Risk-Neutral Skewness and Stock Outperformance

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Abstract

This study examines whether out-of-the-money (OTM) option prices, which determine the Risk-Neutral Skewness (RNS) of the underlying stock return distribution, contain information with respect to subsequent stock *outperformance*. A long-only portfolio containing the stocks with the highest values of RNS, or the biggest increases in RNS (ΔRNS) relative to the previous trading day, yields significant risk-adjusted performance in the *post-ranking week* during the period 1996-2014. This outperformance is mainly driven by stocks that are relatively underpriced and are exposed to greater downside risk. These findings are consistent with a trading mechanism, according to which investors may choose to exploit perceived stock underpricing by buying (selling) OTM call (put) options due to their embedded leverage, rather than directly buying the underlying stock, to avoid exposure to its potential downside risk. In this case, the option market leads the stock market with respect to *positive* price discovery, but due to the absence of severe limits-to-arbitrage for the long-side, the price correction signalled by RNS is very quick, typically overnight.

JEL classification: G12, G13, G14.

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I. Introduction

In the real world of incomplete capital markets characterized by limits-to-arbitrage and information asymmetry, option payoffs cannot be perfectly replicated by the underlying assets, and hence options are not redundant assets as in the Black and Scholes (1973) paradigm (Ross (1976), Detemple and Selden (1991), and Back (1993)). An informed investor may choose to trade in the option market, if it is sufficiently liquid, to exploit the higher leverage embedded in options (Black (1975)), or to disguise her information signal in the presence of noise traders (An, Ang, Bali, and Cakici (2014)). As a consequence, option prices may convey information that is not already incorporated into the price of the underlying asset. In fact, there is a growing body of evidence that various option-based variables can predict future stock returns.[1]

With respect to information extracted from option prices, Xing, Zhang, and Zhao (2010) find that stocks which exhibit the steepest implied volatility smirks subsequently underperform. Ofek, Richardson, and Whitelaw (2004) and Cremers and Weinbaum (2010) document that stocks which feature the most negative call-put implied volatility spreads, reflecting deviations from put-call parity due to relatively expensive puts, yield abnormally negative returns. An et al. (2014) find that stocks with large increases (decreases) in put (call) implied volatilities over the previous month are characterized by low future returns. Finally, Rehman and Vilkov (2012) and Stilger, Kostakis, and Poon (2017) find that a strongly negative Risk-Neutral Skewness (RNS) value, arising from very expensive out-of-the-money

[1]Pan and Poteshman (2006) show that the put-to-call option volume ratio is inversely related to future stock returns. Hu (2014) finds that option-induced stock order imbalance is positively related to next-day stock returns. Johnson and So (2012) show that a high option-to-stock volume ratio predicts low stock performance. Similar is the conclusion of Ge, Lin, and Pearson (2016), who additionally document the ability of option volume associated with synthetic long positions to positively predict stock returns. Moreover, a number of studies have also examined the informational content of option-based variables in the context of: expected stock returns based on analyst price targets (Bali, Hu, and Murray, 2017), option returns (Goyal and Saretto (2009), Bali and Murray (2013), and Muravyev (2016)), market timing and asset allocation strategies (Kostakis, Panigirtzoglou, and Skiadopoulos (2011), DeMiguel, Plyakha, Uppal, and Vilkov (2013), and Kempf, Korn, and Saßning (2015)), and earnings announcements and takeovers (Amin and Lee (1997), Jin, Livnat, and Zhang (2012), Chan, Ge, and Lin (2015), Augustin, Brenner, and Subrahmanyam (2015)).

(OTM) puts relative to OTM calls, signals future stock underperformance.

Most of the above studies put forward stock overpricing as an explanation for these predictive relations. In the spirit of Miller (1977), stock overpricing may not be quickly corrected in the underlying market because of various limits-to-arbitrage, most notably short selling constraints. In this case, investors may resort to the option market to trade on their negative news or beliefs, by buying (selling) OTM puts (calls) or synthetically shorting the stock (see Figlewski and Webb, 1993, for a related discussion). Consistent with the demand-based option pricing framework of Gârleanu, Pedersen, and Poteshman (2009) and the evidence in Bollen and Whaley (2004), if risk averse market makers cannot perfectly hedge their positions, this option trading activity will yield a steeper implied volatility smirk, a more negative call-put implied volatility spread, an increase (decrease) in put (call) implied volatility, and a more negative RNS value. This option-implied information is only slowly incorporated into stock prices, giving rise to these predictive relations that hold at least at the monthly frequency.

Different from the above studies, we make two contributions to the literature on the informational content of option prices with respect to future stock returns. First, we examine the informational content of RNS with respect to *stock outperformance*. Since RNS captures the expensiveness of OTM calls relative to OTM puts, a relatively high RNS value can reflect the trading activity of investors who buy (sell) OTM calls (puts) to exploit perceived stock underpricing.[2] Second, we propose and empirically validate a trading mechanism that explains why this positive information may be firstly incorporated in OTM option prices rather than in the underlying stock price. In particular, if the underlying stock is perceived to be underpriced, investors who anticipate a subsequent price correction may resort to the option market to buy (sell) OTM calls (puts) in order to lever up their positions and maximize

[2]To the contrary, the smirk of Xing et al. (2010) is defined as the difference between the implied volatilities of OTM puts and at-the-money (ATM) calls, and hence it ignores the informational content of OTM calls. The call-put volatility spread of Bali and Hovakimian (2009) is computed using only near-the-money and ATM options, ignoring again OTM calls. Similarly, the call-put volatility spread of Cremers and Weinbaum (2010) predominantly reflects near-the-money and ATM options, because it is an open interest-weighted average of spreads across pairs of options with the same strike price and maturity.

their trading profits.[3] However, risk averse market makers may not be able to perfectly hedge their counterparty positions, e.g., due to asymmetric information, transaction costs, stock price jumps, and the downside or inventory risk they may face by buying the underlying stock. In this case, their supply curve of OTM options is not perfectly elastic, and hence they ask for a higher (lower) price to sell (buy) OTM calls (puts), leading to a higher RNS value. As a result, to the extent that market forces subsequently correct this underpricing, a relatively high RNS value or a large increase in RNS (ΔRNS) may signal future stock outperformance.

The signalled outperformance should be stronger if the underlying stock exhibits substantial downside risk. In this case, investors would be more incentivized to buy OTM calls, rather than buying the stock itself, to lever up their long positions without being exposed to downside risk (see Back, 1993, and Pan and Poteshman, 2006, for related arguments). At the same time, risk averse market makers would require a higher premium to write these OTM calls because they would have to resort to the underlying market to hedge their option position, and hence they would also be exposed to the greater downside risk. In sum, a relatively high RNS or ΔRNS value should be even more informative with respect to the future outperformance of an underpriced stock if its downside risk is more pronounced.

It is also expected that the RNS signal should be informative for stock outperformance if options are sufficiently liquid in absolute terms or relatively to the underlying stock. Otherwise, if their bid-ask spreads are too large, the incentive to resort to the option market to speculate on stock underpricing becomes weaker because round-trip transaction costs could eliminate the anticipated trading profit. In addition, if options are too thinly traded relative to the underlying stock, an informed investor may choose not to trade in the option market to avoid revealing her information.

The stock outperformance that a high RNS value may signal should be *short-lived*

[3]Bali and Murray (2013) provide examples of synthetic skewness assets, which yield a high payoff in the case of a large increase in the price of the underlying stock. The construction of these skewness assets involves buying (selling) OTM calls (puts).

since RNS is computed from publicly available OTM option prices. This conjecture is also consistent with the notion of arbitrage asymmetry (see Stambaugh, Yu, and Yuan, 2015); stock underpricing should be rather quickly corrected by arbitrageurs without facing the constraints that apply in the case of stock overpricing.

We empirically test the above conjectures. To this end, we use two rather diverse proxies for stock mispricing: the distance between the actual stock price and the option-implied stock value (DOTS) of Goncalves-Pinto, Grundy, Hameed, van der Heijden, and Zhu (2016), and the composite mispricing rank (MISP) of Stambaugh et al. (2015) and Stambaugh and Yuan (2017). We measure stock downside risk by using a direct as well as an indirect proxy. The direct proxy is the expected idiosyncratic skewness (EIS^P) of the underlying stock returns under the physical measure introduced by Boyer, Mitton, and Vorkink (2010). The indirect proxy is the estimated shorting fee (ESF) of Boehme, Danielsen, and Sorescu (2006).[4] In addition, we utilize the average relative bid-ask spread (RSPREAD) of the options used to calculate the RNS value to capture option liquidity in absolute terms and the average daily option-to-stock volume ratio (O/S) in the prior 12 months to proxy for the option liquidity relative to the underlying stock.

Our results corroborate the conjectured trading mechanism. First, we find that the long-only quintile portfolio of stocks with the highest RNS (ΔRNS) values significantly outperforms, yielding a Fama-French-Carhart (FFC) alpha of 12 (10) basis points (bps) in the post-ranking week with a Newey-West (NW) t-stat of 3.11 (3.15). *A fortiori*, the intersection of the highest RNS and the highest ΔRNS quintiles yields an FFC alpha of 21 bps in the post-ranking week (NW t-stat: 4.03).

Second, we find that a relatively high RNS value becomes a strong signal for subsequent outperformance mainly for stocks that are also perceived to be underpriced and for stocks whose downside risk is more pronounced. In fact, we find that both stock underpricing and pronounced downside risk are reinforcing mechanisms of the RNS signal with respect

[4]In line with the arguments and the evidence of Grullon, Michenaud, and Weston (2015), stock downside risk is expected to be greater in the absence of short selling constraints, i.e., when the shorting fee is low.

to subsequent stock outperformance. Using triple-sorted portfolios, we find that a portfolio of stocks that exhibit higher than median RNS values, are relatively underpriced, and are exposed to greater downside risk yields a strongly significant FFC alpha of 22 bps *per week*.

Third, we find that the stock outperformance signalled by RNS is significant only when options are fairly liquid relative to the underlying stock and their bid-ask spreads are not too high. Fourth, we decompose the post-ranking weekly returns of the RNS- (ΔRNS-) sorted portfolios and find that most of this abnormal performance is earned on the first post-ranking day. We further decompose the first post-ranking daily returns into their overnight and intraday components and find that the signalled outperformance is entirely earned overnight.

Last, we examine whether RNS simply captures stock price pressure. This would have implied that its positive relation with future stock returns could be a manifest of a short-term reversal effect (see Goncalves-Pinto et al. (2016)). Rejecting this potential concern, we show that RNS exhibits an almost zero rank correlation with the 1-, 3-, and 5-day cumulative stock return. Equally importantly, the positive RNS gradient with respect to post-ranking stock returns remains intact, even when we firstly condition upon positive, zero or negative stock returns on, or up to the portfolio sorting day.

Collectively, our results corroborate the arguments of Easley, O'Hara, and Srinivas (1998) and An et al. (2014) on cross-market predictability by showing that the expensiveness of OTM calls relative to OTM puts predicts future stock returns. Different from the existing literature though, which predominantly argues that this predictive ability is attributable to negative information being firstly incorporated in option prices and then slowly diffused to stock prices due to limits-to-arbitrage, we show that OTM option prices can also embed positive information with respect to the underlying stock.

Our findings also lend support to the demand-based option pricing framework of Gârleanu et al. (2009) by showing that a relatively high RNS value may reflect excess demand for OTM calls from investors who attempt to exploit stock underpricing. Whereas the prior literature has focussed on option price pressure arising from pessimistic investors buying OTM puts, we show under what conditions the corresponding price pressure due to speculative demand for OTM calls can be informative with respect to stock outperformance. In addition, our results comply with the mechanism of Hu (2014), according to which market makers translate option order imbalance into stock order imbalance in their attempt to hedge their counterparty positions. This mechanism can explain why a relatively high RNS value, arising from excess demand (supply) for OTM calls (puts), predicts stock outperformance.

Our results can also be regarded as complementary to the evidence of Pan and Poteshman (2006) and Ge et al. (2016), who show that high buyer-initiated OTM call option trading volume predicts stock outperformance. Instead of utilizing proprietary signed option trading volume data across different levels of moneyness, the RNS signal we employ conveniently summarizes information embedded in publicly available OTM option prices. To the extent that option prices reflect the impact of informed trading volume, their informational content should be equivalent.

II. Methodology and Data

A. Risk-Neutral Skewness: Computation

We compute the Risk-Neutral Skewness (RNS) of the option-implied stock return distribution using the model-free methodology of Bakshi, Kapadia, and Madan (2003). Using the time t prices of OTM call $(C_t(\tau;K))$ and put $(P_t(\tau;K))$ options with strike price K and time-to-expiration τ, the $RNS(\tau)$ for stock i is defined as:

$$RNS_{i,t}(\tau) = \frac{\exp(r\tau)(W_t(\tau) - 3\mu_t(\tau) V_t(\tau)) + 2\mu_t^3(\tau)}{[\exp(r\tau) V_t(\tau) - \mu_t^2(\tau)]^{3/2}}, \tag{1}$$

where r is the risk-free rate, $\mu_t(\tau)$ is given by

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

and $V_t(\tau)$, $W_t(\tau)$, and $X_t(\tau)$ are the time t prices of $\tau-$maturity quadratic, cubic, and quartic contracts, defined as contingent claims with payoffs equal to the second, third, and fourth power of stock i log return, respectively. The corresponding prices of these three contracts are given by

$$\text{(3)} \qquad V_t(\tau) = \int_{S_t}^{\infty} \frac{2\left(1 - \log\left(\frac{K}{S_t}\right)\right)}{K^2} C_t(\tau; K)\, dK + \int_0^{S_t} \frac{2\left(1 + \log\left(\frac{S_t}{K}\right)\right)}{K^2} P_t(\tau; K)\, dK,$$

$$\text{(4)} \qquad \begin{aligned} W_t(\tau) &= \int_{S_t}^{\infty} \frac{6\log\left(\frac{K}{S_t}\right) - 3\left(\log\left(\frac{K}{S_t}\right)\right)^2}{K^2} C_t(\tau; K)\, dK - \\ &- \int_0^{S_t} \frac{6\log\left(\frac{S_t}{K}\right) + 3\left(\log\left(\frac{S_t}{K}\right)\right)^2}{K^2} P_t(\tau; K)\, dK, \end{aligned}$$

and

$$\text{(5)} \qquad \begin{aligned} X_t(\tau) &= \int_{S_t}^{\infty} \frac{12\left(\log\left(\frac{K}{S_t}\right)\right)^2 - 4\left(\log\left(\frac{K}{S_t}\right)\right)^3}{K^2} C_t(\tau; K) + \\ &+ \int_0^{S_t} \frac{12\left(\log\left(\frac{S_t}{K}\right)\right)^2 + 4\left(\log\left(\frac{S_t}{K}\right)\right)^3}{K^2} P_t(\tau; K)\, dK, \end{aligned}$$

where S_t is the price of the underlying stock adjusted by the discounted value of future dividends.

To compute the integrals that appear in $V_t(\tau)$, $W_t(\tau)$, and $X_t(\tau)$, a continuum of OTM option prices would be required. However, traded equity options are available only at few and discrete strikes. In line with Rehman and Vilkov (2012), Conrad, Dittmar, and Ghysels (2013), and Stilger et al. (2017), we require at least two OTM puts and two OTM calls per stock with the same expiry date to compute RNS on a given day. We interpolate the implied volatilities of the available options, separately for puts and calls, between the lowest and the highest available moneyness using a piecewise Hermite polynomial, and we extrapolate beyond the lowest and the highest moneyness using the implied volatility at each boundary. This way, we fill in 997 grid points in the moneyness range from 1/3 to 3. We convert these implied volatilities to the corresponding option prices via the Black-Scholes formula. Finally, we use these option prices to determine $V_t(\tau)$, $W_t(\tau)$, and $X_t(\tau)$ by numerically computing the corresponding integrals via Simpson's rule.

We use daily prices of OTM equity options with 10 to 180 days-to-maturity. The closing option price is computed as the average of the bid and ask prices. We discard options with zero open interest, zero bid price, negative strike, price less than \$0.50, missing implied volatility, and non-standard settlement. As mentioned above, we also filter out stocks with less than two OTM puts and two OTM calls with the same expiry on a given day. Among the eligible sets of options that satisfy the above criteria, we use the one with the shortest maturity. This choice is consistent with the conjecture that investors who seek to profit from stock underpricing would trade short-dated options because, for a given level of moneyness, they offer considerably higher leverage relative to long-dated options.

B. Data Sources and Firm Characteristics

We obtain daily data on equity options from OptionMetrics IvyDB and on stocks from CRSP. Our stock universe consists of U.S. common stocks (share codes 10 and 11) listed on NYSE, NYSE MKT, and NASDAQ (exchange codes 1, 2, and 3). The sample period is January 1996 to June 2014. The risk-free rate is proxied by the 3-month T-Bill rate from the Federal Reserve H.15 release. Data on daily factor returns are sourced from Kenneth French's website. We also compute overnight and intraday equity factor returns in the spirit of Lou, Polk, and Skouras (2017).

We construct a series of firm-level variables, whose definitions are provided in the

Appendix. In particular, we compute the distance between the actual stock price and the option-implied stock value (DOTS) as in Goncalves-Pinto et al. (2016), the Expected Idiosyncratic Skewness EIS^P of stock returns under the physical measure of Boyer et al. (2010), the Estimated Shorting Fee (ESF) of Boehme et al. (2006), stock return momentum (MOM), market capitalization (MV), and the book-to-market value ratio (B/M). We also use the composite stock mispricing rank (MISP) of Stambaugh et al. (2015) and Stambaugh and Yuan (2017), which is available from Robert Stambaugh's website. A low (high) value for DOTS and MISP indicates that the stock is relatively underpriced (overpriced). A low (high) value for EIS^P and ESF indicates that the stock entails greater (lower) downside risk. As a proxy for option liquidity, we compute the average relative bid-ask spread (RSPREAD) across the OTM options used to compute RNS on a given day. As a proxy for option liquidity relative to stock liquidity, we compute the average daily option-to-stock volume ratio (O/S) in the prior 12 months, using all available options expiring from 10 to 180 days.

C. Descriptive Statistics

Our sample of RNS values consists of 3,121,205 permno-day observations. Table 1 reports the descriptive statistics for the option dataset used to compute these daily RNS values. The average RNS value is −0.41 and the average maturity of the utilized OTM options is 91.8 days. The majority of these OTM options have sizeable open interest, they are not particularly deep-out-of-the-money, and they exhibit a median RSPREAD of 14.6%. Moreover, RNS values are available for a sufficiently large cross-section of stocks on a given day, with a median of 671 stocks.[5]

-Table 1 here-

Next, we examine whether RNS is correlated with firm characteristics that are known to be related to future stock returns or with the stock characteristics we use in the subsequent

[5]In our benchmark analysis, each RNS-sorted quintile portfolio contains, on average, 133 stocks, whereas each ΔRNS quintile portfolio contains, on average, 125 stocks.

portfolio analysis. To this end, Table 2 reports the pairwise Spearman's rank correlation coefficients between RNS and a series of variables; the corresponding Pearson correlation coefficients are very similar. Since our benchmark analysis relies on weekly portfolio sorts every Wednesday, the reported coefficients are the time-series averages of the rank correlation coefficients computed every Wednesday during our sample period.

-Table 2 here-

The conclusion from Table 2 is that RNS is not highly correlated with any of the variables considered. The rank correlation of ΔRNS with these variables is even lower. As a result, stock portfolios constructed on the basis of RNS or ΔRNS do not simply mimic the performance of portfolios constructed on the basis of other stock characteristics. These low rank correlation coefficients also ensure that bivariate or trivariate independently-sorted portfolios on the basis of RNS and other stock characteristics will be well populated.

Of particular interest is the rank correlation of RNS and ΔRNS with DOTS. Goncalves-Pinto et al. (2016) conjecture that DOTS could reflect both stock price pressure and informed trading embedded in option prices. However, they show that it mainly captures stock price pressure, rendering it a meaningful mispricing proxy at the daily frequency. We find that RNS and ΔRNS exhibit relatively low rank correlation with DOTS (average: -0.31). Hence, we claim that RNS does not mimic DOTS, and hence it cannot be regarded as a stock price pressure or mispricing proxy. Supporting further the latter argument, we find that RNS exhibits an even lower rank correlation with MISP, whereas the correlation of ΔRNS with MISP is zero. Finally, consistent with the argument that RNS does not reflect stock price pressure, its average rank correlation coefficient with the stock return on the portfolio sorting day (RET(1)) or the cumulative 5-day stock return (RET(5)) is close to zero.

III. RNS and $\triangle$RNS Portfolio Sorts

The starting point of our analysis is to examine the relation between RNS and future stock returns at the weekly frequency. To this end, we sort stocks in ascending order according to their RNS (ΔRNS) values and assign them to quintile portfolios. For our benchmark results, we construct these portfolios using RNS values computed at market close every Wednesday. Arguably, the level of RNS could be inherently related to a series of firm characteristics (see Dennis and Mayhew, 2002, for an empirical investigation). However, the low degree of persistence of daily RNS values implies that RNS primarily reflects transient price pressure in OTM options.[6] Nevertheless, controlling for potential firm fixed effects, including an option maturity effect, we also sort stocks into quintile portfolios on the basis of the change in their RNS value (ΔRNS) at market close every Wednesday relative to the previous trading day.

A. Portfolio Characteristics

Table 3 reports the average characteristics of the constituent stocks for each RNS-sorted (Panel A) and ΔRNS (Panel B) quintile portfolio. We find that the stocks in the highest RNS quintile have smaller average capitalization relative to the stocks in the lowest RNS quintile.[7] Interestingly, the highest RNS quintile contains stocks that are, on average, characterized as relatively underpriced according to DOTS, but relatively overpriced according to MISP. The stocks in the highest RNS quintile also exhibit, on average, lower exposure to downside risk according to EIS^P and ESF, and their average return on the portfolio sorting day or during the prior five trading days is lower relative to the corresponding average return of the stocks in the lowest RNS quintile. However, it should be noted that, as illustrated by the low rank correlation coefficients between RNS and the rest of the variables

[6] The average AR(1) coefficient of daily RNS values across the firms in our sample is 0.70. In comparison, the corresponding average AR(1) coefficient of daily Risk-Neutral Variance values is much higher (0.96).

[7] RNS takes predominantly negative values. Hence, a relatively high RNS value is defined with respect to the cross-sectional distribution of RNS values on a given day, but it can still have a negative sign.

reported in Table 2, a large cross-sectional variation within each quintile portfolio underlies these average values. We explore this variation using bivariate and trivariate portfolio sorts in the subsequent sections.

-Table 3 here-

Regarding ΔRNS-sorted portfolios, the spread in the average values between the highest and the lowest quintiles mostly disappears for persistent firm characteristics (e.g., MV, B/M, MISP, EIS^P, ESF). This is an expected finding because ΔRNS cancels out firm fixed effects that potentially determine the level of RNS. On the other hand, the corresponding spread in average values for the variables that capture transient information at the daily frequency (e.g., DOTS, RET(1), RET(5)) remains significant. Nevertheless, the low rank correlation coefficients reported in Table 2 ensure that ΔRNS portfolio sorts by no means coincide with stock mispricing or return-based portfolio sorts.

B. Post-Ranking Performance

Table 4 reports the weekly post-ranking performance of RNS-sorted (Panel A) and ΔRNS-sorted (Panel B) quintile portfolios. In particular, we compute weekly equally-weighted portfolio returns by compounding the corresponding daily portfolio returns, calculated from the sorting Wednesday market close until the following Wednesday market close. For both RNS- and ΔRNS-sorted quintiles, we find a monotonically positive gradient in the post-ranking premia as we move from the portfolio with the lowest RNS (ΔRNS) stocks to the portfolio with the highest RNS (ΔRNS) stocks. Most importantly for the focus of our study, we find that the quintile portfolio containing the stocks with the highest RNS (ΔRNS) values yields a significant post-ranking weekly premium of 32 (29) bps.

-Table 4 here-

Next, we examine the post-ranking performance of RNS- and ΔRNS-sorted quintiles on a risk-adjusted basis. We find that the quintile portfolio that goes long the stocks with the highest RNS (ΔRNS) values yields a significant FFC alpha of 12 (10) bps in the post-ranking week with a NW t-stat of 3.11 (3.15).[8,9] To highlight its economic significance, this outperformance corresponds to an annualized FFC alpha of 6.43% (5.33%).

We can draw four remarks based on the findings reported in Panels A and B of Table 4. First, our finding shows that a relatively high RNS (ΔRNS) value can be an informative signal for significant stock outperformance at the weekly frequency. This result is consistent with the argument that the option market may lead the stock market with respect to price discovery. However, contrary to the prior literature, which has predominantly argued that option prices may embed negative information that is not yet reflected in the underlying stock price due to short selling constraints (see, inter alia, Ofek et al. (2004), Xing et al. (2010), and Stilger et al. (2017)), we show that OTM option prices can also embed *positive* information with respect to the underlying stock. Interestingly, it seems challenging to rationalize the consistent ability of the long-only portfolio with the highest RNS (ΔRNS) stocks to yield significant outperformance. This is because limits-to-arbitrage for the long leg of a strategy are much less severe relative to the corresponding limits for the short leg. We take on this task in the subsequent sections.

Second, Table 4 shows that the spread between the highest and the lowest RNS (ΔRNS) quintiles yields an FFC alpha of 24 (25) bps in the post-ranking week, with a NW t-stat of 5.03 (6.65). This finding is consistent with the evidence of Rehman and Vilkov (2012) and Stilger et al. (2017) who show that, at the *monthly* frequency, the relation between RNS and future stock returns is positive.[10] We robustify their evidence by showing that this relation becomes economically and statistically more significant at the weekly frequency

[8]Throughout the study, we compute t-statistics using NW standard errors with the lag length (q) given by the automatic lag selection procedure of Newey and West (1994), where $q = 4(T/100)^{2/9}$ and T is the sample size. In our benchmark analysis, we utilize post-ranking portfolio returns for 962 weeks, hence $q = 7$.

[9]We present results for quintile portfolios to ensure that they contain a large number of stocks, and hence are well diversified throughout our sample period. The documented outperformance is even more significant when we instead consider decile portfolios. In particular, the decile portfolio containing the stocks with the highest RNS (ΔRNS) values yields a highly significant FFC alpha of 19 (12) bps in the post-ranking week.

[10]See also the evidence of Borochin, Chang, and Wu (2017) on the relation between the term structure of RNS and subsequent stock returns.

during our extended sample period.[11] This result implies that the RNS signal is short-lived, and hence more frequent rebalancing strengthens this predictive relation.

Third, contributing further to this strand of the literature, we show that this positive relation also holds when we alternatively use ΔRNS, which is well-suited to capture the transient nature of the information embedded in RNS. Fourth, we find that, at the weekly frequency, the significant abnormal performance of the long-short RNS (ΔRNS) strategy is symmetrically sourced from *both* the underperformance of the lowest RNS (ΔRNS) quintile *and* the outperformance of the highest RNS (ΔRNS) quintile. This is different from the above studies, which argue that this positive relation is mainly driven by the underperformance of the lowest RNS stocks.

Panel C of Table 4 reports the corresponding performance of two bivariate stock portfolios constructed as the intersections of the lowest (highest) RNS and the lowest (highest) ΔRNS independently-sorted quintiles. In line with the argument that relatively high RNS and ΔRNS values can signal subsequent stock outperformance, we find that the portfolio of stocks with the highest RNS and the highest ΔRNS values yields a strongly significant FFC alpha of 21 bps in the post-ranking week (i.e., 11.53% p.a.). Moreover, confirming that RNS and ΔRNS are positively related to future stock returns, the spread between the portfolio with the highest RNS & ΔRNS values and the portfolio with lowest RNS & ΔRNS values yields an FFC alpha of 40 bps in the post-ranking week (NW t-stat: 5.80).

C. Robustness Checks

We conduct a series of tests to examine the robustness of our benchmark results to alternative methodological choices. First, we risk-adjust the post-ranking performance of RNS- and ΔRNS-sorted portfolios using the 5-factor Fama and French (2015) asset pricing model. Second, we sort stocks into quintile portfolios using the corresponding RNS and ΔRNS values computed at market close every Friday (rather than every Wednesday), and

[11] For example, Rehman and Vilkov (2012) find that the corresponding long-short RNS-based strategy yields an FFC alpha of 47 bps *per month* (t-stat: 2.20) during the period 1996-2007.

we estimate their weekly post-ranking performance by compounding daily portfolio returns until the following Friday market close. Third, we construct quintile portfolios by excluding those stocks whose RNS values are computed from OTM option prices associated with zero total trading volume.

The corresponding results are presented in the Supplementary Appendix and they confirm the conclusions of our benchmark analysis. The stock outperformance signalled by relatively high RNS and ΔRNS values becomes stronger and more significant when we use the 5-factor alpha as an alternative metric of risk-adjusted performance. Moreover, the magnitude and the significance of the documented stock outperformance remains intact when we instead use Friday portfolio sorts. In addition, in the case where we consider RNS values computed only from OTM options with positive total trading volume, the quintile portfolio containing the highest RNS stocks yields a similarly strong FFC alpha in the post-ranking week.

In the Supplementary Appendix, we also consider an alternative, "non-parametric" proxy for RNS (NPRNS), which directly measures the relative expensiveness between OTM calls and OTM puts. Following Bali et al. (2017), NPRNS is computed as the difference between the 30-day implied volatilities of OTM calls (deltas $= 0.20$ and 0.25) and OTM puts (deltas $= -0.20$ and -0.25). We compute NPRNS for the stocks in our benchmark analysis, and we construct NPRNS-sorted quintile portfolios at market close every Wednesday. In accordance with our benchmark results, we find that the quintile portfolio which contains the stocks with the highest NPRNS values yields a significant FFC alpha in the post-ranking week.

Finally, in the Supplementary Appendix, we also examine the performance of RNS- and ΔRNS-sorted portfolios using daily rebalancing. We find that the quintile portfolio containing the stocks with the highest RNS (ΔRNS) values yields a highly significant FFC alpha of 10 (9) bps on the *post-ranking day*. These results indicate that the largest part of the weekly stock outperformance documented in our benchmark analysis is earned on the first post-ranking day. A potential implication of this finding is that the positive information embedded in RNS is subsequently quickly incorporated into the underlying stock price. Section VI examines this issue in detail.

IV. Why can RNS Signal Stock Outperformance?

The robust stock outperformance signalled by relatively high RNS and ΔRNS values warrants further analysis to reveal its sources. To this end, we develop and test a trading mechanism that can give rise to this relation. We argue that a relatively high RNS value may reflect price pressure in OTM options, arising from the trading activity of speculators who resort to the option market to hold leveraged long positions on relatively underpriced stocks. To trade on their optimistic beliefs or positive information and maximize their leverage, investors would buy (sell) OTM call (put) options. The purchase of OTM calls is particularly attractive in comparison to directly purchasing the underlying stock because the former entail no exposure to the potential downside risk that holding the stock involves.

If risk averse market makers cannot perfectly hedge their counterparty positions, then consistent with the demand-based option pricing framework of Gârleanu et al. (2009), this trading activity may exercise upward (downward) price pressure on OTM calls (puts). In fact, to hedge their positions, market makers would need to buy the underlying stock, and get exposed to downside and/or inventory risk. As a result, they would require a risk premium to act as counterparties, which is reflected in higher (lower) prices for selling (buying) OTM calls (puts) to the speculators. This mechanism renders OTM calls (puts) relatively more (less) expensive, resulting into a higher RNS value. In turn, a relatively high RNS value is followed by stock outperformance if market participants perceive this option trading activity as an informative signal and subsequently correct the stock underpricing, or if market makers, in their attempt to hedge their positions, translate this option order imbalance into stock order imbalance by buying the stock and hence raising its price (Hu (2014)).

A. The Role of Stock Underpricing

A testable prediction implied by this mechanism is that a relatively high RNS value should be a strong signal for subsequent stock outperformance primarily for those stocks that are perceived to be underpriced. Otherwise, there would be no incentive in the first place for investors to resort to the option market to set up synthetic long positions using OTM options.

To test this prediction, we construct double-sorted portfolios on the basis of RNS and a proxy for stock mispricing. For robustness, we use two alternative proxies for stock mispricing: *i*) the daily DOTS measure of Goncalves-Pinto et al. (2016), and *ii*) the monthly MISP rank of Stambaugh et al. (2015). These two proxies reflect rather diverse sources of information and they capture potential stock mispricing at different frequencies. In fact, they exhibit almost zero rank correlation. To begin with, we construct bivariate conditional portfolios, where we firstly sort stocks into tercile portfolios according to their RNS values at market close every Wednesday, and then, within each RNS tercile, we further sort stocks into terciles according to their mispricing proxy values.

Panel A.1 of Table 5 reports the weekly post-ranking risk-adjusted performance for selected equally-weighted portfolios when DOTS is used as a mispricing proxy. Consistent with the conjectured trading mechanism, we find that the outperformance of the stocks with the highest RNS values is mainly driven by those stocks that are perceived to be the most underpriced. The tercile portfolio with the most underpriced stocks within the highest RNS tercile yields an impressive FFC alpha of 29 bps (NW t-stat: 5.98) in the post-ranking week. To the contrary, the tercile portfolio with the most overpriced stocks within the highest RNS tercile actually yields a significant negative FFC alpha. In fact, the spread between the most underpriced and the most overpriced stocks within the highest RNS tercile yields a strongly significant FFC alpha of 43 bps in the post-ranking week. The conclusion from these results is that a relatively high RNS value is not a sufficient condition per se for subsequent stock outperformance, and hence it cannot be regarded itself as a proxy for stock underpricing.

-Table 5 here-

Panel B.1 of Table 5 reports the corresponding results when MISP is used as a mispricing proxy. The evidence robustifies the previous conclusions. We find that the tercile portfolio with the most underpriced stocks within the highest RNS tercile yields strong outperformance, whereas the corresponding portfolio with the most overpriced stocks yields an almost zero FFC alpha. Hence, these results confirm that a relatively high RNS value carries information regarding future stock outperformance if the stock is perceived to be underpriced in the first place, whereas it is uninformative if the stock is overpriced.

To further examine the interaction between RNS and stock underpricing, we alternatively construct independent double-sorted portfolios. Panels A.2 and B.2 of Table 5 report the weekly post-ranking performance of these portfolios for the DOTS and MISP mispricing proxies, respectively. The independent double-sorted portfolios are well populated. This reflects the low rank correlation coefficients between RNS and DOTS or MISP reported in Table 2 and alleviates the potential concern that a high (low) RNS value may coincide with a low (high) DOTS or MISP value.

The reported results support the argument that the combination of relatively high RNS and stock underpricing strengthens subsequent stock outperformance. Panel A.2 shows that the intersection of the stocks with the highest RNS and lowest DOTS values yields an FFC alpha of 23 bps (NW t-stat: 5.85) in the post-ranking week. To the contrary, the portfolio of stocks with the highest RNS and highest DOTS values yields a highly significant negative FFC alpha. Equally importantly, we find that the portfolio which combines the most underpriced stocks and the stocks with the lowest RNS values fails to deliver a significant FFC alpha. Hence, stock underpricing, as proxied by DOTS, becomes a strong signal for subsequent stock outperformance only when it is associated with a relatively high RNS value, confirming that investors have resorted to the option market to exploit it. In fact, the spread between the portfolio containing the lowest DOTS and highest RNS stocks and the portfolio containing the lowest DOTS and lowest RNS stocks yields a highly significant FFC alpha.[12] Finally, the corresponding results in Panel B.2 further support the argument that a relatively high RNS value ceases to be an informative signal regarding future outperformance for those stocks that are considered to be overpriced. These results also show that a low MISP value cannot be regarded either as a sufficient condition for subsequent stock outperformance; it becomes a valid signal when it is combined with a relatively high RNS value.

B. The Role of Stock Downside Risk

The trading mechanism described above also yields a testable prediction regarding the role of stock downside risk. A relatively high RNS value is expected to be more informative with respect to the future outperformance of a stock if the latter entails greater downside risk. In this case, speculators have a stronger incentive to resort to the option market to trade on their optimistic beliefs rather than directly buying the stock. The RNS signal should also be more informative in this case because market makers would require an even higher risk premium to act as counterparties, and hence the option trading activity of speculators should be more clearly reflected in a higher RNS value.

To test this prediction, we construct double-sorted portfolios on the basis of RNS and a proxy for stock downside risk. For robustness, we use a direct as well as an indirect proxy. The direct proxy is the expected idiosyncratic skewness (EIS^P) of stock returns, introduced by Boyer et al. (2010). A relatively low EIS^P value indicates a higher probability of a large negative stock return in the future. The indirect proxy is the estimated shorting fee (ESF) of Boehme et al. (2006). A lower ESF value indicates looser short selling constraints,

[12]The combination of stock mispricing and RNS is also informative with respect to subsequent stock underperformance. In particular, the portfolio of stocks with the highest DOTS (MISP) and lowest RNS values yields an FFC alpha of -23 (-26) bps in the post-ranking week. Consistent with the arguments of Stilger et al. (2017), this finding shows that the relation they have documented also holds with alternative mispricing proxies, and it becomes stronger at the weekly frequency. Moreover, the combination of stock mispricing and RNS becomes even more impressive in the context of an enhanced investment strategy. For example, a spread strategy that goes long the portfolio with the lowest DOTS & highest RNS stocks and goes short the portfolio with the highest DOTS & lowest RNS stocks would yield an FFC alpha of 46 bps per week.

implying a higher probability of incurring substantially negative stock returns (see Grullon et al. (2015)).

We initially construct bivariate conditional portfolios, where we firstly sort stocks into tercile portfolios according to their RNS values at market close every Wednesday, and then, within each RNS tercile, we sort stocks into terciles according to their downside risk proxy values. Panels A.1 and B.1 of Table 6 report the weekly post-ranking risk-adjusted performance for selected equally-weighted portfolios when EIS^P and ESF are used as a downside risk proxy, respectively.

-Table 6 here-

In line with the prediction of the conjectured trading mechanism, we find that the outperformance signalled by a relatively high RNS value is mainly driven by those stocks that exhibit the most pronounced downside risk. In fact, within the highest RNS tercile, the portfolio of stocks that are the most exposed to downside risk according to EIS^P (ESF) yields a significant FFC alpha of 17 (11) bps in the post-ranking week. To the contrary, within the highest RNS tercile, the portfolio of stocks characterized by the lowest exposure to downside risk does not subsequently outperform. As a result, when stock downside risk is limited, speculators are less incentivized to resort to the option market, and hence a relatively high RNS value does not carry information regarding future stock outperformance.

We also construct independent double-sorted portfolios on the basis of RNS and each of the downside risk proxies. This alternative approach ensures that the classification of stocks' downside risk exposure is made relative to the entire cross-section, not just within each RNS tercile. Panel A.2 (B.2) of Table 6 reports the post-ranking performance of these independent double-sorted portfolios when EIS^P (ESF) is used as a downside risk proxy.

The conclusions derived from the independent double-sorted portfolios are very similar to the ones derived from the conditional portfolio sorting approach. Regardless of the employed proxy, we confirm that it is the intersection of stocks that exhibit the highest RNS values and are the most exposed to downside risk which yields the strongest subsequent outperformance. To the contrary, the intersection of stocks with the highest RNS values and the least pronounced downside risk does not subsequently outperform. Stressing further the important role of downside risk, the spread between these two intersections yields a significant FFC alpha.[13] Concluding, these results further support the proposed trading mechanism, showing that a relatively high RNS value is an informative signal for significant outperformance primarily for those stocks that are the most exposed to downside risk.

C. Stock Underpricing and Downside Risk

In the previous sections, we examined *separately* the role of underpricing and the role of downside risk in explaining the ability of a relatively high RNS value to signal future stock outperformance. However, the ultimate testable prediction of the conjectured trading mechanism is that the *joint* presence of underpricing and pronounced downside risk should further reinforce the ability of a relatively high RNS value to predict stock outperformance.

We test this prediction by constructing independent triple-sorted portfolios. At the market close every Wednesday, we independently sort stocks on the basis of their: *i*) RNS value, *ii*) mispricing proxy value, and *iii*) downside risk proxy value, and classify them as high or low relative to the corresponding median value. The intersection of these three independent classifications yields 8 portfolios for each of the four possible combinations of the mispricing and downside risk proxies. Table 7 reports the weekly post-ranking risk-adjusted performance of these portfolios.

-Table 7 here-

The reported results confirm the validity of the proposed trading mechanism. In particular, we find that the intersection of stocks that exhibit relatively higher RNS values, are

[13]The results in Table 6 also allow us to examine whether the reported stock outperformance is simply driven by a downside risk premium. Rejecting this claim, we find that downside risk alone is not a sufficient condition for subsequent stock outperformance. In fact, the combination of stocks that are the most exposed to downside risk but exhibit the lowest RNS values yields an FFC alpha close to zero. Moreover, within each downside risk classification, we find a positive relation between RNS and post-ranking portfolio performance.

relatively underpriced, and are more exposed to downside risk (i.e., portfolio P5) yields the strongest outperformance in the post-ranking week. This pattern is robust for all mispricing and downside risk proxies. For example, the long-only portfolio of stocks with higher than median RNS values, lower than median DOTS values, and lower than median EIS^P values yields an FFC alpha of 22 bps per week (NW t-stat: 4.92), which corresponds to an annualized FFC alpha of 12.11%. This is a striking result, if one takes into account how broad the adopted classification scheme is.[14]

Note that we find robust and significant stock outperformance only when *all* of the three conditions implied by this mechanism are satisfied (high RNS, underpricing, and pronounced downside risk). Otherwise, in the case where even one of these conditions is not met, stock outperformance becomes either insignificant or not robust to the choice of the mispricing and downside risk proxies (see e.g., P1, P6, and P7).[15]

V. Option Liquidity

Our analysis suggests that speculators may resort to the option market to trade on their optimistic beliefs or positive information regarding a relatively underpriced stock. In line with Easley et al. (1998), their incentive to create synthetic long positions using options should be strong only if the latter are sufficiently liquid in absolute terms or relative to the underlying stock. Otherwise, if their bid-ask spreads are too large, then round-trip transaction costs could eliminate the anticipated trading profit. In addition, if options are

[14] In selecting a classification scheme for triple-sorted portfolios, we face the following tradeoff. On the one hand, a finer classification scheme can reveal the sources of stock outperformance in a sharper way. On the other hand, it may lead to sparsely populated portfolios, and hence the reported performance may be driven by a small number of stocks. The presented classification scheme is rather broad, ensuring that the triple-sorted portfolios are well populated. However, we have also examined alternative classification schemes, such as independently sorting stocks into terciles. In line with our arguments, this finer classification scheme yields an even stronger outperformance for the intersection of stocks that exhibit the highest RNS values, are the most relatively underpriced, and are the most exposed to downside risk. Results are available upon request.

[15] We repeat the analysis described in Section IV by using ΔRNS instead of RNS. The conclusions from this approach are similar to the ones discussed here. A high ΔRNS value is a strong signal for future outperformance for those stocks that are perceived to be underpriced and more exposed to downside risk. We report the corresponding results in the Supplementary Appendix.

too thinly traded relative to the underlying stock, an informed investor may choose not to trade in the option market to avoid revealing her information. Therefore, we expect that a relatively high RNS value would be more informative with respect to subsequent stock outperformance when it is computed from sufficiently liquid options.

To test this hypothesis, we construct double-sorted portfolios on the basis of RNS and a proxy for option liquidity. As a proxy for option liquidity in absolute terms, we employ the average relative bid-ask spread (RSPREAD) of the OTM options used to compute the RNS value. As a proxy for option liquidity relative to the underlying stock liquidity, we use the average daily option-to-stock volume ratio (O/S) in the prior 12 months. A very high value of RSPREAD indicates that the utilized OTM options are highly illiquid. A very low value of O/S indicates that options are highly illiquid relative to the underlying stock.

We initially construct bivariate conditional portfolios, where we firstly sort stocks into quintiles on the basis of their RNS values at market close every Wednesday, and then, within each RNS quintile, we further classify stocks into two categories (High versus Low) according to their option liquidity proxy values. To isolate the effect of highly illiquid options, we classify as high RSPREAD the values that are above the 80th percentile of the corresponding distribution within each RNS quintile. Similarly, we classify as low O/S the values that are below the 20th percentile of the corresponding distribution. Panel A.1 (B.1) of Table 8 reports the weekly post-ranking FFC alphas of selected equally-weighted portfolios when RSPREAD (O/S) is used as a liquidity proxy.

-Table 8 here-

For both proxies, we find that, within the highest RNS quintile, the portfolio of stocks with the highly illiquid options yields an insignificant FFC alpha that is close to zero. To the contrary, within the highest RNS quintile, the portfolio of stocks with the sufficiently liquid options yields a highly significant FFC alpha in the post-ranking week. Hence, in line with the previous arguments, a relatively high RNS value is informative with respect to subsequent stock outperformance only when options are sufficiently liquid in absolute terms or relative to the underlying stock.

For robustness, we alternatively construct independent double-sorted portfolios. This ensures that our classification of stocks into high or low RSPREAD (O/S) is done with respect to the entire cross-sectional distribution of RSPREAD (O/S) values on the corresponding day. Panel A.2 (B.2) of Table 8 presents the post-ranking FFC alphas of these portfolios when RSPREAD (O/S) is used as a proxy. We derive very similar conclusions to the ones derived from the conditional portfolio sorting approach. For any given liquidity proxy, the intersection of the stocks with the highest RNS values and highly illiquid options yields an insignificant FFC alpha, whereas the intersection of the stocks with the highest RNS values and sufficiently liquid options yields strong subsequent outperformance.

VI. Speed of Price Correction

The results in Section III convincingly show that a long-only portfolio of stocks with relatively high RNS or ΔRNS values subsequently yields significant outperformance. Since RNS is computed from publicly available option prices and long-only strategies face negligible limits-to-arbitrage, this robust pattern seems to be at odds with market efficiency. Motivated by this evidence, in this Section we examine how fast the information embedded in RNS is subsequently incorporated into the underlying stock prices.

A. Decomposing Weekly Returns

First, we decompose the weekly performance of RNS- and ΔRNS-sorted portfolios into their performance: *i*) on the first post-ranking trading day, and *ii*) during the rest of the post-ranking week, skipping the first post-ranking trading day. Panel A (Panel B) of Table 9 reports the results of this decomposition for the RNS- (ΔRNS-) sorted portfolios.

-Table 9 here-

We find that most of the abnormal weekly return signalled by RNS is earned on the first post-ranking day. This is consistent with the conjecture that this stock outperformance should be rather short-lived. In particular, the highest RNS and ΔRNS quintiles yield a highly significant FFC alpha of 9 bps on the first post-ranking day. On the other hand, skipping the first post-ranking day, the quintile portfolio which contains the stocks with the highest RNS (ΔRNS) values yields an insignificant FFC alpha of only 3 (1) bps during the rest of the post-ranking week.

These results reveal that stock market participants quickly incorporate the informational content of a relatively high RNS (ΔRNS) value into the underlying stock price. Another important conclusion is that a relatively high RNS (ΔRNS) value contains genuine positive information about the underlying stock, since the stock outperformance earned on the first post-ranking day is not reversed in the following days. Had it subsequently reversed, the outperformance on the first post-ranking day could have simply been a manifestation of uninformative short-term price pressure in the option market, transmitted to the stock market by market makers hedging their positions.

In addition, this performance decomposition shows that the information embedded in the lowest RNS (ΔRNS) values is incorporated in the underlying stock prices at a slower pace. In fact, even if we skip the first post-ranking day, the quintile portfolio containing the stocks with the lowest RNS (ΔRNS) values yields a significant negative FFC alpha of −7 (−8) bps during the rest of the post-ranking week. This finding is consistent with the argument that the negative information embedded in option prices may be slowly diffused to the underlying stock price due to limits-to-arbitrage, such as short-selling constraints.

Equally importantly, even if we skip the first post-ranking day, a long-short RNS- (ΔRNS-) based spread strategy would yield a significant FFC alpha of 10 (9) bps during the rest of the post-ranking week. This finding confirms that the positive relation between RNS and future stock returns is neither driven by next-day return reversals nor can be explained by a potential non-synchroneity bias (see the discussion in Section VI.B).

B. Overnight versus Intraday Returns

We further decompose the performance of RNS- and ΔRNS-sorted portfolios earned on the first post-ranking day into its overnight and intraday components. To this end, we follow Lou et al. (2017) in computing intraday and overnight stock returns. In particular, the intraday return for stock i on day d is defined as:

$$r^i_{intraday,d} = \frac{P^i_{close,d}}{P^i_{open,d}} - 1, \tag{6}$$

where $P^i_{open,d}$ ($P^i_{close,d}$) is the open (close) stock price on day d, and the overnight return for stock i on day d is defined as:

$$r^i_{overnight,d} = \frac{1 + r^i_{close-to-close,d}}{1 + r^i_{intraday,d}} - 1, \tag{7}$$

where $r^i_{close-to-close,d}$ is the standard daily close-to-close return. To estimate FFC alphas, we also construct the intraday and overnight versions of the corresponding factor returns. The risk-free rate is assumed to accrue overnight. Panel A of Table 9 reports the overnight versus the intraday performance decomposition for RNS-sorted portfolios, whereas Panel B reports the corresponding decomposition for ΔRNS-sorted portfolios.

-Table 9 here-

We find that the stock outperformance predicted by relatively high RNS or ΔRNS values is entirely earned overnight. The highest RNS (ΔRNS) quintile yields an overnight FFC alpha of 13 (10) bps with a NW t-stat of 9.69 (8.30). This result further supports the argument that market participants very quickly incorporate the information embedded in publicly observable OTM option prices into the underlying stock price. Moreover, we confirm that relatively high RNS (ΔRNS) values carry positive information about the underlying stock since little of the overnight outperformance is subsequently reversed intraday.

Taken together, the results in this Section indicate a very fast price discovery process and point towards a relatively efficient market mechanism. The ability of relatively high RNS (ΔRNS) values to predict overnight stock outperformance can be further reconciled with market efficiency, if one takes into account the criticism of Battalio and Schultz (2006). It is not certain whether the utilized RNS estimates, computed from closing option prices, were available in real time before the stock market close because the CBOE equity options market was closing two minutes after the close of the underlying stock market for most of our sample period.[16] In that case the documented stock outperformance may not have been practically exploitable. Nevertheless, these results collectively show that the option market can lead the stock market with respect to positive price discovery, too.

VII. Stock Price Pressure and Return Reversals

Our results indicate that the predictive ability of RNS over future stock returns derives from informed trading in OTM options, and that the option market leads the stock market with respect to price discovery. This interpretation is in line with the arguments of prior studies in the literature (see, *inter alia*, Pan and Poteshman (2006), Cremers and Weinbaum (2010), Xing et al. (2010), and An et al. (2014)). To the contrary, the recent study of Goncalves-Pinto et al. (2016) argues that the predictive ability of option-implied measures primarily reflects short-run return reversals following stock price pressure, rather than informed trading in the option market. Contributing to this debate, in this Section we examine whether RNS reflects stock price pressure, and whether its positive relation with future stock returns is simply a manifestation of the well-documented reversal effect of Lehmann (1990) and Jegadeesh (1990).[17]

First, we have documented that the pairwise rank correlation coefficient between RNS and the same-day stock return (RET(1)) or the cumulative 5-day stock return (RET(5)) is

[16] On June 23, 1997, the CBOE changed the closing time for options on individual stocks to 4:02 p.m. (EST). Before June 23, 1997, the closing time for options on individual stocks was 4:10 p.m. (EST). Furthermore, from March 5, 2008, OptionMetrics reports the best (or highest) 3:59 p.m. (EST) bid and offer prices across all exchanges on which the option trades.

[17] For recent evidence, see also Avramov, Chordia, and Goyal (2006) and Nagel (2012).

close to zero (see Table 2). Therefore, we argue that short-term stock depreciation (appreciation) is not mechanically associated with a higher (lower) RNS value, and hence RNS cannot be regarded as a proxy for stock price pressure.

Second, we examine whether the positive relation between RNS and future stock returns is exclusively driven from stocks that have recently experienced price pressure. To this end, we construct bivariate conditional portfolios, where we firstly sort stocks into terciles on the basis of their 1-, 3-, and 5-day cumulative stock returns, respectively, and then, within each return tercile, we further sort stocks into quintiles on the basis of their RNS values. Table 11 reports the weekly post-ranking performance of the corresponding portfolios. Interestingly, we find that the positive relation between RNS and post-ranking alphas is evident within each return tercile, and it is robust regardless of the window used to compute these returns. In fact, within the medium return tercile, where the average 1-, 3-, and 5-day cumulative stock return up to the portfolio sorting day is approximately zero, and hence no price pressure has been experienced, the spread between the highest and the lowest RNS quintiles yields a highly significant FFC alpha of 15, 16, and 19 bps, respectively, in the post-ranking week.

-Table 11 here-

Last, we also find that, within the lowest return tercile, it is the stocks with the highest RNS values that subsequently yield the strongest outperformance. This result is consistent with our trading mechanism because the stocks in the lowest return tercile are more likely to be relatively underpriced due to downward price pressure, and a high RNS value reflects trading activity in the option market to exploit this underpricing. To the contrary, within the lowest return tercile, the stocks with the lowest RNS values subsequently underperform. Hence, we conclude that downward price pressure is not a sufficient condition for subsequent stock outperformance. It is followed by stock outperformance only when it is associated with a relatively high RNS value. We derive similar conclusions when we repeat the analysis of this section using ΔRNS instead of RNS as a criterion to sort stocks in portfolios. The corresponding results are reported in the Supplementary Appendix.

VIII. Conclusions

We examine whether the expensiveness of OTM calls relative to OTM puts, reflected in the RNS of the option-implied stock return distribution, carries information with respect to future stock returns. We find that a relatively high RNS or ΔRNS value carries positive information about the underlying stock and can predict significant stock *outperformance*. Thus, we contribute to the existing literature, which argues that a highly negative RNS value can predict stock underperformance because it embeds negative information about the underlying stock that is not already incorporated in its price due to limits-to-arbitrage.

To explain our findings, we develop and test a mechanism, according to which speculators may choose to trade on their optimistic beliefs or positive information in the option market, buying (selling) OTM calls (puts) to set up leveraged long positions on stocks that they perceive to be relatively underpriced but at the same time entail substantial downside risk. In fact, we find that a long-only portfolio of stocks that exhibit relatively high RNS values, are underpriced, and are exposed to pronounced downside risk subsequently yields a very strong risk-adjusted performance.

Our findings are consistent with the theoretical arguments of Easley et al. (1998) and An et al. (2014) on cross-market predictability, but we crucially demonstrate that the option market can lead the stock market with respect to both negative and positive price discovery. Moreover, we confirm that the positive relation between RNS and future stock returns is indeed driven by informed trading in the option market, rather than being an artefact of a return reversal effect following stock price pressure.

Since RNS is computed from publicly available option prices and long-only strategies face negligible limits-to-arbitrage relative to strategies involving short selling, this evidence poses a challenge to the efficient market framework. We rationalize our findings by showing that the stock outperformance predicted by a relatively high RNS value is very short-lived. In particular, most of the documented abnormal return is earned overnight, implying speedy price correction in the stock market. Hence, depending on whether RNS estimates are available in real time before the stock market close, the documented outperformance may not be practically exploitable.

Appendix: Definitions of Variables

Book-to-Market Value ratio (B/M)

B/M for firm i in month t is given by the ratio of Common Equity (CEQ) to Market Value. CEQ is obtained from Compustat; we use December values of year $y-1$ for the period from June of year y until May of year $y+1$. B/M is computed only for positive CEQ values.

Distance between Stock Price and Option-Implied Stock Value (DOTS)

Following Goncalves-Pinto et al. (2016), $\text{DOTS}_{i,j,d}$ is computed for stock i on day d using a pair j of American-style call and put options written on the stock i with the same maturity T and strike price $K_{i,j}$ as:

$$\text{DOTS}_{i,j,d} = \frac{S_{i,d} - \frac{S^U_{i,j,d}+S^L_{i,j,d}}{2}}{S_{i,d}},$$

where $i)$ $S_{i,d}$ is the actual price of stock i on day d, $ii)$ $S^U_{i,j,d}$ is the no-arbitrage upper bound on stock's i bid price implied by the option pair j on day d, and it is given by:

$$S^U_{i,j,d} = C^{ask}_{i,j,d} + K_{i,j} + \text{PV}_d(\text{DIV}_i) - P^{bid}_{i,j,d},$$

where $C^{ask}_{i,j,d}$ is the ask price of the call option of the pair j on day d, $\text{PV}_d(\text{DIV}_i)$ is the present value of the dividends to be paid on stock i until option expiry, and $P^{bid}_{i,j,d}$ is the bid price of the put option of the pair j, and $iii)$ $S^L_{i,j,d}$ is the no-arbitrage lower bound on stock's i ask price implied by the option pair j on day d, and it is given by:

$$S^L_{i,j,d} = C^{bid}_{i,j,d} + K_{i,j}e^{-rT} - P^{ask}_{i,j,d},$$

where $C^{bid}_{i,j,d}$ is the bid price of the call option of the pair j on day d, r is the risk-free rate, and $P^{ask}_{i,j,d}$ is the ask price of the put option of the pair j.

Finally, $\text{DOTS}_{i,d}$ for stock i on day d is given by the following weighted-average of $\text{DOTS}_{i,j,d}$

across all option pairs $j = 1, 2, ..., J$:

$$\text{DOTS}_{i,d} = 100 \frac{\sum_{j=1}^{J} \left(C_{i,j,d}^{ask} - C_{i,j,d}^{bid} + P_{i,j,d}^{ask} - P_{i,j,d}^{bid} \right)^{-1} \text{DOTS}_{i,j,d}}{\sum_{j=1}^{J} \left(C_{i,j,d}^{ask} - C_{i,j,d}^{bid} + P_{i,j,d}^{ask} - P_{i,j,d}^{bid} \right)^{-1}}$$

Estimated Shorting Fee (ESF)

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

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

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 m, we use the fitted part of the following regression model:

$$\begin{aligned} \text{ISKEW}_{i,m}^P \;=\; & \gamma_0 + \gamma_1 \text{ISKEW}_{i,m-60}^P + \gamma_2 \text{IVOL}_{i,m-60}^P + \gamma_3 \text{MOM}_{i,m-60} + \gamma_4 \text{TURN}_{i,m-60} + \\ & + \gamma_5 \text{NASD}_{i,m-60} + \gamma_6 \text{SMALL}_{i,m-60} + \gamma_7 \text{MED}_{i,m-60} + \Gamma\, \text{IND}_{i,m-60} + \epsilon_{i,m} \end{aligned}$$

This cross-sectional regression is estimated every month. ISKEW$_i^P$ and IVOL$_i^P$ 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 denotes the cumulative stock return from month $m-12$

to month $m-1$. 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 takes the value 1 if the firm is listed on NASDAQ and 0 otherwise. SMALL takes the value 1 if the firm is in the bottom three size deciles and 0 otherwise. MED 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. We use the 30 industry classifications of Fama and French (1997).

Idiosyncratic Skewness under the physical measure (ISKEW^P)

Following Boyer et al. (2010) $\text{ISKEW}^P_{i,m}$ for firm i in month m is computed as:

$$\text{ISKEW}^P_{i,m} = \frac{1}{(N(d)-2)} \frac{\sum_{t\in D} \varepsilon^3_{i,d}}{\left(\text{IVOL}^P_{i,m}\right)^3}$$

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.

Idiosyncratic Volatility under the physical measure (IVOL^P)

$\text{IVOL}^P_{i,m}$ for firm i in month m is computed as:

$$\text{IVOL}^P_{i,m} = \left(\frac{1}{N(d)-1} \sum_{d\in D} \varepsilon^2_{i,d}\right)^{1/2}$$

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^P.

Momentum (MOM)

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

Option Relative Bid-Ask Spread (RSPREAD)

RSPREAD on day d for option j written on stock i is given by:

$$\text{RSPREAD}_{i,j,d} = \frac{\text{ASK}_{i,j,d} - \text{BID}_{i,j,d}}{(\text{ASK}_{i,j,d} + \text{BID}_{i,j,d})/2}.$$

The average RSPREAD on day d across the OTM options $j = 1, 2, ..., J$ used to compute RNS for stock i is given by:

$$\overline{\text{RSPREAD}_{i,d}} = \frac{\sum_{j=1}^{J} \text{RSPREAD}_{i,j,d}}{\#\text{options}},$$

where #options is the number of the OTM options used.

Option-to-Stock Trading Volume Ratio (O/S)

O/S on day d for firm i is given by:

$$\text{O/S}_{i,d} = \frac{\text{OPTION\_VOLUME}_{i,d} \cdot 100}{\text{STOCK\_VOLUME}_{i,d}}$$

where $\text{OPTION\_VOLUME}_{i,d}$ is the total number of option contracts traded on day d, with each contract pertaining to 100 shares of firm i, and $\text{STOCK\_VOLUME}_{i,d}$ is the number of shares of firm i traded on day d. To compute $\text{OPTION\_VOLUME}_{i,d}$, we use all options expiring from 10 to 180 days. We then compute the average daily O/S ratio using a 12-month rolling window.

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Table 1: Descriptive Statistics

This Table reports descriptive statistics for the set of the out-of-the-money (OTM) call and put options used to compute permno-day Risk-Neutral Skewness (RNS) estimates during the period January 1996–June 2014. Moneyness denotes the ratio of the underlying stock price to the strike price of the OTM call and put option, respectively. Average moneyness is computed across the OTM options used per permno-day RNS estimate. Total open interest refers to the number of open contracts for the OTM options used per permno-day RNS estimate. Each contract pertains to 100 shares. RSPREAD is the relative bid-ask spread of the OTM option used. Average RSPREAD is computed across the OTM options used per permno-day RNS estimate. The total number of permno-day RNS estimates is 3,121,205.

	Mean	St. Dev.	5th pctl	25th pctl	Median	75th pctl	95th pctl
RNS	-0.4113	0.3193	-0.9453	-0.5831	-0.3889	-0.2136	0.0376
Days to expiration of OTM options per RNS estimate	91.81	47.36	23	46	94	130	169
Average moneyness of OTM call options	0.8928	0.0585	0.7851	0.8606	0.9031	0.9364	0.9670
Average moneyness of OTM put options	1.1496	0.0852	1.0472	1.0887	1.1332	1.1917	1.3054
No. of OTM options per RNS estimate	5.55	2.62	4	4	5	6	9
Total open interest of OTM options	7,312.61	20,225.40	154	609	1,838	6,075	30,359
Average RSPREAD of OTM options	0.1848	0.1557	0.0404	0.1029	0.1461	0.2132	0.4539
No. of permnos with RNS estimate per day	671.08	221.62	346	468	671	864	1,012

Table 2: Rank Correlation Coefficients

This Table reports the time-series averages of weekly pairwise Spearman's rank correlation coefficients. For each pair of variables, their rank correlation coefficient is computed every Wednesday, i.e., the benchmark portfolio-sorting day. The sample period is January 1996–June 2014. RNS is the Risk-Neutral Skewness, and ΔRNS is the change in the RNS estimate relative to the previous trading day. MV stands for firm market value. B/M denotes firm book-to-market value ratio. MOM is the cumulative stock return from month *t-12* to month *t-1*. DOTS is the distance between the actual stock price and the option-implied stock value computed as in Goncalves-Pinto et al. (2016). MISP denotes the composite mispricing rank of Stambaugh and Yuan (2016). EIS^P stands for the expected idiosyncratic skewness of daily stock returns under the physical measure computed as in Boyer et al. (2010). ESF denotes the estimated shorting fee for each stock computed as in Boehme et al. (2006). RET(1) is the daily stock return. RET(5) is the cumulative 5-day stock return. RSPREAD denotes the average relative bid-ask spread of the out-of-the-money options used to compute RNS. O/S stands for the average daily option-to-stock trading volume ratio over the previous 12 months. For the variables that are available at daily frequency, their Wednesday values are used. For the variables that are available at monthly frequency, their end-of-month values prior to each Wednesday are used.

	RNS	ΔRNS	MV	B/M	MOM	DOTS	MISP	EIS^P	ESF	RET(1)	RET(5)	RSPREAD	O/S
RNS	1												
ΔRNS	0.27	1											
MV	-0.31	0.00	1										
B/M	-0.05	0.00	-0.24	1									
MOM	-0.00	-0.00	0.23	-0.39	1								
DOTS	-0.31	-0.31	-0.02	0.00	-0.01	1							
MISP	0.12	-0.00	-0.21	0.14	-0.32	0.02	1						
EIS^P	0.10	0.00	-0.48	-0.02	-0.00	0.01	0.13	1					
ESF	0.09	-0.00	0.08	-0.08	-0.05	0.05	0.17	-0.04	1				
RET(1)	-0.06	-0.19	0.02	-0.00	0.02	0.15	-0.01	-0.01	-0.01	1			
RET(5)	-0.05	-0.04	0.03	-0.01	0.03	0.08	-0.02	-0.01	-0.01	0.40	1		
RSPREAD	0.01	-0.01	-0.43	0.02	0.03	0.02	0.06	0.17	0.09	-0.01	-0.01	1	
O/S	-0.01	-0.00	0.08	-0.19	-0.00	0.02	0.06	0.05	0.16	-0.01	-0.01	-0.43	1

Table 3: Characteristics of RNS and ΔRNS-sorted Weekly Quintile Portfolios

This Table reports the average characteristics of quintile stock portfolios sorted on the basis of their Risk-Neutral Skewness (RNS) estimates (Panel A) or the change in their RNS (ΔRNS) estimate relative to previous trading day (Panel B). The portfolio sorting is performed every Wednesday. The sample period is January 1996–June 2014. MV stands for firm market value. B/M denotes firm book-to-market value ratio. MOM is the cumulative stock return from month *t-12* to month *t-1*, winsorized at the 95th percentile. DOTS is the distance between the actual stock price and the option-implied stock value computed as in Goncalves-Pinto et al. (2016). MISP denotes the composite mispricing rank of Stambaugh and Yuan (2016). EIS^P stands for the expected idiosyncratic skewness of daily stock returns under the physical measure computed as in Boyer et al. (2010). ESF denotes the estimated shorting fee for each stock computed as in Boehme et al. (2006). RET(1) denotes the stock return on the sorting day. RET(5) denotes the cumulative 5-day stock return up to the sorting day. RSPREAD denotes the average relative bid-ask spread of the out-of-the-money options used to compute RNS. O/S stands for the average daily option-to-stock trading volume ratio over the previous 12 months. For the variables that are available at daily frequency, their sorting-day values are used. For the variables that are available at monthly frequency, their end-of-month values prior to the sorting day are used. The last line shows the difference (spread) between the portfolio with the highest RNS or ΔRNS stocks and the portfolio with lowest RNS or ΔRNS stocks in each case. **, and * indicate statistical significance of the spread at the 1%, and 5% level, respectively.

Panel A: RNS-sorted Quintile Portfolios

	RNS	ΔRNS	LN(MV)	B/M	MOM	DOTS	MISP	EIS^P	ESF	RET(1)	RET(5)	RSPREAD	O/S
1 (Lowest RNS)	-0.79	-0.07	22.62	0.38	22.40%	0.20	46.86	0.74	0.61	0.25%	0.70%	0.19	11.80%
2	-0.51	-0.02	22.24	0.39	24.62%	0.08	47.08	0.75	0.61	0.19%	0.55%	0.17	10.73%
3	-0.37	-0.00	21.93	0.38	26.09%	0.03	47.99	0.78	0.64	0.15%	0.45%	0.17	10.83%
4	-0.26	0.02	21.65	0.37	26.30%	-0.03	49.29	0.82	0.66	0.08%	0.33%	0.17	11.14%
5 (Highest RNS)	-0.07	0.08	21.28	0.38	25.67%	-0.18	51.36	0.90	0.69	-0.11%	0.08%	0.18	11.89%
Spread (5-1)	0.72**	0.14**	-1.35**	-0.00	3.27%*	-0.37**	4.49**	0.16**	0.08**	-0.36%**	-0.62%**	-0.01	0.08%

Panel B: ΔRNS-sorted Quintile Portfolios

	ΔRNS	RNS	LN(MV)	B/M	MOM	DOTS	MISP	EIS^P	ESF	RET(1)	RET(5)	RSPREAD	O/S
1 (Lowest ΔRNS)	-0.21	-0.51	21.95	0.37	26.96%	0.16	48.57	0.80	0.64	0.78%	0.81%	0.20	11.88%
2	-0.06	-0.43	22.00	0.38	24.56%	0.08	48.43	0.79	0.64	0.36%	0.56%	0.16	10.93%
3	0.00	-0.40	22.02	0.38	24.12%	0.03	48.34	0.78	0.64	0.03%	0.33%	0.15	11.52%
4	0.06	-0.37	22.00	0.39	24.48%	-0.03	48.40	0.78	0.64	-0.25%	0.11%	0.16	11.26%
5 (Highest ΔRNS)	0.22	-0.30	21.96	0.37	26.71%	-0.14	48.49	0.80	0.64	-0.55%	0.06%	0.19	12.11%
Spread (5-1)	0.43**	0.21**	0.01	-0.00	-0.25%	-0.30**	-0.08	0.00	-0.00	-1.32%**	-0.74%**	-0.00*	0.23%

Table 4: RNS and ΔRNS-sorted Weekly Quintile Portfolio Sorts

This Table reports the weekly post-ranking performance of quintile stock portfolios constructed every Wednesday on the basis of their Risk-Neutral Skewness (RNS) estimates (Panel A), and the change in their RNS (ΔRNS) estimates relative to previous trading day (Panel B). The sample period is January 1996–June 2014. Every Wednesday, at market close, stocks are sorted in ascending order according to their RNS values (Panel A) or their ΔRNS values (Panel B), and they are assigned to quintile portfolios. The corresponding equally-weighted portfolio returns are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). Ex Ret denotes the average weekly portfolio return in excess of the risk-free rate. α_{FFC} denotes the weekly portfolio alpha estimated from the Fama-French-Carhart (FFC) 4-factor model. Excess returns and alphas are expressed in percentages. Portfolio loadings (β's) with respect to the market (MKT), size (SMB), value (HML) and momentum (MOM) factors estimated from the FFC model and its adjusted R^2 (R^2 adj.) are also reported. N denotes the average number of stocks per portfolio. The pre-last line in Panel A (Panel B) reports the spread between the portfolio with the highest RNS (ΔRNS) stocks and the portfolio with lowest RNS (ΔRNS) stocks. Panel C reports the corresponding results for two bivariate stock portfolios, constructed as the intersections of the lowest (highest) RNS and the lowest (highest) ΔRNS independently-sorted quintiles. The pre-last line in Panel C reports the spread between these two portfolios. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Quintiles	Ex Ret	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	R^2 adj.	N
Panel A: RNS-sorted Quintile Portfolios								
1 (Lowest RNS)	0.04	-0.12**	1.08**	0.30**	-0.07*	-0.04	0.93	134
		(-4.57)						
2	0.11	-0.07*	1.16**	0.38**	-0.13**	-0.04*	0.94	133
		(-2.45)						
3	0.13	-0.05	1.22**	0.53**	-0.18**	-0.06**	0.93	133
		(-1.73)						
4	0.21	0.01	1.29**	0.63**	-0.23**	-0.08**	0.92	133
		(0.47)						
5 (Highest RNS)	0.32*	0.12**	1.35**	0.78**	-0.28**	-0.14**	0.90	134
		(3.11)						
Spread (5-1)	0.27**	0.24**	0.27**	0.47**	-0.20**	-0.09	0.39	
t(5-1)	(4.34)	(5.03)	(11.78)	(8.73)	(-4.05)	(-1.93)		
Panel B: ΔRNS-sorted Quintile Portfolios								
1 (Lowest ΔRNS)	0.03	-0.16**	1.23**	0.55**	-0.24**	-0.06**	0.92	125
		(-4.50)						
2	0.12	-0.07*	1.21**	0.53**	-0.14**	-0.06*	0.93	125
		(-2.34)						
3	0.15	-0.03	1.22**	0.50**	-0.17**	-0.08**	0.93	125
		(-1.18)						
4	0.20	0.01	1.22**	0.50**	-0.17**	-0.07**	0.93	125
		(0.49)						
5 (Highest ΔRNS)	0.29*	0.10**	1.25**	0.50**	-0.22**	-0.06*	0.92	125
		(3.15)						
Spread (5-1)	0.26**	0.25**	0.02	-0.04	0.02	0.00	0.01	
t(5-1)	(6.60)	(6.65)	(1.09)	(-1.54)	(0.72)	(0.16)		
Panel C: Bivariate RNS & ΔRNS Independently-sorted Portfolios								
RNS 1 (Lowest) & ΔRNS 1 (Lowest)	-0.02	-0.19**	1.12**	0.41**	-0.13**	-0.04	0.85	41
		(-4.41)						
RNS 5 (Highest) & ΔRNS 5 (Highest)	0.41**	0.21**	1.34**	0.69**	-0.30**	-0.09*	0.85	43
		(4.03)						
Spread (5&5- 1&1)	0.43**	0.40**	0.23**	0.28**	-0.16*	-0.05	0.17	
t(5&5- 1&1)	(5.79)	(5.80)	(7.18)	(5.63)	(-2.36)	(-0.96)		

Table 5: Bivariate Portfolio Sorts: Risk-Neutral Skewness and Stock Mispricing

This Table reports the weekly post-ranking risk-adjusted performance of bivariate stock portfolios constructed on the basis of their Risk-Neutral Skewness (RNS) estimates and each of the two stock mispricing proxies used. The sample period is January 1996–June 2014. We use the following two proxies for stock mispricing: i) the distance between the actual stock price and the option-implied stock value (DOTS) of Goncalves-Pinto et al. (2016) in Panel A, and ii) the composite mispricing rank (MISP) of Stambaugh and Yuan (2016) in Panel B. A low (high) value of DOTS or MISP indicates that the stock is relatively underpriced (overpriced). For the conditional portfolios (Panels A.1 and B.1), at market close every Wednesday, stocks are sorted in ascending order according to their RNS estimates and they are assigned to tercile portfolios. Within each RNS tercile portfolio, we further sort stocks according to their Wednesday DOTS values (Panel A.1) or their end-of-month, prior to the sorting Wednesday, MISP values (Panel B.1), and construct again tercile portfolios. For the independent portfolios (Panels A.2 and B.2), at market close every Wednesday, stocks are independently sorted in ascending order according to their RNS estimates and their Wednesday DOTS values (Panel A.2) or their end-of-month, prior to the sorting Wednesday, MISP values (Panel B.2), and they are assigned to tercile portfolios. The intersections of these RNS- and stock mispricing-sorted terciles yield the independent portfolios. The average number of stocks per portfolio is reported in square brackets. In both approaches, equally-weighted returns of the corresponding portfolios are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). We report weekly portfolio alphas (in percentages) estimated from the Fama-French-Carhart (FFC) 4-factor model. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: DOTS

Panel A.1: Conditional Portfolios				Panel A.2: Independent Portfolios			
	DOTS Lowest	DOTS Highest	Spread (Lowest-Highest)		DOTS Lowest	DOTS Highest	Spread (Lowest-Highest)
RNS 1 (Lowest)	0.02	-0.29**	0.32**	RNS 1 (Lowest)	0.06	-0.23**	0.29**
	(0.82)	(-6.48)	(6.48)		(1.35)	(-6.08)	(5.96)
					[44]	[95]	
RNS 3 (Highest)	0.29**	-0.14**	0.43**	RNS 3 (Highest)	0.23**	-0.18**	0.40**
	(5.98)	(-3.34)	(7.90)		(5.85)	(-3.33)	(7.14)
					[106]	[47]	
Spread (3-1)	0.27**	0.15**		Spread (3-1)	0.17**	0.05	
	(5.15)	(2.61)			(3.22)	(0.82)	

Panel B: MISP

Panel B.1: Conditional Portfolios				Panel B.2: Independent Portfolios			
	MISP Lowest	MISP Highest	Spread (Lowest-Highest)		MISP Lowest	MISP Highest	Spread (Lowest-Highest)
RNS 1 (Lowest)	-0.01	-0.25**	0.24**	RNS 1 (Lowest)	-0.01	-0.26**	0.25**
	(-0.50)	(-5.85)	(5.06)		(-0.50)	(-6.03)	(5.36)
					[81]	[59]	
RNS 3 (Highest)	0.15**	0.01	0.14*	RNS 3 (Highest)	0.15**	0.05	0.10
	(3.94)	(0.10)	(2.35)		(4.00)	(0.93)	(1.84)
					[57]	[83]	
Spread (3-1)	0.16**	0.25**		Spread (3-1)	0.16**	0.31**	
	(4.01)	(4.44)			(4.18)	(5.60)	

Table 6: Bivariate Portfolio Sorts: Risk-Neutral Skewness and Downside Risk

This Table reports the weekly post-ranking risk-adjusted performance of bivariate stock portfolios constructed on the basis of their Risk-Neutral Skewness (RNS) estimates and each of the two proxies used for stock downside risk. The sample period is January 1996–June 2014. We use the following two proxies for stock downside risk: i) the expected idiosyncratic skewness (EIS^P) of daily stock returns under the physical measure of Boyer et al. (2010) in Panel A, and ii) the estimated stock shorting fee (ESF) of Boehme et al. (2006) in Panel B. A low (high) value of EIS^P or ESF indicates that the stock is exposed to greater (lower) downside risk. For the conditional portfolios (Panels A.1 and B.1), at market close every Wednesday, stocks are sorted in ascending order according to their RNS estimates and they are assigned to tercile portfolios. Within each RNS tercile portfolio, we further sort stocks according to their end-of-month, prior to the sorting Wednesday, EIS^P (Panel A.1) or ESF values (Panel B.1), and construct again tercile portfolios. For the independent portfolios (Panels A.2 and B.2), at market close every Wednesday, stocks are independently sorted in ascending order according to their RNS estimates and their end-of-month, prior to the sorting Wednesday, EIS^P (Panel A.2) or ESF values (Panel B.2), and they are assigned to tercile portfolios. The intersections of these RNS- and stock downside risk-sorted terciles yield the independent portfolios. The average number of stocks per portfolio is reported in square brackets. In both approaches, equally-weighted returns of the corresponding portfolios are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). We report weekly portfolio alphas (in percentages) estimated from the Fama-French-Carhart (FFC) 4-factor model. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: EIS^P

Panel A.1: Conditional Portfolios				Panel A.2: Independent Portfolios			
	EIS^P Lowest	EIS^P Highest	Spread (Lowest-Highest)		EIS^P Lowest	EIS^P Highest	Spread (Lowest-Highest)
RNS 1 (Lowest)	0.01	-0.15**	0.16**	RNS 1 (Lowest)	-0.00	-0.17**	0.16**
	(0.29)	(-4.12)	(3.16)		(-0.05)	(-4.28)	(2.94)
					[59]	[48]	
RNS 3 (Highest)	0.17**	-0.01	0.17**	RNS 3 (Highest)	0.17**	0.01	0.16**
	(3.77)	(-0.15)	(3.05)		(3.60)	(0.27)	(2.92)
					[51]	[68]	
Spread (3-1)	0.16**	0.15*		Spread (3-1)	0.17**	0.18**	
	(3.41)	(2.43)			(3.48)	(3.08)	

Panel B: ESF

Panel B.1: Conditional Portfolios				Panel B.2: Independent Portfolios			
	ESF Lowest	ESF Highest	Spread (Lowest-Highest)		ESF Lowest	ESF Highest	Spread (Lowest-Highest)
RNS 1 (Lowest)	-0.02	-0.19**	0.17**	RNS 1 (Lowest)	-0.02	-0.22**	0.20**
	(-0.71)	(-4.35)	(4.03)		(-0.67)	(-4.57)	(4.35)
					[73]	[48]	
RNS 3 (Highest)	0.11*	-0.05	0.16**	RNS 3 (Highest)	0.10*	-0.02	0.12*
	(2.35)	(-0.89)	(2.92)		(2.17)	(-0.36)	(2.30)
					[58]	[64]	
Spread (3-1)	0.13**	0.14**		Spread (3-1)	0.12**	0.20**	
	(2.98)	(2.59)			(2.70)	(3.68)	

Table 7: Trivariate Independent Portfolio Sorts: RNS, Stock Mispricing and Downside Risk

This Table reports the weekly post-ranking risk-adjusted performance of trivariate stock portfolios constructed on the basis of their Risk-Neutral Skewness (RNS) estimates, each of the two proxies used for stock mispricing, and each of the two proxies used for stock downside risk. The sample period is January 1996–June 2014. We use the following two proxies for stock mispricing: i) the distance between the actual stock price and the option-implied stock value (DOTS) of Goncalves-Pinto et al. (2016), and ii) the composite mispricing rank (MISP) of Stambaugh and Yuan (2016). A low (high) value of DOTS or MISP indicates that the stock is relatively underpriced (overpriced). We use the following two proxies for stock downside risk: i) the expected idiosyncratic skewness (EIS^P) of daily stock returns under the physical measure of Boyer et al. (2010), and ii) the estimated stock shorting fee (ESF) of Boehme et al. (2006). A low (high) value of EIS^P or ESF indicates that the stock is exposed to greater (lower) downside risk. Every Wednesday, at market close, stocks are independently sorted in ascending order according to: 1) their RNS estimates, 2) their Wednesday DOTS values or their end-of-month, prior to the sorting Wednesday, MISP values, and 3) their end-of-month, prior to the sorting Wednesday, EIS^P or ESF values, and they are classified for each sorting criterion as Low (L) or High (H) relative to the corresponding median value. The intersections of these three classifications yield 8 portfolios. The corresponding equally-weighted portfolio returns are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). We report weekly portfolio alphas (in percentages) estimated from the Fama-French-Carhart (FFC) 4-factor model. The average number of stocks per portfolio is reported in square brackets. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

	Stock Mispricing Proxy	DOTS		MISP	
	Downside Risk Proxy	EIS^P	ESF	EIS^P	ESF
P1	RNS Low & DOTS/ MISP Low & EIS^P/ ESF Low	0.11** (2.91) [55]	0.06 (1.74) [69]	0.05 (1.49) [79]	0.03 (1.22) [95]
P2	RNS Low & DOTS/ MISP Low & EIS^P/ ESF High	-0.03 (-0.77) [45]	-0.02 (-0.59) [37]	-0.02 (-0.64) [58]	-0.06 (-1.27) [46]
P3	RNS Low & DOTS/ MISP High & EIS^P/ ESF Low	-0.07* (-2.03) [76]	-0.03 (-1.08) [86]	-0.04 (-0.94) [53]	-0.03 (-1.00) [57]
P4	RNS Low & DOTS/ MISP High & EIS^P/ ESF High	-0.20** (-5.84) [70]	-0.24** (-5.71) [70]	-0.22** (-5.50) [59]	-0.19** (-4.39) [59]
P5	RNS High & DOTS/ MISP Low & EIS^P/ ESF Low	0.22** (4.92) [70]	0.16** (3.84) [79]	0.15** (3.76) [59]	0.13** (2.86) [67]
P6	RNS High & DOTS/ MISP Low & EIS^P/ ESF High	0.12** (2.98) [76]	0.09 (1.92) [78]	0.07 (1.78) [54]	0.01 (0.28) [49]
P7	RNS High & DOTS/ MISP High & EIS^P/ ESF Low	-0.04 (-0.89) [45]	-0.04 (-0.80) [47]	0.11* (2.33) [58]	0.08 (1.62) [55]
P8	RNS High & DOTS/ MISP High & EIS^P/ ESF High	-0.17** (-3.52) [54]	-0.20** (-3.90) [59]	-0.01 (-0.12) [77]	-0.00 (-0.05) [85]

Table 8: Bivariate Portfolio Sorts: Risk-Neutral Skewness and Option Liquidity

This Table reports the weekly post-ranking risk-adjusted performance of bivariate stock portfolios constructed on the basis of their Risk-Neutral Skewness (RNS) estimates and each of the two proxies used for option liquidity. The sample period is January 1996–June 2014. We use the following two proxies for option liquidity: i) the average relative bid-ask spread (RSPREAD) of the OTM options used to compute these RNS estimates in Panel A, and ii) the average daily option-to-stock trading volume ratio (O/S) over the previous 12 months in Panel B. A high value of RSPREAD indicates that the OTM options are illiquid. A low value of O/S indicates that the options are illiquid relative to the underlying stock. For the conditional portfolios (Panels A.1 and B.1), at market close every Wednesday, stocks are sorted in ascending order according to their RNS estimates and they are assigned to quintile portfolios. Within each RNS quintile portfolio, we further sort stocks according to their Wednesday RSPREAD values (Panel A.1) or their end-of-month, prior to the sorting Wednesday, O/S values (Panel B.1), and classify them into two portfolios: i) Low, if the RSPREAD (O/S) value is below the 80^{th} (20^{th}) percentile of the corresponding cross-sectional distribution, or ii) High, if the RSPREAD (O/S) value is above the 80^{th} (20^{th}) percentile. Results are reported only for the portfolios within the lowest and the highest RNS quintiles. For the independent portfolios (Panels A.2 and B.2), at market close every Wednesday, stocks are independently sorted into quintile portfolios according to their RNS estimates, and into two portfolios according to their Wednesday RSPREAD values (Panel A.2) or their end-of-month, prior to the sorting Wednesday, O/S values (Panel B.2): i) Low, if the RSPREAD (O/S) value is below the 80^{th} (20^{th}) percentile of the corresponding cross-sectional distribution, or ii) High, if the RSPREAD (O/S) value is above the 80^{th} (20^{th}) percentile. The intersections of these RNS- and option liquidity-sorted portfolios yield the independent portfolios. Results are reported only for the intersections that involve the lowest and the highest RNS quintiles. The average number of stocks per portfolio is reported in square brackets. In both approaches, equally-weighted returns of the corresponding portfolios are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). We report weekly portfolio alphas (in percentages) estimated from the Fama-French-Carhart (FFC) 4-factor model. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: RSPREAD

Panel A.1: Conditional Portfolios	RSPREAD Low	RSPREAD High	Spread (Low-High)	Panel A.2: Independent Portfolios	RSPREAD Low	RSPREAD High	Spread (Low-High)
RNS 1 (Lowest)	-0.12**	-0.14**	0.02	RNS 1 (Lowest)	-0.12**	-0.16**	0.04
	(-4.37)	(-2.90)	(0.51)		(-4.26)	(-3.17)	(0.83)
					[102]	[32]	
RNS 5 (Highest)	0.14**	0.03	0.11	RNS 5 (Highest)	0.14**	0.05	0.10
	(3.45)	(0.41)	(1.59)		(3.45)	(0.76)	(1.35)
					[103]	[31]	
Spread (5-1)	0.26**	0.17*		Spread (5-1)	0.26**	0.21**	
	(5.06)	(2.21)			(5.05)	(2.73)	

Panel B: O/S

Panel B.1: Conditional Portfolios	O/S High	O/S Low	Spread (High-Low)	Panel B.2: Independent Portfolios	O/S High	O/S Low	Spread (High-Low)
RNS 1 (Lowest)	-0.13**	-0.09*	-0.04	RNS 1 (Lowest)	-0.14**	-0.08	-0.06
	(-4.50)	(-2.08)	(-0.85)		(-4.77)	(-1.83)	(-1.27)
					[100]	[25]	
RNS 5 (Highest)	0.12**	0.02	0.10	RNS 5 (Highest)	0.13**	0.01	0.12
	(2.84)	(0.45)	(1.64)		(2.98)	(0.14)	(1.90)
					[102]	[24]	
Spread (5-1)	0.25**	0.12		Spread (5-1)	0.27**	0.09	
	(4.63)	(1.87)			(4.87)	(1.42)	

Table 9: RNS and ΔRNS-sorted Portfolios: Decomposing Weekly Returns

This Table reports a decomposition of the weekly post-ranking performance of quintile stock portfolios constructed every Wednesday on the basis of their Risk-Neutral Skewness (RNS) estimates (Panel A), or the change in their RNS (ΔRNS) estimates relative to previous trading day (Panel B). The sample period is January 1996–June 2014. Every Wednesday, at market close, stocks are sorted in ascending order according to their RNS values (Panel A) or their ΔRNS values (Panel B), and they are assigned to quintile portfolios. We compute: i) equally-weighted portfolio returns at market close of the first post-ranking trading day, and ii) equally-weighted portfolio returns at market close of the following Wednesday skipping the first post-ranking trading day. Ex Ret denotes the average portfolio return for the corresponding holding period in excess of the risk-free rate. α_{FFC} denotes the portfolio alpha for the corresponding holding period estimated from the Fama-French-Carhart (FFC) 4-factor model. Excess returns and alphas are expressed in percentages. The pre-last line in Panel A (Panel B) shows the spread between the portfolio with the highest RNS (ΔRNS) stocks and the portfolio with lowest RNS (ΔRNS) stocks. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: RNS-sorted Quintile Portfolios

First Post-Ranking Trading Day			Skip First Post-Ranking Trading Day		
Quintiles	Ex Ret	α_{FFC}	Quintiles	Ex Ret	α_{FFC}
1 (Lowest RNS)	0.01	-0.05**	1 (Lowest RNS)	0.03	-0.07**
		(-4.76)			(-2.97)
2	0.03	-0.04**	2	0.08	-0.02
		(-3.31)			(-0.92)
3	0.06	-0.02	3	0.08	-0.03
		(-1.40)			(-1.15)
4	0.12*	0.03	4	0.09	-0.01
		(1.83)			(-0.38)
5 (Highest RNS)	0.19**	0.09**	5 (Highest RNS)	0.13	0.03
		(4.21)			(0.91)
Spread (5-1)	0.18**	0.14**	Spread (5-1)	0.10	0.10*
t(5-1)	(5.81)	(5.86)	t(5-1)	(1.85)	(2.43)

Panel B: ΔRNS-sorted Quintile Portfolios

First Post-Ranking Trading Day			Skip First Post-Ranking Trading Day		
Quintiles	Ex Ret	α_{FFC}	Quintiles	Ex Ret	α_{FFC}
1 (Lowest ΔRNS)	0.01	-0.08**	1 (Lowest ΔRNS)	0.03	-0.08**
		(-4.75)			(-2.58)
2	0.04	-0.04**	2	0.08	-0.03
		(-2.67)			(-1.14)
3	0.07	-0.01	3	0.08	-0.02
		(-0.49)			(-0.85)
4	0.11*	0.03	4	0.09	-0.01
		(1.95)			(-0.41)
5 (Highest ΔRNS)	0.17**	0.09**	5 (Highest ΔRNS)	0.12	0.01
		(5.23)			(0.50)
Spread (5-1)	0.17**	0.17**	Spread (5-1)	0.09**	0.09**
t(5-1)	(8.53)	(8.55)	t(5-1)	(3.07)	(3.03)

Table 10: RNS and ΔRNS-sorted Portfolios: Decomposing First Post-Ranking Day Returns

This Table reports a decomposition of the first post-ranking trading day performance of quintile stock portfolios constructed every Wednesday on the basis of their Risk-Neutral Skewness (RNS) estimates (Panel A), or the change in their RNS (ΔRNS) estimates relative to previous trading day (Panel B). The sample period is January 1996–June 2014. Every Wednesday, at market close, stocks are sorted in ascending order according to their RNS values (Panel A) or their ΔRNS values (Panel B), and they are assigned to quintile equally-weighted portfolios. We compute: i) overnight portfolio returns from the market close of the ranking day (Wednesday) to the market open of the first post-ranking trading day, and ii) intraday portfolio returns from the market open to the market close of the first post-ranking trading day. Ex Ret denotes the average portfolio return in excess of the risk-free rate. The risk-free rate is deducted only from the overnight portfolio return. α_{FFC} denotes the portfolio alpha estimated from the Fama-French-Carhart (FFC) 4-factor model, using the corresponding overnight and intraday factor returns. Returns and alphas are expressed in percentages. The pre-last line in Panel A (Panel B) shows the spread between the portfolio with the highest RNS (ΔRNS) stocks and the portfolio with lowest RNS (ΔRNS) stocks. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: RNS-sorted Quintile Portfolios

Overnight Performance			Intraday Performance		
Quintiles	Ex Ret	α_{FFC}	Quintiles	Ret	α_{FFC}
1 (Lowest RNS)	-0.02	-0.05**	1 (Lowest RNS)	0.03	-0.01
		(-6.59)			(-0.58)
2	0.00	-0.03**	2	0.03	-0.01
		(-3.94)			(-1.07)
3	0.03	-0.00	3	0.03	-0.02
		(-0.52)			(-1.36)
4	0.08**	0.05**	4	0.04	-0.02
		(5.01)			(-1.01)
5 (Highest RNS)	0.18**	0.13**	5 (Highest RNS)	0.01	-0.05**
		(9.69)			(-2.64)
Spread (5-1)	0.20**	0.18**	Spread (5-1)	-0.02	-0.04*
t(5-1)	(10.67)	(10.94)	t(5-1)	(-0.86)	(-2.01)

Panel B: ΔRNS-sorted Quintile Portfolios

Overnight Performance			Intraday Performance		
Quintiles	Ex Ret	α_{FFC}	Quintiles	Ret	α_{FFC}
1 (Lowest ΔRNS)	-0.01	-0.05**	1 (Lowest ΔRNS)	0.02	-0.03*
		(-4.56)			(-2.15)
2	0.02	-0.01	2	0.02	-0.03*
		(-1.28)			(-2.32)
3	0.05	0.01	3	0.03	-0.02
		(1.94)			(-1.63)
4	0.07**	0.04**	4	0.03	-0.01
		(5.12)			(-1.03)
5 (Highest ΔRNS)	0.13**	0.10**	5 (Highest ΔRNS)	0.04	-0.01
		(8.30)			(-0.69)
Spread (5-1)	0.14**	0.15**	Spread (5-1)	0.02	0.02
t(5-1)	(9.40)	(9.48)	t(5-1)	(1.53)	(1.56)

Table 11: Bivariate Conditional Portfolio Sorts: Return Reversals and Risk-Neutral Skewness

This Table reports the weekly post-ranking risk-adjusted performance of bivariate stock portfolios constructed on the basis of their cumulative returns up to the sorting day and their Risk-Neutral Skewness (RNS) estimates. The sample period is January 1996–June 2014. Every Wednesday, at market close, stocks are sorted in ascending order according to their: i) Wednesday return (RET(1)) in Panel A, ii) cumulative 3-day return up to Wednesday (RET(3)) in Panel B, and iii) cumulative 5-day return up to Wednesday (RET(5)) in Panel C, and they are assigned to tercile portfolios. Within each cumulative stock return tercile portfolio, we further sort stocks according to their RNS estimates, and construct quintile portfolios. The corresponding equally-weighted portfolio returns are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). Weekly portfolio alphas (in percentages) are estimated from the Fama-French-Carhart (FFC) 4-factor model. Mean RET(1), Mean RET(3), and Mean RET(5) denote the average RET(1), RET(3), and RET(5) values, respectively, for the stocks in each cumulative stock return tercile portfolio. Alphas are reported for each cumulative stock return tercile across all RNS quintiles as well as for the lowest and the highest RNS quintiles within each cumulative stock return tercile. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: RET(1)

	Mean RET(1)	All RNS Quintiles	RNS 1 (Lowest)	RNS 5 (Highest)	Spread (5-1)
RET(1) Low	-0.02**	0.02	-0.16**	0.26**	0.42**
		(0.72)	(-3.77)	(4.37)	(6.25)
RET(1) Medium	0.00	-0.02	-0.11**	0.04	0.15**
		(-1.13)	(-3.53)	(0.98)	(2.92)
RET(1) High	0.03**	-0.06	-0.11**	0.04	0.16*
		(-1.74)	(-2.79)	(0.75)	(2.34)
Spread (Low-High)	-0.05**	0.09	-0.05	0.21**	
		(1.79)	(-0.91)	(2.68)	

Panel B: RET(3)

	Mean RET(3)	All RNS Quintiles	RNS 1 (Lowest)	RNS 5 (Highest)	Spread (5-1)
RET(3) Low	-0.04**	0.09*	-0.07	0.30**	0.37**
		(2.34)	(-1.44)	(4.41)	(5.03)
RET(3) Medium	0.00	0.00	-0.09**	0.07	0.16**
		(0.11)	(-2.90)	(1.58)	(3.14)
RET(3) High	0.05**	-0.16**	-0.22**	-0.07	0.15*
		(-4.29)	(-5.07)	(-1.36)	(2.46)
Spread (Low-High)	-0.09**	0.25**	0.15*	0.37**	
		(4.23)	(2.32)	(4.19)	

Panel B: RET(5)

	Mean RET(5)	All RNS Quintiles	RNS 1 (Lowest)	RNS 5 (Highest)	Spread (5-1)
RET(5) Low	-0.05**	0.10*	-0.10	0.34**	0.45**
		(2.36)	(-1.95)	(5.54)	(6.21)
RET(5) Medium	0.00*	0.01	-0.07*	0.13**	0.19**
		(0.28)	(-2.55)	(2.61)	(3.41)
RET(5) High	0.06**	-0.16**	-0.21**	-0.10	0.11
		(-4.54)	(-4.36)	(-1.69)	(1.69)
Spread (Low-High)	-0.12**	0.26**	0.11	0.44**	
		(4.41)	(1.47)	(5.26)	

Risk-Neutral Skewness and Stock Outperformance

Supplementary Appendix

S1. Five-Factor Alphas

In the main body of the study, we measure risk-adjusted performance using FFC alphas. To address the potential concern that our benchmark results may be driven by the choice of factors to perform this risk-adjustment, this Section alternatively reports alphas estimated from the 5-factor Fama and French (2015) asset pricing model (FF5).

Similar to our benchmark analysis, we sort stocks in ascending order according to their RNS or ΔRNS values at market close every Wednesday and assign them to quintile portfolios. Their weekly equally-weighted returns are computed by compounding the corresponding daily portfolio returns from the sorting Wednesday market close until the following Wednesday market close. Table S1 reports the weekly post-ranking FF5 alphas of RNS-sorted (Panel A) and ΔRNS-sorted (Panel B) quintiles.

-Table S1 here-

We find that the quintile portfolio that goes long the stocks with the highest RNS (ΔRNS) values yields a significant FF5 alpha of 18 (14) bps in the post-ranking week with a NW t-stat of 4.93 (4.54). This abnormal performance corresponds to an annualized FF5 alpha of 9.8% (7.55%). Hence, the stock outperformance predicted by relatively high RNS and ΔRNS values is much more significant, both statistically and economically, if the FF5 model is used to perform the risk-adjustment. This result derives from the fact that the highest RNS and ΔRNS quintiles actually exhibit a negative loading to the profitability (RMW) and investment (CMA) factors that the FF5 model introduces. Concluding, we confirm that the stock outperformance documented in our benchmark analysis cannot be attributed to potentially omitted risk factors.

Finally, Panel C of Table S1 reports the corresponding FF5 alphas of two bivariate stock portfolios constructed as the intersections of the lowest (highest) RNS and the lowest (highest) ΔRNS independently-sorted quintiles. In line with the results from the univariate portfolios, we find that the portfolio of stocks with the highest RNS and the highest ΔRNS values yields an FF5 alpha of 27 bps in the post-ranking week (NW t-stat: 5.21), which is greater than the corresponding FFC alpha reported in the main body of the study.

S2. Friday Sorts

In our benchmark analysis, we construct portfolios on the basis of RNS and ΔRNS values at market close every Wednesday, and compute their weekly post-ranking returns until the following Wednesday market close. To examine whether the choice of the portfolio sorting day may affect our results, we alternatively construct portfolios using the corresponding RNS and ΔRNS values at market close every Friday, and compute their weekly returns by compounding the corresponding daily portfolio returns until the following Friday market close. Panel A (B) of Table S2 reports the post-ranking performance of RNS-sorted (ΔRNS-sorted) quintiles.

-Table S2 here-

We find that the quintile portfolio that goes long the stocks with the highest RNS (ΔRNS) values yields an FFC alpha of 13 (10) bps in the post-ranking week, with a NW t-stat of 3.46 (2.99). If anything, the abnormal performance of the stock portfolio with the highest RNS values becomes stronger using Friday sorts. Hence, we conclude that our benchmark results are not driven by the choice of the portfolio sorting day.

S3. Options with Positive Total Trading Volume

Following prior studies in the literature (see, *inter alia*, Rehman and Vilkov (2012), ?), our benchmark analysis utilizes RNS values that are computed from OTM option prices associated with positive open interest. There is no requirement that each of these OTM options should exhibit positive trading volume. As a result, a portion of the daily RNS values in our sample have been extracted from the prices of OTM options exhibiting zero total trading volume on the corresponding day. We still expect the quoted bid-ask prices to be rather informative due to the sizeable open interest associated with these options.

Nevertheless, to alleviate the potential concern that our results may be affected by RNS values that are extracted from OTM option prices associated with zero total trading volume, we repeat the benchmark portfolio analysis excluding these RNS values. Table S3 reports the weekly post-ranking performance of RNS-sorted quintile portfolios constructed at market close every Wednesday. Reflecting the exclusion of RNS values associated with zero OTM option total trading volume, each RNS-sorted quintile now consists of 109 stocks, on average, i.e., 24 fewer stocks relative to the benchmark analysis.

-Table S3 here-

We find that the quintile portfolio that goes long the stocks with the highest RNS values yields an even higher FFC alpha relative to the benchmark results, which is equal to 13 bps, and is strongly significant (NW t-stat: 3.03). Hence, we conclude that the stock outperformance signalled by relatively high RNS values becomes even more pronounced when these RNS values are computed from OTM options with positive total trading volume.

S4. Non-Parametric Risk-Neutral Skewness

Throughout our study, we claim that RNS captures the expensiveness of OTM calls relative to OTM puts. Hence, the ability of a relatively high RNS value to predict stock outperformance arises from the fact that the former indicates relatively expensive OTM calls due to transient price pressure in the option market.

To confirm the validity of this argument, this Section uses an alternative, direct measure of relative expensiveness between OTM calls and puts. In particular, following Bali, Hu, and Murray (2017), we compute a "non-parametric" proxy for RNS (NPRNS). We define NPRNS as

$$\text{NPRNS} = \frac{\text{CIV}_{20} + \text{CIV}_{25}}{2} - \frac{\text{PIV}_{-20} + \text{PIV}_{-25}}{2},$$

where CIV_{20} (CIV_{25}) is the implied volatility of the 0.20 (0.25) delta call and PIV_{-20} (PIV_{-25}) is the implied volatility of the -0.20 (-0.25) delta put. To compute NPRNS, we use the corresponding 30-day implied volatilities sourced from OptionMetrics' Volatility Surface file.

Apart from using a direct measure of relative expensiveness between OTM calls and puts, this approach serves two additional purposes. First, by alternatively using this "non-parametric" measure, we ensure that the conclusions of our benchmark analysis are not driven by the methodological choices made to compute the RNS measure of Bakshi, Kapadia, and Madan (2003). Second, by utilizing 30-day implied volatilities, we alleviate the potential concern that our benchmark results may be affected by the fact that RNS values are not computed from constant maturity OTM options.

We sort stocks in ascending order according to their NPRNS values at market close every Wednesday, and assign them to quintile portfolios. For comparability with our benchmark results, this portfolio analysis utilizes only those stocks that also have valid RNS values on the corresponding day. Table S4 reports the weekly post-ranking risk-adjusted performance of the NPRNS-sorted portfolios.

-Table S4 here-

In line with our benchmark results, we find a clear positive gradient in the post-ranking premia and FFC alphas as we move from the lowest NPRNS quintile to the highest NPRNS quintile. Most importantly for the focus of our study, we find that the quintile portfolio containing the stocks with the highest NPRNS values yields a significant FFC alpha of 9 bps in the post-ranking week, with a NW t-stat of 2.64. Hence, using this ”non-parametric” measure, we confirm the conclusion of our benchmark analysis that the stocks with the relatively most expensive OTM calls subsequently outperform.

We also note that the lowest NPRNS quintile subsequently yields a significant negative FFC alpha, confirming the conjecture that the relatively most expensive OTM puts predict stock underperformance. Finally, the spread between the highest and the lowest NPRNS quintiles yields an economically and statistically significant FFC alpha of 29 bps in the post-ranking week.

S5. Daily Rebalancing

Our benchmark analysis shows that a relatively high RNS or ΔRNS value, reflecting transient price pressure in the option market, predicts subsequent stock outperformance at the weekly frequency. Consistent with speedy price correction in the stock market, we find that this outperformance is short-lived. It is mainly earned on the first post-ranking day and, more specifically, overnight. A corollary of these findings is that, with daily rebalancing, the portfolio with the highest RNS or ΔRNS values should yield an even stronger outperformance. This Section examines the validity of this argument.

We sort stocks in ascending order according to their RNS or ΔRNS values at market close on each trading day of our sample period (i.e., a total of 4,648 trading days), and assign them to quintile portfolios. We then compute their equally-weighted returns on the next trading day. Panel A (B) of Table S5 reports the daily post-ranking FFC alphas of RNS-sorted (ΔRNS-sorted) quintiles.

-Table S5 here-

We find that the quintile portfolio that goes long the stocks with the highest RNS (ΔRNS) values yields a significant FFC alpha of 10 (9) bps on the *post-ranking day*, with a NW t-stat of 10.25 (11.49). Highlighting its economic significance, this abnormal performance corresponds to an annualized FFC alpha of approximately 28% (25%). Moreover, Panel C of Table S5 shows that the intersection of the stocks in the highest RNS and the highest ΔRNS quintiles yields an FFC alpha of 18 bps on the post-ranking day (NW t-stat: 13.95).

These results confirm, at the daily frequency, the ability of relatively high RNS and ΔRNS values to predict stock outperformance. Additionally, these findings validate the conjecture that the documented outperformance becomes much stronger when portfolio rebalancing becomes more frequent, and hence they are consistent with the argument that it is short-lived due to speedy price correction in the stock market.

S6. ΔRNS and Stock Underpricing

This Section repeats the analysis of Section IV.A in the main body of the study regarding the role of stock underpricing, using ΔRNS instead of RNS. We construct double-sorted portfolios on the basis of ΔRNS and each of the stock mispricing proxies (DOTS & MISP). To begin with, we construct bivariate conditional portfolios, where we firstly sort stocks into tercile portfolios according to their ΔRNS values at market close every Wednesday, and then, within each ΔRNS tercile, we further sort stocks into terciles according to their mispricing proxy values. Panel A.1 (B.1) of Table S6 reports the weekly post-ranking risk-adjusted performance for selected equally-weighted portfolios when DOTS (MISP) is used as a mispricing proxy.

-Table S6 here-

The results confirm the conclusions derived in the main body of the study. Regardless of the mispricing proxy used, we find that the outperformance of the stocks with the highest ΔRNS values is mainly driven by those stocks that are perceived to be the most underpriced.

For example, the lowest DOTS tercile within the highest ΔRNS tercile yields a highly significant FFC alpha of 21 bps in the post-ranking week (NW t-stat: 4.82). To the contrary, the highest DOTS tercile within the highest ΔRNS tercile significantly underperforms. In fact, for both proxies, the spread between the most underpriced and the most overpriced stocks within the highest ΔRNS tercile yields a significant FFC alpha in the post-ranking week.

To further examine the interaction between ΔRNS and stock underpricing, we alternatively construct independent double-sorted portfolios. Panel A.2 (B.2) of Table S6 reports the post-ranking performance of the corresponding portfolios when DOTS (MISP) is used as a stock mispricing proxy. The reported results corroborate the argument that the combination of a high ΔRNS value and stock underpricing strengthens subsequent outperformance. For example, we find that the intersection of the stocks with the highest ΔRNS & lowest DOTS values yields an FFC alpha of 18 bps (NW t-stat: 4.85) in the post-ranking week. To the contrary, the portfolio of stocks with the highest ΔRNS & highest DOTS values yields a highly significant negative FFC alpha.

S7. ΔRNS and Stock Downside Risk

This Section repeats the analysis of Section IV.B in the main body of the study regarding the role of stock downside risk, using ΔRNS instead of RNS. We construct double-sorted portfolios on the basis of ΔRNS and each of the stock downside risk proxies (EIS^P & ESF). We initially construct bivariate conditional portfolios, where we firstly sort stocks into tercile portfolios according to their ΔRNS values at market close every Wednesday, and then, within each ΔRNS tercile, we further sort stocks into terciles according to their downside risk proxy values. Panel A.1 (B.1) of Table S7 reports the weekly post-ranking FFC alphas for selected equally-weighted portfolios when EIS^P (ESF) is used as a downside risk proxy.

-Table S7 here-

The results reported in Table S7 are in line with the ones presented in the main body of the study. We find that the outperformance signalled by a high ΔRNS value is mainly driven by those stocks that exhibit the most pronounced downside risk. Within the highest ΔRNS tercile, the portfolio of stocks that are the most exposed to downside risk according to EIS^P (ESF) yields an FFC alpha of 14 (10) bps in the post-ranking week, with a NW t-stat of 3.64 (2.47). To the contrary, within the highest ΔRNS tercile, the portfolio of stocks characterized by the lowest exposure to downside risk does not subsequently yield significant outperformance.

We also construct independent double-sorted portfolios on the basis of ΔRNS and each of the downside risk proxies. Panel A.2 (B.2) of Table S7 reports the post-ranking performance of these independent double-sorted portfolios when EIS^P (ESF) is used as a downside risk proxy. The conclusions derived from the independent double-sorted portfolios are very similar to the ones derived from the conditional portfolio sorting approach. Regardless of the proxy used, we confirm that it is the intersection of stocks that exhibit the highest ΔRNS values and are the most exposed to downside risk which yields the strongest subsequent outperformance. To the contrary, the intersection of stocks with the highest ΔRNS values and the least pronounced downside risk does not significantly outperform.

S8. ΔRNS, Stock Underpricing, and Downside Risk

This Section repeats the analysis of Section IV.C in the main body of the study, using ΔRNS instead of RNS. To this end, we construct independent triple-sorted portfolios. In particular, at market close every Wednesday, we independently sort stocks on the basis of their: *i*) ΔRNS value, *ii*) mispricing proxy value, and *iii*) downside risk proxy value, and classify them as high or low relative to the corresponding median value. The intersection of these three independent classifications yields 8 portfolios. Table S8 reports their weekly post-ranking FFC alphas.

-Table S8 here-

These results lead to conclusions that are similar to the ones we derived in our benchmark analysis, lending further support to the proposed trading mechanism. We find that the intersection of stocks that exhibit high ΔRNS values, are relatively underpriced, and are more exposed to downside risk (i.e., portfolio P5) yields the strongest outperformance in the post-ranking week. This pattern is robust for both mispricing proxies and both downside risk proxies. For example, the long-only portfolio of stocks with higher than median ΔRNS values, lower than median DOTS values, and lower than median EIS^P values yields an FFC alpha of 18 bps in the post-ranking week, with a NW t-stat of 4.54. To the contrary, if even one of the conditions laid out by the conjectured trading mechanism is not met, stock outperformance becomes either weaker or insignificant (see portfolios P1, P6, and P7).

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Table S1: RNS and ΔRNS-sorted Quintile Portfolios: Five-factor Alphas

This Table reports the weekly post-ranking risk-adjusted performance of quintile stock portfolios constructed every Wednesday on the basis of their Risk-Neutral Skewness (RNS) estimates (Panel A), or the change in their RNS (ΔRNS) estimates relative to previous trading day (Panel B). The sample period is January 1996–June 2014. Every Wednesday, at market close, stocks are sorted in ascending order according to their RNS values (Panel A) or their ΔRNS values (Panel B), and they are assigned to quintile portfolios. The corresponding equally-weighted portfolio returns are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). α_{FF5} denotes the weekly portfolio alpha estimated from the Fama-French 5-factor (FF5) model. Alphas are expressed in percentages. We also report portfolio loadings (β's) with respect to the market (MKT), size (SMB), value (HML), profitability (RMW) and investment (CMA) factors estimated from the FF5 model as well as its adjusted R^2 (R^2 adj.). The pre-last line in Panel A (Panel B) shows the spread between the portfolio with the highest RNS (ΔRNS) stocks and the portfolio with lowest RNS (ΔRNS) stocks. Panel C reports the corresponding results for two bivariate stock portfolios, constructed as the intersections of the lowest (highest) RNS and the lowest (highest) ΔRNS independently-sorted quintiles. The pre-last line in Panel C reports the spread between these two portfolios. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Quintiles	α_{FF5}	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	R^2 adj.
Panel A: RNS-sorted quintile portfolios							
1 (Lowest RNS)	-0.12**	1.07**	0.29**	-0.01	-0.05	-0.11*	0.93
	(-4.34)						
2	-0.06*	1.15**	0.36**	-0.04	-0.05	-0.16**	0.94
	(-2.22)						
3	-0.02	1.17**	0.47**	-0.03	-0.18**	-0.26**	0.93
	(-0.78)						
4	0.05	1.23**	0.55**	-0.03	-0.24**	-0.31**	0.93
	(1.61)						
5 (Highest RNS)	0.18**	1.25**	0.63**	0.01	-0.46**	-0.41**	0.92
	(4.93)						
Spread (5-1)	0.29**	0.18**	0.34**	0.02	-0.42**	-0.30**	0.45
t(5-1)	(6.29)	(7.30)	(7.24)	(0.21)	(-4.72)	(-3.25)	
Panel B: ΔRNS-sorted quintile portfolios							
1 (Lowest ΔRNS)	-0.12**	1.17**	0.48**	-0.07*	-0.22**	-0.27**	0.93
	(-3.66)						
2	-0.04	1.17**	0.46**	-0.01	-0.20**	-0.21**	0.94
	(-1.52)						
3	-0.01	1.17**	0.44**	-0.01	-0.19**	-0.26**	0.94
	(-0.24)						
4	0.04	1.16**	0.43**	-0.01	-0.22**	-0.25**	0.93
	(1.73)						
5 (Highest ΔRNS)	0.14**	1.18**	0.43**	-0.03	-0.24**	-0.30**	0.93
	(4.54)						
Spread (5-1)	0.26**	0.01	-0.05	0.04	-0.02	-0.04	0.00
t(5-1)	(6.72)	(0.58)	(-1.57)	(1.19)	(-0.43)	(-0.74)	
Panel C: Bivariate RNS & ΔRNS Independently-sorted Portfolios							
RNS 1 (Lowest) & ΔRNS 1 (Lowest)	-0.18**	1.09**	0.38**	-0.05	-0.09	-0.15	0.86
	(-4.06)						
RNS 5 (Highest) & ΔRNS 5 (Highest)	0.27**	1.25**	0.56**	-0.05	-0.39**	-0.38**	0.86
	(5.21)						
Spread (5&5- 1&1)	0.45**	0.15**	0.18**	-0.00	-0.30**	-0.24*	0.20
t(5&5- 1&1)	(6.43)	(4.90)	(4.06)	(-0.05)	(-3.34)	(-2.29)	

Table S2: RNS and ΔRNS-sorted Quintile Portfolios: Friday Sorts

This Table reports the weekly post-ranking performance of quintile stock portfolios constructed every Friday on the basis of their Risk-Neutral Skewness (RNS) estimates (Panel A), or the change in their RNS (ΔRNS) estimates relative to previous trading day (Panel B). The sample period is January 1996–June 2014. Every Friday, at market close, stocks are sorted in ascending order according to their RNS values (Panel A) or their ΔRNS values (Panel B), and they are assigned to quintile portfolios. The corresponding equally-weighted portfolio returns are computed at market close of the following Friday (i.e., post-ranking weekly returns). Ex Ret denotes the average weekly portfolio return in excess of the risk-free rate during the examined period. α_{FFC} denotes the weekly portfolio alpha estimated from the Fama-French-Carhart (FFC) 4-factor model. Excess returns and alphas are expressed in percentages. We also report portfolio 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 adjusted R^2 (R^2 adj.). N denotes the average number of stocks in each portfolio. The pre-last line in Panel A (Panel B) shows the spread between the portfolio with the highest RNS (ΔRNS) stocks and the portfolio with lowest RNS (ΔRNS) stocks. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: RNS-sorted quintile portfolios

Quintiles	Ex Ret	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	R^2 adj.	N
1 (Lowest RNS)	-0.00	-0.17**	1.07**	0.29**	-0.06	-0.03	0.92	133
		(-5.84)						
2	0.13	-0.05*	1.14**	0.39**	-0.09**	-0.05*	0.94	133
		(-1.98)						
3	0.14	-0.05	1.20**	0.57**	-0.14**	-0.06*	0.93	133
		(-1.95)						
4	0.21	0.01	1.25**	0.68**	-0.18**	-0.08**	0.92	133
		(0.42)						
5 (Highest RNS)	0.33*	0.13**	1.34**	0.81**	-0.27**	-0.18**	0.90	133
		(3.46)						
Spread (5-1)	0.33**	0.30**	0.27**	0.52**	-0.20**	-0.15**	0.41	
t(5-1)	(5.18)	(5.94)	(8.27)	(9.39)	(-3.40)	(-3.11)		

Panel B: ΔRNS-sorted quintile portfolios

Quintiles	Ex Ret	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	R^2 adj.	N
1 (Lowest ΔRNS)	-0.01	-0.19**	1.21**	0.55**	-0.24**	-0.07**	0.92	125
		(-5.37)						
2	0.08	-0.10**	1.18**	0.58**	-0.15**	-0.09**	0.93	124
		(-3.71)						
3	0.19	0.01	1.20**	0.51**	-0.11**	-0.08**	0.93	124
		(0.18)						
4	0.25*	0.07*	1.20**	0.52**	-0.12**	-0.07**	0.93	124
		(2.23)						
5 (Highest ΔRNS)	0.28*	0.10**	1.21**	0.52**	-0.19**	-0.10**	0.92	124
		(2.99)						
Spread (5-1)	0.28**	0.28**	0.00	-0.03	0.06	-0.02	0.01	
t(5-1)	(6.72)	(6.71)	(0.20)	(-1.13)	(1.33)	(-1.29)		

Table S3: RNS-sorted Quintile Portfolios: OTM Options with Positive Trading Volume

This Table reports the weekly post-ranking performance of quintile stock portfolios constructed every Wednesday on the basis of their Risk-Neutral Skewness (RNS) estimates, excluding those estimates derived from OTM options with zero total trading volume. The sample period is January 1996–June 2014. Every Wednesday, at market close, stocks are sorted in ascending order according to their RNS values and they are assigned to quintile portfolios. The corresponding equally-weighted portfolio returns are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). Ex Ret denotes the average weekly portfolio return in excess of the risk-free rate during the examined period. α_{FFC} denotes the weekly portfolio alpha estimated from the Fama-French-Carhart (FFC) 4-factor model. Excess returns and alphas are expressed in percentages. We also report portfolio 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 adjusted R^2 (R^2 adj.). N denotes the average number of stocks in each portfolio. The pre-last line shows the spread between the portfolio with the highest RNS stocks and the portfolio with lowest RNS stocks. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Quintiles	Ex Ret	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	R^2 adj.	N
1 (Lowest RNS)	0.03	-0.13**	1.09**	0.29**	-0.12**	-0.04	0.92	109
		(-4.63)						
2	0.12	-0.06*	1.19**	0.35**	-0.19**	-0.04	0.93	109
		(-2.09)						
3	0.13	-0.05	1.25**	0.50**	-0.23**	-0.05*	0.92	109
		(-1.70)						
4	0.20	0.01	1.33**	0.61**	-0.30**	-0.06*	0.91	109
		(0.18)						
5 (Highest RNS)	0.33*	0.13**	1.38**	0.75**	-0.37**	-0.16**	0.88	109
		(3.03)						
Spread (5-1)	0.30**	0.26**	0.29**	0.46**	-0.24**	-0.12*	0.36	
t(5-1)	(4.25)	(4.80)	(11.24)	(7.62)	(-4.20)	(-2.29)		

Table S4: Non-Parametric RNS-sorted Quintile Portfolios

This Table reports the weekly post-ranking performance of quintile stock portfolios constructed every Wednesday on the basis of their Non-Parametric Risk-Neutral Skewness (NPRNS) estimates. NPRNS is defined as the difference between the 30-day implied volatilities of OTM calls (deltas=0.20 and 0.25) and OTM puts (deltas=-0.20 and -0.25). The sample period is January 1996–June 2014. Every Wednesday, at market close, stocks are sorted in ascending order according to their NPRNS values and they are assigned to quintile portfolios. The corresponding equally-weighted portfolio returns are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). Ex Ret denotes the average weekly portfolio return in excess of the risk-free rate during the examined period. α_{FFC} denotes the weekly portfolio alpha estimated from the Fama-French-Carhart (FFC) 4-factor model. Excess returns and alphas are expressed in percentages. We also report portfolio 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 adjusted R^2 (R^2 adj.). N denotes the average number of stocks in each portfolio. The pre-last line shows the spread between the portfolio with the highest NPRNS stocks and the portfolio with lowest NPRNS stocks. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Quintiles	Ex Ret	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	R^2 adj.	N
1 (Lowest NPRNS)	-0.02	-0.20**	1.42**	0.76**	-0.26**	-0.32**	0.90	134
		(-4.37)						
2	0.14	-0.04	1.29**	0.49**	-0.20**	-0.11**	0.93	133
		(-1.31)						
3	0.20*	0.01	1.17**	0.40**	-0.10**	-0.01	0.94	133
		(0.40)						
4	0.21*	0.04	1.08**	0.39**	-0.11**	0.04	0.94	133
		(1.88)						
5 (Highest NPRNS)	0.27*	0.09**	1.13**	0.57**	-0.21**	0.04	0.90	134
		(2.64)						
Spread (5-1)	0.29**	0.29**	-0.29**	-0.19**	0.05	0.36**	0.44	
t(5-1)	(4.34)	(5.28)	(-9.03)	(3.76)	(0.79)	(7.25)		

Table S5: RNS and ΔRNS-sorted Daily Quintile Portfolio Sorts

This Table reports the daily post-ranking performance of quintile stock portfolios constructed on the basis of their Risk-Neutral Skewness (RNS) estimates (Panel A), and the change in their RNS (ΔRNS) estimates relative to previous trading day (Panel B). The sample period is January 1996–June 2014. Each trading day, at market close, stocks are sorted in ascending order according to their RNS values (Panel A) or their ΔRNS values (Panel B), and they are assigned to quintile portfolios. The corresponding equally-weighted portfolio returns are computed at market close of the following trading day (i.e., post-ranking daily returns). Ex Ret denotes the average daily portfolio return in excess of the risk-free rate. α_{FFC} denotes the daily portfolio alpha estimated from the Fama-French-Carhart (FFC) 4-factor model. Excess returns and alphas are expressed in percentages. Portfolio loadings (β's) with respect to the market (MKT), size (SMB), value (HML) and momentum (MOM) factors estimated from the FFC model and its adjusted R^2 (R^2 adj.) are also reported. N denotes the average number of stocks per portfolio. The pre-last line in Panel A (Panel B) reports the spread between the portfolio with the highest RNS (ΔRNS) stocks and the portfolio with lowest RNS (ΔRNS) stocks. Panel C reports the corresponding results for two bivariate stock portfolios, constructed as the intersections of the lowest (highest) RNS and the lowest (highest) ΔRNS independently-sorted quintiles. The pre-last line in Panel C reports the spread between these two portfolios. t-values calculated using Newey-West standard errors with 9 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Quintiles	Ex Ret	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	R^2 adj.	N
Panel A: RNS-sorted Quintile Portfolios								
1 (Lowest RNS)	-0.04	-0.07**	1.04**	0.28**	-0.05*	-0.05**	0.93	134
		(-11.96)						
2	-0.01	-0.04**	1.11**	0.40**	-0.12**	-0.05**	0.94	133
		(-7.38)						
3	0.01	-0.03**	1.18**	0.54**	-0.19**	-0.06**	0.93	133
		(-4.23)						
4	0.06*	0.02*	1.25**	0.63**	-0.25**	-0.06**	0.92	133
		(2.16)						
5 (Highest RNS)	0.14**	0.10**	1.31**	0.76**	-0.29**	-0.12**	0.89	134
		(10.25)						
Spread (5-1)	0.18**	0.17**	0.27**	0.49**	-0.23**	-0.07*	0.36	
t(5-1)	(12.18)	(14.00)	(15.93)	(12.97)	(-6.50)	(-2.18)		
Panel B: ΔRNS-sorted Quintile Portfolios								
1 (Lowest ΔRNS)	-0.06*	-0.10**	1.18**	0.54**	-0.22**	-0.08**	0.92	125
		(-13.73)						
2	-0.01	-0.05**	1.17**	0.52**	-0.16**	-0.06**	0.93	124
		(-7.04)						
3	0.03	-0.01	1.17**	0.51**	-0.16**	-0.06**	0.93	124
		(-1.04)						
4	0.07**	0.03**	1.19**	0.51**	-0.18**	-0.05**	0.93	124
		(5.22)						
5 (Highest ΔRNS)	0.13**	0.09**	1.21**	0.49**	-0.24**	-0.06**	0.91	124
		(11.49)						
Spread (5-1)	0.19**	0.19**	0.04**	-0.05*	-0.02	0.01	0.01	
t(5-1)	(19.48)	(19.30)	(2.85)	(-2.36)	(0.88)	(0.98)		
Panel C: Bivariate RNS & ΔRNS Independently-sorted Portfolios								
RNS 1 (Lowest) & ΔRNS 1 (Lowest)	-0.09**	-0.13**	1.07**	0.35**	-0.10**	-0.06**	0.85	42
		(-14.31)						
RNS 5 (Highest) & ΔRNS 5 (Highest)	0.22**	0.18**	1.31**	0.66**	-0.32**	-0.09**	0.82	43
		(13.95)						
Spread (5&5- 1&1)	0.31**	0.31**	0.24**	0.31**	-0.22**	-0.03	0.16	
t(5&5- 1&1)	(18.19)	(18.62)	(10.40)	(7.94)	(-5.15)	(-1.11)		

Table S6: Bivariate Portfolio Sorts: ΔRNS and Stock Mispricing

This Table reports the weekly post-ranking risk-adjusted performance of bivariate stock portfolios constructed on the basis of the change in their Risk-Neutral Skewness (ΔRNS) estimates relative to the previous trading day and each of the two stock mispricing proxies used. The sample period is January 1996–June 2014. We use the following two proxies for stock mispricing: i) the distance between the actual stock price and the option-implied stock value (DOTS) of Goncalves-Pinto et al. (2016) in Panel A, and ii) the composite mispricing rank (MISP) of Stambaugh and Yuan (2016) in Panel B. A low (high) value of DOTS or MISP indicates that the stock is relatively underpriced (overpriced). For the conditional portfolios (Panels A.1 and B.1), at market close every Wednesday, stocks are sorted in ascending order according to their ΔRNS estimates and they are assigned to tercile portfolios. Within each ΔRNS tercile portfolio, we further sort stocks according to their Wednesday DOTS values (Panel A.1) or their end-of-month, prior to the sorting Wednesday, MISP values (Panel B.1), and construct again tercile portfolios. For the independent portfolios (Panels A.2 and B.2), at market close every Wednesday, stocks are independently sorted in ascending order according to their ΔRNS estimates and their Wednesday DOTS values (Panel A.2) or their end-of-month, prior to the sorting Wednesday, MISP values (Panel B.2), and they are assigned to tercile portfolios. The intersections of these ΔRNS- and stock mispricing-sorted terciles yield the independent portfolios. The average number of stocks per portfolio is reported in square brackets. In both approaches, equally-weighted returns of the corresponding portfolios are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). We report weekly portfolio alphas (in percentages) estimated from the Fama-French-Carhart (FFC) 4-factor model. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: DOTS

Panel A.1: Conditional Portfolios	DOTS Lowest	DOTS Highest	Spread (Lowest-Highest)	Panel A.2: Independent Portfolios	DOTS Lowest	DOTS Highest	Spread (Lowest-Highest)
ΔRNS 1 (Lowest)	0.03	-0.34**	0.36**	ΔRNS 1 (Lowest)	0.04	-0.27**	0.31**
	(0.75)	(-6.97)	(7.11)		(0.83)	(-6.65)	(6.06)
					[40]	[94]	
ΔRNS 3 (Highest)	0.21**	-0.13**	0.34**	ΔRNS 3 (Highest)	0.18**	-0.20**	0.37**
	(4.82)	(-3.47)	(6.73)		(4.85)	(-4.05)	(6.84)
					[98]	[44]	
Spread (3-1)	0.19**	0.21**		Spread (3-1)	0.14**	0.07	
	(3.93)	(4.43)			(2.85)	(1.43)	

Panel B: MISP

Panel B.1: Conditional Portfolios	MISP Lowest	MISP Highest	Spread (Lowest-Highest)	Panel B.2: Independent Portfolios	MISP Lowest	MISP Highest	Spread (Lowest-Highest)
ΔRNS 1 (Lowest)	-0.04	-0.24**	0.20**	ΔRNS 1 (Lowest)	-0.05	-0.24**	0.19**
	(-1.13)	(-4.91)	(3.45)		(-1.34)	(-4.98)	(3.36)
					[64]	[65]	
ΔRNS 3 (Highest)	0.13**	-0.00	0.13*	ΔRNS 3 (Highest)	0.13**	-0.01	0.14*
	(3.89)	(-0.10)	(2.23)		(4.20)	(-0.12)	(2.37)
					[64]	[65]	
Spread (3-1)	0.17**	0.24**		Spread (3-1)	0.18**	0.23**	
	(4.27)	(4.32)			(4.51)	(4.46)	

Table S7: Bivariate Portfolio Sorts: ΔRNS and Downside Risk

This Table reports the weekly post-ranking risk-adjusted performance of bivariate stock portfolios constructed on the basis of the change in their Risk-Neutral Skewness (ΔRNS) estimates relative to the previous trading day and each of the two proxies used for stock downside risk. The sample period is January 1996–June 2014. We use the following two proxies for stock downside risk: i) the expected idiosyncratic skewness (EIS^P) of daily stock returns under the physical measure of Boyer et al. (2010) in Panel A, and ii) the estimated stock shorting fee (ESF) of Boehme et al. (2006) in Panel B. A low (high) value of EIS^P or ESF indicates that the stock is exposed to greater (lower) downside risk. For the conditional portfolios (Panels A.1 and B.1), at market close every Wednesday, stocks are sorted in ascending order according to their ΔRNS estimates and they are assigned to tercile portfolios. Within each ΔRNS tercile portfolio, we further sort stocks according to their end-of-month, prior to the sorting Wednesday, EIS^P (Panel A.1) or ESF values (Panel B.1), and construct again tercile portfolios. For the independent portfolios (Panels A.2 and B.2), at market close every Wednesday, stocks are independently sorted in ascending order according to their ΔRNS estimates and their end-of-month, prior to the sorting Wednesday, EIS^P (Panel A.2) or ESF values (Panel B.2), and they are assigned to tercile portfolios. The intersections of these ΔRNS- and stock downside risk-sorted terciles yield the independent portfolios. The average number of stocks per portfolio is reported in square brackets. In both approaches, equally-weighted returns of the corresponding portfolios are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). We report weekly portfolio alphas (in percentages) estimated from the Fama-French-Carhart (FFC) 4-factor model. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: EIS^P

Panel A.1: Conditional Portfolios				Panel A.2: Independent Portfolios			
	EIS^P Lowest	EIS^P Highest	Spread (Lowest-Highest)		EIS^P Lowest	EIS^P Highest	Spread (Lowest-Highest)
ΔRNS 1 (Lowest)	-0.01	-0.20**	0.19**	ΔRNS 1 (Lowest)	0.00	-0.20**	0.21**
	(-0.19)	(-4.18)	(3.32)		(0.11)	(-4.35)	(3.58)
					[53]	[54]	
ΔRNS 3 (Highest)	0.14**	0.05	0.10	ΔRNS 3 (Highest)	0.15**	0.06	0.10
	(3.64)	(1.18)	(1.74)		(3.79)	(1.40)	(1.74)
					[52]	[54]	
Spread (3-1)	0.15**	0.25**		Spread (3-1)	0.15**	0.26**	
	(3.70)	(4.74)			(3.46)	(4.88)	

Panel B: ESF

Panel B.1: Conditional Portfolios				Panel B.2: Independent Portfolios			
	ESF Lowest	ESF Highest	Spread (Lowest-Highest)		ESF Lowest	ESF Highest	Spread (Lowest-Highest)
ΔRNS 1 (Lowest)	0.01	-0.21**	0.21**	ΔRNS 1 (Lowest)	-0.00	-0.22**	0.21**
	(0.17)	(-3.77)	(4.08)		(-0.10)	(-4.09)	(4.21)
					[62]	[52]	
ΔRNS 3 (Highest)	0.10*	0.01	0.08	ΔRNS 3 (Highest)	0.09*	-0.01	0.11*
	(2.47)	(0.26)	(1.66)		(2.40)	(-0.28)	(2.19)
					[62]	[52]	
Spread (3-1)	0.09**	0.22**		Spread (3-1)	0.10**	0.21**	
	(2.70)	(4.16)			(2.90)	(3.95)	

Table S8: Trivariate Independent Portfolio Sorts: ΔRNS, Stock Mispricing and Downside Risk

This Table reports the weekly post-ranking risk-adjusted performance of trivariate stock portfolios constructed on the basis of the change in their Risk-Neutral Skewness (ΔRNS) estimates relative to the previous trading day, each of the two proxies used for stock mispricing, and each of the two proxies used for stock downside risk. The sample period is January 1996–June 2014. We use the following two proxies for stock mispricing: i) the distance between the actual stock price and the option-implied stock value (DOTS) of Goncalves-Pinto et al. (2016), and ii) the composite mispricing rank (MISP) of Stambaugh and Yuan (2016). A low (high) value of DOTS or MISP indicates that the stock is relatively underpriced (overpriced). We use the following two proxies for stock downside risk: i) the expected idiosyncratic skewness (EIS^P) of daily stock returns under the physical measure of Boyer et al. (2010), and ii) the estimated stock shorting fee (ESF) of Boehme et al. (2006). A low (high) value of EIS^P or ESF indicates that the stock is exposed to greater (lower) downside risk. Every Wednesday, at market close, stocks are independently sorted in ascending order according to: 1) their ΔRNS estimates, 2) their Wednesday DOTS values or their end-of-month, prior to the sorting Wednesday, MISP values, and 3) their end-of-month, prior to the sorting Wednesday, EIS^P or ESF values, and they are classified for each sorting criterion as Low (L) or High (H) relative to the corresponding median value. The intersections of these three classifications yield 8 portfolios. The corresponding equally-weighted portfolio returns are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). We report weekly portfolio alphas (in percentages) estimated from the Fama-French-Carhart (FFC) 4-factor model. The average number of stocks per portfolio is reported in square brackets. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

	Stock Mispricing Proxy	DOTS		MISP	
	Downside Risk Proxy	EIS^P	ESF	EIS^P	ESF
P1	ΔRNS Low & DOTS/ MISP Low & EIS^P/ ESF Low	0.15** (3.61) [46]	0.06 (1.57) [55]	0.06 (1.68) [65]	0.03 (0.82) [76]
P2	ΔRNS Low & DOTS/ MISP Low & EIS^P/ ESF High	-0.08 (-1.81) [44]	-0.04 (-0.76) [42]	-0.05 (-1.30) [52]	-0.07 (-1.40) [45]
P3	ΔRNS Low & DOTS/ MISP High & EIS^P/ ESF Low	-0.08* (-1.97) [69]	-0.05 (-1.57) [77]	-0.03 (-0.56) [52]	-0.04 (-1.05) [53]
P4	ΔRNS Low & DOTS/ MISP High & EIS^P/ ESF High	-0.23** (-6.46) [72]	-0.24** (-5.18) [74]	-0.25** (-5.75) [64]	-0.18** (-3.77) [68]
P5	ΔRNS High & DOTS/ MISP Low & EIS^P/ ESF Low	0.18** (4.54) [71]	0.15** (4.15) [84]	0.12** (3.48) [64]	0.13** (3.58) [76]
P6	ΔRNS High & DOTS/ MISP Low & EIS^P/ ESF High	0.12** (3.39) [70]	0.09* (2.02) [67]	0.10** (3.11) [53]	0.03 (0.55) [45]
P7	ΔRNS High & DOTS/ MISP High & EIS^P/ ESF Low	-0.06 (-1.53) [44]	-0.00 (-0.12) [48]	0.08 (1.80) [53]	0.08 (1.73) [53]
P8	ΔRNS High & DOTS/ MISP High & EIS^P/ ESF High	-0.13** (-2.93) [45]	-0.18** (-3.53) [49]	0.01 (0.12) [64]	0.00 (0.01) [67]

Table S9: Bivariate Conditional Portfolio Sorts: Return Reversals and ΔRNS

This Table reports the weekly post-ranking risk-adjusted performance of bivariate stock portfolios constructed on the basis of their cumulative returns up to the sorting day and the change in their Risk-Neutral Skewness (ΔRNS) estimates relative to the previous trading day. The sample period is January 1996–June 2014. Every Wednesday, at market close, stocks are sorted in ascending order according to their: i) Wednesday return (RET(1)) in Panel A, ii) cumulative 3-day return up to Wednesday (RET(3)) in Panel B, and iii) cumulative 5-day return up to Wednesday (RET(5)) in Panel C, and they are assigned to tercile portfolios. Within each cumulative stock return tercile portfolio, we further sort stocks according to their ΔRNS estimates, and construct quintile portfolios. The corresponding equally-weighted portfolio returns are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). Weekly portfolio alphas (in percentages) are estimated from the Fama-French-Carhart (FFC) 4-factor model. Mean RET(1), Mean RET(3), and Mean RET(5) denote the average RET(1), RET(3), and RET(5) values, respectively, for the stocks in each cumulative stock return tercile portfolio. Alphas are reported for each cumulative stock return tercile across all ΔRNS quintiles as well as for the lowest and the highest ΔRNS quintiles within each cumulative stock return tercile. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: RET(1)

	Mean RET(1)	ΔRNS 1 (Lowest)	ΔRNS 5 (Highest)	Spread (5-1)
RET(1) Low	-0.02**	-0.14**	0.17**	0.31**
		(-2.70)	(3.51)	(5.04)
RET(1) Medium	-0.00	-0.16**	0.11**	0.27**
		(-3.91)	(3.09)	(5.48)
RET(1) High	0.03**	-0.19**	-0.02	0.17**
		(-3.69)	(-0.35)	(3.23)
Spread (Low-High)	-0.05**	-0.05	0.19**	
		(-0.71)	(2.72)	

Panel B: RET(3)

	Mean RET(3)	ΔRNS 1 (Lowest)	ΔRNS 5 (Highest)	Spread (5-1)
RET(3) Low	-0.04**	-0.11*	0.27**	0.38**
		(-2.08)	(4.77)	(5.98)
RET(3) Medium	0.00	-0.10**	0.09*	0.19**
		(-2.72)	(2.36)	(4.10)
RET(3) High	0.05**	-0.24**	-0.11*	0.13*
		(-4.28)	(-2.19)	(2.48)
Spread (Low-High)	-0.09**	0.13	0.38**	
		(1.61)	(4.84)	

Panel B: RET(5)

	Mean RET(5)	ΔRNS 1 (Lowest)	ΔRNS 5 (Highest)	Spread (5-1)
RET(5) Low	-0.05**	-0.07	0.30**	0.36**
		(-1.22)	(5.41)	(5.67)
RET(5) Medium	0.00	-0.09*	0.06	0.16**
		(-2.41)	(1.63)	(3.24)
RET(5) High	0.06**	-0.26**	-0.09	0.17**
		(-4.77)	(-1.79)	(3.22)
Spread (Low-High)	-0.11**	0.19*	0.38**	
		(2.47)	(5.02)	