09	0.09
3	0.19	0.04	−0.10	0.12	0.12
4	−0.02	−0.16	−0.20	−0.03	−0.03
High	−0.44	−0.59	−0.49	−0.31	−0.31
High-Low	−0.62**	−0.67***	−0.32	−0.40*	−0.40*
t-stat.	(−2.01)	(−3.14)	(−1.63)	(−1.91)	−1.94)
Panel E: Alpha of portfolios sorted by 12-month RNS					
Low	0.22	0.12	−0.14	0.13	0.13
2	0.23	0.10	−0.17	0.14	0.14
3	0.22	0.07	−0.10	0.14	0.14
4	0.01	−0.13	−0.16	−0.01	−0.01
High	−0.60	−0.75	−0.59	−0.43	−0.43
High-Low	−0.82***	−0.86***	−0.46**	−0.56***	−0.56***
t-stat.	(−2.43)	(−3.63)	(−2.12)	(−2.47)	(−2.52)

Panel A of Table 3 reports the performance of portfolios sorted by 1-month RNS (RNS1M). Portfolio returns illustrate a strong positive relation between 1-month RNS and future stock returns over the subsequent month. A zero-cost trading strategy that longs the highest quintile and shorts the lowest quintile portfolio exhibits significant positive alphas relative to the CAPM, FF3, FF5, FFC4 and FFCP5 models at the 1% level. In particular, the zero-cost high-low strategy has significantly positive monthly alphas relative to all benchmark models ranging from 0.83% (9.96% annualized) relative to FF3 model to 0.95% (11.4% annualized) relative to FFCP5 model. In addition, as we move from the lowest to highest RNS1M quintile portfolio, we find that 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. (2017). 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 3 reports the performance of portfolios sorted by 3-month RNS (RNS3M). 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 that longs the highest quintile and shorts the lowest quintile portfolio exhibits positive and significant alphas for some models, it is insignificant for others. 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 becomes weaker.

Panel C of Table 3 reports the performance of portfolios sorted by 6-month RNS (RNS6M). Portfolio returns exhibit a weak relation between 6-month RNS and future stock returns over the subsequent month. The zero-cost hedging strategy results 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 3. Here we report the performance of portfolios sorted by 9-month RNS (RNS9M). Portfolio returns show a negative relation between 9-month RNS and future stock returns. The zero-cost strategy that longs the highest quintile and shorts the lowest quintile portfolio exhibits negative alphas, significant for all models except the FF5. These results show that as the term increases to 9 months, the relation between RNS and future stock returns becomes negative.

Finally, Panel E of Table 3 reports the performance of portfolios sorted by 12-month RNS (RNS12M). Portfolio returns illustrate a strong negative relation between 12-month RNS and future stock returns over the subsequent month. The zero-cost trading strategy that longs the highest and shorts the lowest quintile portfolio exhibits significantly negative alphas for all benchmark models, ranging from −0.46% (−5.52% annualized) at the 5% significance level relative to the FF5 model to −0.86% (−10.32% annualized) at the 1% significance level relative to the FF3 model.

This significant negative 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 a 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 together, we find that 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., 2017), 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 different predictive directions 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 2, 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 cross-sectional regression methodologies to show that the term spread possesses much stronger predictive power for future equity returns than either the short-term or the 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 a portfolio sorting approach. 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 quintiles. We then employ this ranking to construct an equal-weighted portfolio for each quintile over the subsequent month, forming 5 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 possible autocorrelation and conditional heteroscedasticity in returns.

In Table 4, we present the equal-weighted portfolio performance of monthly quintile portfolio based on RNSTS, the long-short term spread on RNS. From the table, Portfolio returns illustrate a strong negative relation between the term spread and future portfolio returns over the subsequent month. The zero-cost trading strategy that longs the highest quintile and shorts the lowest quintile portfolio exhibits negative alphas relative to all five models which are significant at the 1% level. The zero-cost strategy has significantly negative monthly alphas ranging from −1.07% (−12.84% annualized) relative to the FF5 model to −1.33% (−15.96% annualized) relative to the FF3 model. As we move from the lowest to highest RNSTM quintile portfolio, we find that 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 is greater than that of the 1-month RNS and 12-month RNS individually. Notably, they are also greater than most existing anomalies in the general asset pricing literature.

Table 4
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 quintile 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), 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 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.

Alpha of portfolios sorted by term spread of RNS					
Quintile	CAPM Alpha	FF3 Alpha	FF5 Alpha	FFC4 Alpha	FFCP5 Alpha
Low	0.57	0.42	0.19	0.52	0.52
2	0.36	0.23	0.02	0.30	0.30
3	0.13	0.01	−0.14	0.08	0.09
4	−0.22	−0.34	−0.35	−0.24	−0.24
High	−0.75	−0.91	−0.87	−0.70	−0.70
High-Low	−1.32***	−1.33***	−1.07***	−1.22***	−1.22***
t-stat.	(−5.69)	(−7.21)	(−6.56)	(−6.52)	(−6.61)

4.2. Fama-MacBeth regression

Next, we conduct (Fama and MacBeth, 1973) cross-sectional regressions to confirm the return predictability of RNSTS, defined as the 1-month to 12-month 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 5 reports the cross-sectional coefficients for 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 −0.0100 which is 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 −0.0071 but still remains significant at the 1% 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 highly significant at the 1% level.

To summarize, both the portfolio sorting and cross-sectional regression strategies demonstrate 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

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 Sections 3 and 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 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

Table 5
Fama–MacBeth cross-sectional regressions of monthly excess stock returns on lagged term spread of RNS. 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	0.0239***	0.0213*	0.0244**
	(1.45)	(2.37)	(1.79)	(2.13)
RNSTS	−0.0100***	−0.0071***	−0.0065***	−0.0066***
	(−3.83)	(−4.43)	(−4.40)	(−4.38)
BETA		0.0005	0.0004	0.0004
		(0.23)	(0.22)	(0.22)
log(MV)		−0.0011*	−0.0008	−0.0010*
		(−1.91)	(−1.40)	(−1.79)
BM		0.0004	−0.0002	−0.0002
		(0.28)	(−0.11)	(−0.15)
MOM		0.0001	−0.0004	−0.0004
		(0.05)	(−0.19)	(−0.17)
REV		−0.0002	−0.0003	−0.0003
		(−0.81)	(−1.07)	(−1.03)
ILLIQ*10^4		−0.4827*	−0.4665*	−0.4463
		(−1.69)	(−1.66)	(−1.50)
RET			−0.0219***	−0.0211***
			(−4.35)	(−4.23)
PRICE*10^{-2}			−0.0035	−0.0036
			(−1.34)	(−1.33)
IVOL			0.0078	−0.0078
			(0.06)	(−0.06)
OPVOL*10^{-4}				−0.0015
				(−1.20)
OPEN*10^{-4}				0.0002*
				(1.91)
R-squared	0.0069	0.0740	0.0886	0.0912
Observations	358,802	235,652	235,652	234,418

after controlling for long-term RNS and other variables. We then aggregate all firm-specific coefficients of each month following the (Fama and MacBeth, 1973) procedure and compute Newey–West standard errors with five lags.

Table 6 reports the cross-sectional 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 0.0010 at the 5% 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., 2017) 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 6 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 crashes 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), and Kim et al. (2011a,b),

Table 6

Fama–MacBeth cross-sectional regressions of quarterly SUE on lagged RNS of different maturities. 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	−0.0028***	0.0022	0.0069**	0.0067**
	(−3.14)	(1.17)	(2.20)	(1.96)
RNS1M	0.0010**	0.0011***	0.0011***	0.0011***
	(2.07)	(2.36)	(2.50)	(2.51)
RNS12M	−0.0052***	−0.0033***	−0.0026***	−0.0027***
	(−3.43)	(−2.89)	(−2.55)	(−2.63)
BETA		−0.0001	0.0003*	0.0003**
		(−0.44)	(1.87)	(2.10)
log(MV)		−0.0001	−0.0002*	−0.0002
		(−1.02)	(−1.74)	(−1.42)
BM		−0.0042**	−0.0045**	−0.0045**
		(−2.32)	(−2.28)	(−2.26)
MOM		0.0002	0.0007***	0.0008***
		(0.81)	(3.70)	(3.65)
REV		−0.0001	0.0000	0.0000
		(−1.28)	(0.51)	(0.51)
ILLIQ*10^4		−0.0030	0.0071	−0.0274
		(−0.02)	(0.05)	(−0.20)
RET			0.0028***	0.0029***
			(3.72)	(3.77)
PRICE*10^{-2}			−0.0017***	−0.0018***
			(−2.89)	(−3.02)
IVOL			−0.0998***	−0.1022***
			(−3.07)	(−3.08)
OPVOL*10^{-4}				−0.0001
				(−0.90)
OPEN*10^{-4}				−0.0000
				(−0.24)
R-squared	0.0066	0.0415	0.0491	0.0510
Observations	313,726	210,267	210,267	209,383

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 cross-sectional regression approach by first conducting a monthly logistic regression of the future monthly price crash dummy on current short- and long-term RNS, controlling for a set of firm characteristics. We then aggregate coefficients across all months and compute the Newey–West standard errors with five lags for each coefficient. In Table 7, Column (1) reports the cross-sectional coefficients for the 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 and MacBeth, 1973) cross-sectional regression of price crash indicator variables two through six months ahead on short- and long-term RNS in the current month in Columns (2) through (6) respectively. Among all these regressions, the coefficients of short-term RNS remain significantly negative, indicating that the predictive power of short-term RNS for avoiding price crashes persists for at least 6 months. The coefficients on long-term RNS become insignificant, suggesting that the skewness preference effect of low expected returns only persists for one month.

These results are consistent with Bates (1996), confirming the relation between short-term RNS and jump processes. As emphasized by Cont and Tankov (2003, Ch. 15.6), strong skewness and smiles at short maturities can be generated by jump processes. We next turn to the information content of long-term RNS regarding the underlying return processes.

[3] See Appendix B for details.

Table 7
Fama–MacBeth cross-sectional logistic regressions of monthly stock price crash on lagged RNS of different maturities. This table reports the Fama–MacBeth coefficients of cross-sectional logistic regressions 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 (12 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	−1.3512***	−1.3701***	−1.4917***	−1.5043***	−1.4829***	−1.3554***
	(−6.86)	(−6.99)	(−7.89)	(−8.10)	(−6.92)	(−6.48)
RNS_1M	−0.1048***	−0.0926***	−0.0866***	−0.0981***	−0.1124***	−0.0958***
	(−4.08)	(−3.49)	(−2.72)	(−2.98)	(−3.36)	(−2.87)
RNS_12M	0.2181***	0.0904	0.0663	0.0584	0.0622	−0.0005
	(3.95)	(1.38)	(1.18)	(1.08)	(1.09)	(−0.01)
BETA	−0.0362*	−0.0215	−0.0242	−0.0200	−0.0203	−0.0186
	(−1.89)	(−1.09)	(−1.44)	(−1.03)	(−1.09)	(−1.03)
log(MV)	−0.0418***	−0.0505***	−0.0469***	−0.0494***	−0.0509***	−0.0593***
	(−3.19)	(−4.04)	(−3.88)	(−4.01)	(−3.81)	(−4.22)
BM	−0.2443***	−0.2520***	−0.2502***	−0.2441***	−0.2348***	−0.2468***
	(−7.29)	(−7.60)	(−7.09)	(−7.33)	(−6.95)	(−7.31)
MOM	0.0951***	0.0450*	−0.0011	−0.0110	−0.0184	−0.0520***
	(3.86)	(1.89)	(−0.05)	(−0.49)	(−1.02)	(−2.38)
REV	0.0013	−0.0036	−0.0074	−0.0121*	−0.0109*	−0.0095
	(0.19)	(−0.49)	(−1.12)	(−1.95)	(−1.68)	(−1.32)
ILLIQ*10^6	−0.6637***	−0.7444***	−0.6917***	−0.7648***	−0.8078***	−0.8891***
	(−4.63)	(−5.84)	(−4.95)	(−5.68)	(−6.48)	(−5.44)
RET	−0.4508***	−0.0330	0.1539	−0.0442	0.1876**	0.1374
	(−4.17)	(−0.43)	(1.60)	(−0.49)	(2.25)	(1.56)
PRICE*10^{-2}	−0.0182	0.0587	0.0838	0.1144*	0.1145*	0.1046
	(−0.30)	(1.05)	(1.41)	(1.87)	(1.76)	(1.55)
IVOL	−3.4572***	−1.0521	0.8302	2.2693	2.3300	1.7347
	(−2.38)	(−0.74)	(0.55)	(1.52)	(1.51)	(1.16)
OPVOL*10^{-4}	0.1100*	−0.3021***	−0.1945***	−0.2159**	−0.3850***	−0.3328***
	(1.93)	(−2.73)	(−3.25)	(−2.23)	(−2.93)	(−2.71)
OPEN*10^{-4}	−0.0131***	−0.0016	−0.0040	−0.0062	−0.0034	−0.0036
	(−3.39)	(−0.61)	(−1.11)	(−1.16)	(−0.68)	(−0.97)
Observations	232,506	231,038	229,499	227,795	226,154	224286

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. (2017), 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. (2017) 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 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 both short- and long-term RNS measure.

Table 8 tests whether stocks characterized by higher hedging demand exhibit more negative RNS values. Following Stilger et al. (2017), three measures are used as hedging demand proxies: the ratio between aggregate put option volume and total option volume (PAOV) (Taylor 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. In order to match the 1-month maturity of short-term RNS, only options with maturity from 10 to 45 days are used to calculate the PAOV and AOI. Analogously, in order to match the 12-month maturity of long-term RNS only options with maturity from 319 to 456 days are used to calculate these two measures. Panel A of Table 8 reports the time-series average of 1-month RNS for quintile portfolios sorted by investor hedging demand. As each of the three hedging demand measures increases, short-term RNS decreases monotonically.

Panel B of Table 8 reports the time-series average of the 12-month RNS for quintile portfolios sorted by investor hedging demand. As each of the three hedging demand measures increases, both short- and long-term RNS decrease monotonically. This pattern is statistically significant, as the average short- and long-term RNS in highest hedging demand quintile is lower than that in lowest

Table 8
Average short- and long-term 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 of short-term RNS, only options with maturity from 10 to 45 days are used to calculate the PAOV and AOI. Correspondingly, in order to match 12 month maturity of long-term RNS, only options with maturity from 319 to 456 days are used to calculate these 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.

Quintile	Put-to-all Volume Ratio	Aggregate Open Interest	Z score Default Risk
Panel A: Short-term RNS and hedging demand			
Low	−0.3012	−0.2503	−0.2878
2	−0.3433	−0.2954	−0.3037
3	−0.3623	−0.3257	−0.3190
4	−0.3750	−0.3495	−0.3310
High	−0.3671	−0.3750	−0.3235
Q5–Q1	−0.0658***	−0.1247***	−0.0358***
T	(−17.31)	(−13.18)	(−11.11)
Panel B: Long-term RNS and hedging demand			
Low	−0.5702	−0.5938	−0.5296
2	−0.5963	−0.6049	−0.5636
3	−0.5934	−0.6164	−0.6034
4	−0.6161	−0.6221	−0.6459
High	−0.6216	−0.6395	−0.6142
Q5–Q1	−0.0514***	−0.0456***	−0.0845***
T	(−5.26)	(−2.68)	(−8.01)

quintile at the 1% significance level. This confirms that options with higher hedging demand have more negative RNS values as suggested by Stilger et al. (2017).

Panel A-1 of Table 9 tests whether the underperformance of stocks with the lowest 1-month RNS (RNS1M) is driven by relative overpricing. It reports the performance of double sorted portfolios by 1-month RNS and proxies for overvaluation for the sample period from 1996 to 2015. We use the maximum daily stock returns over the previous month (MAX) (Bali et al., 2011) and the expected idiosyncratic skewness (EIS) (Boyer et al., 2010) as the overvaluation proxies. 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 overvaluation proxy. We find that among three portfolios of stocks with the lowest 1-month RNS, the portfolios with highest MAX (EIS) underperform the portfolio with lowest MAX (EIS) by 1.0012 (0.9030)% per month at the 1% significance level. The underperformance of the portfolio with the lowest 1-month RNS stocks is driven by the stocks exhibiting the highest degree of overpricing.

Panel A-2 of Table 9 tests whether short-sale constraints drive the underperformance of the low 1-month RNS stocks. 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 the 1% significance level. 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 panel A of Table 8 and panel A of Table 9 show that hedging demand and short-sale constraint drive the return predictability of 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.

Although the long-term RNS decreases with measures of hedging demand in Panel B of Table 8, its behavior is inconsistent with hedging demand as shown in Panel B of Table 9. The hedging demand interpretation implies a positive relation between RNS and future stock return, inconsistent with the negative relation observed for long-term RNS. To further investigate the relation between long-term RNS and overvaluation as well as short-sale constraint, Panel B-1 of Table 9 reports the performance of double sorted portfolios by 12-month RNS and overvaluation proxies (MAX and EIS), while Panel B-2 reports that for double sorts by 12-month RNS and short-selling constraint (IVOL). We find the underperformance of the highest long-term RNS portfolio is mainly caused by stocks that are overpriced and hard to short. For example, within the tercile portfolios with highest MAX, EIS, and IVOL, the highest 12-month RNS tercile portfolio underperforms the lowest 12-month RNS tercile portfolio by 1.0015%, 0.7335%, and 0.9257%, respectively.

These results indicate 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 (Bali et al., 2011). Another possible

Table 9
Double sorted portfolios by hedging demand and RNS of different terms. In this table, Panels A and B report the performance of double sorted portfolios by 1-month Risk-Neutral Skewness and 12-month Risk-Neutral Skewness respectively with overvaluation and short-sale constraint proxies for the sample period from 1996 to 2015. Stock overvaluation is proxied by the maximum daily stock returns over the last month (MAX) and expected idiosyncratic skewness (EIS). Short-sale constraint is proxied by idiosyncratic volatility (IVOL). In the end of each month, stocks are sorted into tercile portfolios in ascending order by RNS. Within each RNS tercile portfolio, stocks are further sorted to tercile portfolios in ascending order based on the overvaluation or short-sale constraint proxies. We report abnormal returns relative to the Fama and French (1993) model. 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: Short-term RNS

Panel A-1: 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)	

	EIS low	EIS medium	EIS high	Difference
RNS1M low	0.1384	−0.1986	−0.7646***	−0.9030***
	(1.29)	(−1.51)	(−4.31)	(−4.86)
RNS1M medium	0.2697**	0.0147	−0.4366**	−0.7063***
	(2.06)	(0.10)	(−2.29)	(−3.52)
RNS1M high	0.4841***	0.3557**	0.1408	−0.3433*
	(3.46)	(2.11)	(0.74)	(−1.81)
Difference	0.3457***	0.5542***	0.9054***	
	(3.17)	(4.06)	(4.77)	

Panel A-2: 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)	

Panel B: Long-term RNS

Panel B-1: Stock overvaluation

	MAX low	MAX medium	MAX high	Difference
RNS12M low	0.2995***	0.0800	−0.0110	−0.3105***
	(2.60)	(0.70)	(−0.08)	(−3.03)
RNS12M medium	0.3008**	−0.0259	−0.2003	−0.5010***
	(2.20)	(−0.18)	(−1.36)	(−3.81)
RNS12M high	0.0425	−0.5328***	−1.0125***	−1.0550***
	(0.23)	(−2.47)	(−3.73)	(−4.98)
Difference	−0.2570	−0.6129***	−1.0015***	
	(−1.40)	(−2.76)	(−3.64)	

	EIS low	EIS medium	EIS high	Difference
RNS12M low	0.2152**	0.0290	0.1269	−0.0883
	(2.25)	(0.24)	(0.87)	(−0.66)
RNS12M medium	0.4113***	0.0003	−0.0224	−0.4337***
	(2.89)	(0.00)	(−0.16)	(−2.86)
RNS12M high	0.0876	−0.2413	−0.6066***	−0.6942***
	(0.45)	(−1.33)	(−2.68)	(−3.72)
Difference	−0.1275	−0.2704	−0.7335***	
	(−0.60)	(−1.38)	(−3.66)	

(*continued on next page*)

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.

Table 9 (*continued*).

Panel B-2: Short-selling constraint				
	IVOL low	IVOL medium	IVOL high	Difference
RNS12M low	0.2567***	0.0964	0.0143	−0.2424**
	(2.44)	(0.76)	(0.11)	(−2.07)
RNS12M medium	0.1932	−0.0118	−0.1064	−0.2996*
	(1.51)	(−0.08)	(−0.70)	(−1.93)
RNS12M high	−0.1346	−0.4556*	−0.9114***	−0.7768***
	(−0.66)	(−1.93)	(−3.39)	(−2.89)
Difference	−0.3913**	−0.5519**	−0.9257***	
	(−2.16)	(−2.29)	(−3.40)	

5.4. Skewness preference and informed trading

Under the assumption of common information across the stock and option markets and the consequent 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. The significance of hedging demand and short-sale constraint proxies in the short-term RNS portfolio performance is consistent with the activities of informed hedgers and speculators. The positive relationship between short-term RNS and future returns suggests that their participation in the short-term option market impounds new material 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 Tables 3, 6 and 7 all suggest that long-term RNS carries a negative risk premium, consistent with skewness preference. This provides indirect evidence that long-term RNS is a good proxy of the underlying stocks' expected skewness. Panel B-1 of Table 9 provides additional evidence. The maximum daily return over the previous month (MAX) and expected idiosyncratic skewness (EIS) can also be interpreted as two physical skewness measures which proxy for lottery-like payoffs and bear negative risk premium implied by skewness preference theory. Panel B-1 of Table 9 shows these two measures are negatively priced in the cross-section of stock returns, consistent with Bali et al. (2011) and Boyer et al. (2010). These results also show that the underperformance of the highest physical skewness portfolio, whether in terms of MAX or EIS, is concentrated in stocks with the highest long-term RNS.

For example, in the tercile portfolios with the highest MAX and EIS, the highest 12-month RNS portfolio underperforms the lowest 12-month RNS portfolio by 1.0015% and 0.7335%, respectively. The double-sorted highest MAX (EIS) and highest long-term RNS portfolio underperform the double-sorted lowest MAX (EIS) and lowest long-term RNS portfolio by 1.301% (0.9487%) per month. The performance of double-sorted portfolios shows that the physical skewness measure and long-term risk-neutral skewness measure not only have the same function in pricing stock returns, but also complement each other. By combining both long-term risk-neutral and physical skewness measures, we construct the portfolio that carries the most negative risk premium consistent with skewness preference for its lottery-like payoffs.

To further demonstrate the relation between the term structure of RNS and the physical skewness measure, Panels A and B of Table 10 show the average MAX and EIS of quintile portfolios sorted by short-term and long-term RNS. These two panels show both long- and short-term RNS have positive relation with physical skewness measure; however, sorts on long-term RNS produce a greater variation in physical skewness. For example, the quintile portfolio with the highest 12-month RNS has 0.0485 (t-statistic=33.12) higher average MAX and 0.5810 (t-statistic=13.78) higher average EIS than the quintile portfolio with the lowest 12-month RNS, while the corresponding MAX and EIS spreads for 1-month RNS are only 0.0099 and 0.2225 with lower t-statistics. This is consistent with the pattern observed in Table 2: as the maturity increases, the Pearson correlation between RNS and MAX (EIS) increases from 0.05 (0.14) to 0.28 (0.35). These results are consistent with the interpretation of long-term RNS as the more accurate representation of the underlying stocks' expected skewness. This difference between short-term and long-term RNS underscores the importance of stochastic volatility and volatility asymmetries in underlying return processes necessary to represent a term structure of the volatility surface and long-term skewness (Bates, 1996; Barndorff-Nielsen, 1997; Barndorff-Nielsen and Shephard, 2001; Carr et al., 2003; Nicolato and Venardos, 2003).

6. The factor structure of the RNS term structure

The difference in predictive coefficients between short-term and long-term RNS for the cross-section of returns observed in the preceding analysis implies that the term structure of RNS itself contains information about the future distribution of the underlying asset. To map this information content more formally, we conduct a factor analysis on the RNS term structure to reduce its dimensionality and to identify the number of distinct informative signals it contains. In doing so, we rely on prior insights from the interest rate term structure literature.

6.1. The RNS slope factor and the cross-section of returns

Significant works in this literature, such as Nelson and Siegel (1987), Litterman and Scheinkman (1991) and Christensen et al. (2011), find that yield curves are usually explained by the level, slope, and curvature factors. In the same spirit, we perform a factor

Table 10
Average physical skewness measure of quintile portfolios sorted by short- and long-term RNS. This table reports the time-series average of the average Physical Skewness measure for quintile portfolios sorted by short- and long-term RNS. We measure physical skewness using maximum daily return over the last month (MAX) and expected idiosyncratic skewness (EIS). The differences in average physical skewness between the highest and the lowest RNS 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.

RNS1M quintile	Max daily return	Expected idiosyncratic skewness
Panel A: Short-term RNS and physical skewness measure		
Low	0.0524	0.2485
2	0.0582	0.2871
3	0.0621	0.3248
4	0.0638	0.3956
High	0.0623	0.4710
Q5–Q1	0.0099***	0.2225***
T	(11.91)	(12.02)
Panel B: Long-term RNS and physical skewness measure		
Low	0.0382	0.1077
2	0.0479	0.1981
3	0.0575	0.3022
4	0.0687	0.4301
High	0.0866	0.6887
Q5–Q1	0.0485***	0.5810***
T	(33.12)	(13.78)

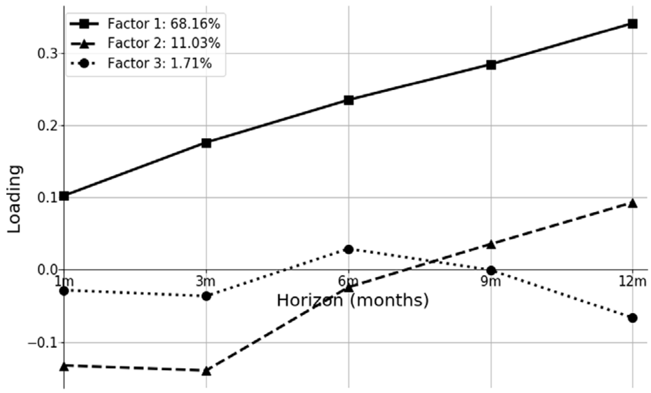

Fig. 1. Factor Analysis of RNS Across Different Maturities. This figure shows the loadings of three factors obtained from the factor analysis of RNS with five maturities. All firm-month observations are used for factor analysis. The solid, dashed and dotted line indicates the loadings on 1-month RNS, 3-month RNS, 6-month RNS, 9-month RNS and 12-month RNS of the first, second, and third factor, respectively. The percentage of variance explained by each factor is presented in the legend.

analysis on RNS measures across five fixed maturities at the 1, 3, 6, 9, and 12-month horizons of all firm-month observations to check whether a similar factor structure exists.

We present the loadings of three extracted factors on five RNS measures in Fig. 1. The first factor can be explained as the level factor of the RNS term structure, as it loads positively on RNS of all terms. That is, an increase in the first factor tends to push up the level of RNS of all maturities, though it affects the long-term RNS more. The second factor has a positive loading on long-term RNS and a negative loading on short-term RNS, thus it can be treated as the slope factor, which has a similar meaning to the term spread of RNS. The increase of this slope factor tends to push up the long-term RNS and push down the short-term RNS, creating the term spread of RNS identified earlier. The third factor indicates the curvature of the RNS term structure because its loading on RNS is positive only when the horizon of RNS reaches 6 month. The increase of third factor tends to push up the middle-term RNS. We observe that the first two factors capture a total of 79.19% of the variation of the RNS term structure, explaining 68.16% and 11.03% of it respectively. The third factor explains only 1.71% of the variation in RNS term structure, indicating it is unlikely to be meaningful.

We next explore how prior-month values of the RNS term structure factors affect the current month's cross-sectional excess underlying returns, summarizing the outcome in Table 11. We consider several specifications, each with additional levels of controls. Model (1) considers the explanatory power of the factors in isolation. Model (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 (ILLIQ). 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).

Table 11

Fama–MacBeth cross-sectional regressions of monthly excess stock returns on lagged RNS term structure factors. This table reports the Fama–MacBeth coefficients of cross-sectional regressions of monthly excess stock returns on lagged factors of the RNS term structure during the period 1996–2015. We perform a factor analysis of the RNS term structure across five fixed maturities at the 1, 3, 6, 9, and 12-month horizons for each firm-month observation. Model (1) considers the explanatory power of the factors in isolation. Model (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 (ILLIQ). 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	0.0101	0.0239***	0.0228*	0.0254**
	(1.59)	(2.42)	(1.93)	(2.24)
Factor 1	0.0189*	0.0128	0.0132*	0.0134*
	(1.89)	(1.57)	(1.70)	(1.74)
Factor 2	−0.1063***	−0.0786***	−0.0745***	−0.0742***
	(−3.33)	(−3.99)	(−4.30)	(−4.24)
Factor 3	0.2775	0.1493	0.1668	0.1635
	(1.48)	(1.25)	(1.57)	(1.54)
BETA		0.0000	0.0002	0.0001
		(0.02)	(0.10)	(0.08)
log(MV)		−0.0007	−0.0006	−0.0007*
		(−1.23)	(−1.01)	(−1.29)
BM		0.0004	−0.0001	−0.0001
		(0.27)	(−0.06)	(−0.09)
MOM		0.0004	−0.0003	−0.0003
		(0.17)	(−0.13)	(−0.11)
REV		−0.0002	−0.0003	−0.0003
		(−0.85)	(−1.05)	(−1.00)
ILLIQ*10^4		−0.5456*	−0.5341*	−0.5058*
		(−1.90)	(−1.89)	(−1.69)
RET			−0.0204***	−0.0196***
			(−4.04)	(−3.90)
PRICE*10^{-2}			−0.0027	−0.0027
			(−1.01)	(−1.01)
IVOL			−0.0011	−0.0172
			(−0.01)	(−0.15)
OPVOL*10^{-4}				−0.0017
				(−1.35)
OPEN*10^{-4}				0.0002*
				(1.86)
R-squared	0.0243	0.0795	0.0927	0.0953
Observations	358,802	235,652	235,652	234,418

Consistent with prior results, we find that the values of the level and slope factors from the preceding month have opposite and significant coefficients in the cross-section of excess returns at the 10% and 1% levels respectively. This explanatory power is robust to the inclusion of size, value, systematic risk, liquidity, momentum, and reversal controls defined above. The level factor has positive loadings on short-term RNS and long-term RNS, which have opposite pricing effects. The positive coefficient of the level factor on future stock returns, significant at the 10% level, suggests that the short-term RNS's positive effect weakly dominates the long-term RNS's negative effect. The negative cross-sectional coefficient of the slope factor, significant at the 1% level, further confirms the similarity between itself and the term spread of RNS. The curvature factor does not appear to be priced in the cross-section of excess returns, which is consistent with its insignificant contribution in explaining the variability of the RNS term structure and the negligible effect of middle-term RNS on future equity returns. Among the three factors, the slope factor exhibits the most significant predictive power on the cross-section of stock returns, indicating that the slope factor captures the majority of the price information in the RNS term structure. This analysis further confirms the importance of the term spread measure of RNS in explaining the cross-section of equity returns.

6.2. An economic state variable interpretation of the RNS slope factor

The results in Table 11 above suggest that the RNS term structure slope factor contains information about future stock returns similar to the RNS term spread. In this section we establish the economic foundation for this factor using a vector autoregression (VAR) analysis of macroeconomic state variables following the approach of Petkova (2006). We include macroeconomic state variables that have a relation to the equity premium as described in Welch and Goyal (2008).[4] The VAR model uses monthly values of the equal-weighted average of SLOPE,[5] the RNS term structure slope factor across all optionable stocks, MKTRP, the market risk

4 We are grateful to Amit Goyal for providing these data on his website at http://www.hec.unil.ch/agoyal/.

5 Substituting a value-weighted version of SLOPE in the analysis produces similar results, which we omit for brevity.

Table 12

RNS term structure slope factor and macroeconomic variables. This table reports coefficients from a monthly vector autoregressive model of the slope factor of the RNS term structure (SLOPE) along with macroeconomic variables related to equity expected returns. Here MKTRP is the S&P 500 return net of the T-bill rate, EP is the log ratio of trailing 12-month S&P 500 earnings to current S&P price, TERM is the term spread as the difference between long-term T-Bonds and short-term T-Bills, and DEF is the default spread as the difference between long-term corporate bonds and T-Bonds. T-statistics are in parentheses. ***, ** and * indicate 1%, 5%, and 10% significance levels, respectively.

	SLOPE	MKTRP	EP	TERM	DEF
$SLOPE_{t-1}$	0.5653***	−0.2273	0.2894	0.0494***	0.0173***
	(9.92)	(−0.91)	(0.67)	(3.02)	(2.81)
$MKTRP_{t-1}$	−0.0503***	0.0611	0.3624***	0.0029	−0.0094***
	(−3.35)	(0.92)	(3.17)	(0.67)	(−5.83)
EP_{t-1}	0.0037*	0.0055	0.9304***	−0.0010*	0.0005**
	(1.91)	(0.63)	(62.32)	(−1.83)	(2.46)
$TERM_{t-1}$	0.1845***	0.1733	1.5078***	0.9385***	−0.0077
	(3.13)	(0.67)	(3.36)	(55.59)	(−1.21)
DEF_{t-1}	1.1063***	0.2494	−10.5121***	−0.0745	0.9321***
	(4.44)	(0.23)	(−5.54)	(−1.04)	(34.73)
INTERCEPT	0.0152***	0.0256	−0.1654***	−0.0031*	0.0019***
	(2.70)	(1.04)	(−3.87)	(−1.92)	(3.07)
Observations	238	238	238	238	238

premium as the S&P 500 return net of the risk-free rate, EP, the log ratio of trailing 12-month S&P 500 earnings to current S&P price, TERM, the term spread as the yield difference between long-term Treasury bonds and short-term bills, and DEF, the default spread as the yield difference between BAA and AAA-related corporate bond yields. We present the output of the VAR model in Table 12.

We observe that SLOPE is negatively related to last month's MKTRP with a coefficient of −0.0503, and positively related to the last month's TERM and DEF spreads with coefficients of 0.1845 and 1.1063, all significant at the 1% level. It is furthermore weakly related to last month's EP ratio with a coefficient of 0.0037 significant at the 10% level, and autocorrelated with a coefficient of 0.5653, statistically significant at the 1% level. Last month's SLOPE is also a predictor of both TERM and DEF spreads with coefficients of 0.0494 and 0.0173, both significant at the 1% level. These results suggest that the SLOPE factor only reacts to last month's market returns, but both predicts and is predicted by last month's bond term and default spreads.

To understand the economic magnitude, we estimate the implied risk premium for the SLOPE factor. Based on the time series of monthly SLOPE, the standard deviation is 0.0187. According to Model (4) in Table 11, the coefficient of the SLOPE factor in predicting next month return is -0.0742. Therefore, the estimated risk premium for a one standard deviation in SLOPE is −1.67% per year ($= -0.0742 \times 0.0187 \times 12$).

Furthermore, we can estimate the impact of each economic factor on the SLOPE risk premium based on Table 12. In particular, one standard deviation's increase of MKTRP (0.0426) results in a change of −0.0021 (-0.0503×0.0426) in SLOPE. From Model (4) in Table 11, the estimated risk premium for a one standard deviation in the MKTRP factor is 0.19% ($-0.0021 \times (-0.0742) \times 12$). Similarly, we estimate the risk premiums caused by a one standard deviation in the TERM and DEF factors to be −0.21% and −0.42% per year, respectively.

To better understand which components of the SLOPE factor drive its relation with the (Welch and Goyal, 2008) state variables, we also estimate VAR models with equal-weighted RNS at each of our five constant maturities in Tables C.1 through C.5 in Appendix C. Since the SLOPE factor is a linear combination of RNS at these maturities, this allows us to see which part of the term structure of RNS drives the factor's sensitivity to macroeconomic state variables.

The results in Appendix C show that the one-month (12-month) RNS is positively (negatively) related to last month's MKTRP at the 5% statistical significance level, suggesting that short-term option investors bet on continuation of trends whereas long-term ones bet on reversals. Last month's values of TERM have a relation to current short-term 1-month and 3-month RNS, with positive coefficients with statistical significance at the 5% level. This is consistent with informed traders in the short-term market taking bullish positions due to a positive signal about future economic growth. In contrast, only long-term 6-, 9-, and 12-month RNS have a relation to future TERM spreads with positive coefficients significant at the 1% level. Consistent with skewness preference theory, positive skewness expectations imply a high demand for stocks. This shift away from long-term bonds to stocks leads to an increase in the long-term bond yield and subsequently a high TERM yield spread. Furthermore, only the one-month RNS component of SLOPE is significantly related to the DEF spread. A high credit risk environment appears to lead short-term option investors to form a bearish market expectation, as indicated by the negative coefficient of DEF in predicting 1-month RNS at the 1% significance level. On the other hand, one-month RNS can negatively predict the DEF spread at the 5% significance level, consistent with previous evidence that short-term option traders may have superior information about the future.

These results suggest that the SLOPE factor of the RNS term structure, and therefore the RNS term spread itself, have a statistically significant relation to macroeconomic state variables that provides intuition for its ability to explain cross-sectional and time-series equity returns.

7. Conclusion

This paper contributes to the ongoing debate in the skewness pricing literature about the direction of the relationship between individual stock risk-neutral skewness (RNS) and future underlying asset returns. Specifically, we identify differences in the information content across the term structure of RNS.

Using a large sample of stock and options data from 1996 to 2015, we document positive predictability of future stock returns from short-term RNS, which is consistent with the informed trading and hedging demand literature (Xing et al., 2010; Stilger et al., 2017; Bollen and Whaley, 2004; Garleanu et al., 2009), and negative predictability from 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 return predictor, the term spread of RNS, which is defined as the long-term RNS minus short-term RNS. This predictor is constructed to capture information sets at both ends of the RNS term structure. The quintile portfolio with the highest RNS term spread underperforms the quintile 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 that 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. (2017). This evidence suggests that these informed market participants mainly trade short-term options, which produces the different (similar) information sets between the short-term (long-term) skewness expectations in the option and equity markets. 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 more accurate measure of expected underlying asset skewness as implied by skewness preference.

To provide more direct evidence that long-term RNS proxies for the underlying stocks' expected skewness, we compare it with two well-known physical skewness measures bearing negative risk premia. We find that the long-term RNS measure has a strong positive correlation with these two measures. In addition, both physical and long-term RNS measures complement each other in identifying stocks with the most negative risk premium for lottery-like payoffs.

A factor analysis of the RNS term structure, inspired by prior work in the factor structure of bond yields curves by Nelson and Siegel (1987), Litterman and Scheinkman (1991) and Christensen et al. (2011), confirms the existence of two distinct informational components priced in the cross-section of excess returns. We find a level factor that is priced positively consistent with our findings for the short-term RNS, and a slope factor that is priced negatively consistent with our findings for the RNS term spread. We find that the RNS term structure slope factor, which is most significantly related to both cross-sectional and time-series stock returns, is significantly related to macroeconomic state variables for the equity premium.

Our finding of the maturity-varying directionality of return predictability from RNS helps resolve the ongoing debate between two strands of the skewness pricing 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 the skewness preference theory. Our results confirm the validity of both hypotheses, with the RNS from short-term options producing a positive relationship with future returns consistent with superior information, and the RNS from long-term options producing a negative one consistent with skewness preference.

CRediT authorship contribution statement

Paul Borochin: Conceptualization, Investigation, Data Curation, Methodology, Writing - original draft, Writing - review and editing. **Hao Chang:** Conceptualization, Investigation, Data Curation, Methodology, Writing - original draft, Writing - review and editing. **Yangru Wu:** Conceptualization, Investigation, Methodology, Writing - original draft, Writing - review and editing.

Appendix A

In this section we use an equilibrium model to show how informed trading and skewness preference can be reconciled with each other and can lead to different pricing effects on future stock returns. Our model builds on the equilibrium asset pricing model of Mitton and Vorkink (2007), who use a one-period economy with two type of investors with heterogeneous preference for skewness to generate the negative risk premium of skewness. The first type, which is referred as a "Traditional Investor", has a mean–variance utility function. The second type, the "Lotto Investor", has identical preferences to the traditional investor over mean and variance but also has preference for skewness. We extend (Mitton and Vorkink, 2007) by changing the one-period economy to a multi-period economy and dividing the lotto investor type into two subtypes, the "Informed Lotto Investor" and "Uninformed Lotto Investor". Informed lotto investors are able to estimate the skewness of risky securities more accurately than uninformed ones. By making these extensions, we bring the role of informed trading into the asset pricing framework and demonstrate its ability to generate a positive skewness risk premium.

Following Mitton and Vorkink (2007), we assume that the investable universe consists of three risky assets and a riskless bond that pays an interest rate r per period. $\mathbf{V}$ denotes the covariance matrix of the three risky assets one period ahead. In addition, the distribution of asset returns are allowed to be skewed. In a departure from Mitton and Vorkink (2007), we assume that there are n periods in the economy and that all risky securities pay off at time n. The current time is time 0. In this example we set $n = 10$ without loss of generality.

The future wealth of each investor type is denoted as W and its mean, variance and skewness are $E(W)$, $Var(W)$ and $Skew(W)$. We assume all types of investors know $\mathbf{V}$. At a certain time t, they believe the distribution of asset returns are i.i.d in each of the remaining periods from time t to time n.

The "Traditional investor" has a standard quadratic utility function over wealth

$$U(W) = E(W) - \frac{1}{2\tau} Var(W), \tag{A.1}$$

where W is the future wealth and τ ($\tau > 0$) is the coefficient of risk aversion. The "Informed Lotto investor" has a mean–variance–skewness utility function:

$$U(W) = E(W) - \frac{1}{2\tau} Var(W) + \frac{1}{3\phi} Skew(W), \tag{A.2}$$

Here ϕ ($\phi > 0$) is the coefficient controlling preference for skewness. A preference for positive skewness is indicated by positive values of ϕ. Here we assume the informed Lotto investors know the true value for the idiosyncratic skewness and coskewness of all risky assets so they can estimate $Skew(W)$ precisely.

The third investor type, the "Uninformed Lotto investor", has the same utility function but his/her estimate for the idiosyncratic skewness of a stock may be biased. Therefore, this type's estimate for the third moment of the future wealth, $\widehat{Skew(W)}$, which measures the downside risk of his/her future wealth, may deviate from its true value $Skew(W)$. The corresponding preference is given by

$$U(W) = E(W) - \frac{1}{2\tau} Var(W) + \frac{1}{3\phi} \widehat{Skew(W)}, \tag{A.3}$$

For simplicity, we assume every uninformed lotto investor believes his/her skewness estimate is correct and he/she does not know about the existence of informed lotto investors. We further assume that traditional investors do not care about the third moment of their wealth distribution when making investment decision. Thus, whether or not they are informed about the skewness of the joint distribution of risky assets has no effect on asset prices and asset holdings of this investor type in equilibrium.

Let $\mathbf{X}_j^{(t)} = \left[x_{j,1}^{(t)}, x_{j,2}^{(t)}, x_{j,3}^{(t)}\right]'$ be an 3×1 vector that denotes every jth type investor's dollar amount in each of the three risky assets at time t. Let $\mathbf{R}^{(t,n)} = \left[R_1^{(t,n)}, R_2^{(t,n)}, R_3^{(t,n)}\right]'$ denote the average return of each period from time t to time n in equilibrium. The wealth these investments generate at time n is $W_j^{(n)} = W_j^{(t)}(1+(n-t)r) + \mathbf{X}_j^{(t)\prime}(n-t)(\mathbf{R}^{(t,n)} - r\mathbf{1})$. Here $W_j^{(t)}$ represents every jth type investor's endowment at time t. For simplicity, we assume simple interest in this economy.

The objective of each investor type is to maximize his/her utility function, such as Eqs. (A.1) and (A.2) or (A.3), subject to their budget constraint. In the spirit of Mitton and Vorkink (2007), a traditional investor's demand function is given by,

$$\mathbf{X}_T^{(t)} = \tau\left((n-t)\mathbf{V}\right)^{-1}(n-t)(\mathbf{R}^{(t,n)} - r\mathbf{1}) = \tau\mathbf{V}^{-1}(\mathbf{R}^{(t,n)} - r\mathbf{1}), \tag{A.4}$$

Here subscript T signifies traditional investors. As the distribution of 3 risky assets are believed to be i.i.d, $(n-t)\mathbf{V}$ are believed to be the covariance matrix of 3 risky assets from time t to time n.

For an informed lotto investor, the solution is described by the following equation,

$$(n-t)(\mathbf{R}^{(t,n)} - r\mathbf{1}) - \frac{1}{\tau}(n-t)\mathbf{V}\mathbf{X}_{IL}^{(t)} + \frac{1}{\phi}\left[\left(x_{IL,1}^{(t)}(n-t)\mathbf{M}_1 + x_{IL,2}^{(t)}(n-t)\mathbf{M}_2 + x_{IL,3}^{(t)}(n-t)\mathbf{M}_3\right)\mathbf{X}_{IL}^{(t)}\right] = 0, \tag{A.5}$$

where subscript IL signifies informed lotto investors and $\mathbf{M}_1$, $\mathbf{M}_2$, and $\mathbf{M}_3$ are matrices defined as:

$$\mathbf{M}_i = \begin{bmatrix} M_{i11} & M_{i12} & \cdots & M_{i1n} \\ M_{i21} & M_{i22} & \cdots & M_{i2n} \\ \vdots & \vdots & \ddots & \vdots \\ M_{in1} & M_{in2} & \cdots & M_{inn} \end{bmatrix} \tag{A.6}$$

with $i = 1, 2, \ldots, n$ and where arbitrary elements of $\mathbf{M}_i$, denoted as M_{ijk}, is denoted as $M_{ijk} = E\left[(R_i - \bar{R}_i)(R_j - \bar{R}_j)(R_k - \bar{R}_k)\right]$ and $\bar{R}_i = E\left[R_i\right]$. R_i is the return of Asset i in one period. Three general types of skewness elements exist in the 'M' skewness matrices: M_{iii}, which represents the idiosyncratic skewness of Asset 'i', M_{iik}, which represents the curvilinear interaction of Asset 'i' and 'j', and M_{ijk}, which represents the triplicate product moment of the Assets 'i', 'j' and 'k'. The above equation (A.5) can be simplified as,

$$(\mathbf{R}^{(t,n)} - r\mathbf{1}) - \frac{1}{\tau}\mathbf{V}\mathbf{X}_{IL}^{(t)} + \frac{1}{\phi}\left[\left(x_{IL,1}^{(t)}\mathbf{M}_1 + x_{IL,2}^{(t)}\mathbf{M}_2 + x_{IL,3}^{(t)}\mathbf{M}_3\right)\mathbf{X}_{IL}^{(t)}\right] = 0. \tag{A.7}$$

Here we assume informed lotto investors know $\mathbf{M}_1$, $\mathbf{M}_2$, and $\mathbf{M}_3$. While uninformed lotto investors may not have such information. Their estimation of $\mathbf{M}_1$, $\mathbf{M}_2$, and $\mathbf{M}_3$ at time t are denoted as $\hat{\mathbf{M}}_1^{(t)}$, $\hat{\mathbf{M}}_2^{(t)}$, and $\hat{\mathbf{M}}_3^{(t)}$. Therefore, for uninformed lotto investor, the solution is implied by the following equation,

$$(\mathbf{R}^{(t,n)} - r\mathbf{1}) - \frac{1}{\tau}\mathbf{V}\mathbf{X}_{UL}^{(t)} + \frac{1}{\phi}\left[\left(x_{UL,1}^{(t)}\hat{\mathbf{M}}_1^{(t)} + x_{UL,2}^{(t)}\hat{\mathbf{M}}_2^{(t)} + x_{UL,3}^{(t)}\hat{\mathbf{M}}_3^{(t)}\right)\mathbf{X}_{UL}^{(t)}\right] = 0. \tag{A.8}$$

Table A.1
Model parameter values. This table shows the parameters we use to solve the numerical solutions of our theoretical equilibrium model. Among them, we use the same parameters of the risk-aversion and skewness preference parameters (τ, ϕ) and the covariance matrix (**V**) elements as in Mitton and Vorkink (2007).

Parameter	Variable	Value
Risk-aversion coefficient	τ	2.50
Skewness-preference coefficient	ϕ	2.50
Variance of Asset 1 returns	σ_1^2	0.20
Variance of Asset 2 returns	σ_2^2	0.35
Variance of Asset 3 returns	σ_3^2	0.25
Correlation coefficient, Assets 1 and 2	$\rho_{1,2}$	0.08
Correlation coefficient, Assets 1 and 3	$\rho_{1,3}$	0.15
Correlation coefficient, Assets 2 and 3	$\rho_{2,3}$	0.10
Number of periods	n	10
Total number of investors	N	300
Total investment on each asset at time 0	D	100
The proportion of traditional investors	P_T	1/2
The default proportion of informed lotto investors	P_{IL}	1/4
The default proportion of uninformed lotto investors	P_{UL}	1/4

We assume without loss of generality that the total investment in each risky asset at time 0 is $D = 100$, and that the total number of investors is $N = 300$. Among all investors, the proportion of traditional investors and informed lotto investors are P_T and P_{IL}, respectively. Therefore, the proportion of uninformed lotto investors is $P_{UL} = 1 - P_T - P_{IL}$. We fix the proportion of traditional investors to be 1/2, i.e., $P_T = 1/2$. And by default we set the proportion of each type of lotto investors to be 1/4, i.e., $P_{IL} = P_{UL} = 1/4$. To clear the market, at time t, we have the following conditions:

$$\mathbf{X}_T^{(t)} N P_T + \mathbf{X}_{IL}^{(t)} N P_{IL} + \mathbf{X}_{UL}^{(t)} N(1 - P_T - P_{IL}) = D\mathbf{1}, \tag{A.9}$$

By solving equations (A.4) and (A.7)–(A.9), we can obtain the equilibrium return from time t to time n for 3 risky assets, $\mathbf{R}^{(t,n)}$, and the equilibrium holdings for risky assets of one investor of all types, $\mathbf{X}_T^{(t)}$, $\mathbf{X}_{UL}^{(t)}$ and $\mathbf{X}_{IL}^{(t)}$.

Table A.1 presents the parameters we use to obtain the numerical solutions to our theoretical equilibrium model. Following Mitton and Vorkink (2007), we use the same parameters of the risk-aversion and skewness preference parameters (τ, ϕ) and the covariance matrix (**V**) elements, and we assume that the return distributions of Assets 1 and 3 are completely characterized by the first two moments (i.e., no skewness). Asset 1 represents a large-cap stock with low variance and high average correlation to other stocks, and Asset 3 represents a small-cap stock with high variance and low average correlation to other stocks. However, the return distribution of Asset 2 is allowed to be skewed, and its skewness is allowed to be idiosyncratic, which is equivalent to setting $M_{ijk} = 0$ for all i, j, k except for the case $i = j = k = 2$.

We assume the information about M_{ijk} is known to all investors, with the exception that informed and uninformed lotto investors may have a different understanding of the value of M_{222}. I.e., these two types of investors may have different opinions about how skewed the return distribution of Asset 2 is. Given these specifications, Eq. (A.7) and (A.8) can be simplified as,

$$(\mathbf{R}^{(t,n)} - r\mathbf{1}) - \frac{1}{\tau}\mathbf{V}\mathbf{X}_{IL}^{(t)} + \frac{1}{\phi}[0, M_{222}{x_{IL,2}^{(t)}}^2, 0]' = 0, \tag{A.10}$$

and

$$(\mathbf{R}^{(t,n)} - r\mathbf{1}) - \frac{1}{\tau}\mathbf{V}\mathbf{X}_{UL}^{(t)} + \frac{1}{\phi}[0, \hat{M}_{222}^{(t)}{x_{UL,2}^{(t)}}^2, 0]' = 0, \tag{A.11}$$

We assume that at time 0, informed lotto investors learnt the true value of M_{222}, while the uninformed lotto investors are not able to do this until time 1. The uninformed lotto investors' estimation for M_{222} at time 0 is denoted as $\hat{M}_{222}^{(0)}$. Under this framework, we can study the role of informed trading in determining the equilibrium return of assets from time 0 to time 1, $\mathbf{R}^{(0,1)}$, especially the equilibrium return of Asset 2, $R_2^{(0,1)}$.

We compute $\mathbf{R}^{(0,1)}$ in two steps. First, at time 0, we solve the equilibrium average one-period return of risky assets from time 0 to time n, $\mathbf{R}^{(0,n)}$. Second, at time 1, we solve the average one-period return from time 1 to time n, $\mathbf{R}^{(1,n)}$. Then $\mathbf{R}^{(0,1)}$ is computed as $\mathbf{R}^{(0,1)} = n\mathbf{R}^{(0,n)} - (n-1)\mathbf{R}^{(1,n)}$.

The RNS of Asset 2 at time 0 can be proxied by the idiosyncratic skewness of Asset 2 implied by the equilibrium asset prices, assuming all lotto investors, including both informed and uninformed, have the same information. We denote the RNS of Asset 2 by $\tilde{M}_{222}$. It satisfies the following equation:

$$(\mathbf{R}^{(t,n)} - r\mathbf{1}) - \frac{1}{\tau}\mathbf{V}\mathbf{X}_{L}^{(t)} + \frac{1}{\phi}[0, \tilde{M}_{222}^{(t)}{x_{L,2}^{(t)}}^2, 0]' = 0, \tag{A.12}$$

where $\mathbf{X}_L^{(t)}$ is the average holding of each lotto investor, which can be calculated as $\mathbf{X}_L^{(t)} = \left(\frac{P_{IL}}{P_{IL}+P_{UL}}\right)\mathbf{X}_{IL}^{(t)} + \left(\frac{P_{UL}}{P_{IL}+P_{UL}}\right)\mathbf{X}_{UL}^{(t)}$. Therefore, $\tilde{M}_{222}^{(t)}$ is given by

$$\tilde{M}_{222}^{(t)} = \phi\left[\frac{1}{\tau}\mathbf{V}\mathbf{X}_L^{(t)} - (\mathbf{R}^{(t,n)} - r\mathbf{1})\right]_2 / {x_{L,2}^{(t)}}^2. \tag{A.13}$$

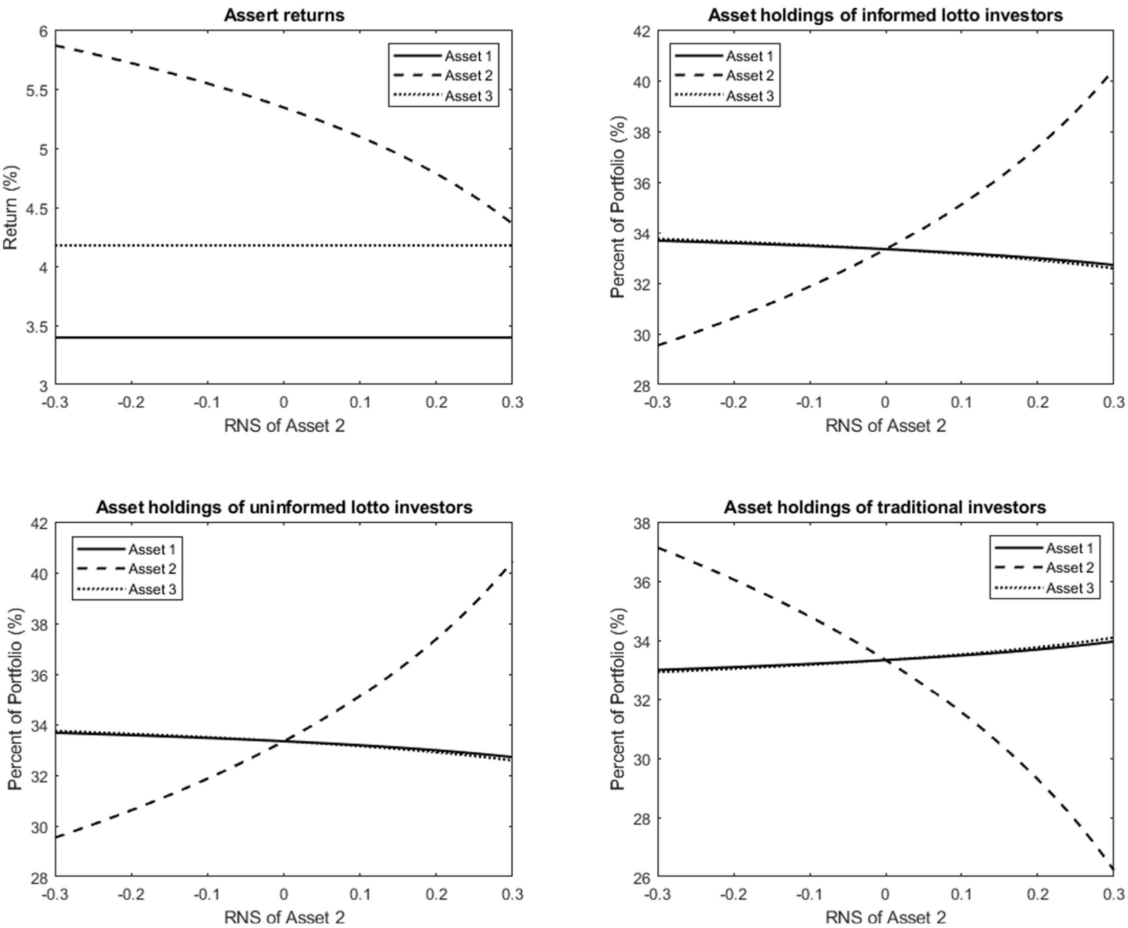

Fig. A.1. Asset returns and demands when $\hat{M}_{222} = M_{222}$. In this case, uninformed lotto investors and informed ones are classified as the same type of investors.

Our main focus is to study relationship between the RNS of Asset 2 at time 0, $\tilde{M}^{(0)}_{222}$, and the subsequent return of Asset 2 from time 0 to time 1, $R^{(0,1)}_2$ under different scenarios. To begin with, we study the special scenario where $\hat{M}^{0}_{222} = M_{222}$, i.e., uninformed investors know the true value of the idiosyncratic skewness of Asset 2 at time 0. In this case, uninformed lotto investors and informed lotto investors have the same demand for each risky asset in equilibrium and can be classified as the same type of investors, which is the "Lotto Investor" in Mitton and Vorkink (2007). Thus we expect a negative correlation between $\tilde{M}^{(0)}_{222}$ and $R^{(0,1)}_2$, as suggested by Mitton and Vorkink (2007). The asset returns and asset holdings of one investor of each type given different RNS values are shown in Fig. A.1. We can see that as the RNS of Asset 2 increases, lotto investors have more demand for holding Asset 2 and the return of Asset 2 decreases.

The above relation between RNS and subsequent return of Asset 2 also holds when the change of RNS is purely driven by the change of skewness estimate of uninformed lotto investors, while the true value of skewness is fixed. For example, let us set the true value of Asset 2's skewness to be 0.1, i.e., $M_{222} = 0.1$, and let uninformed lotto investors' skewness estimate $\hat{M}^{(0)}_{222}$ vary from −0.3 to 0.3. Then the corresponding asset returns and asset holdings of one investor of each type given different RNS values are shown in Fig. A.2. In this case, when RNS increases, the skewness estimate of uninformed lotto investors increases, so the demand for holding Asset 2 from uninformed lotto investors increases and Asset 2 tends to be overpriced. Therefore, the return of Asset 2 goes down. At the same time, the demand for holding Asset 2 from informed lotto investors and traditional investors decreases.

When the change of RNS is purely driven by the change of true value of skewness and the skewness estimate of uninformed lotto investors is fixed, the informed trading may play a dominant role and result in a positive relationship between RNS and stock return. For example, let us set the skewness estimate of uninformed lotto investors to be 0.1, i.e., $\hat{M}^{(0)}_{222} = 0.1$, and set the true value of skewness M_{222} to vary from −0.3 to 0.3, then the corresponding asset returns and asset holdings of one investor of each type given different RNS values are shown in Fig. A.3. In this case, when RNS increases, the true value of skewness increases, so the demand for holding Asset 2 from informed lotto investors increases and that from uninformed lotto investors and traditional investors decreases. When the buying demand from informed lotto investors becomes large enough, the RNS reflects the predictive information for the true skewness. Higher RNS suggests that true skewness should be higher, so there should be more demand for Asset 2 after uninformed lotto investors realize the true skewness of Asset 2 at time 1. Correspondingly its price goes up at time 1. Because of their superior information, informed lotto investors buy Asset 2 from other investors in advance (at time 0) and make profits when its price increases at time 1.

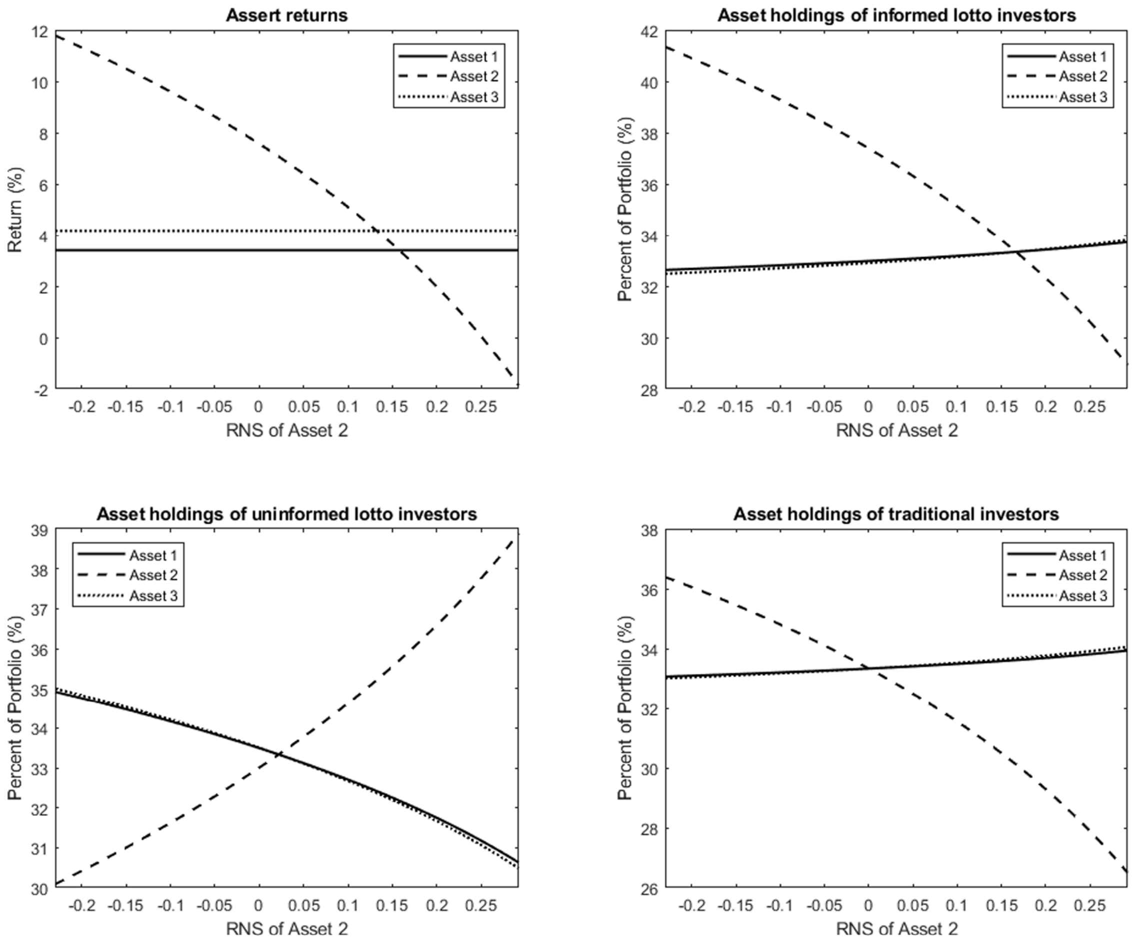

Fig. A.2. Asset returns and demands when RNS is driven by the true value of skewness. We set $\hat{M}_{222} = 0.1$ and let M_{222} vary from −0.3 to 0.3.

In reality, the change of RNS can be driven by the changes of both true skewness and uninformed lotto investors' skewness estimate. So its relation with future stock return can be either positive or negative, depending on how much effects the inside information has on trading in equilibrium, e.g., how much the proportion of informed traders is. To study this question, we let the proportion of informed lotto investors change and check the correlation between RNS and future stock return. And we generate RNS series by changing both true skewness value and uninformed lotto investors' skewness estimate. In particular, we generate $\hat{M}^{(0)}_{222}$ by the uniform distribution between −0.15 to 0.15 and M_{222} by the uniform distribution between −0.3 to 0.3. We keep the proportion of lotto investors to be 50%, but let the proportion of informed lotto investors over all lotto investors change from 0 to 100%. Given specific values of $\hat{M}^{(0)}_{222}$, M_{222} and the proportion of informed lotto investors, we compute the RNS at time 0 and return from time 0 to time 1 for Asset 2. Therefore, given a certain proportion of lotto investors, we can compute the correlation between RNS and Asset 2's subsequent return. The correlation against the proportion of informed lotto investors over all lotto investors is shown in Fig. A.4.

Based on Fig. A.4, when there is a small proportion of informed lotto investors, the relation between RNS and subsequent asset return is negative. This is because given a small number of informed lotto investors, RNS is predominately driven by the skewness estimate of uninformed lotto investors. Thus it mainly reflects the skewness estimate of uninformed investors as well as the their demand for holding Asset 2. In this case, informed traders successfully hide their inside information in asset prices. When the proportion increases to some threshold (16%), the correlation becomes positive and continues to increase when the proportion increases. This results from the fact that as the number of informed lotto investors increases, RNS starts to reflect the informed traders' predictive information about Asset 2's skewness. The correlation reaches the peak when the proportion of informed traders arrives at a certain point (67%). After that if the number of informed traders continue to increase, the correlation decreases. The correlation becomes negative after the proportion exceeds 88%, because as most of lotto investors are informed lotto investors, their belief about Asset 2's skewness tends to become "public information" rather than "inside information", and skewness preference starts to dominate the relation between RNS and stock return again. When the proportion reaches 100%, all lotto investors are "informed investors" and the true skewness of Asset 2 becomes completely public. Thus there is no ground for informed trading, and the correlation drops to a very negative value, which is close to −1 in this example.

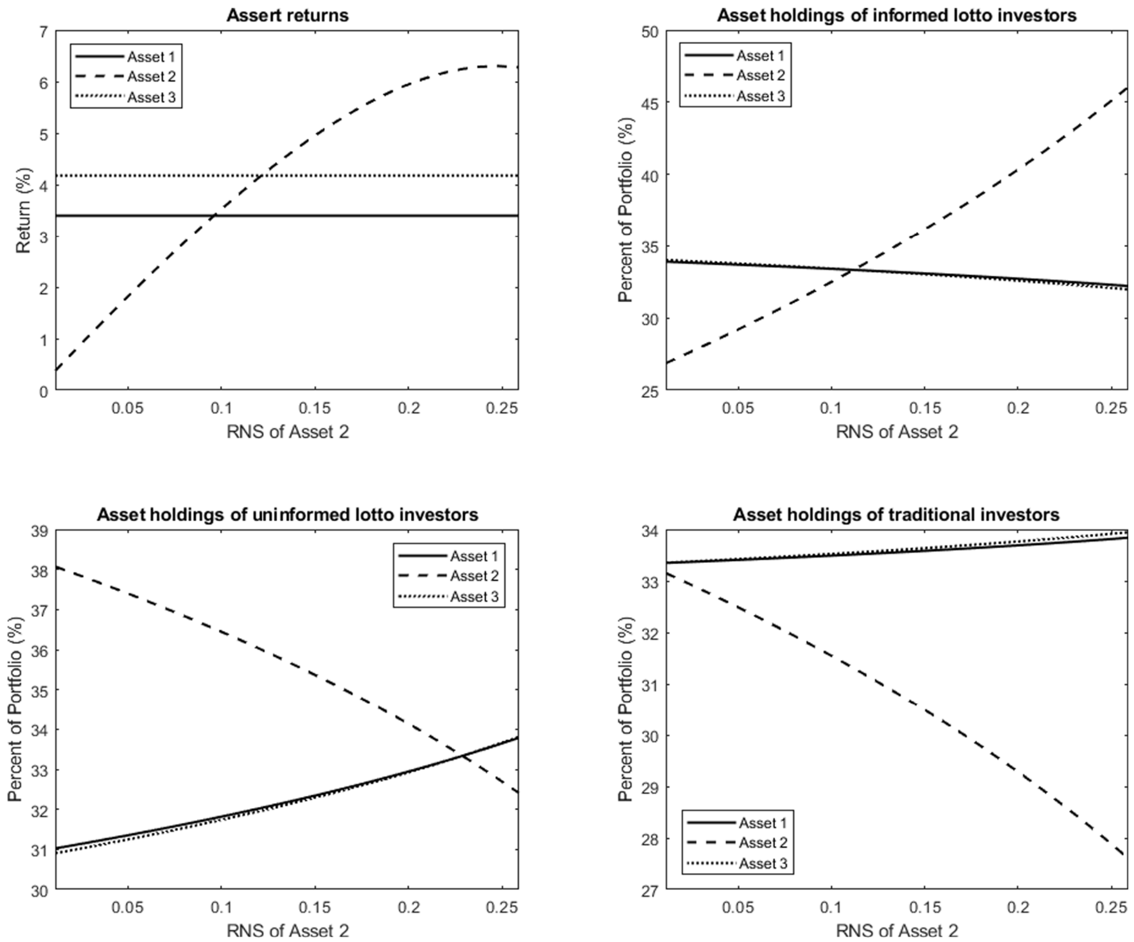

Fig. A.3. Asset returns and demands when RNS is driven by the true value of skewness. We set $\hat{M}_{222} = 0.1$ and let M_{222} vary from -0.3 to 0.3.

For simplicity, we do not formally bring options into this equilibrium model. If we extend the model by formally adding options at different moneyness, we can expect to obtain similar findings as options provide more vehicles for hedging or speculation and help to back out the implied skewness of stocks. Our empirical findings about the negative risk premium of the long-term RNS are consistent with the negative relation between RNS and future stock return when the proportion of informed investors is small as shown in Fig. A.4. Furthermore, our findings about the positive risk premium of short-term RNS in our paper are consistent with the positive relation between RNS and future stock return when informed traders are more prevalent, as shown in Fig. A.4. Our empirical results are consistent with this theoretical equilibrium, as we demonstrate that short-term RNS contains more accurate firm-specific information than long-term RNS does.

Appendix B

The definitions of the variables are detailed as follows. The corresponding summary statistics are presented in Table 1.

BKM1M

Risk-neutral (option-implied) skewness with 1 month to expiration. With standardized OTM options maturing in 30 days of firm i on the last day of month t, 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 of firm i on the last day of month t, BKM3M 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).

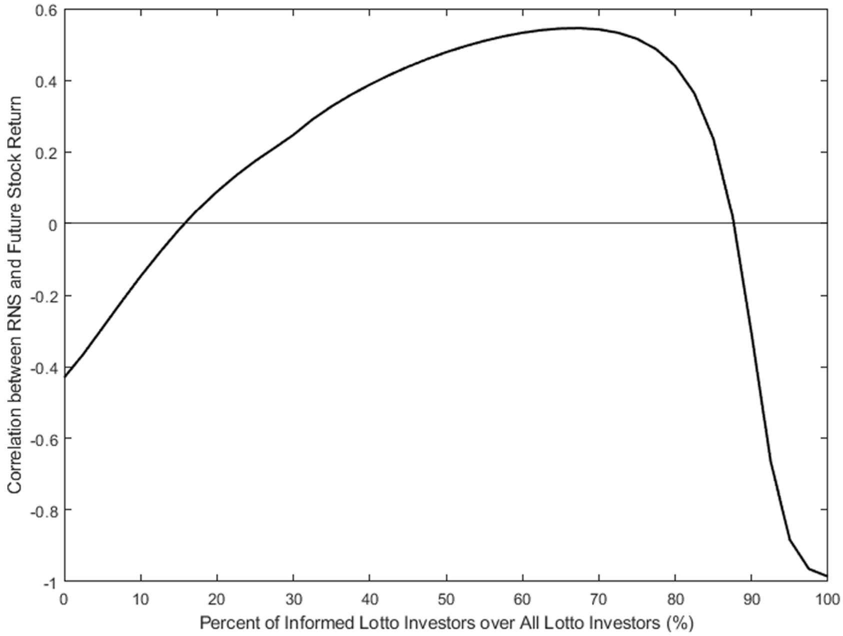

Fig. A.4. Correlation between RNS and subsequent asset return given different proportion of informed lotto investors over all lotto investors.

BKM6M

Risk-neutral (option-implied) skewness with 6 month to expiration. With standardized OTM options maturing in 152 days of firm i on the last day of month t, BKM6M 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 of firm i on the last day of month t, BKM9M 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 of firm i on the last day of month t, BKM12M 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 market cap. The market cap is computed as the closing share price times the number of shares outstanding (in thousands).

BM

The 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 the end of month $t-12$ to the end of month $t-1$.

REV

Reversal for firm i is calculated as its stock return from the end of month $t-1$ to the end of month t.

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.

Table C.1
One-month RNS and macroeconomic state variables. This table reports coefficients from a vector autoregressive model of equal-weighted average RNS along with macroeconomic state variables related to equity expected returns. Here MKTRP is the S&P 500 return net of the T-bill rate, EP is the log ratio of trailing 12-month S&P 500 earnings to current S&P price, TERM is the term spread as the difference between long-term T-Bonds and short-term T-Bills, and DEF is the default spread as the difference between long-term corporate bonds and T-Bonds. T-statistics are in parentheses. ***, ** and * indicate 1%, 5%, and 10% significance levels, respectively.

	RNS1M	MKTRP	EP	TERM	DEF
$RNS1M_{t-1}$	0.5473***	0.07167	−0.0360	−0.0009	−0.0030**
	(9.70)	(1.43)	(−0.41)	(−0.27)	(−2.40)
$MKTRP_{t-1}$	0.1881**	0.0635	0.3600***	0.0024	−0.0096***
	(2.54)	(0.96)	(3.14)	(0.55)	(−5.91)
EP_{t-1}	−0.0085	0.0048	0.9320***	−0.0007	0.0006***
	(−0.90)	(0.56)	(63.57)	(−1.23)	(2.90)
$TERM_{t-1}$	0.6256**	−0.0357	1.6865***	0.9607***	0.0043
	(2.23)	(−0.14)	(3.90)	(57.93)	(0.70)
DEF_{t-1}	−3.0290***	0.2085	−9.9785***	0.0619	0.9567***
	(−2.92)	(0.23)	(−6.23)	(1.01)	(42.04)
INTERCEPT	−0.1530***	0.0414	−0.1689***	−0.0021	0.0014**
	(−4.83)	(1.47)	(−3.45)	(−1.12)	(2.02)
Observations	238	238	238	238	238

Table C.2
Three-month RNS and macroeconomic state variables. This table reports coefficients from a vector autoregressive model of equal-weighted average RNS along with macroeconomic state variables related to equity expected returns. Here MKTRP is the S&P 500 return net of the T-bill rate, EP is the log ratio of trailing 12-month S&P 500 earnings to current S&P price, TERM is the term spread as the difference between long-term T-Bonds and short-term T-Bills, and DEF is the default spread as the difference between long-term corporate bonds and T-Bonds. T-statistics are in parentheses. ***, ** and * indicate 1%, 5%, and 10% significance levels, respectively.

	RNS3M	MKTRP	EP	TERM	DEF
$RNS3M_{t-1}$	0.8402***	0.0741	−0.1887**	0.0046	−0.0005
	(22.85)	(1.51)	(−2.23)	(1.42)	(−0.40)
$MKTRP_{t-1}$	0.0656	0.0655	0.3539***	0.0026	−0.0096***
	(1.33)	(0.99)	(3.12)	(0.59)	(−5.85)
EP_{t-1}	−0.0069	0.0053	0.9286***	−0.0006	0.0006***
	(−1.09)	(0.63)	(63.73)	(−1.04)	(2.99)
$TERM_{t-1}$	0.4774**	−0.1740	2.2710***	0.9435***	0.0012
	(2.21)	(−0.60)	(4.57)	(49.18)	(0.17)
DEF_{t-1}	−0.7976	0.0619	−10.8816***	0.0997	0.9795***
	(−1.22)	(0.07)	(−7.25)	(1.72)	(44.97)
INTERCEPT	−0.0966***	0.0589	−0.2577***	0.0006	0.0020*
	(−3.67)	(1.67)	(−4.26)	(0.26)	(2.32)
Observations	238	238	238	238	238

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,b), 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

The maximum of daily returns for firm i during the month t.

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.

Table C.3
Six-month RNS and macroeconomic state variables. This table reports coefficients from a vector autoregressive model of equal-weighted average RNS along with macroeconomic state variables related to equity expected returns. Here MKTRP is the S&P 500 return net of the T-bill rate, EP is the log ratio of trailing 12-month S&P 500 earnings to current S&P price, TERM is the term spread as the difference between long-term T-Bonds and short-term T-Bills, and DEF is the default spread as the difference between long-term corporate bonds and T-Bonds. T-statistics are in parentheses. ***, ** and * indicate 1%, 5%, and 10% significance levels, respectively.

	RNS6M	MKTRP	EP	TERM	DEF
$RNS6M_{t-1}$	0.9592***	0.0436	−0.1369**	0.0070***	0.0005
	(41.46)	(1.14)	(−2.09)	(2.82)	(0.49)
$MKTRP_{t-1}$	−0.0047	0.0662	0.3504**	0.0029	−0.0100***
	(−0.12)	(1.00)	(3.09)	(0.68)	(−5.81)
EP_{t-1}	−0.0033	0.0043	0.9310***	−0.0006	0.0006**
	(−0.65)	(0.51)	(64.17)	(−1.09)	(3.08)
$TERM_{t-1}$	0.1257	−0.1878	2.4628***	0.9165***	−0.0033
	(0.63)	(−0.57)	(4.33)	(42.30)	(−0.40)
DEF_{t-1}	0.0080	−0.3478	−9.8772***	0.0808	0.9833***
	(0.02)	(−0.43)	(−7.04)	(1.51)	(48.34)
INTERCEPT	−0.0339	0.0495	−0.2514***	0.0030	0.0026***
	(−1.58)	(1.40)	(−4.15)	(1.29)	(2.98)
Observations	238	238	238	238	238

Table C.4
Nine-month RNS and macroeconomic state variables. This table reports coefficients from a vector autoregressive model of equal-weighted average RNS along with macroeconomic state variables related to equity expected returns. Here MKTRP is the S&P 500 return net of the T-bill rate, EP is the log ratio of trailing 12-month S&P 500 earnings to current S&P price, TERM is the term spread as the difference between long-term T-Bonds and short-term T-Bills, and DEF is the default spread as the difference between long-term corporate bonds and T-Bonds. T-statistics are in parentheses. ***, ** and * indicate 1%, 5%, and 10% significance levels, respectively.

	RNS9M	MKTRP	EP	TERM	DEF
$RNS9M_{t-1}$	0.9843***	0.0320	−0.0770	0.0066***	0.0005
	(51.46)	(1.05)	(−1.47)	(3.35)	(0.73)
$MKTRP_{t-1}$	−0.0465	0.0666	0.3515**	0.0032	−0.0095***
	(−1.12)	(1.01)	(3.08)	(0.73)	(−5.80)
EP_{t-1}	−0.0025	0.0037	0.9328***	−0.0007	0.0006**
	(−0.47)	(0.44)	(64.07)	(−1.30)	(3.05)
$TERM_{t-1}$	−0.0322	−0.1883	2.2700***	0.9043***	−0.0050
	(−0.15)	(−0.54)	(3.80)	(40.24)	(−0.58)
DEF_{t-1}	0.0635	−0.5170	−9.4206***	0.0489	0.9809***
	(0.12)	(−0.63)	(−6.65)	(0.92)	(48.03)
INTERCEPT	−0.0151	0.0443	−0.2171***	0.0032	0.0027**
	(−0.72)	(1.33)	(−3.78)	(1.50)	(3.28)
Observations	238	238	238	238	238

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. And traded options with maturity from 10 to 45 days are used to compute 1-month PAOV. We use 12-month PAOV to proxy hedging demand for long-term options. And traded options with maturity from 319 to 456 days are used to compute 12-month PAOV.

EIS

Expected idiosyncratic skewness for firm i in the end of the month t is the forecast of expected idiosyncratic skewness observed at the end of month t for the distribution of daily returns over months $t+1$ through $t+60$, calculated using the same method in Boyer, Mitton, and Vorkink (2010). We first compute idiosyncratic skewness, ISKEW, for each firm-month observation by calculating the skewness of residuals of daily firm-level residuals of the Fama and French (1993) three-factor model regression over the past 60 months. The variable $\mathrm{ISKEW}_{i,t}$ is set to be missing at the end of month t if the number of observable returns is less than 250. We then estimate cross-sectional regressions separately at the end of each month t in our sample, $\mathrm{ISKEW}_{i,t} = \beta_0^t + \beta_1^t \mathrm{ISKEW}_{i,t-60} + \beta_1^t \mathrm{IVOL}_{i,t-60} + \gamma^t X_{i,t-60} + \varepsilon_{i,t}$, where $X_{i,t-60}$ is a vector of additional firm-specific variables observable at the end of month $t-60$. These variables include the momentum from the end of month $t-60-12$ through the end of month $t-60-1$, the sum of daily turnover for firm i over the month $t-60-12$, dummy variable indicating firm i in the bottom tercile ranked by size at the end of month $t-60$, dummy variable indicating firm i in the middle tercile ranked by size at the end of month $t-60$, and dummies for 16 of the 17 industries defined by Ken French to create the “17 Industry Portfolios” on his website. We then use

Table C.5
Twelve-month RNS and macroeconomic state variables. This table reports coefficients from a vector autoregressive model of equal-weighted average RNS along with macroeconomic state variables related to equity expected returns. Here MKTRP is the S&P 500 return net of the T-bill rate, EP is the log ratio of trailing 12-month S&P 500 earnings to current S&P price, TERM is the term spread as the difference between long-term T-Bonds and short-term T-Bills, and DEF is the default spread as the difference between long-term corporate bonds and T-Bonds. T-statistics are in parentheses. ***, ** and * indicate 1%, 5%, and 10% significance levels, respectively.

	RNS12M	MKTRP	EP	TERM	DEF
$RNS12M_{t-1}$	0.9885***	0.0255	−0.0487	0.0057***	0.0006
	(54.61)	(1.03)	(−1.14)	(3.55)	(0.83)
$MKTRP_{t-1}$	−0.1063**	0.0664	0.3536**	0.0032	−0.0095***
	(−2.19)	(1.00)	(3.09)	(0.74)	(−5.80)
EP_{t-1}	−0.0018	0.0033	0.9336***	−0.0008	0.0006***
	(−0.29)	(0.39)	(63.87)	(−1.47)	(3.00)
$TERM_{t-1}$	−0.0621	−0.1843	2.1304***	0.9008***	−0.0057
	(−0.24)	(−0.53)	(3.55)	(40.10)	(−0.66)
DEF_{t-1}	−0.0259	−0.6123	−9.2889***	0.0259	0.9787***
	(−0.04)	(−0.73)	(−6.42)	(0.48)	(47.01)
INTERCEPT	−0.0085	0.0410	−0.1985***	0.0029	0.0027***
	(−0.37)	(1.30)	(−3.65)	(1.42)	(3.48)
Observations	238	238	238	238	238

the regression parameters from the above regression, along with information observable at the end of each month t, to estimate expected idiosyncratic skewness for firm i, $E_t[\mathrm{ISKEW}_{i,t+60}] = \beta_0^t + \beta_1^t \mathrm{ISKEW}_{i,t} + \beta_1^t \mathrm{IVOL}_{i,t} + \gamma^t X_{i,t}$.

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. And traded options with maturity from 10 to 45 days are used to compute 1-month AOI. We use 12-month AOI to proxy hedging demand for long-term options. And traded options with maturity from 319 to 456 days are used to compute 12-month AOI.

ZD

Zmijewski (1984) Z-score, which measures 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.

Appendix C

See Tables C.1–C.5

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