Risk Neutral Skewness Predicts Price Rebounds and so can Improve Momentum Performance*

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This version: April, 2020

Abstract

Positive option-implied risk-neutral skewness (RNS) predicts next-month abnormal underlying stock returns driven by upward rebounds of previously undervalued stocks. The RNS anomaly is strongest in periods of post-recession rebounds when momentum crashes occur. Furthermore, the momentum anomaly is strongest (weakest) in stocks with the most negative (positive) RNS. We generalize our findings to non-optionable stocks by constructing an RNS factor-mimicking portfolio, finding that a momentum strategy that avoids performance reversals has meaningfully superior performance. Our results hold after controlling for trading frictions, firm characteristics, and common risk factors.

Keywords: Risk Neutral Skewness; Momentum; Return Predictability

JEL classification: G12, G13

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*We thank seminar participants at University of Miami, Santa Clara University, University of Waterloo, Rutgers University, 2018 OptionMetrics Research Conference, Wilfrid Laurier University, University of Toronto, University of Wisconsin - Whitewater, Lord Abbett LLC, 2019 SFA Annual Meeting, 2018 ITAM Finance Conference, 2017 FMA Annual Meeting, McMaster University, and Citadel LLC for their helpful comments. This paper replaces an earlier draft titled "What Information Does Risk Neutral Skewness Contain? Evidence From Price Rebounds and Momentum Crashes". All remaining errors are our own.

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1 Introduction

The seminal work of Bakshi, Kapadia, and Madan (2003) spurred an ongoing investigation into the information content of the moments of the option-implied risk-neutral distribution of underlying returns. The literature thus far finds at times contradictory evidence about the information content of risk-neutral skewness (RNS), the third moment of this distribution. High positive RNS has been argued to have a negative relationship with returns due to behavioral preferences for lottery stocks (Conrad, Dittmar, and Ghysels, 2013), a positive relationship due to low RNS proxying for overvaluation, particularly in the presence of short-sale constraints (Stilger, Kostakis, and Poon, 2016), and a positive relationship due to price pressure (Bali, Hu, and Murray, 2018). Notably, unpublished work by Rehman and Vilkov (2012) suggests that RNS may more generally relate to undervaluation as well as overvaluation. Building on this insight, we consider the relationship of RNS to both the past and future price path of stocks to shed additional light on this issue, help resolve potentially contradictory findings, and better understand the information channel for the relationship between RNS and future underlying returns.

Contemporaneous RNS estimated at the end of the month has a positive correlation with returns for the underlying stock over the following month, and we find evidence consistent with relative undervaluation as the driver of this positive performance. An equal-weighted zero-cost portfolio sort on high (ie, most positive) minus low (most negative) RNS exhibits significant abnormal monthly returns of 94 bp, of which 39 bp is due to the short leg consistent with an overvaluation explanation advanced by prior literature (Stilger, Kostakis, and Poon, 2016). However, the remaining 55 bp is due to the long leg, contrary to an overvaluation explanation, consistent with evidence that RNS can reflect undervaluation also (Rehman and Vilkov, 2012). Furthermore, a value-weighted equivalent high minus low RNS portfolio has abnormal returns of approximately 70 bp with 48 bp due to the long leg and only 21 bp due to the short leg. Across both portfolio weightings, the observed greater magnitude of the excess and abnormal return contribution of the high-RNS long leg is contrary to the overvaluation explanation that assumes information is contained in the low-RNS short leg. Furthermore, we show that the long leg of the zero-cost high-low RNS portfolio has a positive and significant conditional beta during market rebounds while the short leg does not, suggesting a dynamic not captured by overvaluation under short-sale constraints. We therefore consider an alternative explanation to the RNS anomaly as an indicator of stock price rebounds.

Figure 1 demonstrates the path-dependence of RNS with respect to the past and future performance of the underlying stock. At the end of each portfolio formation month ($t = 0$) we rank stocks into RNS quintiles, form portfolios, and plot the portfolio's past and future equal-weighted excess returns for Q1 (low RNS) and Q5 (high RNS). The Figure shows that both high and low RNS stocks experience reversals in their performance. The Q1 (low RNS) stocks have higher historical performance before portfolio formation and lower, though still positive, performance after. Conversely, the Q5 (high RNS) stocks exhibit negative performance before portfolio formation and a positive rebound afterward. The behavior of the RNS Q1 portfolio is consistent with the explanation of worse future performance by overvalued and short-sale-constrained stocks. However, the positive rebound observed in the RNS Q5 portfolio is not consistent with this explanation. Value-weighted portfolios produce very similar results which we suppress for brevity.

Consistent with the trend reversal of negative momentum stocks observed in the RNS Q5 portfolio in Figure 1, we find that the RNS anomaly is related to the momentum crash phenomenon in which a reversal of trends causes a reversal in the momentum anomaly (Daniel and Moskowitz, 2016). The authors show that momentum strategies can experience infrequent negative returns, especially at the end of market recessions and high market volatility periods as low-momentum stocks rebound. They demonstrate that the market beta of the momentum strategy becomes more negative during these periods, giving it asymmetric negative exposure to the rebound. We find that the RNS anomaly has a positive beta during market-wide rebounds, giving it an opposite asymmetric positive exposure. Due to its predictive power for firm-specific rebounds and its negative relationship with momentum returns, we conjecture that RNS can be used to identify upward rebounds and improve the performance of momentum by avoiding rebound-driven crashes. We demonstrate this by forming a winner minus loser momentum strategy within RNS terciles and finding significant differences in its performance across them.

The momentum strategy in the high RNS tercile experiences the worst performance around market rebounds following recessionary periods. This effect is not driven by small firms, as we find that the momentum strategy earns the lowest returns in recessions and periods of high market volatility in the highest RNS tercile for both middle and high size terciles. Conversely, the lowest RNS tercile yields the strongest momentum performance for both middle and high firm size terciles.

To generalize this finding to stocks without traded options necessary to compute the RNS characteristic, we construct a characteristic-mimicking portfolio. This allows us to address a larger universe of tradeable assets, which both increases the economic significance of our finding as well as its robustness. By relaxing the requirement of stocks having the traded options necessary to compute the RNS characteristic, we eliminate a potential selection bias in our results. We hypothesize that non-optionable stocks with similar price rebound patterns will have exposure to this factor-mimicking portfolio constructed from optionable stocks predicted to have price rebounds from a sort on the RNS characteristic, and find evidence consistent with this hypothesis. Stocks with a high RNS characteristic, as well as those with a high skewness characteristic-mimicking portfolio loading, experience substantially more frequent positive performance reversals at the individual firm level and have the lowest firm-specific valuation component using the Rhodes-Kropf, Robinson, and Viswanathan (2005) industry multiples method of decomposing the market to book ratio. Loadings on the skewness factor mimicking portfolio predict future realized skewness, consistent with its validity as a proxy for RNS. Furthermore, a momentum strategy on stocks with the lowest skewness factor-mimicking portfolio loadings has significantly improved performance, confirming the ability of the RNS characteristic to identify and avoid the momentum crash phenomenon.

These results are not driven by small, illiquid, or high trading cost stocks. The improvement in the risk-return tradeoff of the momentum strategy introduced by the avoidance of momentum crashes using low-RNS stocks is more significant than that of the risk-managed momentum strategy suggested by Barroso and Santa-Clara (2015), suggesting the performance reversal information captured in the RNS characteristic has meaningful economic value.

This study contributes to the asset pricing anomaly literature, to our understanding of the pricing of risk-neutral skewness as a factor and as a characteristic, and to its relationship with future realized outcomes. Bakshi, Kapadia, and Madan (2003) demonstrate that RNS is related to the moments of the physical distribution moderated by the risk aversion parameter. More recent work by Kozhan, Neuberger, and Schneider (2013) and Harris and Qiao (2018) relates option-implied and historical skewness as a time-varying skewness risk premium. Notably, Harris and Qiao (2018) find that more than 40% of the skewness risk premium is explained by the prior month's returns, a reversal pattern similar to the behavior that we find for the relationship between RNS and next month's price rebounds which drive momentum crashes. In related work, Borochin, Chang, and Wu (2018) demonstrate that the positive relation between RNS and future returns is concentrated in short-maturity options.

It also adds to our understanding of the relationship between measures of the asymmetry of the distribution of underlying asset and its future performance. In particular, recent findings on the option-implied asymmetry of variance by Kilic and Shaliastovich (2018) and Tang (2018)[1] suggest that these variance asymmetries predict returns also. Tang (2018) finds that this return predictability is not explained by crash risk, which is an important

[1]Kilic and Shaliastovich (2018) uses separate measures of option-implied upside and downside semi-variance, whereas Tang (2018) focuses on the spread between the two.

determinant of the variance risk premium (Bollerslev and Todorov, 2011; Bollerslev, Todorov, and Xu, 2015). By controlling for these alternative asymmetyr measures, our findings suggest a difference between crash risk as it relates to the asymmetry of the option-implied variance and the variance risk premium, and price rebounds (or downturns) as they relate to option-implied skewness.

It also demonstrates that momentum crashes can be identified and avoided, significantly improving the anomaly's performance. We add to the skewness pricing literature by documenting that high RNS stocks predict positive stock performance, particularly after a period of underperformance, and this reversal has a relationship with the momentum crash phenomenon documented in Daniel and Moskowitz (2016). We observe this behavior using both the RNS characteristics in optionable stocks as well as all CRSP stocks regardless of optionability using stock loadings on our novel constructed risk-neutral skewness factor. We demonstrate this behavior both at the market-wide level and at the individual stock level, and identify undervaluation-driven rebounds as the information channel.

The study is organized as follows: In Section 2, we describe the data and methods used to construct the RNS measure and firm-specific valuation errors. Section 3 examines the market timing sensitivity of the zero-investment RNS portfolio, demonstrating that its performance is strongest when momentum crashes are most likely, and tests the ability of the RNS anomaly to isolate momentum crashes documented in Daniel and Moskowitz (2016) using portfolio sorts. Section 4 constructs the SKEW factor-mimicking portfolio and shows it can also be used to isolate stock-specific rebounds caused by undervaluation, extending our results to all stocks and removing the potential selection bias in the RNS analysis restricting us to stocks with traded options only. We also evaluate the economic significance of our findings by estimating the performance of a momentum strategy constructed to avoid skewness-implied stock rebounds on its own and relative to other momentum strategies. Section 5 concludes.

2 Data and Variable Construction

In this section, we describe the data and the method used to extract option-implied risk neutral skewness (RNS) for individual stocks. Bakshi, Kapadia, and Madan (2003) provide intuition for interpreting RNS by demonstrating that under power and exponential utility it has a linear relationship with physical skewness, but with a negative offset driven by risk aversion and physical skewness and kurtosis. This implies that RNS is a function of all three physical moments and of the coefficient of risk aversion, providing a wealth of potential information content about the underlying asset. We follow the approach of Bakshi, Kapadia, and Madan (2003) to extract RNS from both volatility surface data as well as traded options data. The relationship of RNS to physical skewness, as well as the details of the RNS estimation methodology are described in Appendix A.

We use the volatility surface at the 30 day maturity from Ivy DB's OptionMetrics to estimate each stock's RNS to improve cross-sectional comparability. The volatility surface file contains constant-maturity implied volatility data for each day created from traded option data using a kernel smoothing algorithm. These interpolations are made separately for calls and puts at constant discrete time horizons starting with 30 day maturities. A standardized option is only included if there are at least two traded contracts with non-negative implied volatility for each firm on each day.[2]

We use the volatility surface data at the minimum 30 day maturity horizon for two reasons. First, these short-term options are calculated using option trade data which has the highest liquidity and therefore the most frequently-updated prices. Second, the fixed maturity of the interpolation makes our results better comparable through time than those recovered from traded option data at varying maturity. We use deltas of 0.20 through 0.45

[2] We also use traded options data to replicate our RNS calculation following Bakshi, Kapadia, and Madan (2003). In this specification we require that at a given day, a stock has no fewer than two OTM calls and two OTM puts with the same maturity, using equal numbers of OTM calls and puts for each stock for each day. If there are more OTM calls than puts available, we use those OTM calls that are the least out-of-the-money. For each day's calculation, we keep the shortest common maturity of greater than 10 days. Our results are mutually consistent cross the two samples of standardized and traded data.

for OTM calls, and -0.20 through -0.45 for OTM puts.

We proxy the risk-free rate using 30-day Treasury bill rates. Following prior literature, we use a piecewise Hermite polynomial to interpolate the implied volatility between the observed available options at the observed highest and lowest moneyness, extrapolating from the last observed implied volatility for more extreme levels. This enables us to define implied volatility over a moneyness range of 1/3 to 3. We take corresponding option prices for each interpolated implied volatility over this range, and use Simpson's rule to calculate the integrals defining the volatility, cubic, and quartic contracts from Bakshi, Kapadia, and Madan (2003) in Eq. (A.6), (A.7), and (A.8) respectively. We obtain data on stock returns from CRSP, calculating monthly returns from 1996 to 2016 for all individual securities with common shares outstanding. We also obtain the book value of equity from Compustat. We merge our RNS data with the data from CRSP and Compustat and our sample finally contains 592,480 firm-month combinations from January 1996 to April 2016.

We compute last quarter's firm-specific valuation error $Overvaluation_{q-1}$ using the Rhodes-Kropf, Robinson, and Viswanathan (2005) decomposition which splits the quarterly logarithm of the market-to-book ratio into three parts: firm-specific error, time-series sector error, and long-run market to book value following Eq. (3) from their paper:

$$m_{i,t} - b_{i,t} = \underbrace{m_{i,t} - v(\theta_{i,t}; a_{j,t})}_{firm} + \underbrace{v(\theta_{i,t}; a_{j,t}) - v(\theta_{i,t}; a_j)}_{sector} + \underbrace{v(\theta_{i,t}; a_j) - b_{i,t}}_{long-run}. \tag{1}$$

This decomposition relies on a firm having a long-run, target, market-to-book ratio equal to that of its industry. Firm valuations are estimated using multiples of book value, leverage, and net income which is able to explain the vast majority of the cross-sectional variation of within-industry market-to-book ratios. The long-run firm value is identified from multiples of the three variables estimated over the entire time series, while sector-wide deviations are identified using quarter-specific sector-wide multiples. The firm-specific component accounts for any additional deviations. The more positive the firm-specific valuation error, the greater the firm's overvaluation.

Table 1 Panel A shows the descriptive statistics for risk neutral skewness (RNS), as well as other firm-specific data used in the subsequent analysis: the log of market capitalization $\ln MV$, the monthly return RET_t and its one-month lag RET_{t-1}, the cumulative performance over the past eleven months with a one-month lag $RET_{t-12,t-2}$, the intermediate horizon past performance $RET_{t-12,t-7}$, the recent past performance $RET_{t-6,t-2}$, the market beta β^i_M, the log of monthly stock trading volume $\ln VOLUME$, and the book-to-market ratio BM. By construction, our measure of past performance skips the prior month's return alleviating concerns that RNS in month $t-1$ is mechanically negatively related to past returns in months $t-6, t-2$. The sample consists of 592,480 firm-month observations from Jan 1996 through April 2016. Notably, the firm-specific valuation error $Overvaluation_{q-1}$ has positive means and medians at 0.292 and 0.320 respectively, though not statistically different from zero in the sample of 485,072 firm-months for which it is available.[3] We describe variable definitions in Appendix B.

In measuring momentum, we separate cumulative past performance into two components following the insight from Novy-Marx (2012). He finds that intermediate-horizon performance matters most for the momentum anomaly, and we follow this definition of intermediate-horizon past performance as $RET_{t-12,t-7}$. We report the means, medians, and standard deviations as well as 5th and 95th percentiles across securities during the sample period in Panel A of Table 1. The mean risk neutral skewness is -0.198 while its median is -0.235. Comparing the mean and median of RET_t shows that returns under the physical distribution are positively skewed, but the cumulative returns over the past eleven months are negatively skewed. The average β^i_M in our sample is 1.313, while the median β^i_M is 1.175. In Panel B of Table 1, we report the time series average of cross-sectional correlation coefficients

[3]The firm-specific valuation error is very close to zero in the Rhodes-Kropf, Robinson, and Viswanathan (2005) dataset as well as in our full sample before merging with optionable firms.

between our variables. The lower triangular matrix presents the Pearson correlation matrix; the upper triangular matrix shows the nonparametric Spearman correlation matrix. We observe that while its overall correlations are low, the RNS characteristic for optionable stocks is most correlated with our size measure MV and our momentum measures at all horizons, providing an intuitive motivation for the relationship between RNS and momentum.

Table 2 presents the cross-sectional relationship between contemporaneous risk neutral skewness (RNS) and future stock returns controlling for contemporaneous firm characteristics. Consistent with Rehman and Vilkov (2012) and Stilger, Kostakis and Poon (2016), RNS has a positive coefficient of 0.716 with significance at the 1% level in column (1) of Table 2. Column (2) of Table 2 presents Fama MacBeth (1973) regressions of excess returns on firm characteristics: β_M^i, log of market capitalization lnMV, log of the BM book-to-market ratio, one month lagged return RET_{t-1}, momentum, and log of stock trading volume lnVOLUME. We use cumulative returns over past eleven months lagged one month $RET_{t-12,t-2}$ as proxies of momentum in columns (2) and (3).

The one month lagged return RET_{t-1} negatively predicts future returns, consistent with the short-term momentum reversal effect. Momentum over the past eleven months with a one-month lag positively predicts future expected return, consistent with prior results on the momentum anomaly. Coefficients on other firm characteristics are insignificant. Column (3) of Table 2 presents the cross-sectional findings for risk neutral skewness (RNS) controlling for firm characteristics. The magnitude of the RNS coefficient becomes smaller compared with column (1), decreasing to 0.675 from 0.716, but remains significant controlling for firm characteristics. Columns (4) and (5) use the Novy-Marx (2012) intermediate-term returns $RET_{t-12,t-7}$ while columns (6) and (7) use short-term returns $RET_{t-6,t-2}$ as proxies of momentum. We find that the coefficients on $RET_{t-12,t-7}$ are significant at the 5% level with a higher magnitude, and the coefficients on $RET_{t-6,t-2}$ are insignificant, consistent with Novy-Marx (2012).

We also consider the RNS anomaly in light of recent findings on the option-implied asymmetry of variance by Kilic and Shaliastovich (2018) and Tang (2018) in column (8) of Table 2. We use a subsample of traded options data to control for AVAR, the difference between option-implied upside and downside semi-variance, following Tang (2018) as described in Appendix B. This alternative measure of the asymmetry of the implied distribution of underlying returns uses options across all strikes, unlike the RNS measure that emphasizes options in the tails of the moneyness spectrum. We have 141,050 firm-month observations in this subsample. We find that AVAR has a positive coefficient, which is consistent with what Tang (2018) finds. However, after controlling for AVAR, RNS still has positive and significant coefficient: 0.939 with a significance of 1%.

We also investigate the relationship of RNS to historical skewness in Table 2. Recent work by Kozhan, Neuberger, and Schneider (2013) and Harris and Qiao (2018) connects the two as a time-varying skewness risk premium. Harris and Qiao (2018) find that this skewness risk premium is explained by the prior month's returns, suggestive of the relationship between RNS and next month's price rebounds in Figure 1. The coefficient on historical skewness HS in columns (2) through (7) of Table 2 is also positive, but does not materially diminish the magnitude or significance of RNS in column (1). These results suggest that the skewness risk premium and asymmetric variance are not strongly related to the RNS anomaly that is the focus of our study.

To better understand its explanatory power for stock returns, we sort all stocks for which option-implied RNS can be computed into RNS quintiles. We present the quintile portfolio characteristics and excess returns as well as abnormal returns benchmarked to the Carhart (1997) four-factor model in Table 3. In the top sub-panel of Panel A we tabulate portfolio characteristics, finding that the portfolio with the highest RNS has negative past performance consistent with the historical performance of high-RNS stocks in Figure 1. Notably, firm-specific prior quarter valuation error $Overvaluation_{q-1}$ is monotonically decreasing in RNS quintiles ranging from 0.363 in RNS Q1 to 0.090 in RNS Q5. Given the sample mean and median firm error values of 0.292 and 0.320 respectively in Table 1, this pattern suggests that the relative undervaluation of RNS Q5 firms may explain the upward rebound pattern in returns for RNS Q5 firms in Figure 1. In the bottom sub-panel, the zero-cost high minus low RNS portfolio has significantly positive monthly abnormal returns relative to the Carhart (1997) four factor model with a magnitude of 0.94% at the 1% significance level. The equally weighted excess return is also positive and significant at the 1% level with a magnitude of 0.89%. These results are broadly consistent with the excess return and abnormal return of 0.61% and 0.55% in Stilger, Kostakis, and Poon (2016). The portfolio with the lowest RNS has a Carhart alpha of -0.39% significant at the 1% level while the portfolio with highest RNS has a Carhart alpha of 0.55% significant at the 1% level. These results confirm that there is a statistically significant positive relation between RNS and future stock returns and further confirm prior evidence in Table 2 that the stocks with the most negative RNS underperform in the future, but also indicate that those with the highest RNS outperform. They contradict the results of Conrad, Dittmar and Ghysels (2013) due to a difference in the way the RNS characteristic is defined: we capture RNS at the end of the prior month, whereas this prior study averages it over the preceding quarter. This approach is likely to yield more precise signal about the forward-looking risk neutral skewness of the underlying asset due to greater noise over the quarterly averages used by Conrad, Dittmar, and Ghysels (2013).

Table 3 Panel B presents analogous results for value-weighted portfolios by RNS quintile. This weighting scheme de-emphasizes the role of small stocks in portfolio characteristics and abnormal returns. The firm-specific prior quarter valuation error $Overvaluation_{q-1}$ is again monotonically decreasing in RNS quintiles though no longer directly comparable to the equal-weighted sample statistics in Table 1, primarily because value-weighting emphasizes the effect of the most overvalued firms resulting in more positive average firm errors by quintile. As before, the zero-cost RNS portfolio has significantly positive monthly abnormal (excess) returns relative to Carhart (1997) four factor model with a magnitude of 0.70% (0.71%) at the 1% significance level. Notably, the value weighted portfolio results presented in Table 3 Panel B confirm the result from Panel A that the portfolio with the highest RNS generates significant positive alpha and excess returns. This finding contradicts the short sale constraints explanation advanced for the RNS anomaly.[4] Our finding that both legs of the zero-cost portfolio generate significant returns suggests that the short sale constraint explanation cannot fully describe the RNS anomaly.

To test the robustness of this finding, we replicate the data and January 1996 to December 2012 time period of Stilger, Kostakis, and Poon (2016). The summary statistics for the replication subsample are highly similar. We are able to reproduce the result that an equal-weighted long-short portfolio sorted by RNS has abnormal returns concentrated in the short leg. Consistent with the findings in Table 3, however, in the same sample the abnormal returns to a value-weighted portfolio are again concentrated in the long leg. This finding is not compatible with an overvaluation based or short sale constraint based explanation for the RNS anomaly advanced by prior literature.

Furthermore, this set of results holds both for traded option data and constant-maturity standardized options data both in our full sample and the replication subsample.[5] If the short-sale constraint explanation of the RNS anomaly were sufficient, we would expect only the short leg of the RNS sorts to produce abnormally negative returns as overvalued but short-sale constrained stocks lose value.

3 The Risk Neutral Skewness Anomaly and Momentum

3.1 RNS Anomaly Sensitivity to Market Cycles

We are thus compelled to turn to additional explanations of the RNS anomaly. Its negative correlation with past performance in Table 1 and the negative factor loading of RNS on the UMD momentum factor in Table 3 suggest that the RNS anomaly is related to momentum

[4] See Stilger, Kostakis, and Poon (2016) whose empirical results show that the RNS anomaly comes from the short (low RNS) leg of the zero-cost portfolio only rather than the long leg (high RNS).

[5] These results are suppressed for brevity but available upon request.

reversal: the high RNS stocks in the long leg of the zero-cost RNS portfolio outperform because they recover from an undervaluation driven by past negative performance consistent with Figure 1.

The intuition for this comes from Daniel and Moskowitz (2016), who show that negative momentum stocks have time-varying beta in economic recessions and periods of high volatility. Specifically, the conditional betas of negative momentum stocks are low during recessions, but high during subsequent recoveries. When a market downturn reverses, these negative momentum stocks experience strong gains resulting in a momentum crash. In this section we test the conjecture that the positive abnormal return generated by the RNS anomaly is driven by same time-varying betas and option-like payoffs that cause crashes in the momentum strategy.

We run three monthly time series regressions with dependent variables of equal- and value-weighted RNS quintile portfolio returns R_t, with the results tabulated in Panels A and B of Table 4 respectively. In the spirit of Daniel and Moskowitz (2016), we regress contemporaneous RNS portfolio returns on three sequential models that explore its sensitivity to the market cycle.

Panel A Model 1 in Table 4 fits an unconditional CAPM model to equal weighted portfolios sorted on RNS as well as to a zero-cost long-short portfolio:

$$R_t = \alpha_0 + \beta_0 R_{m,t} + \varepsilon_t \tag{2}$$

Here $R_{m,t}$ is the CRSP value-weighted index excess return in month t. Consistent with Daniel and Moskowitz (2016) the unconditional CAPM beta of the zero-cost RNS portfolio is 0.33[6] and the intercept, α_0, is both economically large (.70% per month) and statistically significant.

[6]Daniel and Moskowitz (2016) find the unconditional CAPM beta of the momentum strategy is -0.567. The zero-cost RNS portfolio effectively buys losers and shorts winners due to the negative relationship between RNS and momentum, and is thus analogous to an LMW strategy.

Model 2 fits a conditional CAPM with a recession indicator:

$$R_t = \alpha_0 + (\beta_0 + \beta_B I_{B,t-1})R_{m,t} + \varepsilon_t \tag{3}$$

Here we add $I_{B,t-1}$, an ex-ante recession indicator variable that is set to '1' if the cumulative CRSP VW index return in the past 24 months is negative and zero otherwise. This specification captures changes in market beta during economic recessions. The beta of the RNS portfolio during recessionary periods almost doubles, increasing by 0.24 with a t-statistic of 2.95.

Model 3 introduces a contemporaneous up-market indicator variable $I_{U,t}$:

$$R_t = \alpha_0 + (\beta_0 + I_{B,t-1}(\beta_B + I_{U,t}\beta_{B,U}))R_{m,t} + \varepsilon_t \tag{4}$$

Here $I_{U,t}$ equals '1' if the contemporaneous CRPS VW return is positive and zero otherwise. This specification captures sensitivity to post-recession recovery through the interaction of a negative past performance indicator $I_{B,t-1}$ and a positive current performance indicator $I_{U,t}$. This allows us to test whether the conditional betas of the RNS portfolios differ between recessions and recoveries.

The statistically significant $\hat{\beta}_{B,U}$ of 0.50 in Panel A of Table 4 shows that the zero-cost RNS portfolio is sensitive to post-recession market rebounds. During recessions the zero-cost RNS portfolio betas are 0.25 ($= \hat{\beta}_0 + \hat{\beta}_B$) when the contemporaneous market return is negative and $= \hat{\beta}_0 + \hat{\beta}_B + \hat{\beta}_{B,U} = .75$ when the market return is positive. This difference in time-varying betas means that the long-short RNS portfolio has an asymmetric payoff similar to a call option on the market, losing relatively less value during recessions but gaining relatively more value during subsequent recoveries. For the high RNS quintile, the conditional recession beta is 1.40 (1.22 + 0.18) while the recovery beta is 1.91 (1.40 + 0.51). In contrast, the recovery beta $\hat{\beta}_{B,U}$ for the low RNS quintile is not statistically significant. Therefore, a long-short RNS portfolio has significant positive market exposure to post-recession recoveries. This exposure is driven by the long (high RNS) leg of the zero-cost RNS portfolio, consistent with the rebound behavior observed for positive RNS stocks in Figure 1. This finding provides a more complete explanation for the RNS anomaly relative to the short sale constraint explanation which focuses on the short (low RNS) leg of the portfolio.

Panel B presents analogous results using value-weighted portfolio returns. Model 1 finds a lower but significant beta of .09 and a similar monthly alpha of .66% for the zero-cost RNS portfolio. Model 2 shows that the beta of the zero-cost RNS portfolio is 0.31 higher in recessionary periods with statistical significance. Model 3 confirms the positive relationship between the RNS anomaly and market rebounds observed for equal-weighted results in Panel A, with a .14 beta during recessions but a .43 beta during subsequent recoveries, driven by the large and significant $\hat{\beta}_{B,U}$ of .29.

3.2 Market Rebounds, Momentum, and RNS Portfolio Sorts

We explore the relationship between the RNS anomaly and momentum in greater depth by constructing double sorts on the two characteristics. At the end of each calendar month, we independently sort firms into terciles by momentum as measured by $RET_{t-12,t-7}$ and by RNS estimated on the last trading day as described in Section 2.[7] We use the NYSE, AMEX and NASDAQ universe to set the breakpoints for the RNS terciles, and the NYSE universe for momentum terciles consistent with prior literature (Daniel and Moskowitz, 2016; Barroso and Santa-Clara, 2015). Within each RNS tercile, we regress the equal- and value-weighted momentum portfolio returns on the market timing models defined in Eq. (2)-(4) and report the results on the left and right panels, respectively, in Table 5.

Model 1 fits the unconditional CAPM model to the equal- and value-weighted momentum

[7] Novy-Marx (2012) shows that the momentum anomaly is mainly driven by this intermediate range of past performance.

portfolio return within each RNS tercile following Eq. (2). The market beta of the momentum strategy decreases meaningfully as RNS increases. The differences in $\hat{\beta}_0$ of the momentum strategy between the high and low RNS terciles for equally- and value-weighted portfolios are -0.08 and -0.11 with t-statistics of -2.36 and -1.95 and significance levels of 5% and 10%, respectively.

Model 2 fits a conditional CAPM with the market recession indicator I_B following Eq. (3). The market betas of the equal-weighted momentum portfolios decrease during bear markets by an economically and statistically significant margin ranging from -0.55 to -0.64 across RNS terciles. However, the difference in the conditional recession $\hat{\beta}_B$ of the momentum strategy between the high and low RNS tercile is insignificant. The betas of the value-weighted momentum portfolios also fall by -0.63 to -0.88 during bear markets across RNS terciles, but with a statistically significant difference at the 5% level in $\hat{\beta}_B$ between the high and low tercile. Consistent with our conjecture, high RNS appears to reduce momentum profits during economic recessions.

Model 3 introduces a contemporaneous market recovery indicator variable $I_{U,t}$ as in Eq. (4). The coefficients on this recovery indicator show that the momentum strategy experiences more severe crashes during recoveries as the RNS of the portfolio stocks increases. The equal-weighted momentum strategy in the high RNS tercile has a recovery beta coefficient $\hat{\beta}_{B,U}$ of -0.34 significant at the 10% level, with a slightly larger and more significant effect for value-weighted momentum. While the recession beta $\hat{\beta_B}$ remains negative and significant across all RNS terciles, the $\hat{\beta}_{B,U}$ is significant in the high RNS tercile only in both cases, with the difference in $\hat{\beta}_{B,U}$ across RNS terciles significant at the 1% level. The findings in Table 5 imply that the momentum crash behavior observed by Daniel and Moskowitz (2016) due to the momentum strategy having a negative conditional beta during market recoveries is restricted to the sample of high-RNS stocks.

We next consider the effect of firm size on the relationship between the RNS anomaly and momentum to test whether this result is driven by small stocks that are more sensitive to momentum (Hong, Lim, and Stein, 2000; Grinblatt and Moskowitz, 2004; Fama and French, 2012; Israel and Moskowitz, 2012). We create triple independent tercile sorts by market capitalization, momentum as measured by $RET_{t-12,t-7}$, and RNS at the end of each calendar month. We use the NYSE, AMEX and NASDAQ universe to set RNS breakpoints, and the NYSE universe to set size and momentum breakpoints consistent with prior literature. Within each Size/RNS group, we regress next month's equal- and value-weighted momentum portfolio returns on Model 3 in Eq. (4), reporting the regression results in the left and right panels of Table 6 respectively.

We find that the momentum crash behavior observed in the high-RNS tercile in Table 5 obtains only in the median and high firm size terciles as reported in Table 6. For equally-weighted momentum portfolios, the differences between $\hat{\beta}_{B,U}$ across RNS terciles are -0.42 and -0.46 with t-statistics of -2.45 and -2.06 for median and high size terciles respectively. The differences in value-weighted momentum $\hat{\beta}_{B,U}$ are -0.37 and -0.53 with t-statistics of -2.14 and -1.81 for the median and high size terciles. In contrast, for the low size tercile the difference in conditional rebound $\beta_{B,U}$ is insignificant across terciles of RNS for both equal- and value-weighted portfolios. These findings suggest that the relationship between RNS and momentum is not driven by small stocks, and in fact obtains only in stocks outside of the smallest tercile.

Prior explanations for the RNS anomaly rely on short sale constraints to overvalued firms. To test the role of short sale constraints in the relationship that we find between RNS and momentum crashes, we create independent triple sorts of firms by institutional ownership (IO) as a proxy of short sale constraints (Nagel, 2005), momentum measured by $RET_{t-12,t-7}$ (Novy-Marx, 2012), and the RNS characteristic at the end of each calendar month. We set breakpoints for RNS using the NYSE, AMEX and NASDAQ universe, and the IO and momentum breakpoints using the NYSE firms only as done in prior literature. Within each IO/RNS group, we regress the equal- and value-weighted next month's momentum portfolio returns on Model 3 in Eq. (4).

We report the regression results in Table 7, finding that statistically significant differences in $\hat{\beta}_{B,U}$ across RNS terciles are restricted to the median and high IO terciles containing relatively less short-sale constrained firms for equally weighted momentum portfolios. These differences in $\hat{\beta}_{B,U}$ coefficients are -0.43 and -0.34 with respective t-statistics of -2.19 and -2.06. For value-weighted momentum portfolios, the differences in $\hat{\beta}_{B,U}$ across RNS tercile are negative and significant for all IO terciles. They are -0.54, -0.60 and -0.50 with t-statistics of -1.96, -2.29 and -2.11. We thus find that momentum crashes, which appear to drive the abnormal performance of the long leg of the RNS anomaly in our results from Table 3, are strongest for the high RNS tercile in the median and high IO terciles (low short sale constraint) firms. This result complements the short sale constraints explanation for the RNS anomaly concentrated in small and short sale constrained firms: the rebound phenomenon appears to be strongest for the least short sale constrained firms.

3.3 RNS and Future Realized Skewness

If risk neutral skewness can identify stocks that are about to rebound upward consistent with the evidence in Figure 1, it should also predict realized skewness. We find evidence for this by running a cross-sectional regression of each stock's future realized skewness over the next month FS on the current month's risk neutral skewness RNS, controlling for the historical realized skewness HS over the current month and capturing the time series average of the coefficients. These FS and HS skewness measures are defined in Appendix B. The cross-sectional regression model is

$$FS_{i,t+1} = \alpha_t + \beta_{1,t} RNS_{i,t} + \beta_{2,t} HS_{i,t} + \varepsilon_{i,t+1}$$

where FS is the future realized skewness during month $t+1$, RNS is the risk neutral skewness measured at the end of month t, and HS is the historical realized skewness calculated from daily returns during month t. We report Newey and West (1987) t-statistics adjusted for a 6-

month lag in parentheses. The time series averages of the monthly cross-sectional coefficients, along with their t-statistics for a test of difference from zero in parentheses, are $\overline{\alpha} = 0.183$ (15.01), $\overline{\beta}_1 = 0.059$ (10.83), and $\overline{\beta}_2 = 0.015$ (8.53). The positive statistically significant coefficient $\overline{\beta}_1$ supports the interpretation that risk neutral skewness is a positive predictor of future realized skewness in the cross-section of stocks consistent with the rebound pattern observed in Figure 1, which in turn explains the relationship between RNS and momentum crashes that arise as a consequence of these rebounds (Daniel and Moskowitz, 2016).

4 The Risk Neutral Skewness Factor-Mimicking Portfolio

A significant limitation to our analysis thus far has been the requirement that all stocks used must have the traded options necessary to compute the RNS characteristic. This introduces a potential selection bias into our momentum portfolios that may affect the true relationship between RNS and momentum crashes. To correct for this, we construct a RNS factor-mimicking portfolio (SKEW) to generalize our findings to stocks that do not have the traded options that would allow a direct calculation of RNS. We hypothesize that non-optionable stocks that also exhibit rebound behavior will have exposure to this factor due to the procyclical property of the RNS anomaly described in Table 4. We find evidence consistent with this hypothesis. By testing whether the SKEW factor loading results in inverse momentum behavior similar to the RNS characteristic, we further our understanding of the RNS anomaly and its relationship to momentum to confirm that it is not driven by stock optionability. In addition, this enables us to create a stock-level rebound indicator (and therefore a stock-level momentum crash risk indicator) that is applicable for all stocks, not just those with traded options. We restrict our analysis to common stocks only (those with CRSP share code equal to 10 and 11) and exclude stocks with price lower than \$1 consistent with prior literature.

We construct the SKEW characteristic-mimicking portfolio as follows: at the end of each calendar month, we rank stocks with traded options into five portfolios according to their risk neutral skewness (RNS) characteristic. The SKEW factor is the value-weighted return of a portfolio long the highest RNS quintile Q5 and short the lowest RNS quintile Q1.[8] For each CRSP common stock i we estimate its $\beta_{i,SKEW}$ loading with a rolling window regression

$$Exret_{i,t} = \alpha_i + \beta_{i,M} Mktrf_t + \beta_{i,SKEW} SKEW_t + \varepsilon_{i,t}$$

over the past 60 months of return data. We require at least 24 monthly observations for a valid $\hat{\beta}_{i,SKEW}$ estimate. We merge the factor loading data with CRSP and the past performance data, and the new sample with β_{SKEW} has 862,302 firm-month observations from Mar 1998 to June 2016, an increase of more than 60% of our sample for the same sample period.

To test the validity of SKEW as a characteristic-mimicking portfolio that reproduces the properties of RNS, we repeat our cross-sectional predictive regression of future realized skewness FS during the next month on the current month's estimate of β_{SKEW} in place of RNS controlling for historical skewness HS over the current month:

$$FS_{i,t+1} = \gamma_{0,t} + \gamma_{1,t} \hat{\beta}_{SKEW,i,t} + \gamma_{2,t} HS_{i,t} + \varepsilon_{i,t+1}$$

The time series averages of the monthly cross-sectional coefficient estimates with their respective Newey and West (1987) t-statistics in parentheses are as follows: $\overline{\gamma}_0 = 0.165$ (11.14), $\overline{\gamma}_1 = 0.011$ (2.82), and $\overline{\gamma}_2 = 0.034$ (12.23). The positive significant coefficient $\overline{\gamma}_1$ supports both the validity of the SKEW factor as a proxy for the RNS characteristic and as a predictor of future realized skewness in the cross-section of CRSP stocks.

[8]We also construct an equal-weighted version of the SKEW factor and find slightly stronger results.

4.1 The SKEW Factor, RNS, and Performance Reversals

To further validate the SKEW factor, we next consider whether exposure to SKEW captures the performance reversal behavior we observe for the RNS characteristic in Figure 1 and Table 4. To do this, we apply our market-wide reversal approach to the individual firm level.

Consistent with the market-level rebound indicator from Daniel and Moskowitz (2016), we define a firm-level positive performance reversal indicator as the product of a historical loss indicator and a contemporaneous gain indicator. The historical loss indicator $I_{f,D,t-1}$ takes the value of 1 if the firm's cumulative return in the past 24 months is negative and is set to 0 otherwise.[9] We then define the firm-level contemporaneous gain indicator variable $I_{f,U,t} = 1$ if the excess return of the stock is positive in the current month, and 0 otherwise. Thus, a positive performance reversal indicator at time t can be defined as a historical loss followed by a contemporaneous gain: $I_{f,D,t-1} \times I_{f,U,t}$.

We construct an analogous time t firm-level negative performance reversal indicator for past gains followed by a contemporaneous loss. Here the firm-level historical gain indicator variable $I_{f,U,t-1} = 1$ if the firm's cumulative return over the past 24 months is non-negative, and 0 otherwise. The firm-level contemporaneous loss indicator variable $I_{f,D,t} = 1$ if the excess return of the stock is negative in the current month, and 0 otherwise. Thus, a negative performance reversal indicator at time t is defined as a historical gain followed by a contemporaneous loss: $I_{f,D,t-1} \times I_{f,U,t}$.

To more clearly define the relationship between RNS, SKEW, and performance reversals we tabulate the frequency of both types of reversals in Table 8. This table compares the frequency of positive and negative performance reversals in the current month across quintile portfolios sorted by RNS and β_{SKEW} from the prior month. The results are consistent with Figure 1 and the market-wide rebound results in Table 4: the RNS_{t-1} ($\text{SKEW}_{\beta,t-1}$) Q1 portfolio has a 15.56% (19.77%) positive reversal frequency in the current month t,

[9] We obtain similar results for a shorter time window over the past 12 months.

which monotonically increases with the RNS_{t-1} ($\text{SKEW}_{\beta,t-1}$) Q5 portfolio having a 24.79% (24.63%) contemporaneous positive reversal frequency.

Meanwhile, the RNS_{t-1} ($\text{SKEW}_{\beta,t-1}$) Q1 portfolio has a 31.44% (28.59%) negative reversal frequency, which remains roughly similar across the Q1-Q4 skewness quintiles, but falls off at the highest skewness quintile with the RNS_{t-1} ($\text{SKEW}_{\beta,t-1}$) Q5 portfolio having a 23.65% (24.10%) negative reversal frequency in the current month t. The results in Table 8 support two important conclusions: first, skewness is a meaningful predictor of the frequency of positive performance reversals for individual stocks, with positive reversals frequencies sharply increasing across quintiles of both lagged skewness measures. Second, the SKEW factor loading is very similar to the RNS characteristic in capturing the frequency of these reversals, suggesting it is a valid proxy for risk-neutral skewness for non-optionable stocks.

To better understand the channel that drives the positive relationship between both RNS and SKEW factor loadings with upward rebounds that we observe in Table 8, we also tabulate equal- and value-weighted means of firm-specific valuation error in the prior quarter across quintiles of our two lagged skewness proxies in Table 8. We use last quarter's observation of $Overvaluation_{q-1}$, the firm-specific error from the Rhodes-Kropf, Robinson, and Viswanathan (2005) multiples-based decomposition of the market to book ratio in Eq. (1) to avoid time inconsistencies.[10]

The equal- and value-weighted means of $Overvaluation_{q-1}$ by quintiles of RNS in Table 8 repeat the summary of the variable in Panels A and B of Table 3 respectively. As observed before, an RNS sort produces a monotonically decreasing pattern in firm-specific overvaluation across all quintiles. However, it is important to note that the equal- and value-weighted means of $Overvaluation_{q-1}$ by quintiles of the SKEW factor loading produce a similarly monotonic sort on firm-specific overvaluation also. Due to the inclusion of non-optionable stocks in the quintile means of $Overvaluation_{q-1}$ by the SKEW factor loading,

[10]See Avramov, Kaplanski, and Subrahmanyam (2020) as an example of related work on fundamentals-based misvaluation.

the values across all quintiles are lower than the optionable mean and median of 0.292 and 0.320 respectively for $Overvaluation_{q-1}$ summarized in Table 1. This is consistent with a higher firm-specific error in the optionable subsample for which the RNS characteristic can be computed directly relative to the universe, and highlights the contribution of the SKEW factor in enabling us to address a more representative sample of assets by relaxing the option data constraint.

For both skewness proxies, the more positive the skew the lower the firm-specific error relative to short-run multiples of book value, leverage, and net income. This consistent pattern across both RNS and SKEW factor loading provides additional support for the mutual consistency of the two skewness proxies as well as pointing to a reversal of past undervaluation as the channel by which option-implied skewness positively relates to future performance. The underlying stocks with the most positive skew proxies have the lowest firm-specific valuation error in the prior quarter, consistent with the upward rebound in future performance observed in Figure 1.[11]

We further examine whether a stock's SKEW loading accurately reproduces performance previously observed for its RNS characteristic by plotting the returns of the SKEW portfolio (defined as RNS Q5 minus Q1) and the return on the H-L β_{SKEW} portfolio that is long the stocks in the highest quintile of $\beta_{i,SKEW}$ and short the stocks in the lowest quintile of $\beta_{i,SKEW}$ in Figure 2. The H-L β_{SKEW} portfolio has a higher volatility, but the correlation between SKEW and H-L β_{SKEW} portfolio returns is 0.324 significant at the 1% level.

4.2 The SKEW Factor and Momentum Performance

Next, we investigate whether momentum strategies in the universe of CRSP stocks experience performance differences consistent with the observed relationship between high SKEW loadings and performance reversals. Each calendar month we independently double sort

[11] While firm-specific valuation errors in our sample appear to be skewed right in that their mean is higher relative to that the Rhodes-Kropf, Robinson, and Viswanathan (2005) sample, the monotonic sorts of firm-specific error on skewness proxies is indicative of a systematic past relative undervaluation of the most positively skewed stocks.

all CRSP stocks into quintiles of risk-neutral skewness measured by $\beta_{i,SKEW}$ and deciles of momentum measured by $RET_{t-12,t-7}$. We use the NYSE breakpoints for the β_{SKEW} quintiles and the $RET_{t-12,t-7}$ deciles. Panels A-C of Table 9 present the excess returns, Carhart (1997) four-factor alphas and Pastor and Stambaugh (2003) five factor model alphas. The rightmost column of each panel reports the equal-weighted momentum D10-D1 performance in each β_{SKEW} quintile.

These results are consistent with our prior results for the RNS characteristic in optionable stocks. The momentum (high minus low momentum decile) winner-minus-loser (WML) strategy in the lowest β_{SKEW} quintile has the highest excess return, Carhart (1997) four-factor alpha and Pastor and Stambaugh (2003) five-factor alpha: 1.45%, 1.21% and 1.20% per month with t-statistics 2.85, 2.23 and 2.28, respectively. The WML strategy excess return, Carhart (1997) four factor alpha and Pastor and Stambaugh (2003) five-factor alpha all monotonically decrease as β_{SKEW} rank increases. Furthermore, the differences between the highest and lowest β_{SKEW} quintile are statistically significant, suggesting that controlling for the SKEW factor loading improves the performance of the momentum strategy. For comparison purposes we also report the standard momentum strategy's performance using all CRSP stocks, labeled "WML[-12,-7] All". We find that over the full sample period of March 1998 to June 2016, the momentum strategy generates a monthly excess return, Carhart (1997) α, and Pastor and Stambaugh (2003) alpha of 0.80%, 0.50%, and 0.50% with t-statistics of 1.67, 1.61, and 1.60.

Our prior results indicate that the market cycle plays a significant role in the relationship between RNS and momentum, since the momentum crash effect that the long leg of the RNS anomaly picks up is strongest during post-recessionary rebounds. To further explore this, we repeat the β_{SKEW} and momentum double sorts in recessions and expansions and report the five factor Pastor and Stambaugh (2003) alphas in Table 10 Panels A and Panel B, respectively. We define recessions as periods when the cumulative CRSP VW index return in the past 24 months is negative, and as expansions when it is positive. We find that the magnitude of the momentum abnormal return is larger in recessions than in expansions: 3.50% per month versus 0.36% respectively for β_{SKEW} Q1 momentum and 1.55% per month versus 0.13% respectively for momentum using all stocks, consistent with the ability of RNS to predict upward rebounds after periods of underperformance.

To demonstrate that the improvement in momentum performance driven by β_{SKEW} exposure is real and not an artifact of untradeable stock data we report averages of time series median of measures of liquidity, size, and trading cost for the fifty portfolios formed on β_{SKEW} quintiles and $RET_{t-12,t-7}$ deciles in Table C1. In Panel A, we report the mean volume scaled by the number of shares outstanding for each of the fifty portfolios. Across β_{SKEW} quintiles 1 to 5, scaled volume first decreases then increases. This finding provides evidence that the momentum strategy improvement observed in β_{SKEW} Q1 is not driven by stocks that are more illiquid relative to those in the other quintiles. That is, if momentum is tradeable within any quintile group, it is likely to be tradeable in β_{SKEW} Q1.

Similarly, we report log size in Panel B of Table C1. In seven out of ten momentum deciles, firms in β_{SKEW} Q1 are not the smallest. Consistent with the evidence in Table 5, the momentum strategy in β_{SKEW} Q1 does not appear to rely on small stocks, providing additional evidence that our results have actual economic significance.

Finally, we report the mean bid-ask spread scaled by the stock price as a measure of trading costs in Panel C of Table C1. Bid-ask spreads in Q1 of β_{SKEW} are the third or fourth lowest relative to those of other quintiles of β_{SKEW}, depending on momentum decile. Indeed, the highest bid-ask spreads are uniformly in the top quintile of β_{SKEW}, rather than the bottom one. Q1 of β_{SKEW} does not have unusually high trading costs, further supporting the validity of our trading strategy results that capture the economic significance of the RNS as an indicator of stock rebounds.

In untabulated results, we also test whether a related zero-cost skewness factor based on an ex-ante skewness measure by Schneider, Wagner, and Zechner (2020), which is estimated using a portfolio long out-of-the-money calls and short out-of-the-money puts under a weighting scheme different from Bakshi, Kapadia, and Madan (2003) and which is shown by the authors to help explain the distress anomaly, can also explain the relation between skewness and momentum. Substituting the alternative version of the skewness factor in place of SKEW in the analysis in Table 9 does not produce a significant sort on momentum performance across skewness exposure quintiles.

To illustrate the economic significance of the relationship between the RNS anomaly and momentum crashes, we plot the cumulative log returns Figure 3 over the full sample period from March 1998 to June 2016. At the end of June 2016, the momentum strategy on the lowest likelihood of upward rebound stocks in β_{SKEW} Q1 has a cumulative log return of 336.91% whereas the standard [-12,-2] momentum strategy for all CRSP stocks has a cumulative log return of 165.59% and the Novy-Marx (2012) [-12,-7] intermediate-term momentum strategy earning a cumulative 234.10%.

To improve comparability, we scale all strategies to have the same full-sample volatility. We also compare the economic impact of sorting momentum on the rebound indicator SKEW factor loading to two other recent strategies to improve the performance of the momentum anomaly by scaling its exposure: the constant volatility method for the momentum strategy introduced by Barroso and Santa-Clara (2015), and the dynamic weighting strategy of Daniel and Moskowitz (2016). Barroso and Santa-Clara (2015) demonstrate an improvement in momentum (WML) performance by incorporating a variance forecast based on the trailing 126-day volatility of daily momentum returns

$$\hat{\sigma^2}_{WML,t} = 21 \sum_{j=0}^{125} r^2_{WML,d_{t-1}-j}/126 \tag{5}$$

and scaling the standard WML by the ratio of the forecast volatility to a target volatility level.

Daniel and Moskowitz (2016) propose an alternative weighting scheme that incorporates both return and variance forecasts[12]

$$w^*_{t-1} = \frac{1}{2\lambda}\frac{\mu_{t-1}}{\sigma^2_{t-1}} \tag{6}$$

where μ_{t-1} is the forecast of momentum returns from a model that interacts market state and volatility, and σ^2_{t-1} is the forecast of momentum volatility from a model using a GJR-GARCH momentum volatility predictor and the trailing 126-day volatility of momentum daily returns. These two strategies earn 315.04% and 330.98% respectively from March 1998 to June 2016. Notably, the β_{SKEW} Q1 momentum strategy provides the strongest cumulative performance among the five variations of momentum strategies over this time period.

We risk-adjust these findings by measuring both the monthly excess return above the risk-free rate and abnormal returns relative to the Carhart (1997) and Pastor and Stambaugh (2003) models for these five strategies over the March 1998 to June 2016 time period in Table C2. The low-rebound likelihood β_{SKEW} Q1 momentum strategy averages a monthly excess return of 1.45% and a t-statistic of 2.85, and Carhart (1997) and Pastor and Stambaugh (2003) abnormal returns of 1.21% and 1.20% per month with t-statistics of 2.23 and 2.28 respectively. The baseline WML[-12,-2] momentum strategy generates insignificant raw and abnormal returns. The Novy-Marx (2012) refinement of the intermediate-term momentum strategy WML[-12,-7] has a weakly significant excess return, 0.90% with a t-statistic of 1.67, and insignificant abnormal returns: a 0.57% monthly Carhart (1997) and a 0.56% monthly Pastor and Stambaugh (2003) alpha with t-statistics of 1.61 and 1.60, respectively. This performance difference underscores the economic significance of β_{SKEW} as an indicator of momentum crash inducing rebounds.

The two scaled momentum strategies also achieve significant, though slightly lower, excess and abnormal performance. The Barroso and Santa-Clara (2015) risk-managed WML[-12,-

[12]The importance of incorporating both the first and second moments into the optimal scaling of the momentum strategy follows from the authors' findings that the first two moments of momentum returns are inversely correlated due to crashes occurring during market stress periods.

2]* averages 1.23% monthly excess returns significant at the 5% level, and monthly 0.77% Carhart (1997) and 0.76% Pastor and Stambaugh (2003) alphas with t-statistics of 1.98 and 1.99 respectively. The Daniel and Moskowitz (2016) dynamic weighting strategy has an average monthly excess return of 1.29% significant at the 5% level and monthly alphas of 1.13% and 1.12% with t-statistics of 2.29 and 2.29 for the Carhart (1997) and Pastor and Stambaugh (2003) models respectively. These findings support anecdotal observations that the standard momentum strategy is not as profitable in the more recent time period, and indicate that using the SKEW factor-mimicking portfolio to isolate stocks with low rebound likelihood and therefore low momentum crash risk revives the momentum anomaly to an extent comparable to or greater than other recent refinements in the literature.

Figure 3 and Table C2 show the economic impact of RNS as a signal of performance reversals for the momentum strategy and enable a comparison to the economic value of related momentum strategies. We now turn to a relative performance analysis between these strategies. Table 11 presents a performance analysis of the β_{SKEW} Q1 strategy relative to the original momentum strategy WML[-12,-2], the Novy-Marx (2012) intermediate-term momentum strategy WML[-12,-7], the Barroso and Santa-Clara (2015) risk-managed momentum strategy WML[-12,-2]*, and the Daniel and Moskowitz (2016) dynamic weighting strategy DM Dynamic over March 1998 to June 2016.[13] For comparability, we scale all five return series so that they have the same full-sample volatility. Table 11 tabulates the summary statistics of each strategy, their Sharpe ratios, as well as the information ratio, correlation, and alpha of the β_{SKEW} Q1 return series relative to that of each of the other four strategies.

Compared to the baseline WML[-12,-2] momentum strategy, the rebound-avoiding WML[-12,-7] β_{SKEW} Q1 strategy has a higher average annualized return of 17.37% relative to 6.96%, a smaller drawdown of -22.00% relative to -35.17%, as well as a positive information ratio of .42 and an alpha of 1.15% per month significant at the 5% level in the first panel of

[13]We thank Pedro Barroso and Pedro Santa-Clara for sharing their volatility forecast methodology.

Table 11.

To ensure that this superior improvement in WML performance from the incorporation of information in RNS is not simply driven by differences in the definition of momentum, we also compare WML[-12,-7] β_{SKEW} Q1 with the baseline Novy-Marx (2012) momentum strategy WML[-12,-7] in the second panel of Table 11. The β_{SKEW} Q1 momentum strategy maintains a higher annualized return, a smaller drawdown, and a positive information ratio of 0.35 relative to the intermediate-term momentum strategy. Its alpha relative to the baseline intermediate momentum strategy is .82% per month, significant at the 10% level. These findings are consistent with the avoidance of performance reversals in positive-RNS stocks, rather than definitional differences in WML, that drive the performance gap observed.

The upward rebound avoidant β_{SKEW} Q1 momentum strategy also outperforms the Barroso and Santa-Clara (2015) risk-managed WML strategy over the same time period, with a 2.55% higher mean annual return and a 2.71% smaller drawdown in the third panel of Table 11. It has a higher Sharpe ratio and a positive information ratio of .10 and a monthly alpha of .80% significant at the 5% level relative to the risk-managed WML[-12,-2]* strategy.

The β_{SKEW} Q1 strategy has a comparable performance relative to the Daniel and Moskowitz (2016) dynamic weighting strategy in the fourth panel of Table 11 with a 1.86% higher mean annualized return, a 2.71% greater drawdown, comparable Sharpe ratios and an information ratio of .06 along with an insignificant relative alpha.

Overall, the extension of the information content of RNS to non-optionable stocks confirms our prior findings of its path-dependence and predictive power for stock rebounds, and therefore its meaningful relationship to the momentum strategy as a continuation anomaly adversely impacted by these rebounds. The RNS characteristic mimicking SKEW factor has significant economic value on the momentum factor in excess of, or comparable to, other recent advances.

5 Conclusion

We find that the risk neutral skewness (RNS) of the option-implied distribution of underlying returns is a path-dependent characteristic with predictive power for price rebounds, as stocks with more positive RNS have lower past performance but higher future performance. We find evidence that this is consistent with a reversal of past undervaluation: the firm-specific valuation error estimated using the multiples-based decomposition of the market to book ratio following Rhodes-Kropf, Robinson, and Viswanathan (2005) is lowest for the most positively skewed stocks. This suggests that these price rebounds are driven by a reversal of undervaluation. Furthermore, a zero-cost long-short portfolio formed on stocks in the most positive quintile of RNS net of those in the most negative quintile generates positive future returns that are driven by both the long and short legs of the portfolio. This suggests that previous explanations for the RNS anomaly that focus on the overvaluation of the short leg of the zero-cost portfolio are incomplete.

Prior studies (Rehman and Vilkov, 2012; Stilger, Kostakis, and Poon, 2016) document positive abnormal returns to a zero-cost strategy on high minus low RNS driven by the short low-RNS leg, providing evidence that it is caused by overvaluation that occurs in the stocks with the most negative RNS that are also too costly or too risky to sell short. These stocks form the short leg of the zero-cost strategy, and will underperform in the future due to their present overpricing, driving the observed RNS anomaly. However, short sale constraints cannot fully explain the risk neutral skewness anomaly, which we confirm by observing that zero-cost portfolios also produce abnormal returns in the long leg which is not exposed to short-sale constraints and high trading frictions identified by prior studies.

The RNS anomaly is particularly strong during post-recession rebounds, behaving as the inverse of the momentum crash phenomenon described in Daniel and Moskowitz (2016). Indeed, we find evidence consistent with the RNS anomaly being inversely related to momentum crashes, improving our understanding of both anomalies through the link between the two. Individual stocks in the highest RNS quintile are substantially more likely to experience a positive performance reversal, making them a potential landmine for momentum strategies that rely on continuation of trends.

We provide evidence that the winner minus loser (WML) momentum strategy in stocks with the most positive RNS experiences more severe crashes and overall worse performance due to upward rebounds of past losers, whereas the WML strategy's performance is strongest in low-RNS stocks with the least likelihood of rebounds. These results are not driven by small stocks or those with low institutional ownership as a proxy for short-sale constraints (Nagel, 2005). We generalize our findings for the option-implied skewness characteristic to all stocks, regardless of traded options, by constructing a skewness factor-mimicking portfolio SKEW. Stocks with both high RNS, as well as those with high SKEW factor loadings both experience substantially more positive stock-specific performance reversals suggesting that the characteristic-mimicking portfolio captures the skewness characteristic, and both low RNS stocks and low SKEW beta stocks have the lowest firm-specific valuation component of the market to book ratio. This confirms their mutual consistency and provides evidence for undervaluation as the information channel by which option-implied skewness predicts future performance.

Consistent with this, the momentum strategy constructed in the stocks with the lowest SKEW factor loadings earns the highest excess and abnormal returns when benchmarked by the Carhart (1997) four-factor model and the Pastor and Stambaugh (2003) five-factor model. This abnormal performance is not driven by trading frictions, but rather by the avoidance of losses in the momentum strategy driven by stock rebounds. Thus, while the SKEW factor beta cannot predict when momentum crashes will occur, it can help avoid stocks in which momentum crashes are most likely to happen. This pattern is consistent both at the micro and macro levels as option-implied skewness modulates momentum's sensitivity to both stock-specific and market-wide rebounds, and is strongest during market downturns.

The ability of the SKEW characteristic-mimicking portfolio to capture rebound behavior has economic significance as a momentum strategy on stocks with the lowest exposure to SKEW outperforms baseline momentum, the Novy-Marx (2012) intermediate-term momentum, the Barroso and Santa-Clara (2015) risk-managed momentum strategy, and has performance comparable to the Daniel and Moskowitz (2016) dynamic weighting momentum strategy. These results confirm that the RNS anomaly is related to price rebounds and momentum crashes, and that the RNS factor-mimicking SKEW portfolio can help isolate the momentum crash phenomenon. The RNS anomaly is robust to equal- and value-weighting, and exists as both a factor loading on the SKEW portfolio and a stock-specific RNS characteristic.

Formally testing causality between RNS and momentum crashes remains a challenge, as Bakshi, Kapadia, and Madan (2003) point out that RNS is a function of both physical moments and of risk aversion. An estimate of higher physical moments requires a long historical time series, is vulnerable to errors in variables (Merton, 1980; Harvey and Siddique, 2000), and may be particularly misleading around market trend reversals when momentum crashes occur (Daniel and Moskowitz, 2016). The same is true for risk aversion (Gabaix, 2012; Gourio, 2012; Lehnert, Lin, and Wolff, 2014). We leave the decomposition of the RNS price signal into the component due to expected physical moments of the underlying distribution and that due to risk aversion to future research.

We demonstrate that both RNS and the SKEW factor beta can identify stocks that are likely to experience upward rebounds in performance. This information does not appear to be driven by related findings in the skewness risk premium literature (Kozhan, Neuberger, and Schneider, 2013; Harris and Qiao, 2018) or the asymmetric variance literature (Kilic and Shaliastovich, 2018; Tang, 2018). Furthermore, this information is economically significant, particularly for the momentum strategy, and can be reliably extrapolated to all stocks using the factor-mimicking SKEW portfolio. A value-weighted momentum strategy formed on stocks with the lowest risk-neutral skewness factor loading yields 1.21% per month relative to the Carhart (1997) four-factor model and 1.20% per month relative to the Pastor and Stambaugh (2003) five-factor model. Risk-neutral skewness factor loadings allow a simple strategy to avoid momentum crashes in an economically significant way, demonstrating the relationship of the RNS anomaly with price rebounds and momentum crash risk. These findings help improve our understanding of the information content of the option-implied skewness of the distribution of underlying stock returns.

Appendix A

Bakshi, Kapadia, and Madan (2003) Theorem 2 demonstrates that under power or exponential utility, the risk-neutral skewness $SKEW$ of any asset at time t for a time horizon τ can be approximately related to its second, third, and fourth physical moments $\overline{STD}$, $\overline{SKEW}$, and $\overline{KURT}$, as well as the coefficient of risk aversion γ:

$$SKEW_{(t,\tau)} \approx \overline{SKEW}_{(t,\tau)} - \gamma(\overline{KURT}_{(t,\tau)} - 3)\overline{STD}_{(t,\tau)} \tag{A.1}$$

This implies that $SKEW$ will generally be more negative than $\overline{SKEW}$, and the wedge between the two will be greater when distributions are fat-tailed, particularly in the presence of higher volatility, and when risk aversion is high.

Following Bakshi, Kapadia, and Madan (2003), we denote stock n's price on time t by $S_n(t)$ for n= 1,...,N, the interest rate as a constant r, and $S(t) > 0$ with probability 1 for all t, the risk-neutral density as $q[t, \tau; S]$. For simplification, we use S to represent $S(t + \tau)$. For any payoff $H[S]$ that is integrable with respect to risk-neutral density, we use $E^*\{.\}$ to represent the expectation operator under risk-neutral density. Hence:

$$E_t^*\{H[S]\} = \int_0^\infty H[S]q[S]dS \tag{A.2}$$

As shown in Bakshi and Madan (2000), a continuum of OTM European calls and puts can span any payoff function with bounded expectation. To calculate risk neutral skewness, we denote the τ-period return as $R(t,\tau) \equiv ln[S(t+\tau)] - ln[S(t)]$. Then we define the volatility contract, the cubic contract, and the quartic contracts as having the payoffs:

$$H[S] = \begin{cases} R(t,\tau)^2 & \text{volatility contract} \\ R(t,\tau)^3 & \text{cubic contract} \\ R(t,\tau)^4 & \text{quartic contract} \end{cases} \tag{A.3}$$

The fair value of the respective payoff are denoted as: $V_{t,\tau} \equiv E_t^* \{e^{-r\tau} R(t,\tau)^2\}$, $W_{t,\tau} \equiv E_t^* \{e^{-r\tau} R(t,\tau)^3\}$, and $X_{t,\tau} \equiv E_t^* \{e^{-r\tau} R(t,\tau)^4\}$. Then the τ-period risk neutral skewness $SKEW(t,\tau)$ can be calculated as following:

$$\begin{aligned} SKEW(t,\tau) &\equiv \frac{E_t^* \{(R(t,\tau) - E_t^*[R(t,\tau)])^3\}}{\left\{E_t^* \{(R(t,\tau) - E_t^*[R(t,\tau)])\}^2\right\}^{\frac{3}{2}}} \\ &= \frac{e^{r\tau} W(t,\tau) - 3\mu(t,\tau) e^{r\tau} V(t,\tau) + 2\mu(t,\tau)^3}{[e^{r\tau} V(t,\tau) - \mu(t,\tau)^2]^{\frac{3}{2}}} \end{aligned} \tag{A.4}$$

where

$$\begin{aligned} \mu(t,\tau) &\equiv E_t^* ln[\frac{S(t+\tau)}{S(t)}] \\ &= e^{r\tau} - 1 - \frac{e^{r\tau}}{2} V(t,\tau) - \frac{e^{r\tau}}{6} W(t,\tau) - \frac{e^{r\tau}}{24} X(t,\tau) \end{aligned} \tag{A.5}$$

$$V(t,\tau) = \int_{S(t)}^{\infty} \frac{2(1 - ln[\frac{K}{S(t)}])}{K^2} C(t,\tau;K) dK + \int_0^{S(t)} \frac{2(1 + ln[\frac{S(t)}{K}])}{K^2} P(t,\tau;K) dK \tag{A.6}$$

$$\begin{aligned} W(t,\tau) = &\int_{S(t)}^{\infty} \frac{6ln[\frac{K}{S(t)}] - 3(ln[\frac{K}{S(t)}])^2}{K^2} C(t,\tau;K) dK \\ &- \int_0^{S(t)} \frac{6ln[\frac{S(t)}{K}] + 3(ln[\frac{S(t)}{K}])^2}{K^2} P(t,\tau;K) dK \end{aligned} \tag{A.7}$$

$$\begin{aligned} X(t,\tau) = &\int_{S(t)}^{\infty} \frac{12(ln[\frac{K}{S(t)}])^2 - 4(ln[\frac{K}{S(t)}])^3}{K^2} C(t,\tau;K) dK \\ &+ \int_0^{S(t)} \frac{12(ln[\frac{S(t)}{K}])^2 + 4(ln[\frac{S(t)}{K}])^3}{K^2} P(t,\tau;K) dK \end{aligned} \tag{A.8}$$

Appendix B

We detail the construction of our variables below:

AVAR
: Following Tang (2018), given m traded puts with different strikes $K_1 < K_2 < ... < K_m \leq F_{t,T}$ and n traded calls with different strikes $F_{t,T} \leq K_{m+1} < K_{m+2} < ... < K_{m+n}$ with the same expiration date for an underlying stock,

  AVAR $\approx \frac{2}{S_t^2}(\sum_{i=1}^{n-1} C(K_{m+i}) \frac{K_{m+i+1}-K_{m+i-1}}{2} + C(K_{m+n})(K_m - K_{m-1}) - P(K_1)(K_2 - K_1) - \sum_{i=2}^{m} P(K_i) \frac{K_{i+1}-K_{i-1}}{2})$, where $F_{t,T} = S_t(1 + r_f)$.

β_M^i
: Market beta estimated using the Fama and French (1993) model over the past 60 months of returns data

$\beta_{i,SKEW}$
: SKEW factor beta estimated using a market model over the past 60 months of returns data

BM
: The ratio of book equity from COMPUSTAT to market value from CRSP

FS
: Future realized skewness calculated from daily returns over the following month

HS
: Historical realized skewness calculated from daily returns over the preceding month

lnMV
: Log of market capitalization, calculated by multiplying the CRSP closing price on the last day of the month by shares outstanding

lnVOLUME
: Log of monthly stock volume from CRSP

$Over_{q-1}$
: Firm-specific error for the prior quarter using the Rhodes-Kropf, Robinson, and Viswanathan (2005) decomposition of the log of the market-to-book ratio into three components: firm-specific error, time-series sector error, and long-run market-to-book. A more positive firm-specific error indicates a more overvalued firm.

RET$_{t-12,t-n}$
: Cumulative monthly stock performance on the interval $[-12, -n]$ relative to time t

RNS
: Risk-neutral skewness calculated following Bakshi, Kapadia, and Madan (2003) on the last day of each month

SKEW
: The monthly RNS factor-mimicking factor created as an equal-weighted zero-cost portfolio long (short) stocks in the highest (lowest) RNS quintile in the prior month

Appendix C

Table C1: Descriptive Statistics of Portfolios Formed on β_{SKEW} and Momentum.

Description: This table reports the cross-sectional averages of time series medians of volume scaled by shares outstanding, log firm size, and bid-ask spread characteristics within portfolios of firms formed on β_{SKEW} and the Novy-Marx (2012) intermediate-term momentum measured by $RET_{t-12,t-7}$.

Interpretation: The momentum strategy improvement observed in β_{SKEW} Q1 is not driven by stocks that are more illiquid, smaller, or costlier to trade relative to those in the other β_{SKEW} quintiles.

Panel A: Mean Volume Scaled by Shares Outstanding

	Momentum Deciles									
β_{SKEW}	1	2	3	4	5	6	7	8	9	10
1	11.07%	9.17%	8.71%	8.63%	8.59%	8.67%	9.22%	10.00%	11.38%	14.60%
2	10.03%	8.61%	8.00%	8.02%	8.01%	8.26%	8.65%	9.07%	10.27%	13.46%
3	9.96%	8.74%	8.42%	8.65%	8.64%	8.79%	9.21%	9.77%	10.85%	13.63%
4	10.31%	9.39%	9.07%	9.24%	9.27%	9.63%	10.07%	10.71%	11.48%	13.90%
5	12.74%	11.62%	11.50%	11.50%	11.76%	12.50%	12.76%	12.85%	14.07%	16.62%

Panel B: Mean Log Size

	Momentum Deciles									
β_{SKEW}	1	2	3	4	5	6	7	8	9	10
1	4.73	5.35	5.68	5.89	6.03	6.13	6.23	6.23	6.20	5.69
2	4.97	5.74	6.03	6.26	6.37	6.55	6.58	6.56	6.50	6.04
3	4.98	5.73	6.03	6.25	6.39	6.52	6.54	6.59	6.46	5.97
4	4.93	5.66	5.89	6.14	6.24	6.34	6.39	6.39	6.31	5.84
5	4.85	5.36	5.57	5.72	5.78	5.90	5.96	5.98	5.98	5.70

Panel C: Mean Bid Ask Spread Scaled by Price

	Momentum Deciles									
β_{SKEW}	1	2	3	4	5	6	7	8	9	10
1	1.07%	0.83%	0.74%	0.67%	0.63%	0.59%	0.57%	0.53%	0.49%	0.52%
2	1.00%	0.76%	0.65%	0.61%	0.57%	0.55%	0.51%	0.50%	0.49%	0.49%
3	0.98%	0.72%	0.64%	0.57%	0.53%	0.51%	0.49%	0.47%	0.49%	0.50%
4	1.08%	0.75%	0.66%	0.58%	0.56%	0.52%	0.52%	0.51%	0.50%	0.52%
5	1.09%	0.84%	0.77%	0.70%	0.67%	0.65%	0.63%	0.61%	0.60%	0.58%

Table C2: Returns on Momentum Portfolios.

Description: This table presents returns in excess of the risk-free rate and abnormal returns relative to the four factor Carhart (1997) and five factor Pastor and Stambaugh (2003) model for the Novy-Marx (2012) momentum strategy constructed using low-skew stocks only $WML[-12,-7]\beta_{SKEW}$ Q1, the baseline winner-minus-lose (WML) momentum strategy $WML[-12,-2]$, the Novy-Marx (2012) momentum strategy constructed using all CRSP stocks $WML[-12,-7]$, the risk managed momentum strategy of Barroso and Santa-Clara (2015) $WML[-12,-2]*$, and the Daniel and Moskowitz (2016) dynamic strategy over the period from March, 1998 through June, 2016.

Interpretation: The momentum strategy on the quintile of stocks with low rebound likelihoods, and therefore low momentum crash risk, generates higher excess return and higher or comparable abnormal returns compared to other recently proposed refinements to the momentum strategy.

	WML[-12,-7] β_{SKEW} Q1	WML[-12,-2]	WML[-12,-7]	WML[-12,-2]*	DM Dynamic
Excess Return	1.45%*** (2.85)	0.58% (1.11)	0.90%* (1.67)	1.23%** (2.31)	1.29%** (2.29)
Carhart α	1.21%** (2.23)	0.13% (0.81)	0.57% (1.61)	0.77%** (1.98)	1.13%** (2.29)
Carhart + Liq α	1.20%** (2.28)	0.14% (0.82)	0.56% (1.60)	0.76%** (1.99)	1.12%** (2.29)

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Table 1: Descriptive Statistics and Correlations.

Description: Panel A provides the descriptive statistics of risk neutral skewness (RNS) and other variables used in our analysis. The sample consists of 592,480 firm-month observations from Jan 1996 through Apr 2016 drawn from OptionMetrics and CRSP. All variables are defined in Appendix B. Panel B reports the time-series average of cross-sectional correlation coefficients between our variables. The lower triangular matrix presents the Pearson correlations and the upper triangular matrix shows the nonparametric Spearman correlations. Insignificant correlation coefficients are in italics.

Interpretation: The RNS characteristic for optionable stocks is negatively correlated with momentum measures at long, intermediate, and short horizons, providing an intuitive motivation for the relationship between the two qualities.

Panel A: Sample Descriptive Statistics

Variables	N	P5	P50	P95	Mean	STD
RNS	592,480	-0.8640	-0.2352	0.6071	-0.1979	0.5141
lnMV	592,480	11.6988	14.0539	17.0393	14.1604	1.6189
RET_t	592,480	-0.2119	0.0064	0.2282	0.0082	0.1476
RET_{t-1}	592,480	-0.2105	0.0066	0.2312	0.0095	0.1511
$RET_{t-12,t-2}$	592,480	-0.8373	0.0714	0.7280	0.0268	0.4965
$RET_{t-12,t-7}$	592,480	-0.5908	0.0491	0.5419	0.0234	0.3661
$RET_{t-6,t-2}$	592,480	-0.5680	0.0332	0.4624	0.0034	0.3343
β^i_M	592,480	0.2487	1.1753	2.8611	1.3132	0.8513
lnVOLUME	592,480	9.3101	11.4456	13.9695	11.5234	1.4181
BM	592,480	0.1002	0.4610	1.9394	0.9002	2.2429
$Over_{q-1}$	485,072	-0.9800	0.3200	1.5100	0.2915	0.8216

Panel B: Correlation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)RNS	1.00	-0.29	0.01	-0.14	-0.13	-0.06	-0.12	0.11	-0.13	0.04	-0.14
(2)MV	-0.10	1.00	0.04	0.10	0.25	0.17	0.19	-0.26	0.65	-0.14	0.39
(3)RET_t	0.02	*0.00*	1.00	-0.01	0.03	0.03	0.02	-0.03	0.00	0.01	0.08
(4)RET_{t-1}	-0.10	0.01	*-0.01*	1.00	0.02	0.02	0.00	-0.03	0.02	0.01	0.12
(5)$RET_{t-12,t-2}$	-0.10	0.06	0.02	*0.00*	1.00	0.72	0.63	-0.08	0.06	0.04	0.28
(6)$RET_{t-12,t-7}$	-0.05	0.04	0.02	*0.01*	0.75	1.00	0.03	-0.04	0.06	0.01	0.19
(7)$RET_{t-6,t-2}$	-0.10	0.05	*0.02*	*-0.00*	0.68	0.03	1.00	-0.06	0.03	0.04	0.22
(8)β^i_M	0.08	-0.10	*-0.01*	*-0.01*	-0.08	-0.04	-0.07	1.00	0.08	-0.06	-0.04
(9)lnVOLUME	-0.04	0.52	*-0.01*	*-0.00*	*-0.00*	*0.01*	-0.01	0.07	1.00	-0.16	0.25
(10)BM	0.02	-0.05	*0.00*	*0.00*	0.01	*0.00*	0.01	-0.01	-0.03	1.00	-0.57
(11)$Over_{q-1}$	-0.11	0.18	0.08	0.12	0.28	0.18	0.22	-0.03	0.13	-0.54	1.00

Table 2: Fama-MacBeth Cross-Sectional Regressions.

Description: This table presents the firm-level cross sectional regressions of excess returns on risk neutral skewness (RNS) after controlling for beta, size, log book-to-market ratio, short term reversal RET_{-1}, momentum proxies, and stock trading volume $lnVOLUME$. We use three proxies of momentum: $RET_{-12,-2}$ in column (2) and (3), $RET_{-12,-7}$ in column (4) and (5) and $RET_{-6,-2}$ in column (6) and (7). In column (8), we include AVAR as an additional control variable, available only for a subsample of optionable stocks using $RET_{-12,-2}$ as the momentum proxy. All variables are defined in Appendix B. We report Newey and West (1987) t-statistics adjusted for a 6-month lag in parentheses. N is the number of monthly cross-sectional regressions used to compute the coefficients and standard errors. # of obs is the number of firm-month observations in the entire sample.

Interpretation: This table confirms that risk-neutral skewness (RNS) is positively priced in the cross-section of returns even after controlling other firm characteristics, consistent with Rehman and Vilkov (2012) and Stilger, Kostakis and Poon (2016).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Int.	0.825* (1.89)	1.272 (1.41)	0.902 (0.99)	1.040 (1.12)	0.649 (0.70)	0.934 (1.04)	0.552 (0.61)	0.342 (0.13)
RNS	0.716*** (3.97)		0.673 *** (7.40)		0.649 *** (7.21)		0.692 *** (7.27)	0.939 *** (2.65)
β_M		-0.063 (-0.36)	-0.058 (-0.33)	-0.001 (-0.01)	0.002 (0.01)	0.007 (0.03)	0.010 (0.05)	-0.051 (-0.25)
ln(MV)		-0.027 (-0.26)	0.015 (0.15)	-0.007 (-0.06)	0.039 (0.36)	0.003 (0.03)	0.047 (0.47)	0.212 * (1.70)
ln(BM)		-0.003 (-0.04)	-0.007 (-0.10)	0.011 (0.17)	0.008 (0.13)	0.008 (0.11)	0.004 (0.06)	-0.142 (-1.34)
RET_{t-1}		-1.836*** (-2.82)	-1.640** (-2.54)	-1.804*** (-2.70)	-1.624** (-2.46)	-1.826*** (-2.82)	-1.629** (-2.54)	0.334 (0.35)
MOM		0.544 * (1.78)	0.580 * (1.90)	0.631 ** (2.31)	0.648 ** (2.39)	0.532 (1.51)	0.591 * (1.67)	0.734 ** (2.15)
ln(VOL)		-0.024 (-0.28)	-0.033 (-0.39)	-0.031 (-0.33)	-0.042 (-0.45)	-0.031 (-0.36)	-0.040 (-0.46)	-0.235 (-1.48)
HS		0.085 ** (2.33)	0.088 ** (2.42)	0.071 * (1.86)	0.073 * (1.93)	0.077 ** (2.19)	0.080 ** (2.28)	0.209 (1.36)
AVAR								0.329 (0.18)
N	244	244	244	244	244	244	244	244
# of obs	592,480	592,480	592,480	592,480	592,480	592,480	592,480	141,050

Table 3: Risk-Neutral Skewness Sorted Portfolios.

Description: This table shows the characteristics and returns of stock portfolios sorted on option-implied risk-neutral skewness (RNS). Each calendar month, we rank stocks in ascending order by their end-of-month RNS and assign them to quintile portfolios. Panels A and Panel B present the stock characteristics and returns for portfolios sorted by RNS under equal- and value-weights respectively. The upper parts of both panels report the portfolio characteristics. The rightmost two columns present characteristics and t-statistics for a zero-cost high minus low (H-L) RNS portfolio that is long (short) the highest (lowest) RNS quintile. The lower parts of both panels report the portfolio returns, where the rightmost column presents returns of a zero-cost high minus low (H-L) RNS portfolio. The table shows excess returns along with abnormal performance relative to Carhart (1997) momentum factor 4-factor model (α_{FFC}) over the month following portfolio formation. The table also reports the portfolios loadings on the market risk premium (MKT), size (SMB), value (HML), and momentum (UMD) factors. All variables are defined in Appendix B. We report Newey and West (1987) t-statistics adjusted for a 6-month lag in parentheses.

Interpretation: Under both equal- and value weighting both legs of the zero-cost portfolio generate significant returns, suggesting that the short sale constraint explanation proposed by Stilger, Kostakis and Poon (2016) cannot fully describe the RNS anomaly.

Panel A: Equally Weighted RNS Portfolios

	Equally Weighted Portfolio Characteristics						
	1	2	3	4	5	H-L	T
RNS	-0.751	-0.386	-0.235	-0.066	0.446	1.197	23.27
lnMV	14.550	14.676	14.358	13.824	13.336	-1.214	-17.00
BM	0.901	0.788	0.808	0.884	0.997	0.096	4.11
$RET_{t-12,t-2}$	0.067	0.083	0.071	0.006	-0.089	-0.156	-8.12
$RET_{t-12,t-7}$	0.032	0.051	0.050	0.020	-0.027	-0.059	-6.15
$RET_{t-6,t-2}$	0.035	0.033	0.021	-0.014	-0.062	-0.098	-7.74
RET_{t-1}	0.028	0.021	0.014	0.001	-0.015	-0.043	-10.15
lnVOLUME	11.505	11.787	11.688	11.428	11.057	-0.447	-7.49
$Overvaluation_{q-1}$	0.363	0.439	0.399	0.274	0.090	-0.273	-16.80

Equally Weighted Portfolio Returns

	1	2	3	4	5	H-L
ExRet	0.46%	0.69%	0.83%	1.00%	1.35%	0.89%
	(1.31)	(1.73)	(1.99)	(2.25)	(2.91)	(4.11)
α_{FFC}	-0.39%	-0.21%	-0.08%	0.14%	0.55%	0.94%
	(-4.52)	(-2.35)	(-0.93)	(1.21)	(3.34)	(4.65)
β_{MKT}	0.98	1.13	1.18	1.16	1.13	0.15
	(40.31)	(63.63)	(54.32)	(45.58)	(28.37)	(3.33)
β_{SMB}	0.41	0.52	0.59	0.73	0.64	0.22
	(8.64)	(13.24)	(16.23)	(11.72)	(5.77)	(2.77)
β_{HML}	0.30	0.08	0.01	-0.01	0.14	-0.16
	(7.69)	(2.03)	(0.33)	(-0.20)	(2.10)	(-2.42)
β_{UMD}	-0.10	-0.11	-0.16	-0.31	-0.44	-0.35
	(-3.54)	(-5.04)	(-6.24)	(-9.15)	(-8.42)	(-5.19)

Panel B: Value Weighted RNS Portfolios

	Value Weighted Portfolio Characteristics						
	1	2	3	4	5	H-L	T
RNS	-0.675	-0.390	-0.240	-0.078	0.413	1.088	23.50
lnMV	17.274	17.259	16.882	16.372	15.583	-1.691	-12.59
BM	0.505	0.480	0.518	0.600	0.808	0.303	6.39
$RET_{t-12,t-2}$	0.120	0.131	0.132	0.099	0.037	-0.083	-5.27
$RET_{t-12,t-7}$	0.065	0.076	0.077	0.064	0.028	-0.036	-4.66
$RET_{t-6,t-2}$	0.056	0.054	0.055	0.035	0.009	-0.047	-4.83
RET_{t-1}	0.022	0.017	0.012	0.005	-0.002	-0.024	-6.22
lnVOLUME	13.279	13.425	13.280	12.994	12.379	-0.900	-7.38
$Overvaluation_{q-1}$	0.801	0.822	0.788	0.693	0.499	-0.303	-10.19

	Value Weighted Portfolio Returns					
	1	2	3	4	5	H-L
ExRet	0.51%	0.79%	0.98%	0.95%	1.22%	0.71%
	(1.62)	(2.44)	(2.86)	(2.66)	(3.46)	(3.35)
α_{FFC}	-0.21%	-0.00%	0.21%	0.20%	0.48%	0.70%
	(-3.42)	(-0.05)	(2.26)	(1.43)	(3.84)	(4.39)
β_{MKT}	0.95	1.06	1.07	1.05	0.96	0.01
	(63.01)	(55.63)	(50.97)	(30.49)	(34.95)	(0.21)
β_{SMB}	-0.10	-0.04	-0.02	0.06	0.13	0.23
	(-4.86)	(-2.20)	(-0.64)	(1.51)	(2.58)	(3.86)
β_{HML}	0.04	0.01	-0.07	-0.03	0.30	0.25
	(1.01)	(0.31)	(-1.54)	(-0.46)	(6.05)	(3.04)
β_{UMD}	-0.02	-0.00	-0.02	-0.12	-0.22	-0.20
	(-0.77)	(-0.10)	(-0.65)	(-3.56)	(-5.99)	(-3.97)

Table 4: Market Timing Tests of RNS Quintile Portfolios.

Description: This table presents the results of estimating three performance specifications for returns of RNS quintile portfolios and the zero-cost High minus Low RNS portfolio from February 1996 to May 2016. Model 1 fits an unconditional market model: $R_t = \alpha_0 + \beta_0 R_{m,t} + \varepsilon_t$. Model 2 fits a conditional CAPM with the bear market indicator I_B: $R_t = \alpha_0 + (\beta_0 + \beta_B I_{B,t-1})R_{m,t} + \varepsilon_t$ where $I_B = 1$ if the cumulative CRSP VW index return in the past 24 months is negative and $I_B = 0$ otherwise. Model 3 introduces a contemporaneous up-market indicator variable $I_{U,t} = 1$ if the market risk premium is positive, and $I_{U,t} = 0$ otherwise: $R_t = \alpha_0 + (\beta_0 + I_{B,t-1}(\beta_B + I_{U,t}\beta_{B,U}))R_{m,t} + \varepsilon_t$. We report Newey and West (1987) t-statistics adjusted for a 6-month lag in parentheses. Panels A and Panel B report equal- and value-weighted portfolio results respectively.

Interpretation: A long-short RNS portfolio has significant positive exposure to post-recession market recoveries driven by the long (high RNS) leg of the portfolio. This is consistent with the rebound behavior observed for positive RNS stocks in Figure 1, and provides a more complete explanation for the RNS anomaly relative to the short sale constraint explanation which focuses on the short (low RNS) leg.

Panel A: Equally Weighted Portfolio

	RNS Quintile					
	1	2	3	4	5	H-L
Model 1						
$\hat{\alpha_0}$	-0.33%	-0.21%	-0.12%	0.01%	0.38%	0.70%
	(-2.71)	(-1.58)	(-0.80)	(0.04)	(1.62)	(3.76)
$\hat{\beta_0}$	1.05	1.25	1.33	1.39	1.37	0.33
	(39.47)	(43.24)	(39.79)	(31.89)	(27.23)	(7.95)
Model 2						
$\hat{\alpha_0}$	-0.29%	-0.18%	-0.10%	0.06%	0.46%	0.76%
	(-2.44)	(-1.36)	(-0.62)	(0.28)	(2.07)	(4.08)
$\hat{\beta_0}$	0.98	1.19	1.28	1.30	1.21	0.23
	(29.22)	(32.42)	(29.91)	(23.45)	(19.24)	(4.42)
$\hat{\beta_B}$	0.18	0.14	0.13	0.23	0.42	0.24
	(3.35)	(2.44)	(1.90)	(2.59)	(4.23)	(2.95)
Model 3						
$\hat{\alpha_0}$	-0.30%	-0.28%	-0.22%	-0.14%	0.17%	0.47%
	(-2.27)	(-1.96)	(-1.30)	(-0.65)	(0.71)	(2.37)
$\hat{\beta_0}$	0.98	1.20	1.28	1.31	1.22	0.24
	(29.10)	(32.61)	(30.10)	(23.76)	(19.73)	(4.77)
$\hat{\beta_B}$	0.17	0.06	0.03	0.07	0.18	0.01
	(2.55)	(0.81)	(0.35)	(0.61)	(1.43)	(0.05)
$\hat{\beta}_{B,U}$	0.01	0.17	0.21	0.34	0.51	0.50
	(0.09)	(1.76)	(1.81)	(2.28)	(3.07)	(3.68)

Panel B: Value Weighted Portfolio

	RNS Quintile					
	1	2	3	4	5	H-L
Model 1						
	-0.22%	-0.01%	0.18%	0.12%	0.44%	0.66%
$\hat{\alpha_0}$	(-3.16)	(-0.09)	(1.99)	(0.97)	(2.92)	(3.88)
	0.94	1.05	1.08	1.11	1.02	0.09
$\hat{\beta}_0$	(62.07)	(81.83)	(55.29)	(40.33)	(31.00)	(2.33)
Model 2						
	-0.20%	-0.00%	0.18%	0.15%	0.52%	0.72%
$\hat{\alpha_0}$	(-2.97)	(-0.04)	(1.97)	(1.17)	(3.67)	(4.39)
	0.91	1.05	1.08	1.06	0.87	-0.04
$\hat{\beta}_0$	(47.26)	(63.20)	(42.96)	(30.26)	(22.01)	(-0.80)
	0.06	0.01	-0.00	0.12	0.38	0.31
$\hat{\beta_B}$	(2.13)	(0.52)	(-0.10)	(2.09)	(5.96)	(4.24)
Model 3						
	-0.16%	-0.01%	0.12%	0.01%	0.40%	0.56%
$\hat{\alpha_0}$	(-2.09)	(-0.14)	(1.18)	(0.07)	(2.61)	(3.13)
	0.91	1.05	1.08	1.07	0.88	-0.03
$\hat{\beta}_0$	(47.20)	(62.95)	(43.10)	(30.70)	(22.22)	(-0.64)
	0.10	0.01	-0.05	0.00	0.28	0.17
$\hat{\beta_B}$	(2.66)	(0.24)	(-1.06)	(0.04)	(3.46)	(1.87)
	-0.08	0.01	0.11	0.24	0.21	0.29
$\hat{\beta}_{B,U}$	(-1.60)	(0.25)	(1.57)	(2.55)	(1.93)	(2.34)

Table 5: Market Timing Regression of Momentum Returns by RNS Tercile.

Description: At the end of each calendar month, we independently sort firms into terciles on the Novy-Marx (2012) intermediate-term momentum $RET_{t-12,t-7}$ and on RNS. We use the NYSE, AMEX and NASDAQ stock universe to set RNS breakpoints and the NYSE universe to set the $RET_{t-12,t-7}$ breakpoints consistent with prior literature. Within each RNS tercile, we regress the returns of equal- and value-weighted winner-minus-loser momentum (WML) portfolios defined on $RET_{t-12,t-7}$ terciles on market timing models. Model 1 fits an unconditional market model: $R_t = \alpha_0 + \beta_0 R_{m,t} + \varepsilon_t$. Model 2 fits a conditional CAPM with the bear market indicator I_B: $R_t = \alpha_0 + (\beta_0 + \beta_B I_{B,t-1})R_{m,t} + \varepsilon_t$ where $I_B = 1$ if the cumulative CRSP VW index return in the past 24 months is negative and $I_B = 0$ otherwise. Model 3 introduces a contemporaneous up-market indicator variable $I_{U,t} = 1$ if the market risk premium is positive, and $I_{U,t} = 0$ otherwise: $R_t = \alpha_0 + (\beta_0 + I_{B,t-1}(\beta_B + I_{U,t}\beta_{B,U}))R_{m,t} + \varepsilon_t$. We report Newey and West (1987) t-statistics adjusted for a 6-month lag in parentheses.

Interpretation: The crashes due to momentum having a negative conditional beta during market recoveries as described by Daniel and Moskowitz (2016) are driven by the stocks in the highest RNS tercile under both equal- and value-weighting.

	EW				VW			
	RNS Tercile				RNS Tercile			
	L	M	H	H-L	L	M	H	H-L
Model 1								
	0.66%	0.56%	0.51%	-0.15%	0.67%	0.59%	0.57%	-0.10%
$\hat{\alpha_0}$	(2.82)	(2.19)	(1.91)	(-0.95)	(2.32)	(1.92)	(1.69)	(-0.37)
	-0.10	-0.11	-0.18	-0.08	-0.05	-0.06	-0.16	-0.11
$\hat{\beta_0}$	(-2.02)	(-2.00)	(-3.09)	(-2.36)	(-0.78)	(-0.92)	(-2.14)	(-1.95)
Model 2								
	0.54%	0.43%	0.38%	-0.16%	0.53%	0.45%	0.38%	-0.15%
$\hat{\alpha_0}$	(2.45)	(1.79)	(1.49)	(-1.07)	(1.94)	(1.52)	(1.22)	(-0.58)
	0.12	0.13	0.07	-0.04	0.20	0.21	0.19	-0.01
$\hat{\beta_0}$	(1.87)	(1.87)	(1.00)	(-1.04)	(2.62)	(2.59)	(2.18)	(-0.13)
	-0.55	-0.60	-0.64	-0.09	-0.63	-0.69	-0.88	-0.25
$\hat{\beta_B}$	(-5.63)	(-5.59)	(-5.65)	(-1.26)	(-5.18)	(-5.32)	(-6.32)	(-2.22)
Model 3								
	0.59%	0.57%	0.57%	-0.01%	0.45%	0.46%	0.63%	0.18%
$\hat{\alpha_0}$	(2.42)	(2.18)	(2.07)	(-0.08)	(1.50)	(1.45)	(1.86)	(0.67)
	0.11	0.12	0.06	-0.05	0.20	0.21	0.18	-0.02
$\hat{\beta_0}$	(1.83)	(1.77)	(0.88)	(-1.20)	(2.65)	(2.57)	(2.06)	(-0.34)
	-0.52	-0.48	-0.48	0.04	-0.70	-0.68	-0.68	0.02
$\hat{\beta_B}$	(-4.10)	(-3.52)	(-3.32)	(0.44)	(-4.46)	(-4.04)	(-3.80)	(0.15)
	-0.07	-0.25	-0.34	-0.26	0.14	-0.03	-0.43	-0.58
$\hat{\beta}_{B,U}$	(-0.44)	(-1.34)	(-1.75)	(-2.28)	(0.69)	(-0.14)	(-1.83)	(-3.05)

Table 6: Market Timing Regressions with Size, Momentum, and RNS Triple Sorts.

Description: At the end of each calendar month, we independently sort firms into terciles by market capitalization, Novy-Marx (2012) intermediate-term momentum $RET_{t-12,t-7}$, and RNS. We use the NYSE, AMEX and NASDAQ stock universe to set RNS breakpoints and the NYSE universe to set the $RET_{t-12,t-7}$ and size breakpoints consistent with prior literature. Within each Size/RNS group we create equal- and value-weighted portfolios formed on winner minus loser (WML) momentum terciles using $RET_{t-12,t-7}$. We regress the resulting WML portfolio returns on the following time series model: $R_{WML,t} = \alpha_0 + (\beta_0 + I_{B,t-1}(\beta_B + I_{U,t}\beta_{B,U}))R_{m,t} + \varepsilon_t$. We report Newey and West (1987) t-statistics adjusted for a 6-month lag in parentheses.

Interpretation: The momentum crashes during market rebounds observed in the high-RNS tercile in Table 5 occur only in the median and high firm size terciles.

	EW				VW			
	RNS Tercile				RNS Tercile			
	L	M	H	H-L	L	M	H	H-L
Size Tercile 1								
	0.72%	0.60%	0.61%	-0.11%	0.56%	0.54%	0.44%	-0.12%
$\hat{\alpha_0}$	(2.85)	(2.18)	(2.17)	(-0.54)	(2.24)	(1.87)	(1.62)	(-0.58)
	0.08	0.17	0.10	0.02	0.10	0.17	0.12	0.02
$\hat{\beta_0}$	(1.26)	(2.42)	(1.36)	(0.30)	(1.50)	(2.26)	(1.69)	(0.39)
	-0.34	-0.37	-0.37	-0.03	-0.47	-0.34	-0.47	-0.00
$\hat{\beta_B}$	(-2.60)	(-2.55)	(-2.57)	(-0.30)	(-3.59)	(-2.31)	(-3.35)	(-0.04)
	-0.19	-0.45	-0.31	-0.13	-0.14	-0.47	-0.28	-0.14
$\hat{\beta}_{B,U}$	(-1.08)	(-2.36)	(-1.62)	(-0.87)	(-0.83)	(-2.38)	(-1.49)	(-0.93)
Size Tercile 2								
	0.43%	0.40%	0.67%	0.23%	0.52%	0.43%	0.69%	0.17%
$\hat{\alpha_0}$	(1.63)	(1.33)	(2.04)	(0.95)	(1.88)	(1.42)	(2.11)	(0.68)
	0.11	0.12	0.09	-0.01	0.12	0.13	0.09	-0.02
$\hat{\beta_0}$	(1.53)	(1.59)	(1.12)	(-0.17)	(1.63)	(1.69)	(1.12)	(-0.35)
	-0.51	-0.54	-0.64	-0.12	-0.52	-0.55	-0.67	-0.15
$\hat{\beta_B}$	(-3.68)	(-3.50)	(-3.74)	(-0.97)	(-3.56)	(-3.50)	(-3.87)	(-1.13)
	-0.14	-0.21	-0.56	-0.42	-0.20	-0.18	-0.57	-0.37
$\hat{\beta}_{B,U}$	(-0.78)	(-1.04)	(-2.48)	(-2.45)	(-1.06)	(-0.88)	(-2.51)	(-2.14)
Size Tercile 3								
	0.48%	0.62%	0.96%	0.48%	0.42%	0.45%	0.89%	0.47%
$\hat{\alpha_0}$	(1.62)	(1.84)	(2.50)	(1.50)	(1.31)	(1.33)	(1.93)	(1.09)
	0.18	0.20	0.21	0.02	0.19	0.24	0.25	0.06
$\hat{\beta_0}$	(2.41)	(2.26)	(2.12)	(0.30)	(2.29)	(2.72)	(2.09)	(0.52)
	-0.65	-0.66	-0.69	-0.04	-0.69	-0.71	-0.78	-0.09
$\hat{\beta_B}$	(-4.21)	(-3.70)	(-3.44)	(-0.22)	(-4.12)	(-3.99)	(-3.25)	(-0.38)
	0.10	0.04	-0.36	-0.46	0.20	-0.00	-0.34	-0.53
$\hat{\beta}_{B,U}$	(0.47)	(0.18)	(-1.35)	(-2.06)	(0.87)	(-0.01)	(-1.07)	(-1.81)

Table 7: Market Timing Regressions with Institutional Ownership, Momentum, and RNS Triple Sorts.

Description: At the end of each calendar month, we independently sort firms into terciles by institutional ownership (IO), Novy-Marx (2012) intermediate-term momentum $RET_{t-12,t-7}$, and RNS. We use the NYSE, AMEX and NASDAQ stock universe to set RNS breakpoints, and the NYSE universe to set the $RET_{t-12,t-7}$ and IO breakpoints consistent with prior literature. Within each IO/RNS group we create equal- and value-weighted portfolios formed on winner minus loser (WML) momentum terciles using $RET_{t-12,t-7}$. We regress the resulting WML portfolio returns on the following time series model: $R_{WML,t} = \alpha_0 + (\beta_0 + I_{B,t-1}(\beta_B + I_{U,t}\beta_{B,U}))R_{m,t} + \varepsilon_t$. We report Newey and West (1987) t-statistics adjusted for a 6-month lag in parentheses.

Interpretation: The phenomenon of momentum crashes due to market rebounds in high-RNS stocks appears to be strongest for the less short-sale constrained firms in the median and high institutional ownership terciles.

	EW				VW			
	RNS Tercile				RNS Tercile			
	L	M	H	H-L	L	M	H	H-L
IO Tercile 1								
$\hat{\alpha_0}$	0.77%	0.66%	0.56%	-0.21%	0.33%	0.55%	0.92%	0.58%
	(2.82)	(2.31)	(1.89)	(-1.01)	(0.92)	(1.51)	(2.16)	(1.47)
$\hat{\beta_0}$	0.10	0.10	0.10	0.00	0.16	0.21	0.20	0.04
	(1.41)	(1.40)	(1.31)	(0.03)	(1.74)	(2.18)	(1.86)	(0.42)
$\hat{\beta_B}$	-0.56	-0.57	-0.61	-0.05	-0.70	-0.69	-0.85	-0.15
	(-3.91)	(-3.84)	(-3.90)	(-0.47)	(-3.74)	(-3.60)	(-3.85)	(-0.74)
$\hat{\beta}_{B,U}$	-0.06	-0.24	-0.17	-0.11	0.13	-0.04	-0.41	-0.54
	(-0.32)	(-1.23)	(-0.82)	(-0.77)	(0.51)	(-0.16)	(-1.40)	(-1.96)
IO Tercile 2								
$\hat{\alpha_0}$	0.08%	0.37%	0.30%	0.21%	0.35%	0.29%	0.40%	0.05%
	(0.30)	(1.24)	(0.86)	(0.76)	(1.08)	(0.81)	(1.01)	(0.14)
$\hat{\beta_0}$	0.13	0.15	0.06	-0.07	0.26	0.21	0.14	-0.12
	(1.81)	(1.95)	(0.71)	(-0.90)	(3.07)	(2.25)	(1.31)	(-1.26)
$\hat{\beta_B}$	-0.42	-0.51	-0.42	-0.00	-0.55	-0.62	-0.45	0.11
	(-2.88)	(-3.30)	(-2.29)	(-0.00)	(-3.26)	(-3.29)	(-2.12)	(0.56)
$\hat{\beta}_{B,U}$	-0.12	-0.30	-0.55	-0.43	-0.01	-0.01	-0.61	-0.60
	(-0.61)	(-1.47)	(-2.27)	(-2.19)	(-0.05)	(-0.02)	(-2.18)	(-2.29)
IO Tercile 3								
$\hat{\alpha_0}$	0.86%	0.40%	0.49%	-0.37%	0.78%	0.71%	0.05%	-0.73%
	(3.25)	(1.29)	(1.70)	(-1.53)	(2.27)	(1.98)	(0.16)	(-2.15)
$\hat{\beta_0}$	0.14	0.23	0.04	-0.10	0.26	0.29	0.21	-0.05
	(2.09)	(2.89)	(0.60)	(-1.57)	(2.97)	(3.17)	(2.44)	(-0.56)
$\hat{\beta_B}$	-0.54	-0.44	-0.23	0.31	-0.76	-0.66	-0.46	0.30
	(-3.91)	(-2.75)	(-1.52)	(2.46)	(-4.20)	(-3.54)	(-2.55)	(1.70)
$\hat{\beta}_{B,U}$	-0.14	-0.15	-0.48	-0.34	0.18	-0.09	-0.31	-0.50
	(-0.74)	(-0.72)	(-2.39)	(-2.06)	(0.76)	(-0.36)	(-1.33)	(-2.11)

Table 8: Frequencies of Firm-Level Performance Reversals and Firm-Specific Valuation Error by RNS and SKEW Factor.

Description: The top panel of this table shows the frequency of positive or negative firm-level performance reversals in each quintile portfolio sorted by lagged values of one of two firm-level risk-neutral skewness measures: the Bakshi, Kapadia, and Madan (2003) risk neutral skewness (RNS) characteristic and the loading on risk neutral skewness factor (β_{SKEW}). A positive performance reversal indicator at time t is defined as a historical loss followed by a contemporaneous gain: $I_{f,D,t-1} \times I_{f,U,t}$, where the historical loss indicator $I_{f,D,t-1}$ takes the value of 1 if the firm's cumulative return in the past 24 months is negative and is set to 0 otherwise, and the contemporaneous gain indicator variable $I_{f,U,t} = 1$ if the excess return of the stock is positive in the current month, and 0 otherwise. A negative performance reversal indicator is defined as a historical gain followed by a contemporaneous loss: $I_{f,D,t-1} \times I_{f,U,t}$ where the firm-level historical gain indicator variable $I_{f,U,t-1} = 1$ if the firm's cumulative return over the past 24 months is non-negative, and 0 otherwise, and the firm-level contemporaneous loss indicator variable $I_{f,D,t} = 1$ if the excess return of the stock is negative in the current month, and 0 otherwise. The bottom panel presents the variation of $Over_{q-1}$, the prior quarter's firm-specific component of the market to book ratio calculated relative to industry multiples using the approach of Rhodes-Kropf, Robinson, and Viswanathan (2005), by RNS and SKEW measures for month t. Variable definitions are given in Appendix B.

Interpretation: RNS predicts the frequency of positive performance reversals for individual stocks, with positive reversals frequencies sharply increasing across its quintiles. The skewness factor loading β_{SKEW} similarly captures the frequency of these rebounds, suggesting it is a valid proxy for RNS in non-optionable stocks. Stocks with the most positive RNS and highest β_{SKEW} have the lowest firm-specific overvaluation in the prior quarter, consistent with observed upward rebounds in future returns.

	Firm-Level Performance Reversals				
	Lagged Skewness Proxy Quintile				
	1	2	3	4	5
Positive Performance Reversal: $I_{f,D,t-1} \times I_{f,U,t}$ on RNS_{t-1}	15.56%	16.11%	17.60%	20.71%	24.79%
Positive Performance Reversal: $I_{f,D,t-1} \times I_{f,U,t}$ on $\beta_{SKEW,t-1}$	19.77%	17.84%	18.69%	21.23 %	24.63%
Negative Performance Reversal: $I_{f,U,t-1} \times I_{f,D,t}$ on RNS_{t-1}	31.44%	31.70%	30.85%	28.13%	23.65%
Negative Performance Reversal: $I_{f,U,t-1} \times I_{f,D,t}$ on $\beta_{SKEW,t-1}$	28.59%	29.86%	28.90%	27.05%	24.10%
	Firm-Level Overvaluation				
	Lagged Skewness Proxy Quintile				
	1	2	3	4	5
EW $Over_{q-1}$ on RNS_t	0.363	0.439	0.399	0.274	0.090
EW $Over_{q-1}$ on $\beta_{SKEW,t}$	0.212	0.187	0.160	0.113	0.059
VW $Over_{q-1}$ on RNS_t	0.801	0.822	0.788	0.693	0.499
VW $Over_{q-1}$ on $\beta_{SKEW,t}$	0.968	0.814	0.797	0.640	0.591

Table 9: Portfolio Returns Sorted by Loading on RNS Factor (β_{SKEW}) and Momentum ($RET_{t-12,t-7}$).
Description: At the end of each calendar month we sort stocks into five RNS portfolios and construct the skewness factor-mimicking portfolio SKEW as the value-weighted return of the portfolio long (short) the highest (lowest) RNS quintile stocks. For all stocks in CRSP we obtain β_{SKEW} from the rolling window regression $Exret = \alpha + \beta_M Mktrf + \beta_{SKEW} SKEW$ over the past 60 months. We then rank stocks into β_{SKEW} quintiles and Novy-Marx (2012) intermediate-term momentum ($RET_{t-12,t-7}$) deciles. Panels A, B and C present the excess return, Carhart (1997) four-factor alpha, and a five-factor model augmented with the Pastor and Stambaugh (2003) liquidity factor alpha for the resulting value-weighted portfolios. We also report the results for zero-cost H-L portfolios across the SKEW beta and momentum dimensions. For comparison purposes, we also include the returns of momentum decile portfolios for all CRSP stocks in the bottom row of each Panel. We report Newey and West (1987) t-statistics adjusted for a 6-month lag in parentheses.
Interpretation: The momentum strategy that is long stocks in the highest $RET_{t-12,t-7}$ decile and short those in the lowest has the highest excess return and abnormal returns in the lowest β_{SKEW} quintile, consistent with a low likelihood of momentum crash-inducing rebounds in low-skew stocks.

Panel A: Excess Return

β_{SKEW}	Momentum Decile 1	2	3	4	5	6	7	8	9	10	H-L
1	-0.48%	0.12%	0.34%	-0.02%	0.92%	0.42%	0.66%	0.61%	0.78%	0.96%	1.45%
	(-0.69)	(0.18)	(0.77)	(-0.04)	(2.12)	(1.24)	(1.99)	(1.88)	(1.73)	(1.79)	(2.85)
2	-0.17%	0.35%	0.74%	0.81%	0.72%	0.95%	0.65%	0.97%	0.87%	1.06%	1.23%
	(-0.29)	(0.65)	(1.76)	(2.10)	(2.24)	(2.85)	(2.22)	(3.21)	(2.93)	(2.48)	(2.26)
3	0.29%	0.64%	0.83%	0.64%	0.71%	0.66%	0.87%	1.27%	1.31%	1.33%	1.04%
	(0.43)	(1.46)	(2.01)	(1.68)	(2.11)	(1.73)	(2.85)	(3.98)	(3.24)	(3.05)	(1.63)
4	0.87%	1.04%	0.97%	0.92%	0.45%	0.66%	1.01%	0.86%	1.02%	1.31%	0.44%
	(1.73)	(2.24)	(2.45)	(2.32)	(1.16)	(1.96)	(2.80)	(2.32)	(2.83)	(2.44)	(0.83)
5	0.79%	0.82%	0.61%	0.66%	0.83%	0.59%	0.84%	0.61%	0.93%	1.03%	0.25%
	(1.22)	(1.43)	(1.13)	(1.19)	(1.83)	(1.20)	(1.78)	(1.13)	(1.91)	(1.78)	(0.63)
H-L											-1.20%
											(-2.36)
$RET_{t-12,t-7}$	0.17%	0.28%	0.62%	0.46%	0.66%	0.61%	0.70%	0.72%	0.80%	0.97%	0.80%
All	(0.29)	(0.55)	(1.54)	(1.21)	(2.02)	(2.11)	(2.53)	(2.50)	(2.14)	(2.04)	(1.67)

Panel B: 4-Factor Carhart α

β_{SKEW}	Momentum Decile 1	2	3	4	5	6	7	8	9	10	H-L
1	-0.99%	-0.39%	-0.23%	-0.50%	0.47%	-0.08%	0.03%	-0.00%	0.19%	0.22%	1.21%
	(-2.22)	(-0.74)	(-1.10)	(-1.66)	(1.96)	(-0.41)	(0.10)	(-0.00)	(0.85)	(0.77)	(2.23)
2	-0.65%	-0.19%	0.24%	0.27%	0.15%	0.43%	0.11%	0.37%	0.25%	0.30%	0.94%
	(-2.11)	(-0.76)	(1.18)	(1.40)	(0.89)	(1.51)	(0.59)	(1.88)	(1.33)	(1.16)	(2.38)
3	-0.27%	0.08%	0.31%	0.04%	0.17%	0.11%	0.31%	0.64%	0.60%	0.41%	0.68%
	(-0.67)	(0.37)	(1.47)	(0.23)	(0.90)	(0.50)	(1.55)	(2.68)	(1.78)	(1.46)	(1.25)
4	0.32%	0.42%	0.41%	0.27%	-0.20%	0.01%	0.30%	0.12%	0.33%	0.36%	0.04%
	(1.13)	(1.82)	(2.42)	(1.34)	(-0.92)	(0.05)	(1.07)	(0.44)	(1.28)	(1.33)	(0.11)
5	-0.02%	-0.01%	-0.09%	-0.07%	0.13%	-0.17%	0.03%	-0.21%	0.01%	-0.02%	0.00%
	(-0.08)	(-0.04)	(-0.25)	(-0.19)	(0.51)	(-0.60)	(0.08)	(-0.61)	(0.02)	(-0.06)	(0.01)
H-L											-1.21%
											(-2.25)
$RET_{t-12,t-7}$	-0.35%	-0.21%	0.11%	-0.09%	0.08%	0.07%	0.11%	0.10%	0.16%	0.15%	0.50%
All	(-1.54)	(-0.82)	(0.80)	(-0.63)	(0.80)	(0.56)	(0.85)	(0.84)	(1.10)	(0.82)	(1.61)

	Panel C: 5-Factor Liquidity α										
	Momentum Decile										
	1	2	3	4	5	6	7	8	9	10	H-L
β_{SKEW}											
1	-0.99% (-2.22)	-0.39% (-0.75)	-0.24% (-1.10)	-0.50% (-1.66)	0.46% (1.91)	-0.08% (-0.38)	0.03% (0.11)	-0.01% (-0.06)	0.19% (0.84)	0.21% (0.75)	1.20% (2.28)
2	-0.65% (-2.11)	-0.19% (-0.77)	0.23% (1.18)	0.26% (1.41)	0.14% (0.79)	0.42% (1.49)	0.10% (0.58)	0.37% (1.91)	0.25% (1.31)	0.29% (1.16)	0.94% (2.38)
3	-0.26% (-0.65)	0.08% (0.36)	0.32% (1.49)	0.05% (0.25)	0.17% (0.90)	0.11% (0.51)	0.31% (1.57)	0.64% (2.71)	0.59% (1.81)	0.40% (1.48)	0.66% (1.24)
4	0.33% (1.12)	0.43% (1.82)	0.42% (2.43)	0.28% (1.32)	-0.19% (-0.88)	0.02% (0.08)	0.30% (1.07)	0.13% (0.46)	0.33% (1.28)	0.36% (1.34)	0.03% (0.10)
5	-0.02% (-0.06)	-0.01% (-0.02)	-0.09% (-0.26)	-0.06% (-0.16)	0.14% (0.51)	-0.16% (-0.54)	0.03% (0.10)	-0.20% (-0.59)	0.02% (0.05)	-0.01% (-0.04)	0.00% (0.01)
H-L											-1.20% (-2.30)
$RET_{t-12,t-7}$ *All*	-0.35% (-1.54)	-0.21% (-0.82)	0.11% (0.81)	-0.09% (-0.62)	0.08% (0.79)	0.07% (0.59)	0.11% (0.85)	0.10% (0.85)	0.16% (1.10)	0.15% (0.81)	0.50% (1.60)

Table 10: Portfolio Returns Sorted by Loading on RNS Factor (β_{SKEW}) and Momentum ($RET_{t-12,t-7}$) by Macroeconomic Conditions.

Description: We define recessions as periods when the cumulative CRSP VW index return over the past 24 months is negative, and expansions as those when it is positive. At the end of each calendar month we rank stocks into β_{SKEW} quintiles and Novy-Marx (2012) intermediate-term momentum ($RET_{t-12,t-7}$) deciles. Panels A and B present the 5-factor Pastor and Stambaugh (2003) alpha for the value-weighted portfolios in recessions and expansions, respectively. We also report the results for zero-cost H-L portfolios across the SKEW beta and momentum dimensions. We report Newey and West (1987) t-statistics adjusted for a 6-month lag in parentheses.

Interpretation: The magnitude of the momentum abnormal return in low-skew stocks is greater in recessions than in expansions, consistent with the ability of skewness to predict upward rebounds after periods of underperformance.

Panel A: Recessions

β_{SKEW}	Momentum Decile 1	2	3	4	5	6	7	8	9	10	H-L
	-2.12%	-2.17%	-0.96%	-0.21%	0.70%	0.53%	0.44%	-0.01%	0.19%	1.38%	3.50%
1	(-2.01)	(-2.48)	(-1.61)	(-0.38)	(1.45)	(1.15)	(0.88)	(-0.03)	(0.34)	(1.45)	(2.67)
	-0.46%	-0.56%	0.55%	-0.49%	0.04%	0.90%	0.52%	0.35%	0.44%	0.74%	1.20%
2	(-0.61)	(-1.29)	(0.85)	(-1.36)	(0.11)	(1.98)	(1.47)	(1.69)	(1.36)	(1.87)	(1.40)
	-1.21%	-0.03%	-0.11%	0.83%	0.75%	0.26%	0.18%	0.76%	0.75%	1.10%	2.31%
3	(-1.48)	(-0.08)	(-0.38)	(2.10)	(2.85)	(0.72)	(0.74)	(2.22)	(1.31)	(2.06)	(2.15)
	0.32%	0.42%	0.71%	0.56%	-0.25%	-0.29%	0.95%	1.13%	0.38%	0.87%	0.55%
4	(0.81)	(1.11)	(1.96)	(1.38)	(-0.59)	(-0.68)	(2.54)	(2.55)	(0.70)	(2.14)	(1.31)
	0.62%	-0.06%	0.48%	-0.82%	0.12%	-0.08%	0.02%	-0.43%	0.54%	0.30%	-0.31%
5	(1.46)	(-0.11)	(0.70)	(-1.79)	(0.20)	(-0.14)	(0.04)	(-0.97)	(0.85)	(0.82)	(-0.54)
											-3.81%
H-L											(-2.79)
WML[-12,-7]	-0.66%	-0.81%	-0.22%	0.14%	0.31%	0.45%	0.64%	0.42%	0.47%	0.88%	1.55%
All	(-1.52)	(-2.14)	(-0.76)	(0.56)	(1.43)	(1.73)	(4.86)	(2.09)	(1.52)	(1.87)	(2.20)

Panel B: Expansions

β_{SKEW}	Momentum Decile 1	2	3	4	5	6	7	8	9	10	H-L
	-0.45%	0.65%	-0.10%	-0.34%	0.56%	-0.31%	0.14%	-0.13%	0.28%	-0.09%	0.36%
1	(-1.12)	(1.72)	(-0.46)	(-0.95)	(1.95)	(-1.41)	(0.50)	(-0.60)	(1.24)	(-0.31)	(0.90)
	-0.51%	-0.00%	0.03%	0.47%	0.13%	0.43%	-0.02%	0.55%	0.33%	0.33%	0.84%
2	(-1.55)	(-0.02)	(0.18)	(2.63)	(0.59)	(1.04)	(-0.11)	(2.20)	(1.61)	(1.08)	(1.92)
	-0.09%	0.13%	0.36%	-0.30%	-0.07%	0.03%	0.31%	0.40%	0.41%	0.13%	0.22%
3	(-0.18)	(0.48)	(1.40)	(-1.82)	(-0.29)	(0.10)	(1.00)	(1.50)	(1.13)	(0.41)	(0.34)
	0.08%	0.31%	0.24%	0.08%	-0.13%	-0.10%	-0.11%	-0.28%	0.15%	0.20%	0.11%
4	(0.22)	(0.90)	(1.16)	(0.36)	(-0.53)	(-0.42)	(-0.38)	(-1.15)	(0.56)	(0.61)	(0.24)
	-0.24%	0.08%	-0.46%	0.06%	-0.10%	-0.21%	-0.07%	-0.37%	-0.48%	-0.40%	-0.16%
5	(-0.66)	(0.29)	(-1.03)	(0.12)	(-0.30)	(-0.62)	(-0.17)	(-0.89)	(-1.39)	(-1.03)	(-0.42)
											-0.52%
H-L											(-1.08)
WML[-12,-7]	-0.14%	0.26%	0.17%	-0.12%	0.08%	-0.10%	-0.07%	-0.04%	0.11%	-0.01%	0.13%
All	(-0.55)	(1.15)	(1.11)	(-0.76)	(0.60)	(-0.77)	(-0.49)	(-0.31)	(0.65)	(-0.04)	(0.39)

Table 11: Relative Performance of Low SKEW Momentum and Related Strategies.

Description: This table tests the economic significance of the SKEW factor in improving the performance of the momentum strategy relative to the standard momentum strategy over months [-12,-2], the intermediate-term Novy-Marx (2012) momentum strategy over [-12,-7], the Barroso and Santa-Clara (2015) risk-managed momentum strategy, and the Daniel and Moskowitz (2016) dynamic weighting strategy. For comparability, we scale the return series of all strategies to the same level of time series volatility. We present the summary statistics of each scaled return series, their Sharpe ratios and correlations, and the information ratio and alpha of the β_{SKEW} Q1 return series relative to the return series from each of the other momentum strategies. The mean, standard deviation, Sharpe ratio, and information ratio are all annualized.

Interpretation: Using the SKEW factor-mimicking portfolio to isolate stocks with low likelihood of rebounds, and therefore low risk of momentum crashes, improves the momentum anomaly to an extent comparable to or greater than other recent refinements to the momentum strategy.

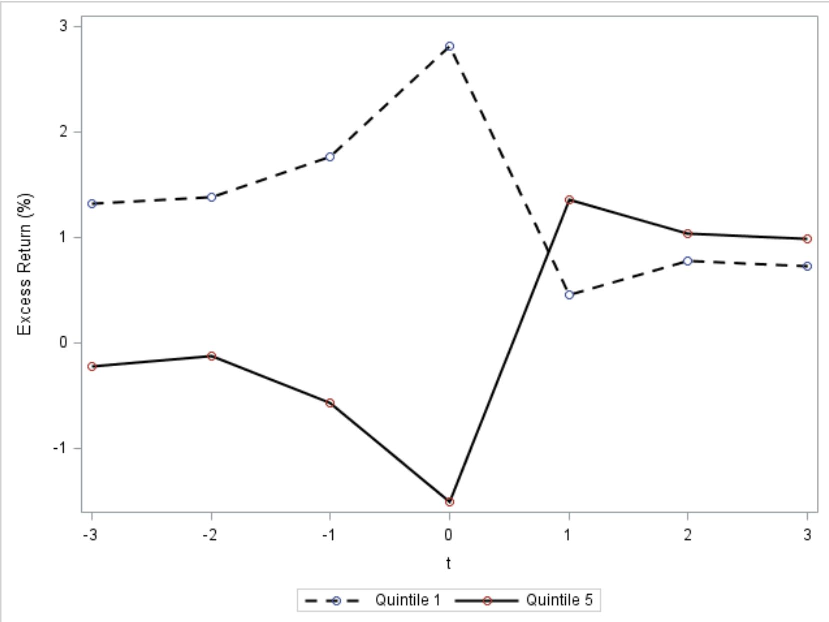
Portfolio	Max	Min	Mean	Std	Kurt	Skew	Sharpe Ratio	Infor. Ratio	Corr	α	t-stat
1998.03 - 2016.06											
WML[-12,-2]	20.19	-35.17	6.96	25.34	5.10	-1.30	0.27	-	-	-	-
β_{SKEW} Q1	29.78	-22.00	17.37	25.34	1.83	0.28	0.69	0.42	0.51	1.15%**	2.26
1998.03 - 2016.06											
WML[-12,-7]	22.70	-24.28	10.76	25.34	1.09	-0.10	0.42	-	-	-	-
β_{SKEW} Q1	29.78	-22.00	17.37	25.34	1.83	0.28	0.69	0.35	0.72	0.82%*	1.81
1998.03 - 2016.06											
WML[-12,-2] *	25.92	-24.71	14.82	25.34	1.13	-0.05	0.58	-	-	-	-
β_{SKEW} Q1	29.78	-22.00	17.37	25.34	1.83	0.28	0.69	0.10	0.50	0.80%**	1.98
1998.03 - 2016.06											
DM Dynamic	32.18	-19.29	15.51	25.34	2.46	0.44	0.61	-	-	-	-
β_{SKEW} Q1	29.78	-22.00	17.37	25.34	1.83	0.28	0.69	0.06	0.19	-0.14%	-0.18

Figure 1: Excess Returns of RNS Quintile Portfolios Before and After Portfolio Formation.

Description: At the end of the portfolio formation month ($t = 0$), we rank stocks into quintiles in ascending order by their risk-neutral skewness (RNS) characteristic. The figure presents equal-weighted and value-weighted portfolio returns for RNS Q1 and Q5 portfolios before and after portfolio formation, illustrating the path-dependent relationship between RNS and performance reversals captured by Q5 (most positive) RNS that leads to momentum crashes. It is noteworthy that Q1 (most negative) RNS also captures a change in excess return magnitude, though not in sign like RNS Q5.

Interpretation: The negative reversal experienced by the Q1 (low RNS) stocks is consistent with the short-sale constraint explanation of the RNS anomaly. However, the reversal of the Q5 (high RNS) stocks cannot be explained by short-sale constraints.

(a) Equal-Weighted Returns



(b) Value-Weighted Returns

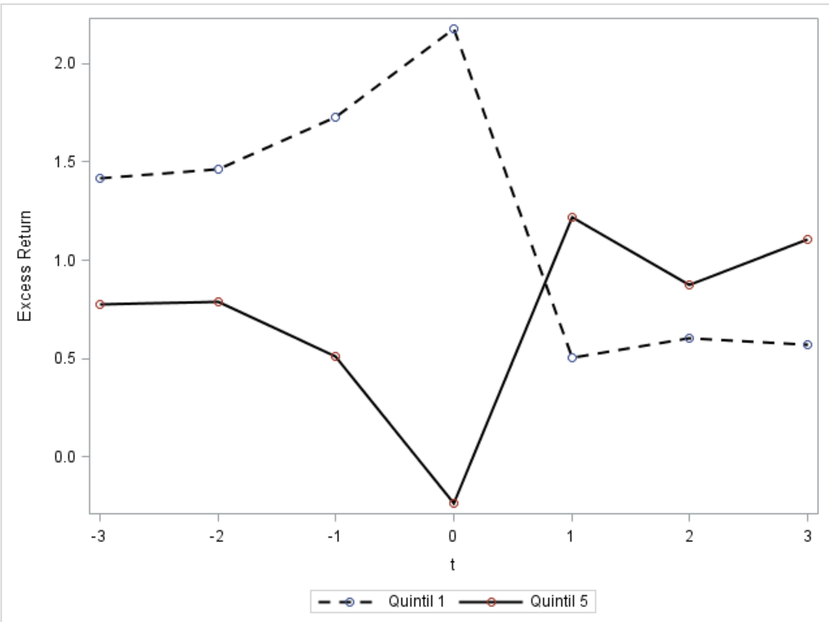


Figure 2: Comparison of Momentum Crash Factor SKEW and H-L β_{SKEW} Portfolio Returns.
Description: Each calendar month, we rank stocks into quintiles in ascending order by their 5-year loadings on the momentum crash factor SKEW β_{SKEW}. We define the H-L β_{SKEW} portfolio as the value-weighted portfolio long (short) the stocks with the highest (lowest) β_{SKEW}. We plot the RNS factor-mimicking portfolio SKEW (effectively the H-L RNS portfolio) and the H-L β_{SKEW} portfolio returns through Mar 1998 to June 2016. The correlation between the two is 0.324 which is significant at the 1% level.
Interpretation: The zero-cost β_{SKEW} portfolio has a higher volatility than the zero-cost RNS factor SKEW, but the correlation between SKEW and the zero-cost β_{SKEW} portfolio returns is 0.324, statistically significant at the 1% level.

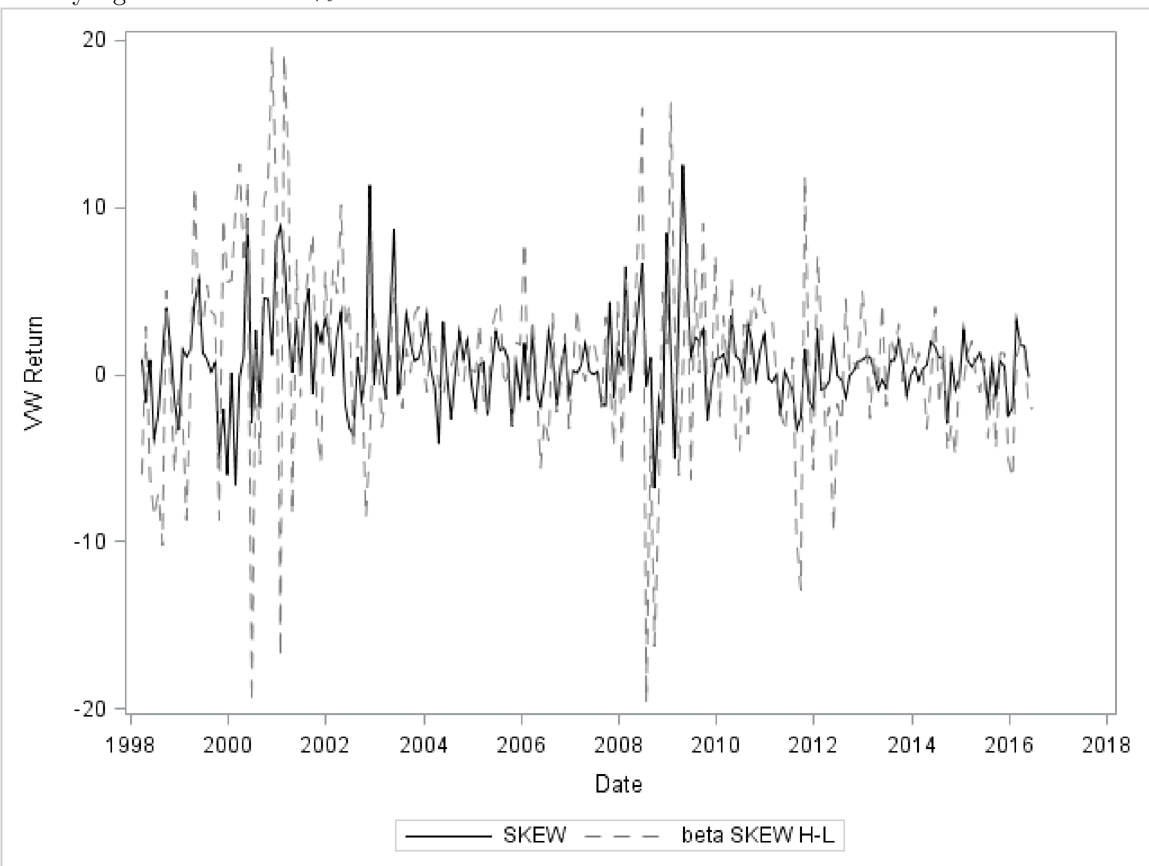


Figure 3: Comparison of Momentum Portfolio Performance with Risk Management and Reversal Avoidance. **Description:** This figure plots the cumulative log monthly returns to the baseline winner-minus-loser momentum (WML) strategy, the risk managed momentum strategy in Barroso and Santa-Clara (2015), the Novy-Marx (2012) momentum strategy constructed using CRSP stocks in β_{SKEW} Q1 avoiding stock rebounds, and the Novy-Marx (2012) momentum strategy constructed using all CRSP stocks over the period from September, 1998 through June, 2016.

Interpretation: A visualization of the extent to which using the SKEW factor-mimicking portfolio to isolate stocks with low likelihood of rebounds, and therefore low risk of momentum crashes, improves momentum performance. Momentum on β_{SKEW} Q1 stocks has the highest cumulative log return relative to other recently proposed momentum improvements.