What Does Risk-Neutral Skewness Tell Us About Future Stock Returns?*

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Abstract

This study documents a positive relationship between the option-implied risk-neutral skewness (RNS) of individual stock returns' distribution and future realized stock returns during the period 1996-2012. A strategy that is long the quintile portfolio with the highest RNS stocks and short the quintile portfolio with the lowest RNS stocks yields an average Fama-French-Carhart alpha of 55 bps per month (*t-stat*: 2.47). The significant underperformance of the portfolio with the most negative RNS stocks is driven by those stocks that are also perceived as relatively overpriced according to a series of overvaluation proxies and are too costly or too risky to sell short, thereby hindering the price correction mechanism. Our findings indicate that a highly negative RNS value, when reflecting high hedging demand for options by investors who perceive the underlying stock as relatively overpriced but hard to sell short, is a robust signal of significant future stock underperformance.

Keywords: Option-Implied Information, Risk-Neutral Skewness, Hedging Pressure, Overvaluation, Short Selling Constraints.

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1 Introduction

This study examines the relationship between the risk-neutral skewness (RNS) of individual stock returns' distribution extracted from option prices, which are inherently forward-looking, and future realized stock returns. We use daily option prices from 1996 to 2012 for a large sample of US stocks. RNS is estimated for each stock using the model-free methodology of Baskhi et al. (2003). We find significant and robust evidence that RNS is positively related to future realized stock returns. In particular, a strategy that is long the quintile portfolio with the highest RNS stocks and short the quintile portfolio with the lowest RNS stocks yields an average return of 61 bps (*t-stat*: 2.24) per month, and Fama-French-Carhart (FFC) alpha of 55 bps (*t-stat*: 2.47) per month. We further decompose RNS into its systematic and unsystematic components to find that the latter drives the positive relationship between RNS and future realized stock returns.

Which of the stocks exhibiting low RNS values subsequently underperform? We find that the significant underperformance of the portfolio with the most negative RNS stocks is mainly driven by those stocks that are also perceived to be relatively overvalued. We use three proxies for relative overvaluation: the expected idiosyncratic skewness under the physical measure (Boyer et al., 2010), the maximum daily stock return in the past month (Bali et al., 2011), and the probability of jackpot stock return in the following year (Conrad et al., 2014). According to these proxies, over-optimistic investors or investors with strong preference for their lottery-like payoffs have temporarily driven up these stock prices. However, RNS does not simply mimic an overvaluation effect, since low RNS does not necessarily coincide with high values of these overvaluation proxies. Using bivariate conditional portfolio sorts, we show that it is the *interplay* between low RNS and high overvaluation that yields future stock underperformance.

Why is highly negative RNS an informative signal of future stock underperformance and the market fails to immediately correct this mispricing? We find that the significant underperformance of the portfolio with the most negative RNS stocks is mainly driven by those stocks that are also too costly or too risky to sell short, thus hindering the price correction mechanism, in line with the arguments of Miller (1977). We use three proxies for short selling constraints: the estimated shorting fee of Boehme et al. (2006), the relative short interest that captures the demand for short selling (see Asquith et al., 2005), and stock returns' idiosyncratic volatility under the physical measure (see Wurgler and Zhuravskaya, 2002). Using bivariate conditional portfolio sorts, we show that it is the *interplay* between low RNS and severe short selling constraints that yields the subsequent stock undeperformance.

In sum, we find that a highly negative RNS value signals future underperformance for those stocks that are also perceived to be relatively overpriced and are too costly or too risky to sell short. Using trivariate independent portfolio sorts, we confirm that all these three conditions are necessary for future stock underperformance. In most of the cases that we examine, the portfolio of stocks with the lowest RNS values, the highest overvaluation and the most severe short selling constraints yields a significantly negative risk-adjusted return of at least -60 bps per month.

These results imply that the predictive ability of highly negative RNS values is driven by the hedging and insurance demand for options by those pessimistic investors who perceive the stock as overvalued but cannot sell it short, and hence resort to trading in the option market. Consistent with the demand-based option pricing framework of Garleanu et al. (2009), these trades substantially move option prices, and hence drive down RNS, because option market makers cannot hedge their positions due to the short selling constraints in the stock market. We confirm that the stocks characterized by the highest hedging demand exhibit, on average, significantly more negative RNS values relative to the other stocks. We use four proxies for investor hedging demand. Following Acharya et al. (2013), we use Zmijewski's (1984) $Z-$score to capture firm default risk and the ratio of CEO stock holdings to their base salary to capture the managerial hedging motive. The third proxy is the ratio of put to all options' trading volume (see Taylor et al., 2009), and the fourth proxy is the aggregate open interest across all options for a given maturity (see Hong and Yogo, 2012).

Our study contributes to the growing literature that utilizes information embedded in option prices to predict future stock returns and to construct investment strategies.[1] Option-implied information may be valuable because it is inherently forward-looking and reflects investors' expectations under the risk-neutral measure about the future evolution of the underlying stock prices (Bates, 1991, Jackwerth and Rubinstein, 1996, and Bakshi et al., 1997). Moreover, estimates of risk-neutral higher moments have become popular because the corresponding estimates from historical returns require long time series, they are rather unstable to the addition of new observations and they are poor predictors of future realized higher moments (see Hansis et al., 2010, and Conrad et al., 2013, for a discussion).

The most directly related studies to ours are the ones by Rehman and Vilkov (2012), Bali and Murray (2013), Conrad et al. (2013), and Bali et al. (2014), who all use the model-free methodology of Bakshi et al. (2003) to estimate RNS. In contrast to Bali and Murray (2013), we examine the relationship between RNS and future realized *stock* returns, while they consider *option portfolios'* returns, finding a *negative* relationship. Contrary to Conrad et al. (2013), who find a *negative* relationship between *quarterly averages* of daily RNS estimates and realized *quarterly* stock returns during the first half of our sample period (i.e., up to 2005), we use RNS estimates extracted on the last trading day of each month to construct portfolios, that is we use the most recent available estimate. We argue that our approach is more appropriate because daily RNS estimates are not highly persistent, and hence averaging this information over a long period only weakens its signal; this fact explains why their results differ from ours. Averaging RNS over a long period is also inappropriate because RNS signals a temporary mispricing, which we find to be corrected within a month. On the other hand, our benchmark evidence is in agreement with the results of Bali et al. (2014), who find a *positive* relationship between RNS and stock returns, but they use

[1]Bali and Hovakimian (2009) find no relation between risk-neutral volatility and future stock returns. Xing et al. (2010) find a negative relation between the steepness of the implied volatility smirk and future stock returns. On the other hand, Cremers and Weinbaum (2010) find that the difference between implied volatilities of call and put options with the same strike and expiration date is positively related to subsequent stock returns. Kostakis et al. (2011), DeMiguel et al. (2013), and Kempf et al. (2014) show that option-implied distributions and their moments, respectively, can help to construct investment strategies and portfolios with superior out-of-sample performance relative to those constructed solely on the basis of historical information. Giamouridis and Skiadopoulos (2012) provide a review of recent studies that examine the value of option-implied information for asset management.

expected stock returns derived from financial analysts' price targets, while we use *realized* stock returns from observable market prices.

Our benchmark results are also in line with the evidence of Rehman and Vilkov (2012). We show that the positive relationship between RNS and future stock returns holds for a longer sample period, including the recent financial crisis. However, contrary to Rehman and Vilkov (2012), who argue that RNS is another proxy for stock overvaluation, we show that this is not true. If low RNS were a valid overvaluation proxy, then all low RNS stocks should subsequently underperform regardless of their partitioning. To the contrary, we find that it is *only* the fraction of low RNS stocks that are *simultaneously* classified as relatively overpriced *and* exhibit severe short selling constraints that significantly underperform. In other words, low RNS is a necessary but not sufficient condition for future stock underperformance; it is the *interplay* between low RNS, relative overvaluation and short selling constraints that yields the underperformance.

The mechanism we put forward to explain our findings is motivated by the evidence of Bollen and Whaley (2004) and the demand-based option pricing framework of Garleanu et al. (2009). Since risk averse market makers cannot perfectly hedge their option positions due to short selling constraints in the stock market, the demand for options impacts their prices. As a result, when investors with negative expectations about future stock returns sell out-of-the-money (OTM) call options and/or buy OTM put options, they drive RNS to very low (negative) values. The effect on RNS from constructing synthetic short stock positions is similar. Investors are more likely to have negative expectations about the future returns of those stocks that are perceived to be relatively overpriced; it is the realization of these negative expectations that yields the positive relationship between RNS and future stock returns. Obviously, for this mechanism to hold there needs to be investor disagreement, otherwise no investor would perceive stocks to be relatively overpriced in the first place. This argument is consistent with the evidence of Friesen et al. (2012), who find that stocks with greater investor belief differences are characterized by more negative RNS values.

The previously described mechanism is also consistent with the sequential trade model of Easley et al. (1998), where at least some informed investors choose to trade in options before trading in the underlying stocks, and hence option prices carry information that leads stock price movements. In our setup, investors with negative expectations with respect to relatively overpriced stocks that are too costly or too risky to sell (short) eventually resort to the option market to hedge against downside risk, driving RNS to very low (negative) values. As a result, RNS extracted from option prices contains valuable information that is not already incorporated into current stock prices due to limits-to-arbitrage. As this mispricing information is diffused to the stock market over time, prices of relatively overvalued stocks subsequently decrease, giving rise to the positive relationship between RNS and future stock returns.

Our empirical evidence is also consistent with the noisy rational expectations model of An et al. (2014), where trading takes place simultaneously in the stock and option markets but the informed investor chooses how much to trade on the basis of the relative magnitude of noise trading present in each market, so as to disguise her trades. Market makers ensure that stock and option prices satisfy arbitrage bounds. However, even though stock and option prices contemporaneously move due to the trades of the informed investor, they do not adjust to a fully revealing equilibrium because of the presence of noise trading. Therefore, information embedded in option trades and prices can predict future stock returns and vice versa. Contributing to this framework, our empirical evidence suggests that limits-to-arbitrage, such as short selling constraints, could also be an important determinant of which market the informed investor chooses to trade.

The rest of this study is organized as follows. Section 2 describes the methodology for extracting risk-neutral moments of stock returns' distributions from option prices and decomposing them into their systematic and unsystematic components. In addition, it provides the details for the dataset used and the data sources for the firm characteristics examined in this study. Section 3 examines the relationship between RNS and future realized stock returns. Section 4 examines the validity of the mechanism that we propose to explain the underperformance of the stocks exhibiting the most negative RNS values, while Section

5 concludes.

2 Data and Methodology

2.1 Risk-Neutral Moments

We use the model-free methodology of Baskhi et al. (2003) to calculate risk-neutral moments for the return distribution of stock i using its option prices. These are the moments of the return distribution under the risk-neutral measure for a given horizon τ, which is equal to the time to maturity of the options used to extract them. As Appendix A shows, following Bakshi et al. (2003) and using OTM call and put options prices at time t, we compute the Risk-Neutral Variance (RNV), Skewness (RNS) and Kurtosis (RNK) for each stock i as:

$$RNV_{i,t}(\tau) = \exp(r\tau) V_t(\tau) - \mu_t(\tau)^2 \tag{1}$$

$$RNS_{i,t}(\tau) = \frac{\exp(r\tau)(W_t(\tau) - 3\mu_t(\tau) V_t(\tau)) + 2\mu_t(\tau)^3}{\left[\exp(r\tau) V_t(\tau) - \mu_t(\tau)^2\right]^{3/2}} \tag{2}$$

$$RNK_{i,t}(\tau) = \frac{\exp(r\tau)\left(X_t(\tau) - 4\mu_t(\tau) W_t(\tau) + 6\mu_t(\tau)^2 V_t(\tau)\right) - 3\mu_t(\tau)^4}{\left[\exp(r\tau) V_t(\tau) - \mu_t(\tau)^2\right]^2} \tag{3}$$

where $V_t(\tau)$, $W_t(\tau)$ and $X_t(\tau)$ are the time t prices of $\tau-$maturity quadratic, cubic and quartic contracts defined, respectively, as contingent claims with payoffs equal to the second, third and fourth power of stock i log returns. The expressions for the prices of these contracts are given in equations (9)-(11) in Appendix A. Moreover, r is the risk-free rate and $\mu_t(\tau)$ is given by:

$$\mu_t(\tau) = \exp(r\tau) - 1 - \frac{\exp(r\tau)}{2} V_t(\tau) - \frac{\exp(r\tau)}{6} W_t(\tau) - \frac{\exp(r\tau)}{24} X_t(\tau) \tag{4}$$

To compute $V_t(\tau)$, $W_t(\tau)$ and $X_t(\tau)$, a continuum of option prices would be required.

However, traded options are available only at discrete strikes. In line with Conrad et al. (2013), we require at least two OTM put options and two OTM call options per stock with the same expiry date. We interpolate the implied volatilities of the available options between the lowest and the highest available moneyness using a piecewise Hermite polynomial separately for put and call options, and we extrapolate outside the lowest and the highest moneyness using the implied volatility at each boundary, so as to fill in 997 grid points in the moneyness range from 1/3 to 3. We then use the Black-Scholes formula to convert the implied volatilities into the corresponding option prices. Finally, using these option prices, we apply Simpson's rule, which is described in Appendix B, to compute the integrals that appear in the formulae of $V_t(\tau)$, $W_t(\tau)$ and $X_t(\tau)$. In a robustness check, we alternatively compute these integrals using directly the available OTM option prices and applying a trapezoidal rule, as in Dennis and Mayhew (2002) and Conrad et al. (2013).

2.2 Systematic and unsystematic components of RNS

We further decompose RNS into its systematic and unsystematic components, following the decomposition approach in Theorem 3 of Bakshi et al. (2003, p. 112).[2] In particular, the systematic component of RNS for firm i on day d is given by:

$$RNS_{i,d,Systematic} = b_i^3 RNV_{m,d}^{3/2} RNS_{m,d} / RNV_{i,d}^{3/2}, \tag{5}$$

where b_i is the risk-neutral beta of firm i, $RNV_{i,d}$ is the risk-neutral variance of firm i on day d, while $RNV_{m,d}$ and $RNS_{m,d}$ denote, respectively, the risk-neutral variance and skewness on day d of the market portfolio proxied by the S&P 500.

Following Bali et al. (2014), we compute risk-neutral betas, b_i, for each firm i, by regressing on a monthly basis daily $RNV_{i,d}$ on $RNV_{m,d}$ using a rolling window of 12 months, and taking the square root of the corresponding slope coefficient. For the cases where this regression approach yields a negative slope coefficient, no risk-neutral beta is computed. In

[2] We would like to thank an anonymous referee for suggesting this decomposition approach.

a robustness check presented in the Supplementary Appendix, we alternatively use stock betas estimated under the physical measure to compute systematic RNS values.

Given the definition of systematic RNS in equation (5), the unsystematic component of RNS for each firm i on day d is given by:

$$RNS_{i,d,Unsystematic} = RNS_{i,d} - RNS_{i,d,Systematic}. \tag{6}$$

We have additionally decomposed RNS into risk-neutral coskewness and idiosyncratic skewness, following the definition of risk-neutral coskewness in Bakshi et al. (2003, p. 114) and the regression decomposition approach of Conrad et al. (2013). This methodology, its limitations and the corresponding results are presented in the Supplementary Appendix.

2.3 Data description and filters

We obtain option data from OptionMetrics. We use daily prices for all OTM options maturing within 10 to 180 days from January 1996 to December 2012. We discard options with zero open interest, zero bid price, negative strike, price less than \$0.50 and non-standard settlement. Moreover, on a given day, we filter out stocks with fewer than two OTM put options and two OTM call options of the same maturity. If more than one maturities are available in OptionMetrics, we use the set of options with the shortest maturity. Closing option prices are calculated as the averages of the closing bid and ask prices. We use the 3-month T-Bill rate from the Federal Reserve H.15 release as a proxy for the risk-free rate. Following Conrad et al. (2013), we exclude stocks with highly illiquid options by discarding those for which RNS values cannot be extracted for at least 10 trading days in a given month. Furthermore, to exclude highly illiquid stocks, we discard those that have less than 750 trading days of non-missing returns in the past 5 years.

Our benchmark portfolio analysis uses as a sorting criterion RNS estimates extracted on the last trading day of each month. This sample of RNS values consists of 128,960 observations. Table 1 presents the descriptive statistics for the option dataset used to compute these RNS values. Their average RNS value is -0.4462 and their average maturity is 86.56 trading days. Most of the OTM options we use are relatively near-the-money and their total trading volume is typically higher than the trading volume of the corresponding ATM options.

-Table 1 here-

2.4 Other firm characteristics

To compute portfolio returns, daily and monthly stock returns and market values are obtained from CRSP. Market value is calculated as the closing share price times the number of shares outstanding. We examine whether the relationship between RNS and stock returns depends on various firm characteristics. The exact definition of these firm characteristics is provided in Appendix C. First, we consider three proxies for relative stock overvaluation: the expected idiosyncratic skewness (EIS^P) of stock returns under the physical measure (see Boyer et al., 2010), the maximum (Max) daily stock return over the previous month (see Bali et al., 2011) and the probability of a stock achieving a Jackpot return (see Conrad et al. 2014). Second, we employ three commonly used proxies for short selling constraints or, more generally, limits-to-arbitrage. In particular, we use the Relative Short Interest (RSI), which reflects investor demand for short selling (see Asquith et al., 2005), and the Estimated Shorting Fee (ESF) measure, proposed by Boehme et al. (2006), that captures the opportunity cost incurred by the short seller. In addition, we use the idiosyncratic volatility of realized stock returns under the physical measure (IVol^P), because arbitrage risk is higher for stocks that exhibit high IVol^P (see Wurgler and Zhuravskaya, 2002).

To examine the relationship between hedging demand and RNS, we use four hedging demand proxies. In particular, we use the ratio of aggregate put options volume to total option volume for a given maturity (see Taylor et al. 2009), and the aggregate open interest across all options for a given maturity (see Hong and Yogo, 2012). Moreover, we follow Acharya et al. (2013) in using the ratio of CEO stock holdings to base salary to proxy for

CEOs' background risk and the Z−score of Zmijewski (1984) to capture firm default risk. As long as managerial risk aversion increases with background risk and the probability of default, these are valid proxies of managerial hedging demand. CEOs' stock holdings and base salaries are sourced from ExecuComp, while annual data items from Compustat are used to calculate the Z−score. We also control for a series of other firm characteristics, such as stock illiquidity (ILLIQ) proxied by Amihud's (2002) price impact ratio, price per share, stock return momentum and reversal, steepness of the implied volatility smile (SKEW), computed as in Xing et al. (2010), and the call-put implied volatility spread, computed as in Bali and Hovakimian (2009).

3 RNS and future stock returns

3.1 RNS portfolio sorts

We firstly form portfolios on the basis of RNS estimates extracted from daily option prices. In particular, on the last trading day of each month t, we sort stocks in ascending order according to their RNS estimates and assign them to quintile portfolios. Table 2 reports the average firm characteristics of the RNS-sorted portfolios. We find that there is a large variation in RNS estimates across firms, rendering it a meaningful sorting criterion. We also find that, on average, the lowest RNS stocks have bigger market values, have performed worse during the past year, they are less illiquid and are traded at higher prices relative to the highest RNS stocks. Moreover, the OTM options used to extract the lowest RNS values are characterized by a significantly higher average total trading volume and total open interest relative to the OTM options used to extract the highest RNS values.

-Table 2 here-

Table 2 also shows that the portfolio of firms exhibiting the lowest RNS values is characterized by lower average EIS^P and Max values relative to the portfolio of firms exhibiting the highest RNS values. This finding implies that low RNS does not mimic other proxies for stock overvaluation. Furthermore, there is no clear-cut conclusion on whether stocks exhibiting the lowest RNS values are, on average, more or less hard to short sell, relative to stocks with the highest RNS values. On one hand, the portfolio with the lowest RNS stocks is characterized by lower average ESF and IVol^P values, but it also exhibits a higher average RSI value, as compared to the portfolio with the highest RNS stocks. Finally, we also find that the lowest RNS stocks exhibit, on average, lower RNV and higher RNK values relative to the highest RNS stocks. We control for all these firm characteristics in the Fama-MacBeth regressions presented below.

Next, we compute the equally-weighted returns of the RNS-sorted quintile portfolios at the end of month $t+1$ (i.e., post-ranking returns). Table 3 reports the average portfolio returns as well as their Fama-French-Carhart alphas (α_{FFC}) estimated from the corresponding 4-factor model. We find that the portfolio of stocks with the lowest RNS values significantly underperforms the portfolio of stocks with the highest RNS values. In particular, a spread strategy that is long the highest RNS quintile portfolio and short the lowest RNS quintile portfolio yields an average return of 61 bps per month (t-stat: 2.24), and α_{FFC} of 55 bps per month (t-stat: 2.47). We also find a monotonic increase in performance as we move from the lowest to the highest RNS portfolio.

-Table 3 here-

Table 3 also reports the loadings (β's) of these portfolios with respect to the excess market (MKT), size (SMB), value (HML) and momentum (MOM) factors using the FFC model. We find that the highest RNS portfolio exhibits significantly higher MKT and SMB beta relative to the lowest RNS portfolio, but it also exhibits significantly lower (and negative) HML beta. Finally, the highest RNS portfolio also exhibits a lower MOM beta, but the difference is negligible in economic terms. Nevertheless, the return spread between the highest and the lowest RNS portfolios cannot be attributed to these differences in factor loadings, and hence it gives rise to an economically and statistically significant alpha. It should be also mentioned that these RNS-sorted portfolios are well diversified, given the average number of stocks (N) per portfolio reported in Table 3.

To ensure that the documented spread is not solely driven by stocks in the extreme ends of the RNS cross-sectional distribution, we calculate the performance of the corresponding spread strategy between the highest and the lowest RNS *tercile* portfolios, i.e., utilizing two-thirds of the RNS distribution. The corresponding results presented in the Supplementary Appendix show that this strategy yields an average return of 52 bps per month (t-stat: 2.30), and α_{FFC} of 47 bps per month (t-stat: 2.58). It should be mentioned that for both tercile and quintile portfolios, this significant spread is mainly driven by the severe underperformance of the portfolios containing the firms with the most negative RNS values (short leg of the strategy). These portfolios yield significant negative alphas of at least -30 bps per month.

We have also examined whether this return spread is affected by nonsynchroneity bias. In line with the argument of Battalio and Schultz (2006), our benchmark portfolio sorting approach may build in a potential nonsynchroneity bias because the stock and option markets do not close simultaneously. Therefore, the option prices recorded in OptionMetrics at the close of the last trading day of the month, and hence the computed RNS, may not be known to investors before the close of the stock market on the same day. To alleviate the concern that our results are driven by this bias, we alternatively calculate portfolio returns using stock prices from the open of the *first* trading day of the *post-ranking month* $t+1$ until the close of the last trading day of the post-ranking month $t+1$.[3] The corresponding results are reported in the Supplementary Appendix. We find that the spread strategy between the highest and the lowest RNS quintile portfolios yields an α_{FFC} equal to 46 bps (t-stat: 2.04). As a result, the documented underperformance of the lowest RNS stocks relative to the highest RNS stocks is genuine and is not driven by nonsynchroneity bias.

[3]We would like to thank an anonymous referee for suggesting this alternative approach.

3.2 Robustness checks

In this subsection, we examine the robustness of our benchmark portfolio results to alternative methodological choices. Table 4 reports the average portfolio returns and α_{FFC} for each of these robustness checks. First, following Dennis and Mayhew (2002) and Conrad et al. (2013), we alternatively compute RNS by using directly the available OTM option prices and applying a trapezoidal rule to compute the integrals that appear in the expressions for $V_t(\tau)$, $W_t(\tau)$ and $X_t(\tau)$. Using this alternative RNS estimate, we sort again stocks into quintile portfolios and calculate their post-ranking performance. As Panel A of Table 4 shows, the portfolio with the highest RNS stocks significantly outperforms the portfolio with the lowest RNS stocks, and the corresponding spread strategy yields an α_{FFC} equal to 49 bps per month (t-stat: 2.81). Again, it is the portfolio with the lowest RNS stocks that yields significant negative risk-adjusted performance. Therefore, our benchmark results are robust to this alternative approach of computing RNS, showing also that the difference between our findings and the results in Conrad et al. (2013) is not due to the method used to calculate RNS.

-Table 4 here-

The second robustness check we carry out is to use the *latest available* daily RNS estimate of the month for each firm as a sorting criterion for portfolio construction, instead of using the RNS estimate on the last trading day of the month as we do in our benchmark results. In this way, we now include stocks that may have been excluded in the benchmark results due to missing RNS on the last trading day of the month. In fact, this approach allows us to include in our sample 100 more stocks, on average, relative to the benchmark case. Panel B of Table 4 shows that the highest RNS stock portfolio still significantly outperforms the lowest RNS stock portfolio and that this spread is mainly driven by the significant negative performance of the latter. The corresponding spread strategy still yields a positive and significant α_{FFC}, equal to 45 bps per month (t-stat: 2.22).

Next, in our attempt to explain why our results differ from the ones reported in Conrad et al. (2013), we alternatively sort firms according to the monthly average value of their daily RNS estimates, instead of using the RNS estimate on the last trading day of the month, as we do in our benchmark results. This is an important modification because daily RNS is considerably time-varying, and hence monthly averages are bound to be very different from the end-of-month daily values.[4] The performance of portfolios constructed on the basis of monthly average RNS values is reported in Panel C of Table 4 and confirms our conjecture. Both the gradient in returns across RNS-sorted portfolios and the spread between the extreme portfolios have now disappeared, yielding no significant pattern. These findings support the argument that the RNS signal used for portfolio sorting should be concurrent with the portfolio formation date. Since daily RNS is considerably time-varying, if it is averaged over long time periods (e.g., over a month or a quarter, as in Conrad et al., 2013), then its signal is blurred and its predictive ability disappears. This is the reason why our results differ from those reported in Conrad et al. (2013).

3.3 Long-term performance of RNS portfolios

We further examine how long it takes the market to correct the mispricing signalled by RNS. To this end, we examine the $t+k$ monthly performance of portfolios constructed on the basis of RNS values on the last trading day of month t. In particular, we compute portfolio returns and alphas during month $t+k$, where $k = 1, 2, ..., 6$. We report these results in the Supplementary Appendix. We find that the spread return between the highest and the lowest RNS stock portfolios is economically and statistically significant only in the first post-ranking month ($t+1$). All of the subsequent $t+k$ monthly returns do not yield any significant spread between the highest and the lowest RNS stock portfolios. These results show that the mispricing signalled by RNS is only temporary, since the market typically corrects it within one month.

[4] In particular, the average AR(1) coefficient of *daily* RNS values across the stocks in our sample is 0.596. This result confirms that RNS is not very persistent if one takes into account that these are daily values. As a benchmark for comparison, the corresponding average AR(1) coefficient of daily RNV values is 0.928.

3.4 Weekly portfolio returns

If the stock mispricing signalled by RNS is temporary, then the post-ranking spread return between the lowest and the highest RNS stock portfolios should be more pronounced under more frequent rebalancing. To test this conjecture, we examine the performance of RNS-sorted portfolios using weekly rebalancing.[5] In particular, we sort stocks into quintile portfolios on the basis of their RNS value estimated on the last trading day of the week and then compute their post-ranking weekly returns. Results are reported in the Supplementary Appendix. Consistent with the argument that RNS signals temporary mispricing, we find that, under weekly rebalancing, the strategy that goes long the quintile portfolio with the highest RNS stocks and short the quintile portfolio with the lowest RNS stocks would yield a strongly significant α_{FFC} of 37 bps *per week* (t-stat: 6.55), which is two-and-a-half times higher than the risk-adjusted return of the same strategy under monthly rebalancing.

We should also note that in the case of weekly portfolio rebalancing, the temporary mispricing information embedded in RNS appears to be more "symmetric". In particular, in this case it is not only the portfolio with the lowest RNS stocks that yields a significantly negative α_{FFC} of -14 bps per week (t-stat: -4.99), but it is also the portfolio with highest RNS stocks that yields a significantly positive α_{FFC} of 24 bps per week (t-stat: 4.71). This finding also leads to the conclusion that a relatively high RNS value may signal stock underpricing, but this effect is far more short-lived than the overpricing signalled by a highly negative RNS value, since it becomes insignificant as we move from weekly to monthly portfolio rebalancing and returns.

3.5 Fama-MacBeth regressions

The previous subsections utilized portfolio sorts to show that stocks exhibiting the lowest RNS values significantly underperform stocks exhibiting the highest RNS values. In this subsection, we further examine how robust is the positive relationship between RNS and

[5] We would like to thank an anonymous referee for this suggestion.

future stock returns using a set of Fama-MacBeth (1973) regressions. In particular, for each month in our sample, we run cross-sectional regressions of excess stock returns on lagged RNS values and a series of other firm characteristics. Table 5 reports the average slope coefficients estimated from these monthly cross-sectional regressions as well as their t-ratios computed using Newey-West standard errors.

Model (1) uses only firms' RNS values as an explanatory variable, documenting a significant positive relationship between RNS and future stock returns. To assess the magnitude of the RNS coefficient, which is equal to 0.0073 (or 0.73% per month), we should bear in mind that the spread in average RNS values between the highest and the lowest quintiles in Table 2 is 0.77. Therefore, the reported RNS coefficient implies that the average return differential between the extreme RNS quintile portfolios should be equal to 56 bps(=0.77*0.0073) per month, which is very close to the spread return reported in Table 3.

Model (2) includes a set of commonly used control variables. In particular, it controls for firms' beta, market value (MV), book-to-market value ratio (B/M), momentum, reversal, stock illiquidity proxied by Amihud's (2002) price impact ratio and price per share. Interestingly, not only the coefficient of RNS remains intact, but it also becomes much more significant in this case. Model (3) additionally controls for RNV and RNK, which are also computed using the model-free methodology of Bakshi et al. (2003). In this case, the magnitude of the RNS coefficient is actually increased relative to the benchmark results, confirming that the relationship between stock returns and RNS is distinct from the relationship between RNV or RNK and stock returns.

-Table 5 here-

The Fama-MacBeth regression coefficient of RNS remains positive and significant even when we additionally control for SKEW in model (4) or the Call-Put Volatility spread in model (5). SKEW is defined as the difference between the implied volatilities of an OTM put and an ATM call option, and hence it is computed on the basis of only two points of the implied volatility curve. On the other hand, RNS takes into account the entire implied volatility curve, and hence its informational content, though related, should be superior to the one of SKEW. A characteristic example is the case of a symmetric implied volatility smile. If this smile is steep, SKEW would be high even though RNS is zero (see also Rehman and Vilkov, 2012). Intuitively, and crucially for the trading mechanism that we propose, RNS captures the expensiveness of OTM puts *relative* to the expensiveness of OTM calls. In particular, we argue that the degree of *relative* expensiveness between OTM puts and calls contains information regarding future stock returns. On the other hand, SKEW ignores the right-hand side of the implied volatility curve, and hence it does not contain any information regarding the relative expensiveness between OTM puts and calls. Similarly, the Call-Put Volatility spread is computed as the difference between the implied volatilities of ATM and very near-the-money put and call options. As a result, it cannot contain either any information regarding the relative expensiveness between OTM puts and calls. This is why neither SKEW nor the Call-Put Volatility spread subsume the significant relationship between RNS and future stock returns.

The coefficient of RNS remains positive and significant also when we include as control variables the total trading volume or open interest of options used to compute RNS in models (6) and (7), respectively. To further examine whether the positive relationship between excess stock returns and RNS is affected by option illiquidity, in model (8) we exclude firm-month observations if the total trading volume of OTM options used to compute RNS is less than half of the total trading volume of all options (i.e., including ATM options). Similarly, in model (9) we exclude firm-month observations if the total open interest of OTM options used to compute RNS is in the lowest 20% of the corresponding cross-sectional distribution on the last trading day of the month. In both cases, the RNS coefficient remains strongly significant and its magnitude is very similar to the one reported in the benchmark results.

Another issue worth examining is whether the short sale ban imposed by SEC and exchanges during September-October 2008 had an effect on the relationship between excess stock returns and RNS.[6] This issue is particularly important because our conjectured mech-

[6] We would like to thank an anonymous referee for suggesting this analysis.

anism to explain this relationship assigns an important role to short selling constraints.[7] To this end, in model (10), we compute Fama-MacBeth regression coefficients excluding the observations of September and October 2008. Moreover, in model (11) we truncate our sample in August 2008 to ensure that the documented relationship is not driven by the turbulent market period during and after the short sale ban or by investors' perception that a short sale ban could be re-imposed even after the initial ban was lifted. In both cases, the results show that the coefficient of RNS remains positive and highly significant even when we exclude the corresponding sample periods. If anything, the magnitude of the RNS coefficient is higher for the pre-August 2008 period.

Finally, we examine whether this relationship was stronger for the firms that were subject to the short sale ban.[8] We interact RNS with a dummy variable (*Short sale ban dummy*) that takes the value 1 for the firms in the short sale ban list during the period September-October 2008, and zero otherwise. We add this interaction variable (RNS*Short sale ban dummy) to our benchmark model (2). Since this interaction variable takes non-zero values only during the two months of the short sale ban period, we cannot estimate such a model using a Fama-MacBeth regression. A feasible alternative is to estimate a panel regression with time fixed effects (month dummies). Results are reported under model (13) in Table 5 and they should be compared with the results of the fixed effects model (12) that does not include the interaction term. In line with our conjectured trading mechanism, we find that the relationship between RNS and stock returns was stronger for firms that were subject to the short sale ban, since the coefficient of the interaction term is positive and equal to 0.0112 (or 1.12% per month). However, this coefficient is found to be statistically insignificant.[9]

[7] Nishiotis and Rompolis (2011) find a significant increase in the magnitude of put-call parity violations during the short sale ban period and show that these violations had significant predictive ability over subsequent stock returns.

[8] We would like to thank George Nishiotis for providing us with the list of firms that were subject to the short sale ban. See also: http://www.sec.gov/rules/other/2008/34-58592.pdf

[9] In unreported results, we have alternatively estimated a pooled OLS regression including this interaction term. In this case, the coefficient of the interaction term is positive (0.1539) and highly significant (t-stat=11.50). However, this estimation approach ignores the time effect that is obviously present, since the regression residuals in a given month are correlated across stocks. Therefore, as Petersen (2009) convincingly shows, this t-statistic is considerably inflated because the standard errors are massively underestimated.

3.6 Systematic and Unsystematic RNS portfolio sorts

In Section 2.2 we described how RNS can be decomposed into its systematic and unsystematic components. Here, we examine which of these two components drives the positive relationship between excess stock returns and RNS. To this end, we use each of these two components' estimates computed on the last trading day of month t to sort stocks in ascending order and form quintile portfolios. Table 6 presents the performance of these portfolios in terms of raw returns and α_{FFC}.

-Table 6 here-

The results reported in Panel A show that there is no clear gradient in performance as we move from the portfolio with the lowest systematic RNS stocks to the portfolio with the highest systematic RNS stocks. Nevertheless, the spread strategy that is long the quintile portfolio with the highest systematic RNS stocks and short the quintile portfolio with the lowest systematic RNS stocks yields a significantly *negative* α_{FFC} that is equal to -72 bps per month (t-stat: -2.48). This significant spread is driven by the severe underperformance of the quintile portfolio containing the stocks with the highest systematic RNS values.

On the other hand, the results in Panel B reveal a clear gradient in performance as we move from the portfolio with the lowest unsystematic RNS stocks to the portfolio with the highest unsystematic RNS stocks. Moreover, the spread strategy that is long the quintile portfolio with the highest unsystematic RNS stocks and short the quintile portfolio with the lowest unsystematic RNS stocks yields a significantly *positive* α_{FFC} that is equal to 55 bps per month (t-stat: 2.16). This significant spread is mainly driven by the severe underperformance of the portfolio containing the stocks with the lowest unsystematic RNS values.

These results show that the performance patterns of the total RNS-sorted portfolios that we reported in Table 3 are resembled only by the *unsystematic* RNS-sorted portfolios. This finding is also corroborated by the average total RNS values of systematic and unsystematic RNS-sorted portfolios. In particular, the gradient of average total RNS values is much steeper in the case of unsystematic RNS-sorted portfolios (Panel B) than in the case of systematic RNS-sorted portfolios (Panel A). Taken together, these results suggest that it is the unsystematic component of RNS that drives the positive relationship between total RNS and future stock returns.

To compute systematic RNS values, we used in equation (5) stocks' risk-neutral betas that are estimated as in Bali et al. (2014). In a robustness check presented in the Supplementary Appendix, we alternatively use betas estimated under the physical measure to perform this decomposition and repeat the previous analysis. The corresponding results are very similar to the ones presented above and confirm our main conclusion that it is the unsystematic component of RNS that drives the positive relationship between total RNS and future stock returns.

We have additionally performed a decomposition of RNS into risk-neutral coskewness and idiosyncratic skewness, using the definition of risk-neutral coskewness of Bakshi et al. (2003, p. 114) and the regression decompositon of Conrad et al. (2013). We report the performance of stock portfolios constructed on the basis of risk-neutral coskewness and idiosyncratic RNS estimates in the Supplementary Appendix. We find that the spread strategy that goes long the quintile portfolio with the highest risk-neutral coskewness stocks and short the quintile portfolio with the lowest risk-neutral coskewness stocks yields a significant *negative* α_{FFC} that is equal to -72 bps per month (t-stat: -2.48). This significant alpha is driven by the severe underperformance of the portfolio containing the stocks with the highest risk-neutral coskewness values. These results indicate a negative relationship between risk-neutral coskewness and post-ranking portfolio returns, resembling the finding of Harvey and Siddique (2000) for coskewness estimated under the physical measure.

On the other hand, the spread strategy that is long the quintile portfolio with the highest idiosyncratic RNS stocks and short the quintile portfolio with the lowest idiosyncratic RNS stocks yields a *positive* α_{FFC} that is equal to 40 bps per month (t-stat: 1.81). This alpha is mostly driven by the significant underperformance of the quintile portfolio containing the stocks with the lowest idiosyncratic RNS values.

4 Which highly negative RNS stocks subsequently underperform?

4.1 Conjectured trading mechanism

In this section, we examine the sources of the positive relationship between RNS and future stock returns that we documented in Section 3. To understand this relationship, we draw insights from the evidence provided in Bollen and Whaley (2004), and the demand-based option pricing framework of Garleanu et al. (2009).

In particular, the trading mechanism we put forward and subsequently test assumes that some pessimistic investors perceive certain stocks as relatively overvalued. Some of these overvalued stocks are also too costly or too risky to sell short. As a result, in line with Miller (1977), short selling constraints hinder the price mechanism from reflecting these investors' beliefs. Therefore, these investors resort to the option market, buying OTM puts, selling OTM calls or creating synthetic short positions on these potentially overvalued stocks in order to hedge their underlying positions and/or speculate on their pessimistic expectations. Since risk-averse market makers cannot perfectly hedge their options positions in the stock market due to the short selling constraints, this hedging demand drives up (down) prices for OTM puts (calls), leading to a highly negative RNS in the option-implied distribution (see Garleanu et al., 2009). In this way, option prices contain information that it is not already embedded in stock prices, consistent with the sequential trade model of Easley et al. (1998) and the noisy rational expectations model of An et al. (2014). As this mispricing information is subsequently diffused to the stock market, relatively overpriced stocks may yield negative returns, giving rise to a positive relationship between RNS and future realized stock returns.

For this conjectured mechanism to be valid, four conditions are necessary to hold: First, stocks characterized by higher hedging demand should exhibit more negative RNS values; otherwise the demand-based arguments of Bollen and Whaley (2004) and Garleanu et al.

(2009) would not hold. Second, the underperformance of the portfolio with the lowest RNS stocks should be driven by those stocks that are also perceived as relatively overpriced; if there is no perceived overpricing, then there are no pessimistic beliefs to be traded in the option market, and hence RNS cannot contain any mispricing information. Third, the underperformance of the portfolio with the lowest RNS stocks should be driven by those stocks that are also too hard to sell short; otherwise, either investors would not need to resort to the option market in the first place or, if they do, their trades would not affect option prices because market makers would be able to hedge their positions in the stock market. Fourth, since overvaluation and short selling constraints are necessary conditions for low RNS stocks to subsequently underperform, then stocks that exhibit all three characteristics should subsequently yield the most negative performance. The following subsections test, in turn, the validity of each of these conditions.

4.2 Investor hedging demand and RNS

We first test whether the stocks characterized by high investor hedging demand exhibit relatively lower RNS values. We use four proxies for investor hedging demand defined in Appendix C: the ratio of aggregate put options volume to all options volume (see Taylor et al. 2009), the aggregate open interest across all options (see Hong and Yogo, 2012), and, following Acharya et al. (2013), the ratio of CEO stock holdings to base salary and the Z−score of Zmijewski (1984) that captures default risk. Using each of these hedging demand proxies, we sort the stocks in our sample into quintile portfolios and calculate their median RNS values. Table 7 shows the time-series averages of these median RNS estimates for the quintile portfolios of stocks characterized by the highest and the lowest investor hedging demand, respectively. We find that for all four proxies, the portfolio of stocks exhibiting the highest hedging demand has significantly lower median RNS values in comparison to the portfolio of stocks exhibiting the lowest hedging demand.

-Table 7 here-

4.3 The role of relative overvaluation

The second necessary condition for the conjectured trading mechanism to hold is that the underperformance of the most negative RNS portfolio is driven by those stocks that are also perceived by some investors to be relatively overpriced.[10] We use three proxies for relative overvaluation: the maximum daily stock return in the previous month (Max, see Bali et al., 2011), Expected Idiosyncratic Skewness under the physical measure (EIS^P, see Boyer et al., 2010), and the probability of a Jackpot return (see Conrad et al., 2014). High values for each of these proxies have been shown to capture relative stock overpricing either because market participants are too optimistic regarding stocks' growth prospects or because they have a strong preference for their lottery-like payoff structure. To test this implication of the conjectured trading mechanism, we construct bivariate conditional portfolios. In particular, we sort stocks into tercile portfolios according to their RNS estimates on the last trading day of each month t and then, within each of these tercile RNS portfolios, we further sort stocks into tercile portfolios according to each of the overvaluation proxies. This conditional sorting approach yields nine portfolios, whose equally-weighted returns we calculate at the end of month $t+1$.

Table 8 reports the Fama-French alpha (α_{FF}) of these portfolios.[11] Regardless of the overvaluation proxy used, we find that the underperformance of the most negative RNS portfolio is driven by the stocks that are classified in the most overpriced tercile. In particular, portfolios of stocks with the highest Max return, EIS^P and Jackpot probability within the most negative RNS tercile yield significant negative alphas of at least -58 bps per month. To the contrary, the corresponding portfolios of stocks exhibiting the lowest values for these overvaluation proxies yield alphas that are not significantly different from zero.

[10] It should be stressed that, as the descriptive statistics of RNS-sorted portfolios reported in Table 2 show, low RNS per se does not typically indicate stock overvaluation, as captured by the proxies that we use in this study. Similarly, stocks that exhibit high values of these overvaluation metrics do not necessarily exhibit low RNS values. For example, in the absence of short selling constraints and other limits-to-arbitrage, if investors perceived a stock to be relatively overvalued, they could hedge themselves in the option market without substantially moving option prices (and hence RNS) because option market makers could hedge their positions in the stock market.

[11] Fama-French-Carhart alphas yield results very similar to the ones presented here and they are readily available upon request.

Moreover, the spread return between the portfolio with the most and the portfolio with the least overpriced stocks within the most negative RNS tercile is significant for all four proxies. Hence, we confirm that the underperformance of the most negative RNS portfolio is driven by the relatively overpriced stocks. In other words, not all stocks with highly negative RNS values underperform, confirming that low RNS per se is not a sufficient condition for stock underperformance, and hence it cannot be considered as another proxy for overvaluation.

-Table 8 here-

Next, to show that neither relative overvaluation is a sufficient condition for subsequent stock underperformance, but that it is the interplay between low RNS and overvaluation that yields the subsequent underperformance, we reverse the order of the bivariate conditional portfolio sorts. In particular, we now first sort stocks into tercile portfolios according to each of the overvaluation proxies, and then within each of these tercile portfolios, we further sort stocks into tercile portfolios according to their RNS values. The post-ranking performance of these bivariate conditional portfolios is presented in Table 9. We find that among the most overvalued stocks, it is the portfolio that contains the lowest RNS stocks that yields the most significant underperformance. This is true for all three overvaluation proxies. To the contrary, among the most overvalued stocks, the portfolio that contains the highest RNS stocks does not significantly underperform.

-Table 9 here-

4.4 The role of short selling constraints

The third necessary condition for the conjectured trading mechanism to hold is that the underperformance of the most negative RNS portfolio is driven by those stocks that are also too costly or too risky to sell short. We use three proxies to capture short selling constraints: Estimated Shorting Fee (see Boehme et al., 2006), Relative Short Interest (see Asquith et al., 2005), and Idiosyncratic Volatility under the physical measure (IVol^P, see

Wurgler and Zhuravskaya, 2002). High values for these proxies typically reflect severe short selling constraints. To test our conjecture, we construct bivariate conditional porrtfolios. In particular, we sort stocks into tercile portfolios according to their RNS estimates on the last trading day of each month t and then within each of these tercile portfolios we further sort stocks into terciles according to each of the short selling constraints proxies. This conditional sorting approach yields nine portfolios, whose equally-weighted returns we calculate at the end of month $t + 1$.

Table 10 reports the risk-adjusted performance (α_{FF}) of these portfolios. Regardless of the short selling constraints proxy used, we find that the underperformance of the most negative RNS portfolio is driven by the stocks that are classified in the tercile with the most severe short selling constraints. In particular, portfolios of stocks with the highest ESF, RSI and IVol^P values within the most negative RNS tercile yield significant negative alphas of at least -64 bps per month. To the contrary, none of the portfolios with the least short selling constrained stocks exhibits significant negative alphas. Finally, within the most negative RNS tercile, the spread return between the portfolio with the most short selling constrained stocks and the portfolio with the least short selling constrained stocks is highly significant. Hence, we confirm that the underperformance of the most negative RNS portfolio is almost exclusively driven by those stocks that are also too costly or too risky to sell short.

-Table 10 here-

Moreover, we argue that severe short selling constraints alone do not necessarily lead to subsequent stock underperformance. For example, in the case where the underlying stock is not perceived to be overpriced in the first place, there is no incentive for investors to resort to the option market to trade and drive RNS to lower values, so the presence of short selling constraints is not associated with subsequent stock underperformance. To show that it is the interplay between low RNS and short selling constraints that signals the subsequent underperformance, we reverse the order of the bivariate conditional portfolio sorts. In particular, we now firstly sort stocks into tercile portfolios according to each of the three short selling constraints proxies, and then within each of these tercile portfolios, we further sort stocks into tercile portfolios according to their RNS values. The post-ranking performance of these bivariate conditional portfolios is presented in Table 11. We find that among the most hard to sell short stocks, it is mainly the portfolio that contains the lowest RNS stocks that yields the most significant underperformance. This is true for all three proxies for short selling constraints. To the contrary, among the most hard to sell short stocks, the portfolio that contains the highest RNS stocks does not significantly underperform.[12]

-Table 11 here-

4.5 Trivariate independent portfolio sorts

The trading mechanism we described in Section 4.1 states that relative stock overvaluation and short selling constraints are necessary conditions for low RNS stocks to subsequently underperform. A direct implication of this mechanism is that those stocks which meet all these three conditions should exhibit the most negative risk-adjusted returns. To test the empirical validity of this implication, we construct trivariate portfolios. To this end, we independently sort stocks on the last trading day of each month according to *i*) their RNS value, *ii*) their overvaluation proxy value, and *iii*) their short selling constraints proxy value, and we classify them as high (H) or low (L) relative to the corresponding median value. The intersection of these three independent classifications yields eight (2x2x2) portfolios. Since we use three alternative proxies for overvaluation and three alternative proxies for short selling constraints, we end up with nine different cases. The risk-adjusted performance of

[12] Another friction that can prevent investors from selling (short) stocks that are perceived to be relatively overpriced is illiquidity. According to the proposed mechanism, the underperformance of the most negative RNS stocks should be more pronounced for stocks that are also highly illiquid. To test this conjecture, we firstly sort stocks into tercile portfolios on the basis of their RNS values and then, within each tercile RNS portfolio, we further sort stocks according to their degree of illiquidity, proxied by Amihud's (2002) price impact ratio (ILLIQ). Consistent with our conjecture, the results reported in the Supplementary Appendix show that the underperformance of the portfolio with the lowest RNS stocks is mainly driven by those stocks that are also highly illiquid. On the other hand, the lowest RNS stocks that are relatively liquid do not yield significant negative risk-adjusted returns. The spread between the most and the least illiquid stocks within the lowest RNS tercile portfolio yields an α_{FF} equal to -55 bps per month (t-stat: -2.23).

these portfolios for each case is reported in Table 12.

-Table 12 here-

The reported results convincingly show that the portfolio of stocks that combine high short selling constraints, high overvaluation, and low RNS (Portfolio P4) yields the most severe underperformance. This finding is consistent across all nine cases that we examine. For most of the cases, this portfolio yields significant negative α_{FF} of at least -60 bps per month. To the contrary, even if only one of these three conditions is not met, portfolio alphas are typically found to be insignificantly different from zero. Taken together, the evidence from the trivariate independently sorted portfolios strongly supports our conjectured trading mechanism, showing that it is the interplay between low RNS, high short selling constraints and overvaluation that leads to significant stock underperformance.

These results also point to the conclusion that the portfolio of stocks that combine relatively high RNS, low overvaluation, and loose short selling constraints (Portfolio P5) subsequently outperform. The explanation for this finding is based on the observation that in the absence of short selling constraints, stocks' downside risk is higher than in the presence of severe short selling constraints (see Grullon et al., 2015). As a result, the safest way for investors to trade their optimistic beliefs for those stocks that are perceived to be relatively undervalued but are also characterized by high downside risk is to purchase OTM calls rather than directly buy and hold the potentially undervalued stock. This demand for OTM calls drives up their price and renders the implied volatility curve less negatively (or more positively) sloped, i.e., it drives up RNS. In this way, a relatively high RNS value for stocks that are perceived to be relatively undervalued but are characterized by high downside risk due to the absence of short selling constraints can incorporate underpricing information, and hence signal subsequent outperformance.

On the other hand, for the potentially undervalued stocks that are characterized by severe short selling constraints, and hence their downside risk is much more limited, the incentive for optimistic investors to resort to the option market is weaker. If downside risk is limited, these investors would be more willing to directly buy and hold the potentially undervalued stock, correcting this mispricing. This mechanism explains the finding for Portfolio P6 in Table 12 that in the presence of high short selling constraints, a relatively high RNS value does not signal subsequent outperformance even though the stock may be perceived as relatively undervalued.

5 Conclusion

This study contributes to the ongoing debate regarding the sign of the relationship between the option-implied risk-neutral skewness (RNS) of individual stock returns' distribution and future realized stock returns (see Rehman and Vilkov, 2012, Conrad et al., 2013, and Bali et al., 2014). In particular, we document a significant positive relationship between RNS and future stock returns during the period 1996-2012. This relationship is remarkably robust once we account for various firm characteristics that have been shown to predict future stock returns. To quantify the magnitude of the RNS-related premium, we sort stocks according to their RNS estimates on the last trading day of each month, assign them to portfolios and calculate their post-ranking monthly returns. A strategy that is long the quintile portfolio with the highest RNS stocks and short the quintile portfolio with the lowest RNS stocks yields an average return of 61 bps (*t-stat*: 2.24) per month, and Fama-French-Carhart alpha of 55 bps (*t-stat*: 2.47) per month. Decomposing RNS into its systematic and unsystematic components, we find that the latter drives the positive relationship between RNS and future stock returns.

To explain this positive relationship, we put forward a mechanism assuming that some investors perceive certain stocks as relatively overpriced. For those stocks that are also too costly or too risky to sell short, this overvaluation cannot be immediately corrected (see Miller, 1977), and hence investors resort to the option market buying OTM puts, selling OTM calls and/or constructing synthetic short positions on these stocks in order to hedge their underlying positions or speculate on their pessimistic expectations. Since risk-averse market makers cannot fully hedge their options positions in the stock market due to the short selling constraints, this hedging demand drives up (down) prices for OTM puts (calls), leading to a highly negative RNS in the option-implied distribution (see Garleanu et al., 2009). In this way, option prices may contain information that it is not already embedded in stock prices, consistent with the sequential trade model of Easley et al. (1998) and the noisy rational expectations model of An et al. (2014). As this mispricing information is diffused to the stock market over time, these relatively overpriced stocks with very low RNS values subsequently underperform, giving rise to a positive relationship between RNS and future realized stock returns.

In fact, our empirical tests confirm the validity of the mechanism described above. First, stocks characterized by higher hedging demand exhibit, on average, more negative RNS values. Second, the underperformance of the portfolio with the lowest RNS stocks is driven by those stocks that are also characterized as relatively overpriced. Third, the underperformance of the portfolio with the lowest RNS stocks is driven by those stocks that are also too costly or too risky to sell short. In conclusion, low RNS is a necessary but not sufficient condition for future stock underperformance. It is the *combination* of low RNS, relative overpricing and short selling constraints that yields stock underperformance.

Appendix A. Risk-Neutral Moments

This Appendix presents the formulae for Risk-Neutral Moments following Bakshi and Madan (2000) and Bakshi et al. (2003). Bakshi and Madan (2000) prove that any payoff function $H(S)$ that is twice continuously differentiable with respect to stock price S can be spanned by a portfolio of zero-coupon bond, stock, and a continuum of OTM options as follows:

$$\begin{aligned} E^{Q}\left[\exp\left(-r\tau\right)H\left(S\right)\right] &= \left(H\left(\bar{S}\right)-\bar{S}H_{S}\left(\bar{S}\right)\right)\exp\left(-r\tau\right)+H_{S}\left(\bar{S}\right)S+ \\ &+\int_{\bar{S}}^{\infty}H_{SS}\left(K\right)C\left(t,\tau;K\right)dK+\int_{0}^{\bar{S}}H_{SS}\left(K\right)P\left(t,\tau;K\right)dK \end{aligned} \quad (7)$$

where $H_S\left(\bar{S}\right)$ denotes the first-order derivative of the payoff function evaluated at a given $\bar{S}$ and $H_{SS}\left(K\right)$ denotes the second-order derivative of the payoff function evaluated at K.

Bakshi et al. (2003) define the payoff of the $\tau-$maturity quadratic, cubic and quartic contract, respectively, as:

$$H(S)=\left\{\begin{array}{lr} R(t,\tau)^{2}, & \text{quadratic contract} \\ R(t,\tau)^{3}, & \text{cubic contract} \\ R(t,\tau)^{4}, & \text{quartic contract} \end{array}\right\}, \quad (8)$$

where $R\left(t,\tau\right)=\log\left(S\left(t+\tau\right)\right)-\log\left(S\left(t\right)\right)$ is the $\tau-$period log stock return. These contracts are essentially contingent claims with payoffs equal to the second, third and fourth power of the log stock return, respectively. Based on the spanning result in (7), Bakshi et al. (2003) show that Risk-Neutral Variance (RNV), Skewness (RNS) and Kurtosis (RNK) are given by equations (1), (2) and (3), respectively, where $V_t\left(\tau\right)$, $W_t\left(\tau\right)$ and $X_t\left(\tau\right)$ denote the time t prices of the quadratic, cubic and quartic contracts and they are given by:

$$V_{t}\left(\tau\right)=\int_{S_{t}}^{\infty}\frac{2\left(1-\log\left(\frac{K}{S_{t}}\right)\right)}{K^{2}}C_{t}\left(\tau;K\right)dK+\int_{0}^{S_{t}}\frac{2\left(1+\log\left(\frac{S_{t}}{K}\right)\right)}{K^{2}}P_{t}\left(\tau;K\right)dK \quad (9)$$

$$W_t(\tau) = \int_{S_t}^{\infty} \frac{6\log\left(\frac{K}{S_t}\right) - 3\left(\log\left(\frac{K}{S_t}\right)\right)^2}{K^2} C_t(\tau;K)\,dK - \\ - \int_0^{S_t} \frac{6\log\left(\frac{S_t}{K}\right) + 3\left(\log\left(\frac{S_t}{K}\right)\right)^2}{K^2} P_t(\tau;K)\,dK \tag{10}$$

$$X_t(\tau) = \int_{S_t}^{\infty} \frac{12\left(\log\left(\frac{K}{S_t}\right)\right)^2 - 4\left(\log\left(\frac{K}{S_t}\right)\right)^3}{K^2} C_t(\tau;K) + \\ + \int_0^{S_t} \frac{12\left(\log\left(\frac{S_t}{K}\right)\right)^2 + 4\left(\log\left(\frac{S_t}{K}\right)\right)^3}{K^2} P_t(\tau;K)\,dK \tag{11}$$

Appendix B. Simpson's rule

Simpson's rule uses quadratic polynomials to approximate the value of a definite integral. Consider the definite integral $\int_a^b f(x)dx$, where $f(x)$ is continuous on $[a,b]$. Defining the step length $h = (b-a)/n$ and $x_j = a + jh$ for $j = 0, 1, ..., n$, Simpson's rule approximate this integral by:

$$\int_a^b f(x)dx \approx \frac{h}{3}\left[f(x_0) + 4f(x_1) + 2f(x_2) + 4f(x_3) + ... + 2f(x_{n-2}) + 4f(x_{n-1}) + f(x_n)\right].$$

Simpson's rule converges to the value of the definite integral at a much faster rate relative to the trapezoidal rule. Define the error of the numerical integration as the absolute difference between the value of the definite integral and the result of numerical integration. If the domain of integration consists of n grid points, then as $n \to \infty$, the error decays at the rate n^4 under Simpson's rule, while it decays at the rate n^2 under the trapezoidal rule (see Section 5.1 in Atkinson, 1989).

Appendix C. Definitions of Variables

This Appendix presents in alphabetical order the definitions of the variables used in the study.

Call-Put Volatility Spread

Following Bali and Hovakimian (2009), the Call-Put Volatility spread is calculated as the difference between the implied volatilities of ATM and very near-the-money call and put options.

CEO Stock Holdings

Following Acharya et al. (2013), the ratio of CEO stock holdings to base salary for firm i is calculated as the number of shares owned by firm's CEO times the share price and divided by the CEO salary. In terms of ExecuComp and Compustat data items, the ratio is given by:

$$CEO = \frac{PRCC\_F \text{ x } SHROWN\_EXCL\_OPTS}{SALARY} \tag{12}$$

We use December values of year $y-1$ for the period from June of year y until May of year $y+1$.

Default risk

Following Acharya et al. (2013), we measure the default risk of firm i, using the Zmijewski (1984) $Z-$score, which is a weighted index of firm's ratios of net income (NI) to total assets (AT), total debt (LT) to total assets and current assets (ACT) to current liabilities (LCT). In terms of Compustat data items, the $Z-$score is computed as:

$$Z = -4.3 - 4.5\frac{NI}{AT} + 5.7\frac{LT}{AT} - 0.004\frac{ACT}{LCT} \tag{13}$$

We use December values of year $y-1$ for the period from June of year y until May of year $y+1$.

Estimated Shorting Fee (ESF)

To compute the ESF for firm i, we use the fitted regression model of Boehme et al. (2006):

$$\begin{aligned} Fee &= 0.07834 + 0.05438VRSI - 0.00664VRSI^2 + 0.000382VRSI^3 - 0.5908Option + \\ &\quad 0.2587Option \cdot VRSI - 0.02713Option \cdot VRSI^2 + 0.0007583Option \cdot VRSI^3 \end{aligned} \tag{14}$$

where RSI is the relative short interest and $VRSI$ is the vicile rank of RSI (i.e., it takes the value 1 if the firm's RSI is below the 5th percentile of all firms' RSI distribution, 2 if the firm is between the 5th and 10th percentile, etc.). We obtain the short interest data from Compustat. *Option* is a dummy variable that takes the value 1 if there is non-zero trading volume for the firms' options in the month and 0 otherwise. Trading volume data for options are sourced from OptionMetrics.

Expected idiosyncratic skewness under the physical measure (EIS^P)

Following Boyer et al. (2010), to estimate EIS^P for firm i in month t, we use the fitted part of the following regression model:

$$\begin{aligned} ISkew^P_{i,t} &= \gamma_0 + \gamma_1 ISkew^P_{i,t-60} + \gamma_2 IVol^P_{i,t-60} + \gamma_3 Mom_{i,t-60} + \gamma_4 Turn_{i,t-60} + \\ &\quad + \gamma_5 NASD_{i,t-60} + \gamma_6 Small_{i,t-60} + \gamma_7 Med_{i,t-60} + \Gamma Ind_{i,t-60} + \varepsilon_{i,t} \end{aligned} \tag{15}$$

This cross-sectional regression is estimated every month. $ISkew^P_{i,t}$ and $IVol^P_{i,t}$ denote, respectively, the idiosyncratic skewness and idiosyncratic volatility for firm i under the physical measure, computed from daily firm-level residuals of the Fama and French (1993) three-factor model over the past 60 months. Mom_t denotes the cumulative stock return from month $t-12$ to month $t-1$. $Turn$ is the average monthly turnover in the past year calculated as the trading volume divided by the number of shares outstanding. Trading volume and number of shares outstanding are both obtained from CRSP. To calculate average monthly turnover, 5 valid monthly observations are required in each year. NASDAQ volume is adjusted for the double counting following Gao and Ritter (2010): NASDAQ volume is divided by 2 for the period from 1983 to January 2001, by 1.8 for the rest of 2001, by 1.6 for 2002-2003, and is unchanged from January 2004 to December 2012. $NASD$ is NASDAQ dummy: it takes the value 1 if the firm is listed on NASDAQ and 0 otherwise. $Small$ is a small firms dummy: it takes the value 1 if the firm is in the bottom three size deciles and 0 otherwise. Med is a medium firms dummy: it takes the value 1 if the firm is in one of the size deciles between the fourth and the seventh and 0 otherwise. Ind are a series of industry classification dummies. Each takes the value 1 if the firm belongs to a certain industry and 0 otherwise. We use the 30 industry classifications of Fama and French (1997).

Idiosyncratic volatility under the physical measure (IVol^P)

$IVol_{i,t}^P$ for firm i in month t is computed as:

$$IVol_{i,t}^P = \left(\frac{1}{N(d)-1} \sum_{d \in D} \varepsilon_{i,d}^2 \right)^{1/2} \tag{16}$$

where $\varepsilon_{i,d}$ is the daily firm-level residual of the Fama and French (1993) three-factor model regression over the past 60 months, D is the set of non-missing daily returns in the past 60 months and $N(d)$ denotes the number of days in D. We require at least 15 observations in the past 60 months to compute $IVol_{i,t}^P$.

Idiosyncratic skewness under the physical measure (ISkew^P)

Following Boyer et al. (2010), $ISkew_{i,t}^P$ for firm i in month t is computed as:

$$ISkew_{i,t}^P = \frac{1}{(N(d)-2)} \frac{\sum_{t \in D} \varepsilon_{i,d}^3}{\left(IVol_{i,t}^P\right)^3} \tag{17}$$

where $\varepsilon_{i,d}$ is the daily firm-level residual of the Fama and French (1993) three-factor model regression over the past 60 months, D is the set of non-missing daily returns in the past 60 months and $N(d)$ denotes the number of days in D. We require at least 15 observations in the past 60 months to compute $ISkew^P_{i,t}$.

Maximum daily return (Max)

Max for firm i in month t is the highest daily stock return during the previous month $t-1$.

Momentum

$Momentum$ for firm i in month t is defined as its cumulative stock return from month $t-12$ to month $t-1$.

Open interest

Open interest for firm i is calculated as the sum of open interest across all put and call options for a given maturity on a given trading day. The options used to compute the aggregate open interest have the same maturity as the options used to estimate RNS.

Probability of a firm achieving a jackpot return (Jackpot)

A *Jackpot* return is defined as a log return greater than 100%. To compute the probability of a firm achieving a jackpot return over the next year, we use the fitted regression model of Conrad et al. (2014):

$$Jackpot = \frac{\exp(\hat{y})}{1+\exp(\hat{y})}, \quad \text{where} \tag{18}$$

$$\begin{aligned} \hat{y} &= -3.29 + 0.06SKEW^P + 0.18RET12 - 0.02AGE - 0.25TANG \\ &\quad +0.29SALEGRTH - 0.43TURN + 0.99STDEV - 0.22SIZE. \end{aligned} \tag{19}$$

SKEW^P denotes the skewness of daily log stock returns in the past 3 months and RET12 is the log return in the past year. AGE is the number of years since the stock first appeared on CRSP and TANG is the asset tangibility, which is defined as the gross value of property, plant, and equipment divided by total assets ($TANG = PPEGT/AT$). SALESGRTH denotes the sales growth during the last year. For asset tangibility and sales growth, we use December values of year $y-1$ during the period from June of year y to May of year $y+1$. TURN is the average monthly turnover in the past 6 months minus the average monthly turnover in the past 18 months. STDEV denotes the volatility of daily returns in the past 3 months and SIZE is the logarithm of market value measured in millions.

Put-to-All Options Volume ratio

The *Put-to-All Options Volume ratio* on a given trading day is the ratio of the total volume across all put options for a given maturity using all available strikes divided by the total volume across all put and call options for the same maturity using again all available strikes. The options used to calculate these volumes have the same maturity as the corresponding options used to estimate RNS.

Relative Short Interest (RSI)

RSI is defined as the outstanding shorts reported by NYSE and NASDAQ divided by the number of shares outstanding. Outstanding shorts are sourced from CRSP.

Reversal

$Reversal$ for firm i in month t is given by its monthly return in the previous month $t-1$.

SKEW

Following Xing et al. (2010), $SKEW$ is defined as the difference between the implied volatilities of an OTM put option and an ATM call option.

Stock Illiqudity (ILLIQ)

We use Amihud's (2002) price impact ratio to proxy for stock illiquidity. In particular, this price impact ratio for stock i over a year y is defined as:

$$ILLIQ_{i,y} = \frac{\sum_{d=1}^{Di,y} |R_{i,d}| / VOLD_{i,d}}{D_{i,y}}$$

where $|R_{i,d}|$ is the absolute daily return of stock i on day d, $VOLD_{i,d}$ is the dollar trading volume of stock i on day d, and $D_{i,y}$ is the number of trading days during year y. We compute $ILLIQ_{i,y}$ using a 12-month rolling window.

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Table 1: Descriptive Statistics for OTM options used to compute Risk-Neutral Skewness

This Table shows the descriptive statistics for the out-of-the-money (OTM) call and put options used to compute Risk-Neutral Skewness (RNS) estimates of individual stock returns' distributions on the last trading day of each month during the period 1996-2012. Moneyness denotes the ratio of the underlying stock price to the strike price of the OTM call and put option, respectively. The open interest and trading volume per OTM option used to compute RNS are measured in thousands of contracts. The last row shows the ratio of total trading volume for the OTM options used to compute RNS on a given trading day and a given expiry date relative to the total trading volume of all options available on the same trading day with the same expiry date.

	Mean	Median	5th pctl	95th pctl	St. Dev.
RNS	-0.4462	-0.4175	-1.0261	0.0197	0.3378
Days to expiration for OTM options	86.56	81	18	169	46.77
Moneyness of OTM call options	0.8958	0.9155	0.7333	0.9925	0.0846
Moneyness of OTM put options	1.1424	1.1048	1.0092	1.3972	0.1346
No. of OTM options used per RNS observation	5.60	5	4	9	2.39
Open interest per OTM option used	1,775.84	296	11	6,943	7,623.33
Trading volume per OTM option used	191.80	1	0	581	1,716.74
Ratio of OTM/All options total trading volume	0.66	0.72	0	1	0.31

Table 2: Characteristics of RNS-sorted Quintile Portfolios

This Table shows the average characteristics of quintile stock portfolios sorted on the basis of their Risk-Neutral Skewness (RNS) estimates on the last trading day of each month *t* during the period 1996-2012. MV stands for firms' market value. B/M stands for the firms' book-to-market value ratio. MOM stands for the cumulative stock return from month *t-12* to month *t-1*. ILLIQ stands for the price impact ratio of Amihud (2002), multiplied by 10^8. PRICE denotes the price per share. EIS^P stands for the expected idiosyncratic skewness of daily stock returns under the physical measure computed as in Boyer et al. (2010). Max denotes the maximum daily stock return over the previous month. $IVol^P$ denotes the idiosyncratic volatility of daily stock returns from month *t-60* to month *t*. ESF denotes the Estimated Shorting Fee for each stock computed as in Boehme et al. (2006). RSI denotes the Relative Short Interest for each stock. Option Volume denotes the total number of traded contracts (in thousands) for the options used to compute RNS on the last trading day of each month *t*. Open Interest denotes the total number of outstanding contracts (in thousands) for the options used to calculate RNS on the last trading day of each month *t*. The pre-last line shows the difference (spread) between the portfolio with the highest RNS stocks and the portfolio with lowest RNS stocks in each case. t-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

RNS Quintiles	RNS	ln(MV)	B/M	MOM	ILLIQ	PRICE	EIS^P	Max	$IVol^P$	ESF	RSI	Option Volume	Open Interest
1 (Lowest RNS)	-0.83	22.65	0.87	0.29	0.22	59.3	0.45	0.051	0.022	0.540	0.073	1,354	13,273
2	-0.52	22.39	0.73	0.31	0.19	51.6	0.50	0.057	0.025	0.529	0.062	827	8,864
3	-0.39	22.11	0.78	0.35	0.28	46.4	0.55	0.062	0.028	0.536	0.059	662	7,599
4	-0.27	21.83	0.78	0.38	0.36	41.9	0.60	0.066	0.030	0.557	0.060	624	6,634
5 (Highest RNS)	-0.06	21.44	0.97	0.42	0.76	38.1	0.68	0.074	0.033	0.569	0.062	811	7,492
5-1	0.77***	-1.21***	0.10	0.13***	0.54***	-21.2***	0.23***	0.023***	0.011***	0.029**	-0.011**	-543***	-5,781***
t(5-1)	(5.79)	(-5.39)	(0.97)	(2.92)	(2.75)	(-5.59)	(4.96)	(5.62)	(5.57)	(2.24)	(-2.37)	(-3.43)	(-4.77)

Table 3: Risk-Neutral Skewness Quintile Portfolio Sorts

This Table shows the characteristics and performance of stock portfolios constructed on the basis of option-implied Risk-Neutral (RN) Skewness estimates of individual stock returns' distributions, during the period 1996-2012. RN Volatility, Skewness and Kurtosis are computed from daily option prices using the model-free methodology of Bakshi et al. (2003), as described in Section 2.1. On the last trading day of each month *t*, stocks are sorted in ascending order according to their RN Skewness estimate and they are assigned to quintile portfolios. We then calculate the equally-weighted returns of these portfolios at the end of the following month *t+1* (i.e. post-ranking monthly returns). Mean return stands for the average monthly portfolio return during the examined period, and α_{FFC} stands for the monthly portfolio alpha estimated from the Fama-French-Carhart (FFC) 4-factor model. The Table also reports the portfolios' loadings (β's) with respect to the market (MKT), size (SMB), value (HML) and momentum (MOM) factors estimated from the FFC model as well as its explanatory power (R^2). Moreover, it reports the average values of RN Skewness, Volatility and Kurtosis and the number of stocks (N) in each portfolio. The pre-last line shows the difference (spread) between the portfolio with the highest RN Skewness stocks and the portfolio with lowest RN Skewness stocks in each case. t-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Quintiles	RN Skewness	Mean return	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	R^2	RN Volatility	RN Kurtosis	N
1 (Lowest RNS)	-0.8268	0.46	-0.32**	1.07***	0.28***	-0.02	0.00	0.90	0.4224	3.6497	127
			(-2.36)	(28.75)	(6.67)	(-0.29)	(0.02)				
2	-0.5249	0.56	-0.29**	1.16***	0.34***	0.03	-0.01	0.93	0.4487	3.2313	127
			(-2.04)	(44.97)	(8.87)	(0.83)	(-0.36)				
3	-0.3866	0.80	-0.08	1.20***	0.45***	-0.05	-0.01	0.92	0.4808	3.1026	127
			(-0.55)	(35.19)	(12.87)	(-0.93)	(-0.15)				
4	-0.2651	0.82	-0.04	1.23***	0.52***	-0.13*	-0.08**	0.89	0.5124	3.0294	127
			(-0.20)	(35.30)	(8.88)	(-1.75)	(-2.04)				
5 (Highest RNS)	-0.0564	1.07	0.23	1.24***	0.65***	-0.31***	-0.09**	0.88	0.5640	3.0346	127
			(1.10)	(26.52)	(10.26)	(-5.50)	(-2.21)				
5-1	0.7704***	0.61**	0.55**	0.17***	0.37***	-0.29***	-0.09*	0.37	0.1416***	-0.6151***	
t(5-1)	(5.79)	(2.24)	(2.47)	(3.53)	(5.74)	(-4.09)	(-1.69)		(5.61)	(-5.29)	

Table 4: Robustness checks

This Table shows the average number of stocks (N), the average monthly returns (mean return), and the monthly Fama-French-Carhart alphas (α_{FFC}) estimated from the corresponding 4-factor model for quintile portfolios constructed on the basis of Risk-Neutral Skewness (RNS) estimates for individual stocks extracted from daily option prices. The sample period is 1996-2012. In Panel A, RNS is estimated using a trapezoidal rule to compute the integrals in equations (9)-(11) of Appendix A. In Panel B, we use the latest available daily RNS estimate of the month as a sorting variable, instead of using only the RNS estimate computed on the last trading day of the month. In Panel C, we take monthly averages of the daily RNS estimates for each firm and use this monthly RNS average as a sorting variable to construct portfolios. The pre-last line in each panel shows the difference (spread) between the quintile portfolio with the highest RNS stocks and the quintile portfolio with the lowest RNS stocks in each case. t-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Alternative method to extract RNS

Quintiles	Mean return	α_{FFC}	N
1 (Lowest RNS)	0.41	-0.43***	127
2	0.69	-0.13	127
3	0.90	0.06	127
4	0.81	-0.07	127
5 (Highest RNS)	0.91	0.07	127
5-1	0.50**	0.49***	
t(5-1)	(2.34)	(2.81)	

Panel B: Latest available RNS estimate of the month as sorting variable

Quintiles	Mean return	α_{FFC}	N
1 (Lowest RNS)	0.51	-0.27**	147
2	0.57	-0.30**	147
3	0.76	-0.11	147
4	0.86	-0.01	147
5 (Highest RNS)	1.02	0.18	147
5-1	0.51**	0.45**	
t(5-1)	(2.14)	(2.22)	

Panel C: Average monthly value of RNS as sorting variable

Quintiles	Mean return	α_{FFC}	N
1 (Lowest RNS)	0.58	-0.19*	147
2	0.91	0.07	147
3	0.67	-0.21	147
4	0.77	-0.10	147
5 (Highest RNS)	0.78	-0.08	147
5-1	0.20	0.11	
t(5-1)	(0.66)	(0.51)	

Table 5: Fama-MacBeth Regressions

This Table reports the Fama-MacBeth coefficients of cross-sectional regressions of monthly excess stock returns on lagged Risk-Neutral Skewness (RNS) and a set of firm characteristics during the period 1996-2012. RNS is computed on the last trading day of each month using the model-free methodology of Bakshi et al. (2003). Models (2)-(13) control for firms' beta, market value (MV), book-to-market value ratio (B/M), momentum, 1-month reversal, stock illiquidity proxied by Amihud's (2002) price impact ratio and price per share. Model (3) additionally controls for RN Volatility and Kurtosis, which are also computed using the model-free methodology of Bakshi et al. (2003). Model (4) controls for the steepness of the option-implied volatility smile (SKEW). Model (5) controls for the spread between the implied volatilities of ATM calls and puts (Call-Put Vol. Spread). Model (6) controls for the total trading volume of options used to compute RNS. Model (7) controls for the total open interest of options used to compute RNS. Model (8) excludes firm-month observations if the total trading volume of OTM options used to compute RNS is less than half of the total option trading volume, including ATM options. Model (9) excludes firm-month observations if the total open interest of OTM options used to compute RNS is in the lowest 20% of the corresponding cross-sectional distribution on the last trading day of the month. Model (10) excludes the observations in September and October 2008. Model (11) reports the Fama-MacBeth regression coefficients for the sample period up to August 2008. Model (12) reports the estimates from a panel regression with time fixed effects (i.e., including month dummies). Model (13) includes the interaction of RNS with a short sale ban dummy variable that takes the value 1 for firms that were subject to the SEC and exchanges' short sale ban during September-October 2008 and zero otherwise. The last row reports the total number of firm-month observations used in each model. t-ratios derived from the time-series of the monthly estimated coefficients using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RN Skewness	0.0073**	0.0080***	0.0118***	0.0048**	0.0073***	0.0087***	0.0083***
	(2.45)	(3.70)	(4.24)	(2.21)	(2.91)	(4.15)	(3.85)
Beta		-0.0021	0.0014	-0.0021	-0.0013	-0.0011	-0.0014
		(-0.50)	(0.38)	(-0.48)	(-0.29)	(-0.26)	(-0.34)
ln(MV)		-0.0004	-0.0018**	-0.0007	-0.0005	0.0006	0.0006
		(-0.41)	(-1.99)	(-0.72)	(-0.44)	(0.51)	(0.46)
B/M		0.0020	0.0015	0.0024	0.0009	0.0021	0.0021
		(1.54)	(1.44)	(1.44)	(0.58)	(1.62)	(1.58)
Momentum		0.0020	0.0032	0.0019	0.0014	0.0023	0.0022
		(0.66)	(1.06)	(0.63)	(0.46)	(0.75)	(0.73)
Reversal		-0.0067	-0.0030	-0.0054	-0.0038	-0.0067	-0.0065
		(-0.88)	(-0.41)	(-0.68)	(-0.49)	(-0.87)	(-0.84)
Stock Illiquidity		-0.1184	-0.0904	-0.2299	-0.1569	-0.1319	-0.1165
		(-0.66)	(-0.51)	(-1.10)	(-0.68)	(-0.74)	(-0.66)
Price per share		0.0044**	0.0015	0.0043**	0.0042**	0.0041**	0.0033*
		(2.33)	(0.66)	(2.11)	(2.22)	(2.17)	(1.65)
RN Volatility			-0.0316***				
			(-3.29)				
RN Kurtosis			0.0054**				
			(2.46)				
SKEW				-0.0444***			
				(-2.65)			
Call-Put Vol. Spread					0.0309		
					(1.36)		
Option Trading Volume						-0.0010***	
						(-2.84)	
Open Interest							-0.0013**
							(-2.02)
Intercept	0.0082	0.0002	0.0369	0.0080	0.0013	-0.0173	-0.0081
	(1.50)	(0.01)	(1.55)	(0.33)	(0.05)	(-0.69)	(-0.33)
Observations	128,960	97,171	97,171	92,046	92,142	97,171	97,171

Table 5: Fama-MacBeth Regressions- continued

	Excl. low volume OTM options (8)	Excl. low open interest OTM options (9)	Excl. Sep.-Oct. 2008 (10)	Until Aug. 2008 (11)	Time Fixed Effects (12)	Time Fixed Effects (13)
RN Skewness	0.0066**	0.0066***	0.0086***	0.0104***	0.0095***	0.0094***
	(2.37)	(2.72)	(3.97)	(4.08)	(6.45)	(6.34)
Beta	-0.0017	-0.0029	-0.0018	-0.0010***	-0.0047***	-0.0046***
	(0.37)	(-0.67)	(-0.42)	(-0.20)	(-5.54)	(-5.48)
ln(MV)	-0.0001	-0.0001	-0.0005	-0.0003	-0.0001	-0.0001
	(-0.09)	(-0.07)	(-0.46)	(-0.23)	(-0.23)	(-0.22)
B/M	0.0024	0.0009	0.0020	0.0027	0.0001	0.0001
	(1.57)	(0.47)	(1.55)	(1.56)	(1.07)	(1.07)
Momentum	0.0019	0.0024	0.0024	0.0043**	0.0003	0.0003
	(0.58)	(0.74)	(0.78)	(2.14)	(0.64)	(0.63)
Reversal	-0.0027	-0.0061	-0.0085	-0.0052	-0.0063**	-0.0062**
	(-0.33)	(-0.74)	(-1.08)	(-0.57)	(-2.23)	(-2.20)
Stock Illiquidity	-0.3794	-0.1923	-0.1669	-0.1391	-0.0217***	-0.0217***
	(-1.40)	(-0.62)	(-0.99)	(-0.66)	(-2.93)	(-2.93)
Price per share	0.0044**	0.0036*	0.0044**	0.0061***	0.0034***	0.0034***
	(2.16)	(1.80)	(2.28)	(2.61)	(3.89)	(3.89)
RNS* Short sale ban dummy						0.0112
						(1.23)
Intercept	-0.0092	-0.0040	0.0031	-0.0085	0.0019	0.0017
	(-0.37)	(-0.16)	(0.13)	(-0.28)	(0.28)	(0.26)
Observations	61,880	78,362	95,422	56,310	97,171	97,171

Table 6: Systematic and Unsystematic Risk-Neutral Skewness Portfolio Sorts

This Table shows the average monthly returns (Mean return), and the monthly Fama-French-Carhart alphas (α_{FFC}) estimated from the corresponding 4-factor model for quintile portfolios constructed on the basis of systematic risk-neutral skewness (RNS) (Panel A) and unsystematic RNS (Panel B) estimates for individual stocks extracted from daily option prices. The sample period is 1996-2012. We follow the methodology of Bakshi et al. (2003), as described in Section 2.2, to decompose total RNS into its systematic and unsystematic components, using risk-neutral stock betas estimated as in Bali et al. (2014). On the last trading day of each month *t*, stocks are sorted in ascending order according to their systematic RNS (Panel A) or unsystematic RNS (Panel B) estimates and they are assigned to quintile portfolios. We then calculate the equally-weighted returns of these portfolios at the end of the following month *t+1* (i.e. post-ranking monthly returns). The Table also reports the average portfolio total RNS value in each case as well as the average number (N) of stocks in each portfolio. The pre-last line shows the difference (spread) between the portfolio with the highest and the portfolio with the lowest systematic RNS (Panel A) or unsystematic RNS (Panel B) stocks in each case. t-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Systematic RNS sorts

Quintiles	Total RNS	Mean return	α_{FFC}	N
1 (Lowest Systematic RNS)	-0.5690	0.77	0.13 (1.09)	109
2	-0.4629	0.92	0.18 (1.33)	109
3	-0.4028	0.97	0.19 (0.89)	109
4	-0.3689	0.84	0.00 (0.05)	109
5 (Highest Systematic RNS)	-0.3423	0.32	-0.59** (-2.45)	109
5-1	0.2267***	-0.45	-0.72**	
t(5-1)	(5.34)	(-0.76)	(-2.48)	

Panel B: Unsystematic RNS sorts

Quintiles	Total RNS	Mean return	α_{FFC}	N
1 (Lowest Unsystematic RNS)	-0.7727	0.51	-0.35** (-2.04)	109
2	-0.4936	0.67	-0.14 (-0.82)	109
3	-0.3670	0.85	0.02 (0.15)	109
4	-0.2645	0.94	0.18 (1.03)	109
5 (Highest Unsystematic RNS)	-0.2483	0.84	0.20 (1.00)	109
5-1	0.5244***	0.33	0.55**	
t(5-1)	(5.57)	(1.33)	(2.16)	

Table 7: Median Risk-Neutral Skewness of Hedging Demand-Sorted Quintile Portfolios

This Table shows the time-series averages of the median portfolio Risk-Neutral Skewness (RNS) estimate for quintile portfolios containing the stocks characterized by the highest and the lowest investor hedging demand, respectively. RNS for each stock is computed from daily option prices using the model-free methodology of Bakshi et al. (2003). The examined period is 1996-2012. We use the following four proxies for investor hedging demand: the ratio of aggregate put options volume to total option volume on a given trading day for a given expiry, the aggregate open interest across all options on a given trading day for a given expiry, the ratio of CEO stock holdings to base salary and the Z-score of Zmijewski (1984) to capture default risk. The pre-last line reports the difference in average RNS values between the highest and the lowest hedging demand quintile portfolios. t-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Put/All Volume ratio	Open Interest	CEO Stock Holdings	Default risk
Lowest Hedging Demand Quintile (1)	-0.3933	-0.3840	-0.3895	-0.3544
Highest Hedging Demand Quintile (5)	-0.4564	-0.4493	-0.4380	-0.4021
5-1	-0.0630***	-0.0653***	-0.0485***	-0.0477***
t(5-1)	(-5.58)	(-3.30)	(-5.20)	(-4.74)

Table 8: Bivariate conditional portfolio sorts: Risk-Neutral Skewness and Overvaluation

This Table shows the performance of bivariate stock portfolios constructed on the basis of Risk-Neutral Skewness (RNS) estimates and each of the overvaluation proxies considered, during the period 1996-2012. RNS is computed from daily option prices using the model-free methodology of Bakshi et al. (2003). We use the following three proxies for stock overvaluation: Expected Idiosyncratic Skewness (EIS^P) estimated from daily stock returns under the physical measure in Panel A, the Maximum (Max) daily stock return over the previous month in Panel B and the probability of a stock achieving a Jackpot return over the next year in Panel C. The definitions and data sources for these variables are provided in Appendix C. On the last trading day of each month *t,* stocks are sorted in ascending order according to their RNS estimate and assigned to tercile portfolios. Within each RNS tercile portfolio, we further sort stocks according to each of the overvaluation proxies and construct again tercile portfolios. We then calculate the equally-weighted returns of these 9 portfolios at the end of the following month *t+1* (i.e. post-ranking monthly returns). The Table reports monthly Fama-French (FF) portfolio alphas estimated from the corresponding 3-factor model. t-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Expected Idiosyncratic Skewness (EIS^P)

	EIS^P Low	EIS^P Medium	EIS^P High	Difference
RNS 1 (Lowest)	0.08	-0.30	-0.58***	-0.67***
	(0.74)	(-1.64)	(-3.57)	(-3.89)
RNS 2	0.21	-0.03	-0.45**	-0.66***
	(1.31)	(-0.18)	(-2.45)	(-3.00)
RNS 3 (Highest)	0.38*	0.14	-0.24	-0.63***
	(1.84)	(0.56)	(-1.21)	(-2.63)
Difference	-0.30	-0.44*	-0.34	
	(-1.49)	(-1.82)	(-1.35)	

Panel B: Maximum past month return (Max)

	Max Low	Max Medium	Max High	Difference
RNS 1 (Lowest)	0.01	-0.22	-0.77***	-0.78***
	(0.06)	(-1.59)	(-3.12)	(-2.59)
RNS 2	0.38***	-0.12	-0.68***	-1.06***
	(2.98)	(-0.62)	(-3.27)	(-4.51)
RNS 3 (Highest)	0.41**	0.08	-0.21	-0.62**
	(2.11)	(0.39)	(-0.78)	(-2.34)
Difference	-0.40**	-0.30	-0.56*	
	(-1.98)	(-1.28)	(-1.87)	

Panel C: Probability of Jackpot return

	Jackpot Low	Jackpot Medium	Jackpot High	Difference
RNS 1 (Lowest)	-0.06	-0.23	-0.60**	-0.54*
	(-0.54)	(-1.63)	(-2.17)	(-1.74)
RNS 2	0.25*	-0.01	-0.48**	-0.73***
	(1.70)	(-0.08)	(-1.96)	(-2.66)
RNS 3 (Highest)	0.26	0.37	-0.04	-0.30
	(1.17)	(1.32)	(-0.15)	(-1.08)
Difference	-0.32	-0.60**	-0.56**	
	(-1.47)	(-2.24)	(-2.23)	

Table 9: Reverse bivariate conditional portfolio sorts: Overvaluation and Risk-Neutral Skewness

This Table shows the performance of bivariate stock portfolios constructed on the basis of each of the overvaluation proxies considered and Risk-Neutral Skewness (RNS) estimates, during the period 1996-2012. We use the following three proxies for stock overvaluation: Expected Idiosyncratic Skewness (EIS^P) estimated from daily stock returns under the physical measure in Panel A, the Maximum (Max) daily stock return over the previous month in Panel B and the probability of a stock achieving a Jackpot return over the next year in Panel C. The definitions and data sources for these variables are provided in Appendix C. RNS is computed from daily option prices using the model-free methodology of Bakshi et al. (2003). On the last trading day of each month *t*, stocks are sorted in ascending order according to an overvaluation proxy and assigned to tercile portfolios. Within each portfolio constructed on the overvaluation proxy, we further sort stocks according to their RNS estimate and construct again tercile portfolios. We then calculate the equally-weighted returns of these 9 portfolios at the end of the following month *t+1* (i.e. post-ranking monthly returns). The Table reports monthly Fama-French (FF) portfolio alphas estimated from the corresponding 3-factor model. t-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Expected Idiosyncratic Skewness (EIS^P)

	RNS 1 (Lowest)	RNS 2	RNS 3 (Highest)	Difference
EIS^P Low	-0.04	0.29	0.37*	0.41**
	(-0.38)	(1.59)	(1.86)	(2.02)
EIS^P Medium	-0.30*	-0.03	0.12	0.43*
	(-1.65)	(-0.15)	(0.55)	(1.76)
EIS^P High	-0.59***	-0.45**	-0.16	0.44*
	(-3.53)	(-2.11)	(-0.79)	(1.90)
Difference	0.55***	0.73***	0.53**	
	(2.90)	(2.71)	(2.25)	

Panel B: Maximum past month return (Max)

	RNS 1 (Lowest)	RNS 2	RNS 3 (Highest)	Difference
Max Low	-0.08	0.30**	0.47***	0.55***
	(-0.65)	(2.34)	(2.87)	(3.78)
Max Medium	-0.26	-0.07	0.14	0.40**
	(-1.48)	(-0.36)	(0.73)	(2.11)
Max High	-0.88***	-0.60**	-0.16	0.72**
	(-3.12)	(-2.53)	(-0.64)	(2.40)
Difference	0.81**	0.90***	0.63**	
	(2.38)	(3.42)	(2.38)	

Panel C: Probability of Jackpot return

	RNS 1 (Lowest)	RNS 2	RNS 3 (Highest)	Difference
Jackpot Low	0.01	0.10	0.22	0.20
	(0.11)	(0.75)	(1.08)	(1.06)
Jackpot Medium	-0.21	0.05	0.25	0.46**
	(-1.11)	(0.32)	(0.98)	(1.98)
Jackpot High	-0.67***	-0.48*	0.20	0.87***
	(-2.42)	(-1.66)	(0.78)	(3.29)
Difference	0.68**	0.59*	0.02	
	(2.26)	(1.96)	(0.07)	

Table 10: Bivariate conditional portfolio sorts: Risk-Neutral Skewness and Short Selling Constraints

This Table shows the performance of bivariate stock portfolios constructed on the basis of Risk-Neutral Skewness (RNS) estimates and each of the short selling constraints proxies, during the period 1996-2012. RNS is computed from daily option prices using the model-free methodology of Bakshi et al. (2003). We use the following three proxies for short selling constraints: Estimated Shorting Fee (ESF) in Panel A, Relative Short Interest (RSI) in Panel B and stock returns' idiosyncratic volatility under the physical measure ($IVol^P$) in Panel C. The definitions and data sources for these variables are provided in Appendix C. On the last trading day of each month *t*, stocks are sorted in ascending order according to their RNS estimate and assigned to tercile portfolios. Within each RNS tercile portfolio, we further sort stocks according to each of the short selling constraints proxies and construct again tercile portfolios. We then calculate the equally-weighted returns of these 9 portfolios at the end of the following month *t+1* (i.e. post-ranking monthly returns). The Table reports monthly Fama-French (FF) portfolio alphas estimated from the corresponding 3-factor model. t-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Estimated Shorting Fee (ESF)

	ESF Low	ESF Medium	ESF High	Difference
RNS 1 (Lowest)	0.03	0.04	-0.64***	-0.67***
	(0.20)	(0.31)	(-2.97)	(-2.96)
RNS 2	0.11	-0.02	-0.47**	-0.59***
	(0.75)	(-0.16)	(-2.15)	(-2.80)
RNS 3 (Highest)	0.43**	0.32	-0.54**	-0.98***
	(2.05)	(1.38)	(-2.21)	(-3.86)
Difference	-0.40**	-0.28	-0.10	
	(-2.20)	(-1.34)	(-0.33)	

Panel B: Relative Short Interest (RSI)

	RSI Low	RSI Medium	RSI High	Difference
RNS 1 (Lowest)	0.21	-0.07	-0.72***	-0.93***
	(1.62)	(-0.53)	(-3.17)	(-3.79)
RNS 2	0.24	-0.13	-0.50**	-0.74***
	(1.50)	(-0.79)	(-2.25)	(-3.22)
RNS 3 (Highest)	0.41	0.27	-0.46**	-0.87***
	(1.63)	(1.19)	(-1.97)	(-3.15)
Difference	-0.19	-0.34*	-0.26	
	(-0.01)	(-1.69)	(-0.80)	

Panel C: Idiosyncratic Volatility ($IVol^P$)

	$IVol^P$ Low	$IVol^P$ Medium	$IVol^P$ High	Difference
RNS 1 (Lowest)	0.00	-0.32**	-0.67***	-0.67**
	(0.03)	(-2.30)	(-2.57)	(-2.25)
RNS 2	0.37***	-0.13	-0.65**	-1.02***
	(3.40)	(-0.73)	(-2.50)	(-3.48)
RNS 3 (Highest)	0.26	0.25	-0.23	-0.49
	(1.50)	(1.08)	(-0.83)	(-1.61)
Difference	-0.25	-0.57**	-0.44	
	(-1.53)	(-2.33)	(-1.54)	

Table 11: Reverse bivariate conditional portfolio sorts:
Short Selling Constraints and Risk-Neutral Skewness

This Table shows the performance of bivariate stock portfolios constructed on the basis of each of the short selling constraints proxies and Risk-Neutral Skewness (RNS) estimates, during the period 1996-2012. We use the following three proxies for short selling constraints: Estimated Shorting Fee (ESF) in Panel A, Relative Short Interest (RSI) in Panel B and stock returns' idiosyncratic volatility under the physical measure ($IVol^P$) in Panel C. The definitions and data sources for these variables are provided in Appendix C. RNS is computed from daily option prices using the model-free methodology of Bakshi et al. (2003). On the last trading day of each month *t*, stocks are sorted in ascending order according to a short selling constraints proxy and assigned to tercile portfolios. Within each portfolio constructed on a short selling constraints proxy, we further sort stocks according to their RNS estimate and construct again tercile portfolios. We then calculate the equally-weighted returns of these 9 portfolios at the end of the following month *t+1* (i.e. post-ranking monthly returns). The Table reports monthly Fama-French (FF) portfolio alphas estimated from the corresponding 3-factor model. t-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Estimated Shorting Fee (ESF)

	RNS 1 (Lowest)	RNS 2	RNS 3 (Highest)	Difference
ESF Low	0.03	0.10	0.34	0.31*
	(0.20)	(0.67)	(1.60)	(1.68)
ESF Medium	0.04	0.07	0.23	0.19
	(0.23)	(0.40)	(1.04)	(0.96)
ESF High	-0.73***	-0.69***	-0.27	0.47
	(-3.45)	(-2.84)	(-1.03)	(1.48)
Difference	0.76***	0.78***	0.60**	
	(3.49)	(3.40)	(2.23)	

Panel B: Relative Short Interest (RSI)

	RNS 1 (Lowest)	RNS 2	RNS 3 (Highest)	Difference
RSI Low	0.22*	0.23	0.35	0.13
	(1.81)	(1.44)	(1.49)	(0.63)
RSI Medium	-0.20	0.14	0.21	0.41**
	(-1.36)	(0.89)	(0.96)	(2.12)
RSI High	-0.73***	-0.67***	-0.33	0.40
	(-3.30)	(-2.96)	(-1.27)	(1.24)
Difference	0.95***	0.91***	0.68**	
	(3.89)	(3.88)	(2.33)	

Panel C: Idiosyncratic Volatility ($IVol^P$)

	RNS 1 (Lowest)	RNS 2	RNS 3 (Highest)	Difference
$IVol^P$ Low	-0.13	0.17	0.33***	0.46***
	(-1.22)	(1.36)	(2.67)	(3.81)
$IVol^P$ Medium	-0.47***	0.00	0.18	0.65***
	(-2.97)	(-0.02)	(0.85)	(3.49)
$IVol^P$ High	-0.68**	-0.67**	0.14	0.82***
	(-2.21)	(-2.56)	(0.50)	(3.00)
Difference	0.55	0.84***	0.19	
	(1.63)	(2.70)	(0.62)	

Table 12: Trivariate independent portfolio sorts: Risk-Neutral Skewness, Overvaluation and Short Selling Constraints

This Table shows the performance of trivariate stock portfolios constructed on the basis of Risk-Neutral Skewness (RNS) estimates, each of the overvaluation proxies and each of the short selling constraints proxies considered, during the period 1996-2012. We use the following three proxies for stock overvaluation: Expected Idiosyncratic Skewness (EIS^P) estimated from daily stock returns under the physical measure, the Maximum (Max) daily stock return over the previous month and the probability of a stock achieving a Jackpot return over the next year. We use the following three proxies for short selling constraints: Estimated Shorting Fee (ESF), Relative Short Interest (RSI) and stock returns' idiosyncratic volatility under the physical measure ($IVol^P$). The definitions and data sources for these variables are provided in Appendix C. On the last trading day of each month *t*, stocks are *independently* sorted according to their i) RNS estimate, ii) overvaluation proxy value and iii) short selling constraints proxy value and classified for each sorting criterion as Low (L) or High (H) relative to the corresponding median value. The intersection of these three classifications yields 8 portfolios. We then calculate the equally-weighted returns of these 8 portfolios at the end of the following month *t+1* (i.e. post-ranking monthly returns). The Table reports monthly Fama-French (FF) portfolio alphas estimated from the corresponding 3-factor model. t-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Overvaluation proxy		EIS^P			Max			Jackpot		
Short selling constraints proxy		ESF	RSI	$IVol^P$	ESF	RSI	$IVol^P$	ESF	RSI	$IVol^P$
P1	RNS L & Overvaluation L & Constraints L	0.13 (0.89)	0.17 (1.30)	0.03 (0.28)	0.19 (1.52)	0.21* (1.75)	0.07 (0.65)	0.05 (0.42)	0.11 (0.93)	0.03 (0.31)
P2	RNS L & Overvaluation L & Constraints H	-0.27 (-1.34)	-0.35* (-1.81)	-0.10 (-0.41)	-0.30* (-1.71)	-0.36* (-1.89)	0.00 (-0.02)	-0.35* (-1.66)	-0.63*** (-3.01)	0.05 (0.14)
P3	RNS L & Overvaluation H & Constraints L	-0.05 (-0.28)	0.15 (0.99)	-0.03 (-0.20)	-0.12 (-0.73)	-0.12 (-0.71)	-0.49*** (-2.58)	0.19 (0.73)	0.29 (0.90)	-0.11 (-0.42)
P4	RNS L & Overvaluation H & Constraints H	-0.49** (-2.45)	-0.61*** (-3.18)	-0.87*** (-3.48)	-0.65*** (-3.20)	-0.64*** (-3.33)	-0.76*** (-2.73)	-0.63*** (-3.15)	-0.57*** (-2.89)	-0.66** (-2.46)
P5	RNS H & Overvaluation L & Constraints L	0.30 (1.52)	0.32 (1.58)	0.48*** (3.26)	0.50*** (2.76)	0.52*** (2.73)	0.36** (2.50)	0.40** (2.03)	0.41* (1.95)	0.26 (1.58)
P6	RNS H & Overvaluation L & Constraints H	0.15 (0.65)	0.16 (0.70)	0.07 (0.27)	0.09 (0.41)	0.12 (0.65)	0.31 (1.10)	0.09 (0.33)	0.00 (-0.02)	-0.07 (-0.22)
P7	RNS H & Overvaluation H & Constraints L	0.36 (1.60)	0.11 (0.43)	0.27* (1.65)	0.12 (0.54)	0.07 (0.28)	0.06 (0.26)	0.31 (1.15)	0.40 (1.35)	0.30 (1.19)
P8	RNS H & Overvaluation H & Constraints H	-0.41* (-1.85)	-0.22 (-1.09)	-0.28 (-1.23)	-0.47** (-2.12)	-0.38* (-1.80)	-0.31 (-1.31)	-0.37 (-1.63)	-0.31 (-1.40)	-0.07 (-0.29)

What Does Risk-Neutral Skewness Tell Us About Future Stock Returns?

Supplementary Online Appendix

1 Tercile Portfolios

The main body of the paper presents results from quintile RNS-sorted portfolios. Here, we present the post-ranking performance of *tercile* portfolios constructed on the basis of firms' RNS values computed on the last trading day of the ranking month t. In this way, we ensure that the documented spread return in our benchmark results is not solely driven by stocks in the extreme ends of the RNS cross-sectional distribution. In particular, Table A.1 reports the average portfolio returns as well as their Fama-French-Carhart (α_{FFC}) alphas estimated from the corresponding 4-factor model during the period 1996-2012. We find that the tercile portfolio of stocks with the most negative RNS values significantly underperforms the tercile portfolio of stocks with the least negative RNS values. In particular, a spread strategy that is long the highest RNS tercile portfolio and short the lowest RNS tercile portfolio yields an average return of 52 bps per month (t-stat: 2.30), and α_{FFC} of 47 bps per month (t-stat: 2.58).

-Table A.1 here-

Table A.1 also reports the loadings (β's) of these portfolios with respect to the excess market (MKT), size (SMB), value (HML) and momentum (MOM) factors using the FFC model as well as its explanatory power. We find that the highest RNS tercile portfolio exhibits significantly higher MKT and SMB beta relative to the lowest RNS tercile portfolio, but it also exhibits significantly lower (and negative) HML beta. Finally, the highest RNS tercile portfolio also exhibits a lower MOM beta, but the difference is very small.

2 Open-to-close Stock Portfolio Returns

Our benchmark results presented in the main body of the paper rely on portfolio returns computed from the closing price of the last trading day of the ranking month t until the closing price of the last trading day of the post-ranking month $t+1$. In line with the evidence of Battalio and Schultz (2006), this approach may be plagued by nonsynchroneity bias. Since the option market closes after the stock market, option prices recorded in OptionMetrics, and hence the computed RNS, may not be known to investors before the close of the stock market on the last trading day of the ranking month t. In that case, the return spread we document in our benchmark results may not be feasible, as investors could not have formed these RNS portfolios at the close of the stock market.

To address this concern, here we alternatively calculate portfolio returns using stock prices from the *open* of the *first* trading day of the *post-ranking month* $t+1$ until the close of the last trading day of the post-ranking month $t+1$.[1] In this way, we ensure that RNS estimates computed from option prices recorded in OptionMetrics on the last trading day of the ranking month t would be available to investors before the beginning of the holding period of the examined trading strategy.[2]

The performance of RNS-sorted tercile and quintile portfolios following this alternative approach is shown in Table A.2 of the Supplementary Appendix. These results show that the documented return spread between the highest and the lowest RNS stock portfolios remains intact. In particular, the 4-factor alpha of the spread between the highest and the lowest RNS quintile stock portfolios is equal to 46 bps per month (t-stat=2.04). Similarly, the 4-factor alpha of the spread between the highest and the lowest RNS tercile stock portfolios is equal to 40 bps per month (t-stat=2.12).[3]

-Table A.2 here-

3 Long-term Performance of RNS Portfolios

Our benchmark results examine the performance of RNS-sorted portfolios only during the first post-ranking month, $t+1$. Here we examine if the strategy that is long the highest RNS stocks and short the lowest RNS stocks continues to yield abnormal returns beyond the first post-ranking month $t+1$. In this way, we can assess how long it takes the market to correct the mispricing signalled by RNS.[4] To this end, we examine the $t+k$ monthly

[1] We would like to thank an anonymous referee for suggesting this alternative approach.

[2] This approach essentially yields the most conservative estimate for the performance of this trading strategy because it assumes that none of the option-implied RNS estimates were available to investors before the close of the stock market on the last trading day of the ranking month t.

[3] To estimate the risk-adjusted performance of these stock portfolios, we had to re-calculate the corresponding returns of the MKT, SMB, HML and MOM factors using monthly stock returns from the open of the first trading day of each month until the close of the last trading day of the month. This is because the factor returns provided on Kenneth French's website are constructed using stock returns from the close of the last trading day of each month until the close of the last trading day of the following month, and hence they are inappropriate for risk-adjusting portfolio returns calculated under this alternative approach.

[4] We would like to thank an anonymous referee for suggesting this analysis.

performance of portfolios constructed on the basis of firms' RNS on the last trading day of month t. In particular, we compute portfolio returns and alphas during month $t+k$, where $k = 1, 2, ..., 6$. Results are reported in Table A.3. We find that the spread return and alpha between the quintile portfolio with the highest and the quintile portfolio with the lowest RNS stocks is economically and statistically significant only in the first post-ranking month, $t+1$. All of the subsequent $t+k$ monthly returns do not yield any significant spread between the highest and the lowest RNS stock portfolios. These results show that the mispricing signalled by RNS is only temporary, since the market corrects most of it within one month.

-Table A.3 here-

4 Fama-MacBeth regressions-Further robustness checks

In this section, we utilize Fama-MacBeth (1973) regressions to further examine how robust is the positive relationship between RNS and future stock returns in the presence of additional control variables, complementing the evidence presented in the main body of the study. In addition to the firm characteristics that we use as control variables in models (2)-(13) of Table 5 in the main paper, here we also control for the utilized overvaluation and short selling constraints proxies.

In particular, models (1)-(3) that are presented in Table A.4 include, in turn, Max, EIS^P, and Jackpot, which are the utilized proxies for stock overvaluation. We find that in the presence of each of these proxies, the positive relationship between excess stocks returns and lagged RNS remains intact. The magnitude and the significance of the RNS coefficient are found to be very similar to the benchmark results presented in Table 5 of the main paper. This finding confirms that RNS does not simply mimic the relationship between overvaluation proxies and future stock returns that has been documented in prior studies (see Boyer et al., 2010, Bali et al., 2011, and Conrad et al., 2014). It should be also mentioned that the Fama-MacBeth coefficient of each overvaluation proxy has the expected negative sign but only the coefficient of EIS^P is statistically significant.

Models (4)-(6) that are presented in Table A.4 include, in turn, ESF, RSI, and IVol^P, which are the utilized proxies for short selling constraints. We find again that the magnitude and significance of the RNS coefficient remain intact across these three models. Moreover, the coefficient of each short selling constraints proxy has the expected negative sign but it is significant only at the 10% level.

-Table A.4 here-

5 RNS and Future Earnings Surprises

In this section we examine whether our benchmark result that firms with low RNS values subsequently yield negative risk-adjusted stock returns can be attributed to the informational content of RNS with respect to firms' future cash flows.[5] To this end, following the approach of Xing et al. (2010, Section IV, p. 655), we sort stocks into quintile portfolios on the basis of their RNS estimates on the last trading day of ranking month t, and then calculate each portfolio's average quarterly earnings surprise over the subsequent $n = 4, 8, 12, 16, 20$, and 24 weeks. Following Xing et al. (2010), earnings surprise (UE) for each firm is defined as the difference between the announced quarterly earnings and the latest consensus earnings forecast before the announcement, if there has been an earnings announcement within the subsequent n weeks. Moreover, standardized quarterly earnings surprise (SUE) is computed as the ratio of earnings surprise (UE) divided by the standard deviation of the latest consensus quarterly earnings forecast. The source of analysts' forecasts data is I/B/E/S.

Results are reported in Table A.5. Overall, these results show that the subsequent underperformance of the lowest RNS stocks cannot be attributed to information that RNS carries regarding firms' decreasing future cash flows. While it is true that, on average, the firms with the lowest RNS estimates typically yield more negative earnings surprises (UE) in the subsequent weeks relative to the firms with the highest RNS estimates, this difference is insignificant. Moreover, this pattern is not robust to the standardization of UE by the volatility of earnings forecasts. In particular, as Table A.5 shows, the firms with the lowest RNS estimates actually yield *less* negative SUE in the subsequent weeks relative to the firms with the highest RNS estimates. This sign reversal from UE to SUE is driven by the firms that drop out of the sample because the standard deviation of their earnings forecasts is not available on I/B/E/S, as these firms are not followed by the required number of analysts. Again, the differences in average portfolio SUE between the firms with the lowest RNS estimates and the firms with the highest RNS estimates are mostly insignificant.[6]

-Table A.5 here-

Rejecting the hypothesis that RNS contains significant information regarding firms' future cash flows is also consistent with our benchmark findings and our conjectured mechanism, i.e., that RNS provides a signal of temporary mispricing that arises due to limits-to-arbitrage in the stock market and that is mostly corrected within the next month.

[5] We would like to thank an anonymous referee for suggesting this analysis.

[6] In addition, following Xing et al. (2010), we have performed Fama-MacBeth regressions of future firms' earnings surprises on their lagged RNS estimates. Results that are readily available upon request confirm the portfolio results presented in Table A.5, since the Fama-MacBeth coefficient of RNS is insignificant and changes sign when we use SUE instead of UE.

6 Systematic and Unsystematic RNS- Physical betas

In this section we repeat the performance analysis of stock portfolios constructed on the basis of the systematic and unsystematic components of RNS. However, instead of using risk-neutral stock betas for the decomposition of RNS into its systematic and unsystematic components, as described in Section 2.2 of the main body of the paper, we alternatively use stock betas estimated under the physical measure. Table A.6 presents the performance of these portfolios in terms of raw returns and α_{FFC}.

-Table A.6 here-

The main conclusions from these results are very similar to the ones derived from the benchmark analysis using risk-neutral betas. In particular, as Panel A of Table A.6 shows, the spread strategy that is long the quintile portfolio with the highest systematic RNS stocks and short the quintile portfolio with the lowest systematic RNS stocks yields a *negative* α_{FFC} that is equal to -57 bps per month (t-stat: -1.90). This spread is mostly driven by the underperformance of the quintile portfolio containing the stocks with the highest systematic RNS values. Moreover, the results in Panel B show that the spread strategy that is long the quintile portfolio with the highest unsystematic RNS stocks and short the quintile portfolio with the lowest unsystematic RNS stocks yields a highly significant *positive* α_{FFC} that is equal to 79 bps per month (t-stat: 2.81). This significant spread is mainly driven by the severe underperformance of the portfolio containing the stocks with the lowest unsystematic RNS values.

In sum, we find that the performance patterns of the total RNS-sorted portfolios that we reported in Table 3 of the main body of the paper are resembled only by the *unsystematic* RNS-sorted portfolios. Therefore, these results confirm the conclusion of our benchmark decomposition analysis that it is the unsystematic component of RNS that drives the positive relationship between total RNS and future stock returns.

7 Risk-Neutral Coskewness and Idiosyncratic Skewness

In this section we perform an alternative decomposition of RNS from the one presented in the main body of the paper. In particular, we decompose RNS into risk-neutral coskewness and idiosyncratic skewness, using the definition of risk-neutral coskewness in Bakshi et al. (2003, p. 114) and the regression decompositon of Conrad et al. (2013). In particular, to derive risk-neutral coskewness, Bakshi et al. (2003) use the single index model defined under the risk-neutral measure:

$$r_{i,d} = a_i + b_i r_{m,d} + e_{i,d} \tag{1}$$

where $r_{i,d}$ is the daily return of stock i, $r_{m,d}$ is the daily market return and $e_{i,d}$ is a zero-mean error term that is independent of $r_{m,d}$. Thus, risk-neutral coskewness for stock i on day d is given by:

$$RNCOSKEW_{i,d} = b_i RNS_{m,d} \frac{RNV_{m,d}}{\sqrt{RNV_{i,d}}} \tag{2}$$

where b_i is the risk-neutral beta of stock i, $RNV_{i,d}$ is the risk-neutral variance of stock i on day d, while $RNV_{m,d}$ and $RNS_{m,d}$ denote, respectively, the risk-neutral variance and skewness on day d of the market portfolio proxied by the S&P 500. Following Bali et al. (2014), we compute risk-neutral betas, b_i, for each stock i, by regressing on a monthly basis $RNV_{i,d}$ on $RNV_{m,d}$ using a rolling window of 12 months, and taking the square root of the corresponding slope coefficient. For the cases where this regression approach yields a negative slope coefficient, no risk-neutral beta is computed. For robustness, we alternatively compute risk-neutral coskewness by plugging in equation (2) stocks' physical betas.

To calculate idiosyncratic RNS, we follow Conrad et al. (2013) and we regress on a monthly basis the daily RNS estimate for each stock i on the corresponding daily risk-neutral coskewness estimate:

$$RNS_{i,d} = \kappa^S_{i,0} + \kappa^S_{i,1} RNCOSKEW_{i,d} + \zeta^S_{i,d}. \tag{3}$$

The idiosyncratic RNS estimate for stock i on day d is given by the sum $\kappa^S_{i,0} + \zeta^S_{i,d}$.[7]

A limitation of this approach is that these regressions typically have low explanatory power. In fact, the average R^2 of these regressions was around 10.5% in our sample. As a result, RNS is almost mechanically captured by idiosyncratic RNS through the error term. Therefore, this regression decomposition approach is not very informative.[8] Nevertheless, for completeness, we present below the performance of stock portfolios constructed on the basis of risk-neutral coskewness and idiosyncratic RNS estimates. Table A.7 presents the results when risk-neutral betas are used to compute risk-neutral coskewness in (2), while

[7] Interestingly, it turns out that, even though the systematic RNS estimates are different from the corresponding risk-neutral coskewness estimates, these two alternative measures yield identical rankings of the stocks in our sample. This is due to the fact that, as one can observe from the corresponding formulae (see also Section 2.2 of the main paper), systematic RNS is a positive transformation of risk-neutral coskewness. As a result, the compositions, and hence the performances of the portfolios constructed on the basis of systematic RNS and risk-neutral coskewness, respectively, are identical. On the other hand, there is no such relationship between unsystematic RNS and idiosyncratic RNS, and hence the compositions and performances of the corresponding portfolios are different.

[8] We would like to thank an anonymous referee for this remark.

Table A.8 presents the corresponding results when physical betas are used.

Panel A of Table A.7 shows that the spread strategy that is long the quintile portfolio with the highest risk-neutral coskewness stocks and short the quintile portfolio with the lowest risk-neutral coskewness stocks yields a significant *negative* α_{FFC} that is equal to -72 bps per month (t-stat: -2.48). This significant spread is driven by the severe underperformance of the quintile portfolio containing the stocks with the highest risk-neutral coskewness values. These results indicate a negative, though not strictly monotonic, relationship between risk-neutral coskewness and post-ranking portfolio returns, resembling the finding of Harvey and Siddique (2000) for coskewness estimated under the physical measure.

On the other hand, as Panel B shows, the spread strategy that is long the quintile portfolio with the highest idiosyncratic RNS stocks and short the quintile portfolio with the lowest idiosyncratic RNS stocks yields a *positive* α_{FFC} that is equal to 40 bps per month (t-stat: 1.81). This spread is mostly driven by the significant underperformance of the quintile portfolio containing the stocks with the lowest idiosyncratic RNS values.

-Table A.7 here-

Very similar are the portfolio performance patterns that are reported in Table A.8. In particular, the quintile portfolio that contains the stocks with the highest risk-neutral coskewness estimates *underperforms* relative to the quintile portfolio that contains the stocks with the lowest risk-neutral coskewness estimates. On the other hand, the quintile portfolio that contains the stocks with the highest idiosyncratic RNS values significantly *outperforms* relative to the quintile portfolio that contains the stocks with the lowest idiosyncratic RNS values.

-Table A.8 here-

With the caveat that under this decomposition approach total RNS is almost mechanically captured by idiosyncratic RNS, these results still show that it is the idiosyncratic component of RNS that drives the positive relationship between total RNS and future stock returns.

8 The Role of Stock Illiquidity

The mechanism we put forward in the main body of the study to explain which of the stocks with low RNS values subsequently underperform crucially relies on the existence of limits-to-arbitrage that prevent investors from selling (short) stocks that are perceived to be relatively overpriced. Another friction that can have such an effect is stock illiquidity.

In this section, we examine how stock illiquidity affects the relationship between RNS and future stock returns.[9] In line with the proposed mechanism, the underperformance of the most negative RNS stocks should be more pronounced for stocks that are also illiquid. To test this conjecture, we firstly sort stocks into tercile portfolios on the basis of their RNS values and then, within each tercile RNS portfolio, we further sort stocks according to their degree of illiquidity. We use Amihud's (2002) price impact ratio (ILLIQ) as a proxy for stock illiquidity. Results are reported in Table A.9. Consistent with our conjecture, we find that the underperformance of the portfolio with the lowest RNS stocks is mainly driven by those stocks that are also highly illiquid. On the other hand, the lowest RNS stocks that are relatively liquid do not yield significant negative risk-adjusted returns. The spread between the most and the least illiquid stocks within the lowest RNS portfolio is economically and statistically significant, yielding α_{FF} equal to -55 bps per month (t-stat: -2.23).

-Table A.9 here-

9 Weekly portfolio returns

In this section, we examine the performance of RNS-sorted portfolios under weekly rebalancing. In particular, we sort stocks into quintile portfolios on the basis of their RNS values estimated on the last trading day of the week and we compute their post-ranking weekly returns using close-to-close stock prices. In this way, we can assess whether the informational content of RNS with respect to stock mispricing is stronger under more frequent rebalancing, and hence to further test the conjecture that this effect is temporary. Results for the performance of the weekly rebalanced RNS-sorted portfolios are reported in Table A.10.

-Table A.10 here-

Consistent with the argument that RNS signals temporary mispricing, the reported results show that under weekly rebalancing, the strategy that goes long the quintile portfolio with the highest RNS stocks and short the quintile portfolio with the lowest RNS stocks would yield a strongly significant α_{FFC} of 37 bps *per week* (t-stat: 6.55), which is two-and-a-half times higher than the risk-adjusted return of the same strategy under monthly rebalancing.

Apart from the fact that the spread return between the highest and the lowest RNS stock portfolios is more significant under weekly rebalancing, the reported results also show that the temporary mispricing information embedded in RNS appears to be more "symmetric". In particular, we find that it is not only the portfolio with the lowest RNS stocks that yields

[9] We would like to thank an anonymous referee for suggesting this analysis.

a significantly negative α_{FFC} of -14 bps per week (t-stat: -4.99), but it is also the portfolio with highest RNS stocks that yields a significantly positive α_{FFC} of 24 bps per week (t-stat: 4.71). The main conclusion from this finding is that a relatively high RNS value may signal stock underpricing, but this effect is far more short-lived than the overpricing signalled by a highly negative RNS value, since it becomes insignificant as we move from weekly to monthly portfolio rebalancing and returns.

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Table A.1: Risk-Neutral Skewness Tercile Portfolio Sorts

This Table shows the characteristics and performance of stock portfolios constructed on the basis of option-implied Risk-Neutral (RN) Skewness estimates of individual stock returns' distributions, during the period 1996-2012. RN Volatility, Skewness and Kurtosis are computed from daily option prices using the model-free methodology of Bakshi et al. (2003), as described in Section 2.1 of the main body of the study. On the last trading day of each month *t*, stocks are sorted in ascending order according to their RN Skewness estimate and they are assigned to tercile portfolios. We then calculate the equally-weighted returns of these portfolios at the end of the following month *t+1* (i.e. post-ranking monthly returns). Mean return stands for the average monthly portfolio return during the examined period and α_{FFC} stands for the monthly portfolio alpha estimated from the Fama-French-Carhart (FFC) 4-factor model. The Table also reports the portfolios' loadings (β's) with respect to the market (MKT), size (SMB), value (HML) and momentum (MOM) factors estimated from the FFC model as well as its explanatory power (R^2). Moreover, it reports the average values of RN Skewness, Volatility and Kurtosis and the number of stocks (N) in each portfolio. The pre-last line shows the difference (spread) between the portfolio with the highest RN Skewness stocks and the portfolio with lowest RN Skewness stocks in each case. t-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Terciles	RN Skewness	Mean return	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	R^2	RN Volatility	RN Kurtosis	N
1 (Lowest RNS)	-0.7166	0.48	-0.32***	1.10***	0.30***	0.01	-0.01	0.93	0.4310	3.4930	212
			(-2.78)	(36.67)	(9.28)	(0.21)	(-0.32)				
2	-0.3877	0.74	-0.13	1.20***	0.44***	-0.06	-0.02	0.93	0.4799	3.1073	212
			(-0.93)	(45.40)	(11.51)	(-1.09)	(-0.67)				
3 (Highest RNS)	-0.1316	1.01	0.15	1.24***	0.61***	-0.23***	-0.09**	0.90	0.5461	3.0282	212
			(0.81)	(34.07)	(9.99)	(-4.19)	(-2.35)				
3-1	0.5850***	0.52**	0.47***	0.14***	0.31***	-0.24***	-0.08*	0.40	0.1151***	-0.4649***	
t(3-1)	(5.79)	(2.30)	(2.58)	(4.12)	(5.67)	(-3.66)	(-1.79)		(5.62)	(-5.30)	

Table A.2: Open-to-Close Monthly Returns of Risk-Neutral Skewness-Sorted Portfolios

This Table shows the characteristics and performance of stock portfolios constructed on the basis of Risk-Neutral Skewness (RNS) estimates of individual stock returns' distributions, during the period 1996-2012. RNS is computed from daily option prices using the model-free methodology of Bakshi et al. (2003). On the last trading day of each month *t*, stocks are sorted in ascending order according to their RNS estimate and they are assigned to tercile (Panel A) or quintile (Panel B) portfolios. We then calculate the equally-weighted returns of these portfolios using opening stock prices on the first trading day of the following month *t+1* and closing stock prices on the last trading day of the following month *t+1*. Mean return stands for the average monthly portfolio return during the examined period and α_{FFC} stands for the monthly portfolio alpha estimated from the Fama-French-Carhart (FFC) 4-factor model. The Table also reports the portfolios' loadings (β's) with respect to the market (MKT), size (SMB), value (HML) and momentum (MOM) factors estimated from the FFC model as well as its explanatory power (R^2). Moreover, it reports the average number of stocks (N) in each portfolio. The pre-last line shows the difference (spread) between the portfolio with the highest RN Skewness stocks and the portfolio with lowest RN Skewness stocks in each case. t-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Tercile Portfolios

Terciles	RN Skewness	Mean return	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	R^2	N
1 (Lowest RNS)	-0.7166	0.52	-0.22*	1.05***	0.31***	-0.11**	-0.05	0.90	212
			(-1.64)	(26.78)	(8.04)	(-2.56)	(-1.35)		
2	-0.3877	0.74	-0.02	1.15***	0.43***	-0.18***	-0.07**	0.90	212
			(-0.16)	(34.45)	(10.72)	(-5.23)	(-2.32)		
3 (Highest RNS)	-0.1316	0.91	0.18	1.20***	0.60***	-0.30***	-0.12***	0.88	212
			(0.97)	(28.45)	(12.2)	(-9.40)	(-3.02)		
3-1	0.5850***	0.39*	0.40**	0.15***	0.30***	-0.19***	-0.07	0.40	
t(3-1)	(5.79)	(1.78)	(2.12)	(3.45)	(7.86)	(-4.96)	(-1.53)		

Panel B: Quintile Portfolios

Quintiles	RN Skewness	Mean return	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	R^2	N
1 (Lowest RNS)	-0.8268	0.49	-0.24*	1.03***	0.30***	-0.10**	-0.02	0.87	127
			(-1.65)	(21.84)	(7.04)	(-2.28)	(-0.71)		
2	-0.5249	0.58	-0.17	1.11***	0.34***	-0.11***	-0.06*	0.89	127
			(-1.13)	(31.86)	(7.52)	(-2.64)	(-1.90)		
3	-0.3866	0.79	0.03	1.15***	0.44***	-0.18***	-0.07*	0.89	127
			(0.22)	(27.32)	(11.16)	(-4.73)	(-1.83)		
4	-0.2651	0.78	0.07	1.18***	0.51***	-0.25***	-0.12***	0.86	127
			(0.34)	(29.63)	(9.34)	(-7.82)	(-2.99)		
5 (Highest RNS)	-0.0564	0.95	0.21	1.21***	0.65***	-0.32***	-0.12***	0.86	127
			(1.10)	(23.71)	(13.67)	(-9.03)	(-2.66)		
5-1	0.7704***	0.45*	0.46**	0.18***	0.35***	-0.22***	-0.09	0.39	
t(5-1)	(5.79)	(1.76)	(2.04)	(3.19)	(8.19)	(-5.69)	(-1.63)		

Table A.3: Long-Term Performance of Risk-Neutral Skewness-Sorted Portfolios

This Table shows the k^{th}-month ahead performance of stock portfolios constructed on the basis of option-implied Risk-Neutral Skewness (RNS) estimates of individual stock returns' distributions, during the period 1996-2012. RNS is computed from daily option prices using the model-free methodology of Bakshi et al. (2003). On the last trading day of each month *t*, stocks are sorted in ascending order according to their RNS estimate and they are assigned to quintile portfolios. We compute the post-ranking equally-weighted returns of these portfolios at the end of the month $t+k$, where k=1, 2, 3, 4, 5, and 6. Mean return stands for the average $t+k$ monthly portfolio return and α_{FFC} stands for the $t+k$ monthly portfolio alpha estimated from the Fama-French-Carhart (FFC) 4-factor model. In each case, the pre-last line shows the difference (spread) between the portfolio with the highest RNS stocks and the portfolio with lowest RNS stocks in each case. t-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Month t+1		Month t+2		Month t+3		Month t+4		Month t+5		Month t+6	
Quintiles	Mean return	α_{FFC}	Mean return	α_{FFC}	Mean return	α_{FFC}	Mean return	α_{FFC}	Mean return	α_{FFC}	Mean return	α_{FFC}
1 (Lowest RNS)	0.46	-0.32**	0.58	-0.20*	0.61	-0.14	0.61	-0.11	0.54	-0.18	0.77	0.09
		(-2.36)		(-1.70)		(-1.13)		(-0.82)		(-1.61)		(0.76)
2	0.56	-0.29**	0.81	-0.02	0.78	-0.03	0.78	0.04	0.75	0.02	0.70	-0.04
		(-2.04)		(-0.14)		(-0.21)		(0.29)		(0.15)		(-0.40)
3	0.80	-0.08	0.70	-0.19	0.82	-0.01	0.79	0.02	0.76	0.02	0.79	0.02
		(-0.55)		(-1.47)		(-0.08)		(0.11)		(0.12)		(0.15)
4	0.82	-0.04	0.64	-0.22	0.95	0.12	0.98	0.21	1.00	0.30	0.96	0.21
		(-0.20)		(-1.28)		(0.60)		(1.04)		(1.31)		(1.06)
5 (Highest RNS)	1.07	0.23	0.62	-0.20	0.95	0.16	0.97	0.24	0.85	0.15	0.79	0.09
		(1.10)		(-0.97)		(0.81)		(1.07)		(0.79)		(0.58)
5-1	0.61**	0.55**	0.04	0.01	0.34	0.30	0.35	0.35	0.30	0.33	0.02	0.00
t(5-1)	(2.24)	(2.47)	(0.18)	(0.03)	(1.14)	(1.37)	(1.20)	(1.55)	(0.99)	(1.51)	(0.06)	(0.03)

Table A.4: Fama-MacBeth regressions-Further robustness checks

This Table reports the Fama-MacBeth coefficients of cross-sectional regressions of monthly excess stock returns on lagged Risk-Neutral Skewness (RNS) and a set of firm characteristics during the period 1996-2012. RNS is computed on the last trading day of each month using the model-free methodology of Bakshi et al. (2003). Models (1)-(6) control for firms' beta, market value (MV), book-to-market value ratio (B/M), momentum, 1-month reversal, stock illiquidity proxied by Amihud's (2002) price impact ratio and price per share. Model (1) additionally controls for the maximum daily stock return over the month (Max). Model (2) controls for the Expected Idiosyncratic Skewness (EIS^P) estimated from daily stock returns under the physical measure. Model (3) controls for the probability of a stock achieving a Jackpot return over the next year. Model (4) controls for the stock's Estimated Shorting Fee (ESF). Model (5) controls for the stock's Relative Short Interest (RSI). Model (6) controls for stock returns' idiosyncratic volatility under the physical measure ($IVol^P$). The last row reports the total number of firm-month observations used in each model. t-ratios derived from the time-series of the monthly estimated coefficients using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
RN Skewness	0.0080***	0.0079***	0.0088***	0.0065***	0.0061**	0.0086***
	(3.72)	(3.42)	(3.94)	(2.66)	(2.44)	(4.28)
Beta	-0.0014	-0.0004	-0.0003	-0.0024	-0.0023	-0.0005
	(-0.34)	(-0.09)	(-0.08)	(-0.68)	(-0.65)	(-0.14)
ln(MV)	-0.0006	-0.0009	-0.0012	-0.0009	-0.0010	-0.0014
	(-0.60)	(-0.96)	(-0.94)	(-1.00)	(-1.09)	(-1.54)
B/M	0.0019	0.0003	0.0017	0.0001	0.0003	0.0013
	(1.54)	(0.42)	(1.45)	(0.20)	(0.66)	(1.13)
Momentum	0.0020	0.0018	0.0012	0.0033	0.0033	0.0027
	(0.67)	(0.56)	(0.42)	(0.89)	(0.89)	(0.90)
Reversal	-0.0068	-0.0059	-0.0069	0.0006	0.0015	-0.0052
	(-0.92)	(-0.71)	(-0.92)	(0.06)	(0.17)	(-0.68)
Stock Illiquidity	-0.1063	-0.1748	-0.1026	-0.3530	-0.3828	-0.0751
	(-0.59)	(-0.70)	(-0.56)	(-1.04)	(-1.12)	(-0.41)
Price per share	0.0043**	0.0036**	0.0056***	0.0021	0.0021	0.0032
	(2.28)	(2.01)	(2.66)	(1.42)	(1.42)	(1.50)
Max	-0.0161					
	(-0.65)					
EIS^P		-0.0059***				
		(-2.62)				
Jackpot			-0.6521			
			(-1.24)			
ESF				-0.0061*		
				(-1.88)		
RSI					-0.0384*	
					(-1.83)	
$IVol^P$						-0.3023*
						(-1.85)
Intercept	0.0049	0.0170	0.0150	0.0218	0.0228	0.0349
	(0.22)	(0.67)	(0.46)	(0.98)	(0.98)	(1.31)
Observations	97,171	81,533	84,032	79,881	79,881	97,171

Table A.5: Risk-Neutral Skewness and Future Earnings Surprises

This Table shows the future quarterly earnings surprise of portfolios constructed on the basis of stocks' Risk-Neutral Skewness (RNS) estimates during the period 1996-2012. RNS is computed from daily option prices using the model-free methodology of Bakshi et al. (2003). On the last trading day of each month *t*, stocks are sorted in ascending order according to their RNS estimate and assigned to quintile portfolios. For each portfolio, we calculate the average firms' quarterly unexpected earnings (UE) during the subsequent n=4, 8, 12, 16, 20, 24 weeks, defined as the difference between announced quarterly earnings and the latest earnings forecast consensus. Similarly, for each portfolio, we calculate the average firms' standardized unexpected earnings (SUE), defined as the ratio of UE divided by the standard deviation of latest consensus quarterly earnings forecast. The source of analysts' forecasts data is I/B/E/S. The Lowest-Highest RNS column shows the difference between the average UE or SUE of the lowest RNS and the highest RNS quintile portfolios. N denotes the average total number of firms across all quintile portfolios, for which UE or SUE have been calculated at each horizon. t-statistics are calculated using Newey-West standard errors with 5 lags are also provided. * indicates statistical significance at the 10% level.

	UE			SUE		
n weeks	Lowest-Highest RNS	t-statistic	N	Lowest-Highest RNS	t-statistic	N
4	-0.0145	-0.82	153	0.3438	1.35	135
8	-0.0046	-0.44	301	0.2764*	1.95	264
12	-0.0044	-0.42	443	0.1576	1.45	391
16	-0.0074	-0.69	504	0.1423	1.33	445
20	-0.0076	-0.70	509	0.1525	1.42	449
24	-0.0078	-0.70	511	0.1547	1.43	450

Table A.6: Systematic and Unsystematic Risk-Neutral Skewness Portfolio Sorts- Physical betas

This Table shows the average monthly returns (Mean return) and the monthly Fama-French-Carhart alphas (α_{FFC}) estimated from the corresponding 4-factor model for quintile portfolios constructed on the basis of systematic risk-neutral skewness (RNS) (Panel A) and unsystematic RNS (Panel B) estimates for individual stocks extracted from daily option prices. The sample period is 1996-2012. We follow the methodology of Bakshi et al. (2003), as described in Section 2.2 of the main body of the study, to decompose total RNS into its systematic and unsystematic components, using *physical stock betas*. On the last trading day of each month *t*, stocks are sorted in ascending order according to their systematic RNS (Panel A) or unsystematic RNS (Panel B) estimates and they are assigned to quintile portfolios. We then calculate the equally-weighted returns of these portfolios at the end of the following month *t+1* (i.e. post-ranking monthly returns). The Table also reports the average portfolio total RNS value in each case as well as the average number (N) of stocks in each portfolio. The pre-last line shows the difference (spread) between the portfolio with the highest and the portfolio with the lowest systematic RNS (Panel A) and unsystematic RNS (Panel B) stocks in each case. t-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Systematic RNS sorts

Quintiles	Total RNS	Mean return	α_{FFC}	N
1 (Lowest Systematic RNS)	-0.4818	0.88	0.14 (0.87)	127
2	-0.4235	0.91	0.13 (0.80)	127
3	-0.3997	0.76	-0.09 (-0.55)	127
4	-0.3969	0.63	-0.25 (-1.24)	127
5 (Highest Systematic RNS)	-0.3579	0.55	-0.43** (-2.06)	127
5-1	0.1240***	-0.33	-0.57*	
t(5-1)	(4.85)	(-1.05)	(-1.90)	

Panel B: Unsystematic RNS sorts

Quintiles	Total RNS	Mean return	α_{FFC}	N
1 (Lowest Unsystematic RNS)	-0.6925	0.25	-0.54*** (-2.92)	127
2	-0.4342	0.58	-0.32* (-1.71)	127
3	-0.3492	0.97	0.09 (0.60)	127
4	-0.3037	0.89	0.01 (0.08)	127
5 (Highest Unsystematic RNS)	-0.2802	1.05	0.26 (1.19)	127
5-1	0.4123***	0.80**	0.79***	
t(5-1)	(5.64)	(2.42)	(2.81)	

Table A.7: Risk-Neutral Coskewness and Idiosyncratic RNS Portfolio Sorts

This Table shows the average monthly returns (Mean return) and the monthly Fama-French-Carhart alphas (α_{FFC}) estimated from the corresponding 4-factor model for quintile portfolios constructed on the basis of Risk-Neutral (RN) Coskewness (Panel A) and Idiosyncratic RNS (Panel B) estimates for individual stocks. The sample period is 1996-2012. We follow the methodology of Bakshi et al. (2003) to extract RNS from daily option prices and the methodology of Conrad et al. (2013), as described in Section 7 of the Supplementary Appendix, to compute RN Coskewness and Idiosyncratic RNS, using risk-neutral stock betas estimated as in Bali et al. (2014). On the last trading day of each month *t*, stocks are sorted in ascending order according to their RN Coskewness (Panel A) or Idiosyncratic RNS (Panel B) estimate and they are assigned to quintile portfolios. We then calculate the equally-weighted returns of these portfolios at the end of the following month *t+1* (i.e. post-ranking monthly returns). The Table also reports the average portfolio total RNS value in each case. The pre-last line shows the difference (spread) between the portfolio with the highest and the portfolio with the lowest RN Coskewness (Panel A) or Idiosyncratic RNS (Panel B) stocks in each case. t-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: RN Coskewness sorts

Quintiles	Total RNS	Mean return	α_{FFC}	N
1 (Lowest RN Coskewness)	-0.5690	0.77	0.13 (1.09)	109
2	-0.4629	0.92	0.18 (1.33)	109
3	-0.4028	0.97	0.19 (0.89)	109
4	-0.3689	0.84	0.00 (0.05)	109
5 (Highest RN Coskewness)	-0.3423	0.32	-0.59** (-2.45)	109
5-1	0.2267***	-0.45	-0.72**	
t(5-1)	(5.34)	(-0.76)	(-2.48)	

Panel B: Idiosyncratic RNS sorts

Quintiles	Total RNS	Mean return	α_{FFC}	N
1 (Lowest Idiosyncratic RNS)	-0.7737	0.42	-0.34*** (-2.69)	109
2	-0.5241	0.74	-0.03 (-0.18)	109
3	-0.4021	0.86	0.07 (0.55)	109
4	-0.3030	0.96	0.16 (0.86)	109
5 (Highest Idiosyncratic RNS)	-0.1430	0.83	0.06 (0.29)	109
5-1	0.6307***	0.41	0.40*	
t(5-1)	(5.58)	(1.54)	(1.81)	

Table A.8: Risk-Neutral Coskewness and Idiosyncratic RNS Portfolio Sorts-Physical betas

This Table shows the average monthly returns (Mean return) and the monthly Fama-French-Carhart alphas (α_{FFC}) estimated from the corresponding 4-factor model for quintile portfolios constructed on the basis of Risk-Neutral (RN) Coskewness (Panel A) and Idiosyncratic RNS (Panel B) estimates for individual stocks. The sample period is 1996-2012. We follow the methodology of Bakshi et al. (2003) to extract RNS from daily option prices and the methodology of Conrad et al. (2013), as described in Section 7 of the Supplementary Appendix, to compute RN Coskewness and Idiosyncratic RNS, using *physical stock betas*. On the last trading day of each month *t*, stocks are sorted in ascending order according to their RN Coskewness (Panel A) or Idiosyncratic RNS (Panel B) estimate and they are assigned to quintile portfolios. We then calculate the equally-weighted returns of these portfolios at the end of the following month *t+1* (i.e. post-ranking monthly returns). The Table also reports the average portfolio total RNS value in each case. The pre-last line shows the difference (spread) between the portfolio with the highest and the portfolio with the lowest RN Coskewness (Panel A) or Idiosyncratic RNS (Panel B) stocks in each case. t-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: RN Coskewness sorts

Quintiles	Total RNS	Mean return	α_{FFC}	N
1 (Lowest RN Coskewness)	-0.4818	0.88	0.14 (0.87)	127
2	-0.4235	0.91	0.13 (0.80)	127
3	-0.3997	0.76	-0.09 (-0.55)	127
4	-0.3969	0.63	-0.25 (-1.24)	127
5 (Highest RN Coskewness)	-0.3579	0.55	-0.43** (-2.06)	127
5-1	0.1240***	-0.33	-0.57*	
t(5-1)	(4.85)	(-1.05)	(-1.90)	

Panel B: Idiosyncratic RNS sorts

Quintiles	Total RNS	Mean return	α_{FFC}	N
1 (Lowest Idiosyncratic RNS)	-0.7750	0.46	-0.34** (-2.41)	127
2	-0.5057	0.63	-0.22 (-1.58)	127
3	-0.3872	0.86	0.01 (0.05)	127
4	-0.2873	0.80	-0.06 (-0.36)	127
5 (Highest Idiosyncratic RNS)	-0.1246	0.97	0.12 (0.61)	127
5-1	0.6304***	0.50**	0.46**	
t(5-1)	(5.76)	(2.18)	(2.35)	

Table A.9: Bivariate conditional portfolio sorts: Risk-Neutral Skewness and Stock Illiquidity

This Table shows the performance of bivariate stock portfolios constructed on the basis of Risk-Neutral Skewness (RNS) estimates and stock illiquidity, during the period 1996-2012. RNS is computed from daily option prices using the model-free methodology of Bakshi et al. (2003). Stock illiquidity (ILLIQ) is proxied by the price impact ratio of Amihud (2002). On the last trading day of each month *t*, stocks are sorted in ascending order according to their RNS estimate and assigned to tercile portfolios. Within each RNS tercile portfolio, we further sort stocks according to their illiquidity proxy values and construct again tercile portfolios. We then calculate the equally-weighted returns of these nine portfolios at the end of the following month *t+1* (i.e. post-ranking monthly returns). The Table reports monthly Fama-French (FF) portfolio alphas estimated from the corresponding 3-factor model. The column labeled 'Difference' reports the alpha of the spread between the portfolio with the most illiquid stocks and the portfolio with the least illiquid stocks within each RNS tercile portfolio. t-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	ILLIQ Low	ILLIQ Medium	ILLIQ High	Difference
RNS 1 (Lowest)	-0.11	-0.22	-0.66***	-0.55**
	(-1.01)	(-1.48)	(-2.92)	(-2.23)
RNS 2	0.24*	-0.03	-0.62**	-0.85***
	(1.75)	(-0.22)	(-2.50)	(-3.23)
RNS 3 (Highest)	0.14	0.17	-0.03	-0.17
	(0.63)	(0.87)	(0.13)	(-0.71)

Table A.10: Risk-Neutral Skewness Quintile Portfolio Sorts- Weekly Rebalancing and Returns

This Table shows the characteristics and performance of stock portfolios constructed on the basis of option-implied Risk-Neutral (RN) Skewness estimates of individual stock returns' distributions, during the period 1996-2012. RN Volatility, Skewness and Kurtosis are computed from daily option prices using the model-free methodology of Bakshi et al. (2003), as described in Section 2.1. On the last trading day of each week, stocks are sorted in ascending order according to their RN Skewness estimate and they are assigned to quintile portfolios. We then calculate the equally-weighted returns of these portfolios at the end of the following week (i.e. post-ranking weekly returns). Mean return stands for the average weekly portfolio return during the examined period, and α_{FFC} stands for the weekly portfolio alpha estimated from the Fama-French-Carhart (FFC) 4-factor model. The Table also reports the portfolios' loadings (β's) with respect to the market (MKT), size (SMB), value (HML) and momentum (MOM) factors estimated from the FFC model as well as its explanatory power (R^2). Moreover, it reports the average values of RN Skewness, Volatility and Kurtosis and the number of stocks (N) in each portfolio. The pre-last line shows the difference (spread) between the portfolio with the highest RN Skewness stocks and the portfolio with lowest RN Skewness stocks in each case. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Quintiles	RN Skewness	Mean return	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	R^2	RN Volatility	RN Kurtosis	N
1 (Lowest RNS)	-0.8270	0.04	-0.14***	1.03***	0.19***	0.02	-0.01	0.93	0.4264	3.6580	131
			(-4.99)	(56.77)	(6.97)	(0.82)	(-0.44)				
2	-0.5297	0.14	-0.04	1.13***	0.31***	-0.05	-0.03	0.92	0.4514	3.2350	131
			(-1.37)	(73.57)	(10.92)	(-1.39)	(-1.43)				
3	-0.3915	0.19	-0.01	1.19***	0.40***	-0.07	-0.04	0.92	0.4836	3.1042	131
			(-0.23)	(56.10)	(12.85)	(-1.62)	(-1.44)				
4	-0.2720	0.26	0.06	1.25***	0.53***	-0.13***	-0.06**	0.91	0.5180	3.0264	131
			(1.64)	(53.05)	(15.74)	(-2.98)	(-2.03)				
5 (Highest RNS)	-0.0680	0.43	0.24***	1.25***	0.60***	-0.17***	-0.11***	0.86	0.5735	3.0162	131
			(4.71)	(36.01)	(12.23)	(-3.62)	(-2.61)				
5-1	0.7591***	0.39***	0.37***	0.22***	0.41***	-0.20***	-0.10**	0.30	0.1470***	-0.6419***	
t(5-1)	(10.37)	(5.10)	(6.55)	(5.27)	(7.21)	(-3.31)	(-1.98)		(10.00)	(-9.44)	