Risk Neutral Skewness Anomaly and Momentum Crashes*

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Abstract

We find a relationship between negative momentum and positive risk-neutral skewness (RNS) in stocks. In economic recessions and high market volatility periods, a zero investment portfolio that is long the stocks with highest RNS and short those with the lowest RNS has significant positive abnormal returns. This paper explores the relationship of the RNS anomaly and momentum crashes and finds that the WML strategy within the highest RNS portfolio experiences the most severe momentum crashes following market declines and high volatility periods. These results hold controlling for size and other firm characteristics. We construct a RNS-based momentum crash predictor and find that a momentum strategy that avoids stocks with the highest likelihood of momentum crashes significantly improves performance.

Keywords: Risk Neutral Skewness; Momentum; Return Predictability

JEL classification: G12, G13

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1 Introduction

We find that in economic recessions and periods of high market volatility a zero investment portfolio on risk-neutral skewness (RNS) has greater positive abnormal returns and a higher market beta. Furthermore, we find a negative relationship between RNS and momentum, so the zero-cost RNS portfolio is effectively short momentum.

Daniel and Moskowitz (2016) find that momentum strategies can experience infrequent negative returns that are persistent especially in economic recessions and high market volatility periods. The market beta of the momentum strategy is lower in periods of high market stress. We conjecture that the risk neutral skewness anomaly picks up momentum crashes. We examine the relation of risk neutral skewness anomaly and momentum crashes by independently sorting our sample by risk neutral skewness and past performance into terciles, resulting in nine portfolios. We form a momentum strategy in each RNS tercile and regress the equally- and value-weighted excess returns of these WML portfolios on a set of time series.

We find that the momentum strategy in the high RNS tercile experiences the most severe crashes. We control for size and find that for the smallest size tercile momentum strategies in all RNS terciles experience a similar level of momentum crashes. However, in the median and large size terciles, the momentum strategies in the highest RNS terciles earn the lowest returns in recessions and periods of high market volatility. Conversely, the lowest RNS tercile experiences the least number of momentum crashes.

To generalize this finding to stocks without traded options necessary to compute RNS, we construct a momentum crash factor using risk neutral skewness data. We find that a momentum strategy on stocks with the lowest momentum crash factor loadings avoids momentum crashes, regardless of whether they have traded options.

This study contributes to the asset pricing anomaly literature, and to our understanding of the pricing of skewness. Stilger, Kostakis, and Poon (2016) have documented that risk-neutral skewness positively predicts expected equity returns. They provide evidence that stocks with the most negative risk neutral skewness are too costly or too risky to sell short and are thus overpriced, predicting poor future performance. However, they also find that short sale constraints cannot fully explain the risk neutral skewness anomaly.

Hirshleifer, Hou, and Teoh (2012) examine whether the accrual anomaly can be explained by rational risk theory or is a misvaluation by investors. They find that it is the accrual anomaly rather than the accrual factor loading that predicts returns, therefore the rational risk theory is rejected in favor of behavioral explanation. Hou, Xue, and Zhang (2015) derive a four-factor model from q-theory to explain the existing 74 anomalies. Stambaugh and Yuan (2017) extract two mispricing factors from eleven anomalies. Stilger et al. (2016) find the risk neutral skewness anomaly, and they contribute the positive abnormal returns to the short sale constraints. We further explore the risk neutral skewness anomaly and find that it picks up the momentum crashes documented in Daniel and Moskowitz (2016).

The remainder of the paper as follows. In Section II, we show the data and method to construct the risk neutral skewness measure. Section III we examine the time-varying beta and option-like payoffs of the zero-investment portfolio traded on risk neutral skewness. In Section IV we examine that whether the risk neutral skewness anomaly picks up the momentum crashes documented in Daniel and Moskowitze (2016). We construct a momentum crash factor using the risk neutral skewness data and examine whether the momentum strategy using stocks with the lowest momentum crash factor loadings can alleviate the crashes in Section V. We conclude in Section VI.

2 Data and Variable Construction

In this section, we describe the data and the method used to extract individual stock risk neutral skewness. Following Bakshi, Kapadia, and Madan (2003), we denote the 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 claim 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:

$$E_t^*\{H[S]\} = \int_0^\infty H[S]q[S]dS \tag{1}$$

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:

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

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:

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

where

$$\begin{aligned} \mu(t,\tau) &\equiv E_t^* ln[\frac{S(t+\tau)}{S(t)}] \\ &= e^{r\tau} - 1 - \frac{e^{r\tau}}{2}V(t,\tau) - \frac{e^{r\tau}}{6}W(t,\tau) - \frac{e^{r\tau}}{24}X(t,\tau) \end{aligned} \tag{4}$$

$$V(t,\tau) = \int_{S(t)}^{\infty} \frac{2(1 - ln[\frac{K}{S(t)}])}{K^2} C(t,\tau;K)dK + \int_0^S (t) \frac{2(1 + ln[\frac{S(t)}{K}])}{K^2} P(t,\tau;K)dK \tag{5}$$

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

$$\begin{aligned} X(t,\tau) = &\int_{S(t)}^{\infty} \frac{12(ln[\frac{K}{S(t)}])^2 - 4(ln[\frac{K}{S(t)}])^3}{K^2} C(t,\tau;K)dK \\ &+ \int_0^S (t) \frac{12(ln[\frac{S(t)}{K}])^2 + 4(ln[\frac{S(t)}{K}])^3}{K^2} P(t,\tau;K)dK \end{aligned} \tag{7}$$

We use the RNS extracted from OTM standardized options data with 30 days to expiration from the Volatility Surface file in Ivy DB's OptionMetrics. The Volatility Surface file contains the interpolated volatility surface for each security on each day, using a methodology based on a kernel smoothing algorithm. This file contains information on standardized options, both calls and puts, with expirations of 30, 60, 91, 122, 152, 182, 273, 365, 547, and 730 calendar days. A standardized option is only included if there exists enough option price data on that date to accurately interpolate the required values.

We use standardized options with 30 days to expiration for two reasons: first, these are the most liquid options, and second, they are the least out-of-the-money on average[1]. We require that at a given day, a stock has at least two OTM calls and two OTM puts with the same maturity. We use equal numbers of OTM calls and puts for each stock for each day. If there are n OTM puts available on day t, we require n OTM call prices. If there are $N > n$ OTM call prices available on day t, we use the n OTM calls that are the least out-of-the-money. We keep the set of options with the shortest maturity if there are more than one maturities available for one stock on a given day.

[1]See Table AI Panel C

We extrapolate the 30-day risk-free rate from Treasury bill rates. We interpolate the implied volatilities of the available options using a piecewise Hermite polynomial separately for put and call options, following Stilger et al. (2016). We also extrapolate outside the lowest and highest moneyness using the implied volatility at each boundary and fill in 997 grid points in the moneyness range from 1/3 to 3. We then use the Black-Scholes model to convert the implied volatilities into the corresponding option prices and then using Simpson's rule to calculate the integrals in equation (5) (6) and (7). 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.

In Table I we present the descriptive statistics for risk neutral skewness, as well as other firm-specific data used in subsequent analysis: market capitalization MV, monthly return RET_t, one-month lagged return RET_{t-1}, cumulative return over the past eleven months lagged one month $RET_{t-12,t-2}$, intermediate horizon past performance $RET_{t-12,t-7}$, recent past performance $RET_{t-6,t-2}$, beta β_M^i, stock trading volume and book-to-market ratio. We calculate market capitalization by multiplying the close price of the last trading day of this month and shares outstanding. RET_t is the monthly return for time t, and $RET_{t-12,t-2}$ is the cumulative return over the period from $t-12$ to $t-2$, capturing the momentum effect.

Following Novy-Marx (2012), we separate the past performance into two components: the intermediate horizon past performance $RET_{t-12,t-7}$ and the recent past performance $RET_{t-6,t-1}$. We estimate firm beta β_M^i by regressing the excess equity returns on the Fama and French (1993) three-factor model over the past sixty months. 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 I. The sample consists of 592,480 firm-month combinations from Jan 1996 through April 2016. The mean risk neutral skewness is -0.198 while the median risk neutral skewness 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 under the physical distribution are negatively skewed. The average β_M^i in our sample is 1.313, while the median β_M^i is 1.175. In Panel B of Table I, we report the time series average of cross section correlation coefficients between the risk neutral skewness and the firm-specific variables. The lower triangular matrix presents the Pearson correlation matrix; the upper triangular matrix shows the nonparametric Spearman correlation matrix.

Table II presents the cross-sectional relationship between risk neutral skewness (RNS) and expected returns controlling for firm characteristics. Consistent with Stilger, Kostakis and Poon (2016) results (0.0073 with significance at the 1% level), the risk neutral skewness RNS has a coefficient of 0.716 with significance at the 1% level in Column (1) of Table II[2]. Column (2) of Table II presents Fama MacBeth (1973) regressions of excess returns on firm characteristics: β_M^i, log of market capitalization (ln(MV)), log of book-to-market ratio (ln(BM)), one month lagged return RET_{t-1}, cumulative returns over past eleven months lagged one month $RET_{t-12,t-2}$, and log of stock trading volume (ln(VOLUME)). One month lagged return RET_{t-1} negatively predicts future return, consistent with the short-term momentum reversal effect. Cumulative returns over the past eleven months lagged month positively predict future expected return, consistent with the momentum effect. Coefficients on other firm characteristics are insignificant. Column (3) of Table II presents the cross-sectional findings for risk neutral skewness (RNS) controlling for firm characteristics. The magnitude of coefficient becomes smaller compared with the coefficient in Column (1) from 0.726 decreased to 0.675. However, the risk neutral skewness still positively predicts future expected return after controlling for the firm characteristics. After adding risk neutral skewness, the significance level of the coefficient on $RET_{t-12,t-2}$ becomes higher, shedding some light on the possible relation between momentum effect and risk neutral skewness which is worth further investigation. In column (4) and (5) we use $RET_{t-12,t-7}$ as a proxy of

[2]We regress excess return $\times$ 100 on risk neutral skewness, so our result is comparable to Stilger, Kostakis and Poon (2016)

momentum effect, while in column (6) and (7) we use $RET_{t-6,t-2}$ as a proxy of momentum effect. We find that the coefficients on $RET_{t-12,t-7}$ are significant at 5% level with a higher magnitude, and the coefficients on $RET_{t-6,t-2}$ are insignificant, consistent with Novy-Marx (2013).

We next create a portfolio sort and report the quintile portfolios' characteristics and excess returns as well as abnormal returns benchmarked by the Carhart (1997) four-factor model (Carhart α) in Table III. In Panel A we present the result for the five equally-weighted portfolios sorted by risk-neutral skewness, which demonstrates a positive relation between risk-neutral skewness and future stock returns over the subsequent month. We also tabulate the portfolio characteristics, finding that the portfolio with the highest RNS has negative past performance. 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%. The excess return and abnormal return of strategy based on risk neutral skewness benchmarked by Carhart (1997) four-factor model are 0.61% and 0.55%, respectively, in Stilger et al. (2016). The portfolio with the lowest RNS has a Carhart alpha -0.39% significant at 1% level while the portfolio with highest RNS has a Carhart alpha 0.55% significant at 1% level. These results confirm that there is a statistically significant positive relation between risk neutral skewness and future stock returns and further confirm that the stocks with the most negative risk neutral skewness are underperformed in the future, which is consistent with the evidence provided in Stilger et al. (2016).

Table III Panel B presents analogous results for five value-weighted portfolios sorted on the risk-neutral skewness. This weighting scheme de-emphasizes the role of small stocks in portfolio abnormal returns. As before, The zero-cost portfolio has significantly positive monthly abnormal returns relative to Carhart (1997) four factor model with a magnitude of 0.70% at the 1% significance level. The value weighted excess return is also positive and significant at the 1% level with a magnitude of 0.71%. As we can see, the abnormal returns are lower compared to those of equally-weighted portfolios. The value weighted portfolio results presented in Table III Panel B reveal that the portfolio with the highest RNS generates significant positive abnormal returns, while the portfolio with the lowest RNS generates significant negative abnormal returns. Our finding contradicts the short sale constraints theory, which predicts that the profit comes from the short (low RNS) leg of the zero-cost portfolio rather than the long leg (high RNS). The finding that both legs generate significant returns suggests that the short sale constraint theory proposed by Stilger et al. (2016) cannot fully explain the risk neutral skewness anomaly.

To provide evidence that our method extracting RNS is comparable to the method used in Stilger et al. (2016), we replicate their results. We follow their procedures to filter the traded option data in OptionMetrics from January 1996 to April 2016. The sample consists of 145,666 firm-month observations from January 1996 to April 2016, and 108,258 firm-month observations over the sample period from January 1996 to December 2012 used in Stilger et al. (2016), comparable to their 128,960 firm-month observations. Table AI presents the summary statistics of the OTM options used in our sample. Panel A reports the descriptive statistics for the full sample period and Panel B reports the summary statistics for the Stilger et al. (2016) sample period. The mean and median RNS over the Stilger et al. (2016) sample period is -0.331 and -0.320 respectively, slightly higher than the mean and median RNS in Stilger et al. (2014), -0.446 and -0.418 respectively. The mean and median days to expiration for the OTM options are 85.03 and 80 respectively, which assemble the Stilger et al. (2016): 86.56 and 81 respectively. The mean moneyness of OTM call options and OTM put options are 0.911 and 1.12 comparing to 0.896 and 1.142 in Stilger et al. (2016). For each stock, we use 5.06 OTM options to compute RNS, comparing 5.60 OTM options in Stilger et al. (2016). Open interest and trading volume per OTM option used are also comparable to the data in Stilger et al. (2016).

Then we sort stocks into quintiles by RNS and report the excess returns as well as abnormal returns benchmarked by the Capital Asset Pricing Model (CAPM α), Fama and French (1993) three-factor model (FF3 α), Fama and French (1993) five factors model(FF5 α), the Carhart (1997) four-factor model (Carhart α) and the Carhart (1997) four factor model with Pastor and Stambaugh (2003) liquidity factor (Carhart + Liq α). We follow the standard procedure to form zero-cost portfolios that are long the stocks in the highest RNS quintile and short the stocks in the lowest quintile. The t-statistics are adjusted using Newey and West (1987) standard errors with a lag of 6 months to control for autocorrelation in returns.

Table AII Panel A presents returns of the five equally-weighted portfolios sorted by risk-neutral skewness and it demonstrates a positive relation between risk-neutral skewness and future stock returns over the subsequent month consistent with the evidence provided in Stilger et al. (2016). The zero cost portfolio has significantly positive monthly abnormal returns relative to all benchmark models ranging from 0.45% at the 5% significance level relative to the CAPM model to 0.58% significant at the 1% level relative to the Fama and French (2015) five-factor model. The raw equal-weighted excess return is also positive and significant at the 1% level with a magnitude of 0.60%. These magnitudes are similar to those reported in Stilger et al. (2016). The portfolio with lowest RNS generates negative abnormal returns ranging from -0.41% at the 5% significance level relative to Fama and French (2015) five factor model to -0.58% significant at 5% level relative to Fama French three factor model while the portfolio has a Carhart alpha -0.32% significant at 5% level benchmarked by Carhart four factor model. These results confirm that there is a statistically significant positive relation between risk neutral skewness and future stock returns and that stocks with the most negative risk neutral skewness underperform in the future.

However, portfolio weighting makes a significant difference relative to the findings of Stilger et al. (2016). Table AII Panel B presents analogous results for five value-weighted portfolios sorted on the risk-neutral skewness. This weighting scheme de-emphasizes the role of small stocks in portfolio abnormal returns. As before, The zero cost portfolio has significantly positive monthly abnormal returns relative to all benchmark models ranging from 0.65% at the 1% significance level relative to the CAPM Model and the Carhart (1997) four factor model with the Pastor and Stambaugh (2003) Liquidity factor to 0.70% significant at the 1% level relative to the Fama and French (2005) five factor model. The raw value weighted excess return is also positive and significant at the 1% level with a magnitude of 0.74%. As we can see, the abnormal returns are higher compared to those of equally-weighted portfolios.

Importantly, the finding contradicts the short sale constraint theory proposed by Stilger et al. (2016). The value weighted results presented in Table AII Panel B show that the portfolio with highest RNS generates significant positive abnormal returns, while the portfolio with lowest RNS generates negative, however insignificant, abnormal returns. The short sale constraints theory predicts that the profit to the zero-cost RNS strategy comes from the short leg of the strategy containing the negative RNS stocks. However, the evidence in Table AII Panel B suggests that the RNS anomaly cannot be explained by only considering the short leg, since value-weighted abnormal returns come from the long leg instead.

We also use 60-, 91-, 122-, 152-, and 182-days standardized options data from the Volatility Surface file in IvyDB's OptionMetrics to extract RNS as a robustness check. We follow the same procedure to extract RNS on the last trading day of each month and use this RNS measures to construct portfolios. Table AI Panel C presents the summary statistics of the OTM options used in our sample. We report the mean, median, five percentile, 95 percentile and standard deviation of RNS extracted from volatility surface, and moneyness of OTM call options and OTM put options used to construct RNS measures over the full sample period on the left panel and the Stilger et al. (2016) sample period on the right panel. The mean and median RNS monotonically decrease as the days to expiration increase from -0.198 and -0.236 for 30 days to expiration to -0.412 and -0.441 for 182 days to expiration for our full sample. The same pattern is observed in the Stilger et al. (2016) sample. We also find that the moneyness of OTM call options monotonically decreases as the days to expiration increase and the moneyness of OTM put options monotonically increases as the days to expiration increase, which means the days to expiration increase, the options used are more out-of-the-money. Therefore, the more negative RNS in Stilger et al. (2016) is caused by options with longer maturity and lower moneyness.

We follow the standard procedure to form zero-cost portfolios that are long (short) the stocks in the highest (lowest) quintile of risk-neutral skewness. To control the autocorrelation in returns, the t-statistics are adjusted using Newey and West (1987) standard errors with a lag of 6 months. In Table AIII Panel A we present results for the five equally-weighted portfolios sorted by risk-neutral skewness for each standardized maturity. The zero cost portfolios have significantly positive monthly abnormal returns relative to Carhart (1997) four-factor model ranging from 0.41% at the 1% significance level for 182 days to maturity to 0.94% significant at the 1% level for 30 days to expiration. The raw equally weighted excess return is also positive and significant at the 1% level with a magnitude ranging from 0.46% for 182 days to maturity to 0.89% for 30 days to maturity. However, we find portfolios with highest RNS have statistically significant positive abnormal returns and portfolios with most negative risk neutral skewness have insignificant abnormal returns for maturities greater than 30 days, providing additional evidence against the short sale constraints channel as the cause of abnormal zero-cost RNS portfolio returns.

Table AIII Panel B presents analogous results for five value-weighted portfolios sorted on the risk-neutral skewness for each days to expiration. This set of results de-emphasizes the role of small stocks in portfolio abnormal returns. As before, The zero cost portfolios have significantly positive monthly abnormal returns relative to Carhart (1997) four-factor model ranging from 0.61% at the 1% significance level for 182 days to maturity to 0.74% significant at the 1% level for 152 days to expiration. The raw value weighted excess returns are also positive and significant at the 1% level with a magnitude ranging from 0.61% for 182 days to maturity to 0.75% for 91 days to maturity. As we can see again, the abnormal returns are higher comparing to equally-weighted portfolios. The value weighted portfolio results presented in Table AIII Panel B confirm that the portfolio with highest RNS generates significant positive abnormal returns, while the portfolio with lowest RNS generates negative but insignificant abnormal returns. This finding also contradicts two implications of the short sale constraints theory. First, abnormal returns should be driven by the short-sale constrained low RNS stocks in the short leg of the zero-cost portfolio (Stilger et al., 2016). Second, since smaller stocks are more likely to be short-sale constrained, the value weighted zero-cost portfolio should underperform the equal-weighted one. Neither of these predictions obtain in our results in Table AIII.

3 Risk Neutral Skewness and Momentum

3.1 Time-Varying Beta and Option-Like Payoffs in RNS portfolios

Daniel and Moskowitz (2016) show that in economic recessions and periods of high market volatility the down-market betas of negative momentum stocks are low, but their up-market betas are very large. Consequently when the market starts to rebound, these negative momentum stocks experience strong gains resulting in a momentum crash. Since Table III demonstrates that stocks with high RNS have negative momentum, in this section we consider whether the positive abnormal return generated by the RNS strategy is related to the time-varying beta and option-like payoffs of the momentum strategy.

We first illustrate these issues with a set of four monthly time series regressions, the results of which are presented in Table IV. The dependent variables are equal- and value-weighted RNS quintile portfolio returns. The independent variables are combinations of

- $\tilde{R}_{m,t}$, the CRSP value-weighted index excess return in month t.
- $I_{B,t-1}$, a recession indicator that equals one if the cumulative CRSP VW index return in the past 24 months is negative and zero otherwise.

- $\tilde{I}_{U,t}$, a contemporaneous up-market indicator variable that is one if the market risk premium is greater than zero and zero otherwise.[3]

We present the regression coefficients for equal- and value-weighted portfolio returns in Table IV Panel A and Panel B, respectively. Panel A Model 1 in Table IV fits an unconditional market model to the equally-weighted RNS-sorted portfolios as well as a long-short portfolio:

$$\tilde{R}_t = \alpha_0 + \beta_0 \tilde{R}_{m,t} + \tilde{\epsilon}_t$$

Consistent with Daniel and Moskowitz (2016) the estimated market beta is 0.33[4] and the intercept, α_0, is both economically large (.70% per month) and statistically significant. The α_0 of the portfolio with the lowest RNS is negative and statistically significant while it is positive and insignificant for the portfolio with the highest RNS, consistent with Stilger et al. (2016).

Model 2 fits a conditional CAPM with the bear market indicator, I_B, as an instrument:

$$\tilde{R}_t = \alpha_0 + (\beta_0 + \beta_B I_{B,t-1}) \tilde{R}_{m,t} + \tilde{\epsilon}_t$$

This specification captures the beta changes in economic recessions. The beta of the strategy during the recessionary periods is significantly higher with a magnitude of 0.24 and a t statistics of 2.95.

Model 3 introduces a contemporaneous up-market indicator variable $I_{U,t}$ that equals 1 if the market risk premium is positive, and equals 0 otherwise:

$$\tilde{R}_t = \alpha_0 + (\beta_0 + I_{B,t-1}(\beta_B + \tilde{I}_{U,t}\beta_{B,U}))\tilde{R}_{m,t} + \tilde{\epsilon}_t$$

[3]We get the market risk premium from the Kenneth French Data Library.

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

This specification allows us to assess the extent to which the up- and down-market betas of the RNS portfolios differ. The highly significant $\hat{\beta_{B,U}}$ of 0.50 shows that the zero-cost RNS portfolio does very well when the market rebounds following a recession. During recessions, the point estimates of the long-short portfolio beta 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 portfolio behaves similarly to a call option on the market, losing relatively little value during downturns, but gaining substantial value during rebounds. For the high RNS quintile, the down-market beta is 1.40 (1.22 + 0.18) while the up-market beta is 1.91 (1.40 + 0.51). In contrast, the up-market beta increment for the low RNS quintile is not statistically significant. The net effect is that a long-short portfolio traded on RNS will have significant positive market exposure to rebounds following bear markets, primarily coming from the long leg (high RNS) of the zero-cost RNS strategy. This finding provides an alternative explanation for the RNS anomaly to the short sale constraint theory, which focuses on the short (low RNS) leg of the strategy.

Panel B presents analogous results using value-weighted portfolio returns as dependent variables. Model 1 finds a lower but significant beta of .09, and a similar monthly alpha of .66% for the zero-cost high minus low RNS strategy. Model 2 shows that the beta of the zero-cost strategy is 0.31 higher in recessionary periods with statistical significance. Model 3 confirms the option-like behavior observed for equal-weighted results in Panel A, with the zero-cost RNS strategy having a .14 beta during market downturns but a .43 beta during subsequent rebounds.

3.2 Market Stress and Risk Neutral Skewness Anomaly

Daniel and Moskowitz (2016) show that the expected return of the WML portfolio should be a decreasing function of the future variance of the market. If risk neutral skewness captures the momentum crashes, the expected return of the long-short portfolio traded on RNS should be an increasing function of the future variance of the market. We test this hypothesis by regressing the RNS sorted portfolio returns as well as the long-short portfolio return on a set of five time-series models and report the regression coefficients in Table V.

We estimate the market variance over the coming month as $\sigma^2_{m,t-1}$, the variance of the daily returns of the market over the 126 days prior to time t. Panel A of Table V presents the regression coefficients of the equal-weighted quintile portfolios. Model 1 and Model 2 regress the RNS-sorted portfolios as well as a long-short portfolio on the bear market indicator $I_{B,t-1}$ and the market variance $\sigma^2_{m,t-1}$ separately:

$$\tilde{R}_t = \gamma_0 + \gamma_0 I_{B,t-1} + \tilde{\epsilon}_t$$

and

$$\tilde{R}_t = \gamma_0 + \gamma_{\sigma^2_{m,t-1}} \sigma^2_{m,t-1} + \tilde{\epsilon}_t$$

Model 3 fits the model including both variables simultaneously:

$$\tilde{R}_t = \gamma_0 + \gamma_0 I_{B,t-1} + \gamma_{\sigma^2_{m,t-1}} \sigma^2_{m,t-1} + \tilde{\epsilon}_t$$

The results are consistent with those from Section 3.1. That is, in periods of high market stress, as indicated by bear markets and high volatility, future long-short portfolio returns are high.

Model 4 runs a regression of RNS sorted portfolio returns on the interaction of the bear market indicator and market variance:

$$\tilde{R}_t = \gamma_0 + \gamma_{int} I_{B,t-1} \sigma^2_{m,t-1} + \tilde{\epsilon}_t$$

The results show that the performance of the risk neutral skewness strategy is particularly good during bear markets with high volatility. In summary, the risk neutral skewness strategy has a better performance in periods of high market volatility. Since the risk neutral skewness strategy is long negative momentum stocks (past losers) and short high momentum stocks (past winners), the high positive returns in the periods of high market stress is the reversal of the momentum crashes defined by Daniel and Moskowitz (2016).

Panel B presents similar results while the dependent variables are value-weighted portfolio returns, suggesting our results are robust to firm size effects.

4 Risk Neutral Skewness Anomaly and Momentum Crashes

4.1 Market Risk in the Momentum and RNS Double Sorted Portfolios

In this section, we explore the performance of momentum strategy across different levels of risk neutral skewness in recessions and periods of high market volatility. At the end of each calendar month, we independently sort firms into terciles by $RET_{T-12,T-7}$[5] and by RNS. In each RNS tercile, we regress the equal- and value-weighted WML portfolio returns on market timing models and report the results on the left and right panels, respectively, in TableVI.

Model 1 fits an unconditional CAPM to the WML portfolio return in each RNS tercile:

$$\tilde{R}_{WML,t} = \alpha_0 + \beta_0 \tilde{R}_{m,t} + \tilde{\epsilon}_t$$

The WML strategy in highest RNS tercile has relative lower market beta. The differences of β_0 between the WML strategy in high and low RNS tercile for equally- and value-weights scheme are -0.08 and -0.10, respectively.

In the left panel, Model 2 fits a conditional CAPM with the bear market indicator I_B:

$$\tilde{R}_{WML,t} = \alpha_0 + (\beta_0 + \beta_B I_{B,t-1}) \tilde{R}_{m,t} + \tilde{\epsilon}_t$$

[5] Norv-Marx (2013) shows that the momentum anomaly is mainly driven by this intermediate-horizon past performance.

This specification is an attempt to capture market-beta differences in economic recessions. For the equally-weighted portfolios, the market betas of the WML portfolios are all economically and statistically significantly lower in the bear markets ranging from -0.70 to -0.64. However, the difference of β_B between the WML strategy in high and low RNS tercile is insignificant. For value-weighted portfolios, the market betas of the WML portfolios are all economically and statistically significantly lower in the bear markets ranging from -0.96 to -0.74. And the difference of β_B between the WML strategy in high and low RNS tercile is marginally significant.

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

$$\tilde{R}_{WML,t} = \alpha_0 + (\beta_0 + I_{B,t-1}(\beta_B + \tilde{I}_{U,t}\beta_{B,U}))\tilde{R}_{m,t} + \tilde{\epsilon}_t$$

This specification allows us to assess the extent to which the up- and down-market betas of the long-short portfolio differ. For the equally-weighted WML strategy in the high RNS tercile, the $\hat{\beta_{B,U}}$ of -0.29 (t-statistic= -1.45) shows that the momentum strategy does badly when the market rebounds following a bear market, although statistically insignificant. When in a bear market, the point estimate of the WML portfolio in high RNS tercile beta is -0.49 $(= \hat{\beta_0} + \hat{\beta_B})$ when the contemporaneous market return is negative and $= \hat{\beta_0} + \hat{\beta_B} + \hat{\beta_{B,U}} =$ -0.78 when the market return is positive. It means that the WML portfolio in the high RNS tercile is effectively short a call option on the market. For the WML portfolio in low RNS tercile, the down-market beta is -0.50 (= 0.14 + (-0.64)) and the point estimate of the up-market beta is -0.50 (= -0.50 + (-0.00)). The up-market beta increment for the WML portfolio in low RNS tercile is insignificantly negative (= -0.00). The difference between the equally-weighted WML portfolios in the high and low RNS tercile is -0.29 with a t-statistic of -2.58. For the value-weighted WML strategy in the high RNS tercile, the $\hat{\beta_{B,U}}$ of -0.34 (t-statistic= -1.40) shows that the momentum strategy does very badly when the market rebounds following a bear market again. When in a bear market, the point estimate of the

WML portfolio in high RNS tercile beta is -0.62 (= $\hat{\beta_0} + \hat{\beta_B}$) when the contemporaneous market return is negative and = $\hat{\beta_0} + \hat{\beta_B} + \hat{\beta_{B,U}}$= -0.96 when the market return is positive. It confirms that the WML portfolio in the high RNS tercile is effectively short a call option on the market. For the WML portfolio in low RNS tercile, the down-market beta is -0.58 (= 0.19 + (-0.77)) and the point estimate of the up-market beta is -0.50 (= -0.58 + 0.08). The up-market beta increment for the WML portfolio in low RNS tercile is insignificantly negative (= 0.08) again. The difference between the value weighted WML portfolios in the high and low RNS tercile is -0.42 with a t-statistic of -2.21. This finding supports that the momentum crashes concentrate in the stocks with highest RNS tercile.

Since we find that the risk neutral skewness is highly correlated with size, in TableVII, we independently sort firms by market capitalization, $RET_{T-12,T-7}$ and RNS into terciles at the end of each calendar month. In each Size/RNS group, we form a WML portfolio and regress the equal- and value-weighted WML portfolio returns on the following time-series model:

$$\tilde{R}_{WML,t} = \alpha_0 + (\beta_0 + I_{B,t-1}(\beta_B + \tilde{I}_{U,t}\beta_{B,U}))\tilde{R}_{m,t} + \tilde{\epsilon}_t$$

We report the regression results on the left and right panels, respectively. We find that the magnitude of up-market beta decrement for the WML in the high RNS tercile is significantly larger than in the low RNS tercile for median and high size terciles. For small size tercile, the difference of $\beta_{B,U}$ is insignificant or even positive for the value weighted portfolios.

Since Stilger at al (2016) find that the short sale constraints could partially explain risk neutral skewness anomaly, in TableVIII, we independently sort firms by institutional ownership (as a proxy of short sale constraints), $RET_{T-12,T-7}$ and RNS into terciles at the end of each calendar month. In each Institutional Ownership/RNS group, we form a WML portfolio and regress the equal- and value-weighted WML portfolio returns on the following time-series model:

$$\tilde{R}_{WML,t} = \alpha_0 + (\beta_0 + I_{B,t-1}(\beta_B + \tilde{I}_{U,t}\beta_{B,U}))\tilde{R}_{m,t} + \tilde{\epsilon}_t$$

We report the regression results on the left and right panels, respectively. We find that the magnitude of up-market beta decrement for the WML in the high RNS tercile is significantly larger than in the low RNS tercile for low and high institutional ownership terciles for value-weighted WML returns while the magnitude of up-market beta decrement for the WML in the high RNS tercile is significantly larger than in the low RNS tercile for median and high institutional ownership terciles for equally-weighted WML returns. This finding is consistent with Stilger et al (2016)'s finding that the return of the zero-cost RNS strategy could be partially explained by the short sale constraints theory.

4.2 Market Volatility and the Momentum and RNS Double Sorted Portfolios

To further examine that the risk neutral skewness captures the momentum crashes effect, we regress the equally- and value-weighted WML portfolio returns in each RNS tercile on a set of five-time series models and report the results on left and right panels, respectively, in TableIX.

The left panel Table IX presents the regression coefficients of the equally-weighted quintile portfolios. Model 1 and Model 2 regresses the WML portfolio return in each RNS tercile on the bear market indicator $I_{B,t-1}$ and the market variance $\sigma^2_{m,t-1}$, separately:

$$\tilde{R}_{WML,t} = \gamma_0 + \gamma_0 I_{B,t-1} + \tilde{\epsilon}_t$$

and

$$\tilde{R}_{WML,t} = \gamma_0 + \gamma_{\sigma^2_{m,t-1}}\sigma^2_{m,t-1} + \tilde{\epsilon}_t$$

The WML strategy in highest RNS tercile experiences the most negative return in the bear markets and in the periods of high market volatility. The difference of $\gamma_{\sigma^2_{m,t-1}}$ between the WML strategy in high and low RNS tercile is -0.30% with a t-statistic -3.85. In the right panel, the difference of $\gamma_{\sigma^2_{m,t-1}}$ between the value-weighted WML returns in high and low RNS tercile is -0.28% with a t-statistic -2.08.

Model 3 fits the model including both variables simultaneously:

$$\tilde{R}_{WML,t} = \gamma_0 + \gamma_0 I_{B,t-1} + \gamma_{\sigma^2_{m,t-1}} \sigma^2_{m,t-1} + \tilde{\epsilon}_t$$

The WML portfolio with the highest RNS has the most negative return in bear markets and in periods of high market volatility. The difference of $\gamma_{\sigma^2_{m,t-1}}$ between the WML portfolios in high and low RNS terciles is -0.31 with a t-statistic -3.34, for the equal weights scheme and -0.32 with a t-statistic -2.01.

Model 4 runs a regression of WML portfolios returns on the interaction of the bear market indicator and market variance:

$$\tilde{R}_{WML,t} = \gamma_0 + \gamma_{int} I_{B,t-1} \sigma^2_{m,t-1} + \tilde{\epsilon}_t$$

These results show that the performance of the momentum strategy in the high RNS tercile is particularly bad during bear markets with high volatility. The difference of γ_{int} between the WML portfolios in high and low RNS terciles is -0.32 with a t-statistic -4.33 for the equal weights scheme and -0.32 with a t-statistic -2.56 for the value weights scheme.

We again independently sort firms by market capitalization, $RET_{T-12,T-7}$ and RNS into terciles at the end of each calendar month and form a WML portfolio in each size/RNS tercile. We then regress the equally- and value-weighted WML portfolio returns on the time series model:

$$\tilde{R}_{WML,t} = \gamma_0 + \gamma_{int} I_{B,t-1} \sigma^2_{m,t-1} + \tilde{\epsilon}_t$$

We report the regression results on the left and right panels of Table X, Panel A, respectively. We find that the momentum returns in high RNS tercile are shown to be particularly poor during bear markets with high market volatility in median size tercile. The coefficient γ_{int} monotonically decreases as the RNS increases in all size terciles for equally-weighted portfolios. For value-weighted portfolios, the coefficient on the interaction of bear market indicator and market variance monotonically decreases as the RNS increases in median and large size terciles.

To investigate whether the finding that the momentum returns in high RNS tercile are particularly poor during bear markets with high market volatility is robust after controlling for institutional ownership, we again independently sort firms by institutional ownership, $RET_{T-12,T-7}$ and RNS into terciles at the end of each calendar month and form a WML portfolio in each institutional ownership/RNS tercile. We then again regress the equally- and value-weighted WML portfolio returns on the time series model:

$$\tilde{R}_{WML,t} = \gamma_0 + \gamma_{int} I_{B,t-1} \sigma^2_{m,t-1} + \tilde{\epsilon}_t$$

We report the regression results on the left and right panels of Table X, Panel B, respectively. We find that the momentum returns in high RNS tercile are shown to be poor during bear markets with high market volatility in all institutional ownership terciles for equal weights scheme. The coefficient γ_{int} monotonically decreases as the RNS increases in all institutional ownership terciles for equally-weighted portfolios. For value-weighted portfolios, the coefficient on the interaction of bear market indicator and market variance monotonically decreases as the RNS increases in small and large institutional ownership terciles. And the differences are both significant at 1% level.

5 Risk Neutral Skewness Factor

We next construct a momentum crash factor (SKEW) to generalize our findings to stocks that do not have traded options that would allow a direct calculation of RNS. 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 confirm that it is not driven by stock optionability. In addition, this enables us to create a momentum crash predictor that is applicable to all stocks, not just those with traded options.

We construct the SKEW factor as follows: at the end of each calendar month, we rank stocks with traded options into five portfolios according to their risk neutral skewness measure (RNS). The risk-neutral skewness factor (SKEW) is the equally-weighted return of the portfolio that long the portfolio with highest RNS and short the portfolio with lowest RNS.

To examine whether the momentum crash factor SKEW produces similar portfolio returns as the RNS characteristic, we plot the momentum crash factor SKEW and the return on the portfolio that long the stocks with highest momentum crash factor loading and short the stocks with lowest momentum crash factor loading in Figure 1. In general, the H-L β_{SKEW} portfolio has a higher volatility. However, these two returns tend to move together. The correlation between SKEW and the H-L β_{SKEW} portfolio return is 0.55 with a significant level of 1%[6].

To examine whether the momentum strategy using the stocks with lower loadings

[6]One possible explanation that risk neutral skewness accurately predicts realized skewness, which would be most positive for stocks about to rebound upward. We test this hypothesis by running a cross-sectional regression of future realized skewness over a month on the risk neutral skewness, controlling for the realized skewness, and find the time series average of the coefficients, following Goyal and Saretto (2009). We first run a cross-sectional regression: $FS_{i,t+1} = \alpha_t + \beta_{1t} RNS_{i,t} + \beta_{2,t} HS_{i,t} + \epsilon_{i,t+1}$ where FV is the future realized volatility over the month t+1, RNS is the risk neutral skewness over the month t, and HV is the realized volatility over the month t each month, then calculate the time-series average of the regression coefficients. We also correct the standard error following Newey and West (1987) with a lag 6. The estimation is as following: FV=0.183 (15.01) +0.059 (10.83) RNS+0.015 (8.53) HV with t-statistics in the parentheses. We also run the regression: $FS_{i,t+1} = \alpha_t + \beta_{1t} \beta_{SKEW,i,t} + \beta_{2,t} HV_{i,t} + \epsilon_{i,t+1}$ and the result is as following: FV=0.162 (13.49) +0.035 (11.69) β_{SKEW}+0.029 (11.92) HV. These findings support our hypothesis that risk neutral skewness and the factor loading on the factor SKEW do predict future realized skewness.

on SKEW experiences less severe momentum crashes and therefore produces superior performance, we use a double sort procedure that sorts all the stocks traded on NYSE, AMEX, and Nasdaq by the factor loading β_{SKEW} and momentum. To estimate the SKEW factor loading, we run the following rolling window regression:

$$Exret = \alpha + \beta_M Mktrf + \beta_{SKEW} SKEW$$

over the past 60 months and β_{SKEW} is the factor loading on the SKEW. We require at lease 24 observations. Each calendar month, we rank stocks in ascending order by their β_{SKEW} and intermediate horizon past performance. We independently assign the ranked stocks to one of five β_{SKEW} groups using the all stocks universe breakpoints, and ten $RET_{t-12,t-7}$ groups using the NYSE breakpoints. Panel A, Panel B and Panel C of Table XI present the excess returns, Carhart αs and αs benchmarked by the Carhart four factors with Pastor and Stambaugh (2003) liquidity factor five factor model for the fifty value-weighted portfolios. The rightmost column presents the excess return, Carhart α and Carhart + Liq α of the momentum portfolio in each β_{SKEW} quintile. The WML strategy in the lowest β_{SKEW} quintile has the highest excess return, Carhart α and Carhart + Liq α: 1.63%, 1.38% and 1.52% per month with t-statistics 2.71, 3.49 and 3.49, respectively. The differences of excess returns, Carhart αs and Carhart + Liq α between the WML portfolio in the highest β_{SKEW} quintile and the lowest β_{SKEW} are all significant, suggesting that controlling for the SKEW factor loading results in superior performance of the momentum strategy. We also reports the WML strategy using all available stocks in each panel labeled as WML[-12,-7] All. We find that over the sample period of April 1998 to June 2016, the momentum strategy traded on the intermediate past loser and winner generates an excess return of 0.84% per month with a t-statistic 1.71. Benchmarked by Carhart four factor model, this strategy generates an abnormal return of 0.56% with a t-statistic 1.93. We also report the firm characteristics for the fifty portfolios formed on β_{SKEW} and $RET_{T-12,T-7}$ in Table AIV. In Panel A, we report the mean volume scaled by the number of shares outstanding for each of the fifty portfolios. From quintile 1 to quintile 5, the volume first decreases then increases. This finding provides evidence that the WML strategy in β_{SKEW} quintile 1 does not use the most illiquid stocks. To prove the WML strategy in β_{SKEW} quintile 1 does not use stocks with high short sale constraints, we report the institutional ownership in Panel B of Table AIV. Except decile 1 of $RET_{T-12,T-7}$, quintile 1 of β_{SKEW} has the highest institutional ownership. This piece of evidence further supports that the WML strategy in β_{SKEW} quintile 1 is a tradable strategy which does not utilize stocks with high short sale constraints. In Panel C, we report the mean bid-ask spread scaled by the stock price. Quintile 1 of β_{SKEW} has the second lowest bid-ask spread, except the first decile of $RET_{T-12,T-7}$, which has the third lowest bid-ask spread. This finding further supports that the stocks in β_{SKEW} quintile 1 do have higher liquidity compared to stocks in other quintiles. We plot the cumulative returns and cumulative Carhart+Liq αs in Figure 2 over the sample period April 1998 to June 2016. At the end of June 2016, the WML strategy in β_{SKEW} quintile 1 has a cumulative return of 1694.80% while the WML strategy using all stocks has a cumulative return of 289.15%. At the end of December 2016[7], the WML strategy in β_{SKEW} quintile 1 has a cumulative abnormal return of 1700.19% while the WML strategy using all stocks has a cumulative abnormal return of 262.29%. The new WML strategy that long the stocks in the top decile of the intermediate past performance and short the stocks in the bottom decile of the intermediate past performance in the bottom quintile of β_{SKEW} greatly improves the performance of the Novy-Marx (2013) WML strategy.

We repeat the double sorts in recessions and expansions and report the Carhart four factors with Pastor and Stambaugh (2003) liquidity factor αs in Table XII Panel A and Panel B, respectively. We find that the magnitude of the WML abnormal return is larger in recessions than in expansion: 1.97% per month versus 1.31% for the lowest β_{SKEW} quintile WML and 1.32% per month versus 0.42% for WML using all stocks.

[7]We get Pastor and Stambaugh (2016) liquidity factor from Wharton Research Data Services and it's only available until December 2015.

To further improve the performance of the low momentum crash factor loading Novy-Marx (2013) WML strategy, we employ the risk management method introduced by Barroso and Santa-Clara (2015). The variance forecast is:

$$\hat{\sigma^2}_{WML,t} = 21 \sum_{j=0}^{125} r^2_{WML,d_{t-1}-j}/126 \tag{8}$$

Then we scale the low momentum crash factor loading WML returns by the forecasted variance:

$$r_{WML[-12,-7]\beta_{SKEW}Q1*,t} = \frac{\sigma_{target}}{\hat{\sigma}_t} r_{WML[-12,-7]\beta_{SKEW}Q1,t} \tag{9}$$

where $r_{WML[-12,-7]\beta_{SKEW}Q1,t}$ is the unscaled low momentum crash factor loading Novy-Marx (2013) WML strategy, $r_{WML[-12,-7]\beta_{SKEW}Q1*,t}$ is the risk-managed low momentum crash factor loading Novy-Marx (2013) WML strategy and σ_{target} is the target level of variance. To have an average weight around 1, we choose 18% as the target variance[8]. Then we compare our two strategy: 1) low momentum crash factor loading Novy-Marx (2013) WML strategy WML[-12,-7] β_{SKEW} Q1 from April 1998 to June 2016 and 2) risk managed, low momentum crash factor loading Novy-Marx (2013) WML strategy WML[-12,-7] β_{SKEW} Q1* from October 1998 to June 2016 to the Barroso and Santa-Clara (2015) risk-managed WML strategy WML[-12,-2]*[9] and to each other in Table XIII. Comparing to the Barroso and Santa-Clara (2015) WML strategy, low momentum crash factor loading Novy-Marx (2013) WML strategy has a much higher average return of 23.64% per year, which is 14.41% higher than the Barroso and Santa-Clara (2015) WML strategy. Although the WML[-12,-7] β_{SKEW} Q1 strategy is much more volatile, the Sharpe Ratio of the strategy is one third higher than the risk-managed WML strategy. The information ratio of WML[-12,-7] β_{SKEW} Q1 compared to WML[-12,-2]* is 0.21.

[8] Barroso and Santa-Clara (2015) choose 12% as the target variance. However, over our sample period, if we pick up 12% target volatility, the weights are mostly below one.

[9] We thank Barroso and Santa-Clara generously share their data with us. Their time series is available until December 2011.

After we scale the strategy by the forecasted variance to manage the risk, the risk managed, low momentum crash factor loading Novy-Marx (2013) has an even higher Sharpe Ratio with a value of 1.16, more than double the Sharpe Ratio of WML[-12,-2]*. Compared with WML[-12,-2]*, the value of the Information Ratio of WML[-12,-7] β_{SKEW} Q1* is a very high: 0.79.

We also compare our two strategies in Panel C Table XIII and find that after we use the risk management method introduced in Barroso and Santa-Clara (2015), the Sharpe Ratio is greatly improved from 0.69 of WML[-12,-7] β_{SKEW} Q1 to 0.96 of WML[-12,-7] β_{SKEW} Q1*. The risk managed strategy has an Information Ratio of 0.90 compared to the plain one.

We report the raw returns, Carhart αs and Carhart + Liq αs of: 1) the plain WML strategy WML[-12,-2], 2) the Barroso and Santa-Clara (2015) risk managed WML strategy WML[-12,-2]*, 3) the Novy-Marx (2013) WML strategy WML[-12,-7], 4) the low momentum crash factor loading Novy-Marx (2013) WML strategy WML[-12,-7] β Q1 and 5) the risk managed low momentum crash factor loading Novy-Marx (2013) WML strategy WML[-12,-7] β Q1* over the sample period through April 1998 to December 2011[10] in Table AV. As we can see, the plain WML strategy generates insignificant raw returns. As defined, the Carhart α and Carhart + Liq α are insignificant. After applying the variance scaled weights, WML[-12,-2]* has a significant raw return, yet, insignificant abnormal returns. The WML strategy suggested by Novy-Marx (2013) WML[-12,-7] has an insignificant raw return, 0.89% with a t-statistic 1.89, while controlling for other risk factors, generates marginal significant abnormal returns: 0.67% per month Carhart α and 0.65% per month Carhart+Liq α, with t-statistics 2.08 and 2.13, respectively. The low momentum crash factor loading Novy-Marv (2013) WML strategy has a much larger raw return with a magnitude of 1.97% and a t-statistic of 3.67. Even controlling for other risk factors, including Carhart momentum factor, this strategy still has an abnormal return with a magnitude 1.77% per month and a t-statistic

[10]For the risk managed low momentum crash factor loading Novy-Marx (2013) WML strategy WML[-12,-7] β Q1*, the sample period is from October 1998 to December 2011

4.03. Controlling the Pastor and Stambaugh (2003) does not change the magnitude and significance of the abnormal return. Although the risk managed low momentum crash factor loading Novy-Marv (2013) WML strategy WML[-12,-7] β Q1* has a relative lower raw return, compared with the unscaled one, its abnormal returns have higher economic significance. The t-statistics for Carhart α and Carhart+Liq α are 4.88 and 4.93, respectively. This finding further supports that in recent two decades, the WML strategy has a hard time to make profit. However, using our momentum crash factor to exclude stocks with high momentum crash factor loadings greatly enhances the performance of the WML strategy.

Figure 3 plots the cumulative monthly returns of four strategies: 1) a baseline Winner-minus-Loser Strategy from Barroso and Santa-Clara (2015) WML[-12,-2], 2) the risk managed momentum strategy in Barroso and Santa-Clara (2015) WML[-12,-2]*, 3) the Novy-Marx (2012) momentum strategy constructed by stocks in β_{SKEW} quintile 1 WML[-12,-7] β_{SKEW} Q1, and 4) the Novy-Marx (2012) momentum strategy constructed by all stocks over the period WML[-12,-7] All from April, 1998 through December, 2011. By the end of December 2011, the low momentum crash factor loading Novy-Marx (2013) WML strategy WML[-12,-7] β_{SKEW} Q1 has a cumulative return of 1325.06%, compared to other WML strategies with cumulative returns ranging from 41.48% for the baseline WML strategy to 205.58% for the Barroso and Santa-Clara (2013) risk-managed WML strategy. This figure demonstrates the superior performance of the WML[-12,-7] β_{SKEW} Q1 over the most recent two decades and the importance to exclude stocks with high momentum crash factor loadings.

Figure 4 compares the risk-managed, low momentum crash factor loading Novy-Marx (2013) strategy WML[-12,-7] β_{SKEW} Q1* with 1) the risk managed momentum strategy in Barroso and Santa-Clara (2015) WML[-12,-2]* and 2) the Novy-Marx (2012) momentum strategy constructed by stocks in β_{SKEW} quintile 1 WML[-12,-7] β_{SKEW} Q1 in Panel A and Panel B, respectively. Again, the cumulative monthly return of WML[-12,-7] β_{SKEW} Q1* is 1190.64%, far better than WML[-12,-2]* which has a cumulative return 130.71% at the end of December 2011. The risk managed low momentum crash factor loading Novy-Marx (2013) strategy has a milder drop in 2009 recession, with a 215.04% drop compared to 808.83% for WML[-12,-7] β_{SKEW} Q1, and a higher cumulative return with a value of 1653.80%, compared with the unscaled one with a cumulative return of 1322.74% at the end of June, 2016. In summary, choosing the stocks with low momentum crash factor loadings to form the WML strategy greatly improves the WML strategy. Meanwhile, combining the risk management method in the Barroso and Santa-Clara (2015) further alleviates the momentum crashes and produces an even higher profit.

6 Conclusion

We find that stocks with higher risk neutral skewness have lower past performance and that a zero-cost portfolio formed on high minus low risk neutral skewness generates positive returns overall, but particularly in post-recession rebounds and during periods of high market volatility. This behavior is the opposite of the momentum crash phenomenon described in Daniel and Moskowitz (2016). We find evidence consistent with the risk-neutral skewness anomaly being inversely related to momentum crashes, providing a potential explanation for it through the link between the two.

This result helps advance our understanding of the prior explanation for the risk-neutral skewness anomaly advanced by Stilger, Kostakis, and Poon (2016). The authors document that a zero-cost strategy on risk-neutral skewness produces abnormal returns. They provide evidence that this is caused by the overpricing of the stocks with the most negative risk neutral skewness that are 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 overpricing. However, they also find that the short sale constraints cannot fully explain the risk neutral skewness anomaly, which we confirm in the context of value-weighted zero-cost portfolios that produce abnormal return from the long (unconstrained), rather than the short (constrained), leg.

We provide evidence that the momentum strategy in the high risk-neutral skewness tercile experiences more severe crashes. We generalize our findings to all stocks, regardless of traded options, by constructing a risk-neutral skewness factor using option data and find that the momentum strategy constructed by the stocks with the lowest factor loadings earns highest excess returns and abnormal returns when benchmarked by Carhart (1997) four-factor model.

These results confirm that the risk-neutral skewness anomaly is related to momentum crashes more strongly than it is to short-sale constraints. The anomaly is robust to equal- and value-weighting, and as both a factor loading and a characteristic. An equal-weighted momentum strategy formed on stocks with the lowest risk-neutral skewness factor loading yields 1.23% per month relative to the Carhart (1997) four-factor model, while a value-weighted strategy produces a similar 1.02% per month. Risk-neutral skewness factor loadings allow a simple strategy to avoid momentum crashes in an economically significant way.

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Appendix A

Table AI: Descriptive Statistics. This table presents the descriptive statistics for the OTM call and put options used to replicate Stilger, Kostakis, and Poon (2016)'s results. Panel A shows the descriptive statistics for the full sample period: January 1996 to April 2016. Panel B presents the descriptive statistics for the sample period of Stilger, Kostakis, and Poon (2016): January 1996 to December 2012. Panel C shows the descriptive statistics using the volatility surface data. Following Stilger, Kostakis, and Poon (2016), moneyness is defined as the ratio of the underlying stock price to the strike price of the OTM call and put options, respectively. The open interest and trading volume per OTM option used to compute RNS are in thousands of contracts. The total trading volume per stock used to extract RNS is in thousands of contracts.

Panel A: Full Sample

Variables	Mean	Median	P5	P95	STD
RNS	-0.3160	-0.3050	-0.7437	0.0520	0.2572
Days to expiration for OTM options	80.89	79	16	169	50.03
Moneyness of OTM call options	0.9210	0.9383	0.7893	0.9943	0.0662
Moneyness of OTM put options	1.1058	1.0722	1.0063	1.3125	0.1083
No. of OTM options used per RNS observation	5.25	4	4	10	3.03
Open interest per OTM option used	1183.53	197	7	4717	4926.94
Trading volume per OTM option used	114.02	1	0	388	902.95
Total trading volume per stock	180.30	0	0	436	2150.82

Panel B: 1996-2012

Variables	Mean	Median	P5	P95	STD
RNS	-0.3318	-0.3200	-0.7496	0.0264	0.2514
Days to expiration for OTM options	85.03	80	18	170	48.92
Moneyness of OTM call options	0.9110	0.9267	0.7763	0.9929	0.0696
Moneyness of OTM put options	1.1206	1.0867	1.0078	1.3392	0.1163
No. of OTM options used per RNS observation	5.06	4	4	8	2.58
Open interest per OTM option used	1442.74	266	10	5768	5610.57
Trading volume per OTM option used	134.00	2	0	503	1038.86
Total trading volume per stock	183.15	0	0	458	2256.82

Panel C: Volatility Surface

	Full Sample					1996-2012				
days	Mean	Median	P5	P95	STD	Mean	Median	P5	P95	STD
					RNS					
30	-0.1984	-0.2360	-0.8645	0.6071	0.5143	-0.2114	-0.2353	-0.8199	0.4874	0.4545
60	-0.2920	-0.3240	-0.9423	0.4573	0.5178	-0.3059	-0.3257	-0.8938	0.3265	0.4520
91	-0.3652	-0.3922	-0.9755	0.3034	0.4940	-0.3829	-0.4010	-0.9302	0.1818	0.4357
122	-0.3929	-0.4186	-0.9856	0.2571	0.4800	-0.4132	-0.4332	-0.9481	0.1518	0.4251
152	-0.4063	-0.4323	-0.9916	0.2375	0.4790	-0.4285	-0.4506	-0.9635	0.1510	0.4298
182	-0.4118	-0.4412	-0.9992	0.2446	0.4897	-0.4347	-0.4616	-0.9754	0.1706	0.4453
					Moneyness of OTM call options					
30	0.9369	0.9478	0.8507	0.9872	0.0450	0.9359	0.9458	0.8531	0.9856	0.0429
60	0.9258	0.9361	0.8372	0.9829	0.0490	0.9251	0.9339	0.8428	0.9804	0.0455
91	0.9212	0.9309	0.8313	0.9813	0.0502	0.9206	0.9288	0.8373	0.9784	0.0466
122	0.9170	0.9266	0.8250	0.9803	0.0518	0.9167	0.9247	0.8316	0.9774	0.0481
152	0.9136	0.9231	0.8193	0.9798	0.0535	0.9134	0.9214	0.8259	0.9769	0.0499
182	0.9104	0.9201	0.8131	0.9794	0.0557	0.9102	0.9184	0.8195	0.9766	0.0523
					Moneyness of OTM put options					
30	1.0519	1.0421	1.0045	1.1347	0.0423	1.0523	1.0432	1.0042	1.1342	0.0420
60	1.0611	1.0509	1.0036	1.1536	0.0488	1.0605	1.0511	1.0025	1.1509	0.0480
91	1.0686	1.0580	1.0043	1.1704	0.0534	1.0679	1.0578	1.0033	1.1685	0.0530
122	1.0750	1.0633	1.0045	1.1839	0.0576	1.0742	1.0630	1.0034	1.1824	0.0574
152	1.0809	1.0681	1.0047	1.1954	0.0614	1.0802	1.0679	1.0037	1.1950	0.0615
182	1.0863	1.0734	1.0050	1.2062	0.0650	1.0859	1.0732	1.0040	1.2071	0.0655

Table AII: Risk-Neutral Skewness Sorted Portfolios: replication of Stilger, Kostakis, and Poon (2016)'s results. This table shows the risk-neutral skewness (RNS) sorted portfolio returns. The risk neutral skewness is computed using traded option data, following Stilger, Kostakis, and Poon (2016). Each calendar month, we rank stocks in ascending order by their risk-neutral skewness and assign the ranked stocks to one of five portfolios. Panel A and Panel B present results for equally-weighted and value-weighted portfolios sorted by risk neutral skewness, respectively. The rightmost column reports the excess return along with the abnormal returns of a self-financing portfolio that long the highest skewed portfolio and short the lowest skewed portfolio. We benchmark the performance using the Capital Asset Pricing Model (CAPM α), Fama and French (1993) 3-factor model (FF3 α), Fama and French (2015) 5 factors model (FF5 α), Carhart (1997) four factor model (Carhart α) and Carhart (1997) four factor plus Pastor and Stambaugh (2003) liquidity factor 5-factor model (Carhart + Liq α) over the month following portfolio formation. The t-statistics are reported in parentheses and adjusted following Newey and West (1987) with a lag of 6 months.

	Risk Neutral Skewness (RNS) Quintiles					
	1	2	3	4	5	5-1
	(Low)				(High)	
Panel A: EW						
Excess Return	0.33%	0.60%	0.95%	0.80%	0.92%	0.60%***
	(0.80)	(1.40)	(2.12)	(1.69)	(1.90)	(2.98)
CAPM α	-0.57%	-0.34%	-0.02%	-0.20%	-0.12%	0.45%**
	(-3.50)	(-2.00)	(-0.12)	(-1.02)	(-0.58)	(2.33)
FF3 α	-0.58%	-0.33%	-0.01%	-0.19%	-0.09%	0.49%**
	(-4.55)	(-2.55)	(-0.06)	(-1.34)	(-0.52)	(2.45)
FF5 α	-0.41%	-0.17%	0.15%	-0.00%	0.16%	0.58%***
	(-3.17)	(-1.39)	(1.21)	(-0.01)	(1.02)	(2.82)
Carhart α	-0.57%	-0.32%	0.03%	-0.14%	-0.04%	0.53%**
	(-4.45)	(-2.55)	(0.19)	(-0.99)	(-0.24)	(2.59)
Carhart + Liq α	-0.57%	-0.33%	0.03%	-0.16%	-0.04%	0.53%**
	(-4.32)	(-2.54)	(0.21)	(-1.03)	(-0.22)	(2.51)
Panel B: VW						
Excess Return	0.59%	0.76%	1.12%	0.97%	1.33%	0.74%***
	(1.62)	(2.12)	(2.98)	(2.30)	(3.33)	(3.26)
CAPM α	-0.20%	-0.04%	0.30%	0.12%	0.45%	0.65%***
	(-1.90)	(-0.34)	(2.39)	(0.75)	(2.28)	(2.80)
FF3 α	-0.15%	-0.01%	0.34%	0.16%	0.52%	0.67%***
	(-1.57)	(-0.11)	(2.82)	(1.07)	(2.58)	(2.88)
FF5 α	-0.09%	0.00%	0.40%	0.18%	0.61%	0.70%***
	(-0.85)	(0.04)	(3.09)	(1.04)	(2.68)	(2.77)
Carhart α	-0.15%	-0.03%	0.31%	0.12%	0.51%	0.66%***
	(-1.74)	(-0.27)	(2.63)	(0.87)	(2.38)	(2.77)
Carhart + Liq α	-0.15%	-0.03%	0.31%	0.13%	0.51%	0.65%***
	(-1.65)	(-0.26)	(2.72)	(0.87)	(2.27)	(2.64)

Table AIII: Risk-Neutral Skewness Sorted Portfolios: using Volatility Surface data. This table shows the risk-neutral skewness (RNS) sorted portfolio returns. Each calendar month, we rank stocks in ascending order by their risk-neutral skewness to five groups. RNS is computed from OptionMetrics Volatility Surface using different days to expiration: 30 days, 60 days, 91 days, 122 days, 152 days and 182 days. Panel A and Panel B present results for equally-weighted and value-weighted portfolios sorted by risk neutral skewness, respectively. The rightmost column reports returns of a self-financing portfolio that long the highest skewed portfolio and short the lowest skewed portfolio. The table shows excess returns along with abnormal performance relative to Carhart (1997) momentum factor 4-factors model (Carhart α) over the month following portfolio formation. The t-statistics are reported in parentheses and adjusted following Newey and West (1987) with a lag of 6 months.

	Panel A: Equally Weighted Portfolio Returns					
	Risk Neutral Skewness (RNS) Quintiles					
	1	2	3	4	5	5-1
	(Low)				(High)	
30 days						
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)
Carhart α	-0.39%	-0.21%	-0.08%	0.14%	0.55%	0.94%***
	(-4.52)	(-2.35)	(-0.93)	(1.21)	(3.34)	(4.65)
60 days						
ExRet	0.62%	0.76%	0.82%	0.99%	1.31%	0.69%***
	(1.99)	(2.30)	(2.41)	(2.88)	(3.80)	(5.40)
Carhart α	-0.11%	-0.04%	-0.02%	0.15%	0.54%	0.66%***
	(-1.05)	(-0.32)	(-0.12)	(1.07)	(3.45)	(4.83)
91 days						
ExRet	0.73%	0.76%	0.88%	1.11%	1.33%	0.60%***
	(2.52)	(2.42)	(2.81)	(3.44)	(4.25)	(4.88)
Carhart α	0.04%	0.01%	0.11%	0.36%	0.60%	0.56%***
	(0.37)	(0.05)	(0.78)	(2.02)	(3.70)	(4.13)
122 days						
ExRet	0.71%	0.75%	0.95%	1.19%	1.32%	0.60%***
	(2.56)	(2.43)	(3.04)	(3.75)	(4.42)	(4.74)
Carhart α	0.07%	0.03%	0.22%	0.48%	0.64%	0.56%***
	(0.64)	(0.23)	(1.36)	(2.61)	(3.60)	(3.92)
152 days						
ExRet	0.72%	0.82%	0.97%	1.20%	1.32%	0.61%***
	(2.59)	(2.78)	(3.39)	(3.79)	(4.61)	(4.20)
Carhart α	0.12%	0.13%	0.26%	0.53%	0.69%	0.57%***
	(0.95)	(0.96)	(1.83)	(2.81)	(4.15)	(3.89)
182 days						
ExRet	0.74%	0.82%	0.98%	1.14%	1.20%	0.46%***
	(2.70)	(2.94)	(3.22)	(3.83)	(4.08)	(2.84)
Carhart α	0.18%	0.14%	0.30%	0.49%	0.59%	0.41%***
	(1.26)	(1.10)	(1.93)	(2.81)	(3.72)	(2.72)

Panel B: Value Weighted Portfolio Returns

Risk Neutral Skewness (RNS) Quintiles

	1 (Low)	2	3	4	5 (High)	5-1
30 days						
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)
Carhart α	-0.21%	-0.00%	0.21%	0.20%	0.48%	0.70%***
	(-3.42)	(-0.05)	(2.26)	(1.43)	(3.84)	(4.39)
60 days						
ExRet	0.55%	0.77%	0.90%	1.07%	1.26%	0.71%***
	(1.91)	(2.65)	(2.87)	(3.45)	(4.33)	(3.51)
Carhart α	-0.10%	0.04%	0.15%	0.33%	0.58%	0.69%***
	(-1.12)	(0.44)	(1.15)	(2.22)	(3.44)	(3.79)
91 days						
ExRet	0.51%	0.76%	0.81%	1.30%	1.26%	0.75%***
	(1.92)	(2.62)	(2.62)	(4.16)	(4.10)	(3.42)
Carhart α	-0.11%	0.07%	0.12%	0.58%	0.57%	0.68%***
	(-0.97)	(0.58)	(0.76)	(2.94)	(2.95)	(3.36)
122 days						
ExRet	0.57%	0.81%	1.03%	1.35%	1.24%	0.67%***
	(2.23)	(2.93)	(3.47)	(4.27)	(4.20)	(3.06)
Carhart α	0.01%	0.14%	0.37%	0.65%	0.63%	0.62%***
	(0.11)	(1.15)	(1.92)	(3.03)	(2.94)	(2.72)
152 days						
ExRet	0.57%	0.72%	0.98%	1.36%	1.31%	0.74%***
	(2.09)	(2.49)	(3.46)	(3.98)	(4.16)	(3.33)
Carhart α	-0.00%	0.07%	0.34%	0.74%	0.73%	0.74%***
	(-0.04)	(0.45)	(2.01)	(3.05)	(3.38)	(3.21)
182 days						
ExRet	0.55%	0.81%	0.88%	1.09%	1.16%	0.61%***
	(2.11)	(2.82)	(2.87)	(3.54)	(3.78)	(2.93)
Carhart α	-0.01%	0.17%	0.25%	0.44%	0.59%	0.61%***
	(-0.09)	(1.05)	(1.33)	(2.42)	(2.83)	(2.88)

Table AIV: Descriptive Statistics of Portfolios Formed on β_{SKEW} and $RET_{T-12,T-7}$. This table reports mean firm characteristics of portfolios formed on β_{SKEW} and $RET_{T-12,T-7}$.

Panel A: Mean Volume Scaled by Shares Outstanding

	Momentum Quintiles									
β_{SKEW}	1	2	3	4	5	6	7	8	9	10
1	24.12%	16.27%	15.33%	13.79%	13.49%	13.44%	14.41%	14.59%	16.39%	23.37%
2	18.33%	13.10%	13.08%	11.86%	12.13%	11.97%	12.37%	12.64%	13.88%	19.36%
3	24.79%	12.62%	10.81%	10.39%	10.43%	10.18%	11.08%	12.09%	13.33%	19.15%
4	28.77%	14.09%	13.65%	12.33%	12.32%	12.42%	12.90%	14.21%	16.37%	21.71%
5	28.22%	18.86%	17.41%	16.98%	19.71%	17.96%	17.11%	18.45%	19.72%	27.90%

Panel B: Mean Institutional Ownership

	Momentum Quintiles									
β_{SKEW}	1	2	3	4	5	6	7	8	9	10
1	40.94%	47.08%	48.46%	48.57%	49.03%	50.02%	50.68%	51.19%	51.39%	47.10%
2	42.24%	44.15%	43.03%	41.02%	40.05%	41.33%	43.97%	46.58%	48.31%	47.26%
3	41.03%	41.07%	38.71%	36.80%	36.14%	37.10%	39.10%	42.48%	45.90%	44.85%
4	40.03%	42.93%	42.32%	41.59%	40.89%	41.52%	42.70%	44.70%	46.72%	45.27%
5	33.82%	40.84%	41.41%	42.21%	42.46%	43.41%	42.61%	44.16%	44.95%	42.81%

Panel C: Mean Bid Ask Spread Scaled by Price

	Momentum Quintiles									
β_{SKEW}	1	2	3	4	5	6	7	8	9	10
1	2.70 %	1.81 %	1.45 %	1.30 %	1.24 %	1.15 %	1.07 %	1.10 %	1.06 %	1.26 %
2	2.50 %	1.63 %	1.35 %	1.23 %	1.15 %	1.06 %	1.07 %	1.05 %	1.05 %	1.14 %
3	2.40 %	1.67 %	1.45 %	1.32 %	1.21 %	1.17 %	1.14 %	1.16 %	1.12 %	1.26 %
4	2.53 %	1.89 %	1.67 %	1.54 %	1.44 %	1.38 %	1.34 %	1.31 %	1.25 %	1.33 %
5	3.01 %	2.27 %	2.17 %	2.04 %	1.95 %	1.90 %	1.88 %	1.76 %	1.67 %	1.67 %

Table AV: Returns on Low Momentum Crash Factor Loading WML Portfolio and Risk Managed, Low Momentum Crash Factor Loading WML Portfolio. This table presents the excess returns, four factor (Carhart (1997) four factors) abnormal returns, and five factor (Carhart (1997) four factors with Pastor and Stambaugh (2005) liquidity factor) abnormal returns of the baseline Winner-minus-Loser Strategy, the risk managed momentum strategy in Barroso and Santa-Clara (2015), the Novy-Marx (2012) momentum strategy constructed by all stocks, and the Novy-Marx (2012) momentum strategy constructed by stocks in β_{SKEW} quintile 1 over the period from April, 1998 through December, 2011, as well as the risk managed Novy-Marx (2012) momentum strategy constructed by stocks in β_{SKEW} quintile 1 over the period from October, 1998 through December, 2011.

	WML[-12,-2]	WML[-12,-2]*	WML[-12,-7] All	WML[-12,-7] β_{SKEW} Q1	WML[-12,-7] β_{SKEW} Q1 *
	0.81%	0.77%	0.89%	1.97%	1.76%
Excess Return	(1.01)	(2.29)	(1.89)	(3.67)	(3.54)
	0.18%	0.51%	0.67%	1.77%	1.60%
Carhart α	(0.69)	(1.83)	(2.08)	(4.03)	(4.88)
	0.20%	0.50%	0.65%	1.75%	1.59%
Carhart + Liq α	(0.75)	(1.82)	(2.13)	(4.19)	(4.93)

Table I: Descriptive Statistics and Correlation. Panel A provides the descriptive statistics of risk neutral skewness (RNS), as well as of the firm-specific variables used in subsequent analysis. In Panel A, we report the summary statistics of our full sample. The sample consists of 592,480 firm-month combinations, constituting monthly observations from Jan 1996 through Apr 2016 from OptionMetrics and CRSP. RNS is risk neutral skewness calculated from options with 30 days to expiration from OptionMetrics volatility surface of by BKM(2003). MV is market capitalization, calculated by multiplying the close price of the last trading day of this month and shares outstanding. RET_t is the monthly return for time t, and RET_{t-1} is the one month lagged monthly return of month t. $RET_{t-12,t-2}$ is the cumulative return over the past eleven months, lagged one month. $RET_{t-12,t-7}$ is the cumulative return over the lagged twelveth months to the lagged seventh month. $RET_{t-6,t-2}$ is the cumulative return over the lagged sixth month to the lagged second month. β^i_M is the market beta. We regress excess returns of stocks on market risk premium over past 60 months, and the coefficient on the market risk premium is the market beta (at least 24 observations). VOLUME is the stock volume over current month. BM is the book-to-market ratio. Panel B reports the time-series average of cross-section correlation coefficients between risk neutral skewness and the firm-specific variables. The lower triangular matrix presents the Pearson correlation matrix; the upper triangular matrix shows the nonparametric Spearman correlation matrix. Insignificant coefficients are in italics.

Panel A: Sample Descriptive

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

Panel B: Correlation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)RNS	1.00	-0.29	0.01	-0.14	-0.13	-0.06	-0.12	0.11	-0.13	0.04
(2)MV	-0.10	1.00	0.04	0.10	0.25	0.17	0.19	-0.26	0.65	-0.14
(3)RET_t	0.02	*0.00*	1.00	-0.01	0.03	0.03	0.02	-0.03	0.00	0.01
(4)RET_{t-1}	-0.10	0.01	*-0.01*	1.00	0.02	0.02	0.00	-0.03	0.02	0.01
(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
(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
(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
(8)β^i_M	0.08	-0.10	*-0.01*	*-0.01*	-0.08	-0.04	-0.07	1.00	0.08	-0.06
(9)lnVOLUME	-0.04	0.52	*-0.01*	*-0.00*	*-0.00*	*0.01*	-0.01	0.07	1.00	-0.16
(10)BM	0.02	-0.05	*0.00*	*0.00*	0.01	*0.00*	0.01	-0.01	-0.03	1.00

Table II: Fama-MacBeth Cross-Sectional Regressions. This table presents the firm-level cross sectional regressions of equity excess returns on risk neutral skewness (RNS) after controlling for beta, size, book-to-market ratio [log(B/M)], short term reversal (RET_{-1}), momentum and stock trading volume [log(VOLUME)]. 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). The coefficients and their Newey-West (1987) t-statistics are reported (t-statistics in parentheses).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.825 *	1.314	0.944	1.079	0.688	0.971	0.591
	(1.89)	(1.45)	(1.04)	(1.16)	(0.73)	(1.08)	(0.65)
RNS	0.716 ***		0.675 ***		0.652 ***		0.694 ***
	(3.97)		(7.41)		(7.22)		(7.28)
β_M		-0.062	-0.057	0.001	0.004	0.008	0.011
		(-0.35)	(-0.32)	(0.00)	(0.02)	(0.04)	(0.05)
ln(ME)		-0.031	0.012	-0.011	0.035	-0.000	0.043
		(-0.30)	(0.11)	(-0.10)	(0.32)	(-0.00)	(0.43)
ln(BM)		-0.003	-0.007	0.011	0.009	0.008	0.004
		(-0.04)	(-0.10)	(0.17)	(0.13)	(0.11)	(0.06)
RET_{t-1}		-1.615 ***	-1.410 **	-1.621 ***	-1.436 **	-1.631 ***	-1.425 **
		(-2.63)	(-2.32)	(-2.61)	(-2.34)	(-2.65)	(-2.34)
Momentum		0.533 *	0.569 *	0.627 **	0.644 **	0.515	0.574
		(1.74)	(1.87)	(2.30)	(2.38)	(1.46)	(1.62)
ln(VOLUME)		-0.023	-0.032	-0.029	-0.040	-0.030	-0.039
		(-0.27)	(-0.38)	(-0.31)	(-0.44)	(-0.35)	(-0.45)

Table III: Risk-Neutral Skewness Sorted Portfolios. This table shows the characteristics and returns of risk-neutral skewness (RNS) sorted portfolios. Each calendar month, we rank stocks in ascending order by their risk-neutral skewness and assign the ranked stocks to one of five groups. Panel A and Panel B present the characteristics and returns for equally-weighted and value-weighted portfolios sorted by risk neutral skewness, respectively. The upper panels report the portfolio characteristics. The rightmost two column presents characteristics of a self-financing portfolio that long the positively skewed portfolio and short the negatively skewed portfolio and t-statistics. The lower panels report the portfolio returns. The rightmost column presents returns of a self-financing portfolio that long the positively skewed portfolio and short the negatively skewed portfolio. The table shows excess returns along with abnormal performance relative to Carhart (1997) momentum factor 4-factors model (Carhart α) over the month following portfolio formation. The table also reports the portfolios loadings (βs) on the market risk premium (MKT), size (SMB), value (HML), and momentum (UMD) factors estimated from the Carhart four-factor model. The t-statistics are reported in parentheses and adjusted following Newey and West (1987) with a lag of 6 months.

Panel A: Equally Weighted Portfolio

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
lnMe	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

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 Portfolio Returns

	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
lnMe	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

	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 IV: Market Timing Regression of RNS quintile portfolios. This table presents the results of estimating four specifications of time-series regressions of the RNS quintile portfolio returns and the long-short portfolio return over the period February 1996 to May 2016. Model 1 fits an unconditional market model to the RNS-sorted portfolios as well as a long-short portfolio: $\tilde{R}_t = \alpha_0 + \beta_0 \tilde{R}_{m,t} + \tilde{\epsilon}_t$. Model 2 fits a conditional CAPM with the bear market indicator, I_B, as an instrument: $\tilde{R}_t = \alpha_0 + (\beta_0 + \beta_B I_{B,t-1})\tilde{R}_{m,t} + \tilde{\epsilon}_t$ where I_B equals to 1 if the cumulative CRSP VW index return in the past 24 months is negative and equals to 0 otherwise. Model 3 introduces a contemporaneous up-market indicator variable $I_{U,t}$ that equals 1 if the market risk premium is positive, and equals 0 otherwise: $\tilde{R}_t = \alpha_0 + (\beta_0 + I_{B,t-1}(\beta_B + \tilde{I}_{U,t}\beta_{B,U}))\tilde{R}_{m,t} + \tilde{\epsilon}_t$. Panel A and Panel B report equally- and value- weighted portfolio results, respectively.

Panel A: Equally Weighted Portfolio

	RNS Quintile					
	1	2	3	4	5	H-L
Model 1						
	-0.33%	-0.21%	-0.12%	0.01%	0.38%	0.70%
$\hat{\alpha_0}$	(-2.71)	(-1.58)	(-0.80)	(0.04)	(1.62)	(3.76)
	1.05	1.25	1.33	1.39	1.37	0.33
$\hat{\beta_0}$	(39.47)	(43.24)	(39.79)	(31.89)	(27.23)	(7.95)
Model 2						
	-0.29%	-0.18%	-0.10%	0.06%	0.46%	0.76%
$\hat{\alpha_0}$	(-2.44)	(-1.36)	(-0.62)	(0.28)	(2.07)	(4.08)
	0.98	1.19	1.28	1.30	1.21	0.23
$\hat{\beta_0}$	(29.22)	(32.42)	(29.91)	(23.45)	(19.24)	(4.42)
	0.18	0.14	0.13	0.23	0.42	0.24
$\hat{\beta_B}$	(3.35)	(2.44)	(1.90)	(2.59)	(4.23)	(2.95)
Model 3						
	-0.30%	-0.28%	-0.22%	-0.14%	0.17%	0.47%
$\hat{\alpha_0}$	(-2.27)	(-1.96)	(-1.30)	(-0.65)	(0.71)	(2.37)
	0.98	1.20	1.28	1.31	1.22	0.24
$\hat{\beta_0}$	(29.10)	(32.61)	(30.10)	(23.76)	(19.73)	(4.77)
	0.17	0.06	0.03	0.07	0.18	0.01
$\hat{\beta_B}$	(2.55)	(0.81)	(0.35)	(0.61)	(1.43)	(0.05)
	0.01	0.17	0.21	0.34	0.51	0.50
$\hat{\beta_{B,U}}$	(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 V: RNS Sorted Portfolio Returns and Estimated Market Variance. This table presents the results of estimating five specifications of time-series regressions of the RNS quintile portfolio returns and the long-short portfolio return over the period February 1996 to May 2016. Model 1 regresses the RNS-sorted portfolios as well as a long-short portfolio on the bear market indicator $I_{B,t-1}$ where I_B equals to 1 if the cumulative CRSP VW index return in the past 24 months is negative and equals to 0 otherwise: $\tilde{R}_t = \gamma_0 + \gamma_0 I_{B,t-1} + \tilde{\epsilon_t}$. Model 2 regresses the RNS-sorted portfolios as well as a long-short portfolio on the market variance $\sigma^2_{m,t-1}$, the variance of the daily returns of the market over the 126 days prior to time t: $\tilde{R}_t = \gamma_0 + \gamma_{\sigma^2_{m,t-1}} \sigma^2_{m,t-1} + \tilde{\epsilon_t}$. Model 3 fits the model:$\tilde{R}_t = \gamma_0 + \gamma_0 I_{B,t-1} + \gamma_{\sigma^2_{m,t-1}} \sigma^2_{m,t-1} + \tilde{\epsilon_t}$. Model 4 runs a regression of RNS sorted portfolio returns on the interaction of the bear market indicator and market variance: $\tilde{R}_t = \gamma_0 + \gamma_{int} I_{B,t-1} \sigma^2_{m,t-1} + \tilde{\epsilon_t}$. Panel A and Panel B present regression results of the equally- and value-weighted portfolios, respectively.

Panel A: Equally Weighted Portfolios

	RNS Quintile					
	1	2	3	4	5	H-L
Model 1						
	0.31%	0.53%	0.62%	0.69%	0.91%	0.60%
$\hat{\gamma_0}$	(0.83)	(1.20)	(1.30)	(1.34)	(1.74)	(2.56)
	-0.19%	-0.12%	0.10%	0.52%	1.14%	1.32%
$\hat{\gamma_B}$	(-0.23)	(-0.12)	(0.10)	(0.48)	(1.02)	(2.66)
Model 2						
	0.17%	0.22%	0.22%	0.23%	0.27%	0.10%
$\hat{\gamma_0}$	(0.40)	(0.44)	(0.41)	(0.40)	(0.46)	(0.40)
	0.07	0.19	0.28	0.38	0.59	0.52
$\hat{\gamma_{\sigma^2_m}}$	(0.38)	(0.92)	(1.25)	(1.58)	(2.42)	(4.90)
Model 3						
	0.19%	0.25%	0.25%	0.26%	0.29%	0.10%
$\hat{\gamma_0}$	(0.45)	(0.51)	(0.47)	(0.44)	(0.48)	(0.37)
	-0.47%	-0.76%	-0.75%	-0.50%	-0.32%	0.15%
$\hat{\gamma_B}$	(-0.50)	(-0.70)	(-0.64)	(-0.39)	(-0.25)	(0.26)
	0.12	0.28	0.36	0.44	0.63	0.51
$\hat{\gamma_{\sigma^2_m}}$	(0.59)	(1.14)	(1.40)	(1.55)	(2.19)	(4.06)
Model 4						
	0.23%	0.40%	0.47%	0.57%	0.79%	0.56%
$\hat{\gamma_0}$	(0.67)	(0.97)	(1.07)	(1.19)	(1.62)	(2.60)
	0.05	0.14	0.22	0.32	0.50	0.46
$\hat{\gamma_{int}}$	(0.29)	(0.73)	(1.08)	(1.41)	(2.22)	(4.59)

Panel B: Value Weighted Portfolios

	RNS Quintile					
	1	2	3	4	5	H-L
Model 1						
	0.50%	0.76%	0.88%	0.74%	0.96%	0.45%
$\hat{\gamma_0}$	(1.58)	(2.15)	(2.38)	(1.87)	(2.53)	(2.39)
	-0.85%	-0.74%	-0.40%	0.08%	0.30%	1.15%
$\hat{\gamma_B}$	(-1.25)	(-0.99)	(-0.50)	(0.10)	(0.37)	(2.84)
Model 2						
	0.41%	0.54%	0.54%	0.32%	0.58%	0.17%
$\hat{\gamma_0}$	(1.12)	(1.35)	(1.28)	(0.73)	(1.35)	(0.80)
	-0.06	0.04	0.17	0.29	0.30	0.36
$\hat{\gamma_{\sigma^2_m}}$	(-0.40)	(0.21)	(0.97)	(1.55)	(1.67)	(4.04)
Model 3						
	0.45%	0.60%	0.59%	0.36%	0.60%	0.15%
$\hat{\gamma_0}$	(1.25)	(1.48)	(1.40)	(0.81)	(1.40)	(0.70)
	-0.97%	-1.12%	-1.08%	-0.80%	-0.53%	0.43%
$\hat{\gamma_B}$	(-1.22)	(-1.28)	(-1.17)	(-0.82)	(-0.57)	(0.93)
	0.05	0.16	0.29	0.38	0.36	0.31
$\hat{\gamma_{\sigma^2_m}}$	(0.29)	(0.84)	(1.44)	(1.75)	(1.72)	(2.98)
Model 4						
	0.38%	0.60%	0.70%	0.58%	0.85%	0.48%
$\hat{\gamma_0}$	(1.26)	(1.80)	(2.01)	(1.57)	(2.41)	(2.70)
	-0.08	-0.01	0.13	0.24	0.23	0.32
$\hat{\gamma_{int}}$	(-0.59)	(-0.04)	(0.78)	(1.41)	(1.41)	(3.84)

Table VI: Market Timing Regression of WML Portfolio Returns. At the end of each calendar month, we independently sort firms by $RET_{T-12,T-7}$ and RNS into terciles. In each RNS tercile, we regress the equally- and value-weighted WML portfolio returns on market timing models and report the results on left and right panels, respectively. Model 1 fits an unconditional CAPM: $\tilde{R}_{WML,t} = \alpha_0 + \beta_0 \tilde{R}_{m,t} + \tilde{\epsilon_t}$. Model 2 fits a conditional CAPM with the bear market indicator I_B: $\tilde{R}_{WML,t} = \alpha_0 + (\beta_0 + \beta_B I_{B,t-1})\tilde{R}_{m,t} + \tilde{\epsilon_t}$. Model 3 introduces a contemporaneous up-market indicator variable $I_{U,t}$: $\tilde{R}_{WML,t} = \alpha_0 + (\beta_0 + I_{B,t-1}(\beta_B + \tilde{I}_{U,t}\beta_{B,U}))\tilde{R}_{m,t} + \tilde{\epsilon}_t$

	EW				VW			
	RNS Tercile				RNS Tercile			
	L	M	H	H-L	L	M	H	H-L
Model 1								
$\hat{\alpha_0}$	0.68%	0.61%	0.54%	-0.14%	0.64%	0.60%	0.61%	-0.03%
	(2.61)	(2.21)	(1.88)	(-0.95)	(2.07)	(1.85)	(1.75)	(-0.12)
$\hat{\beta_0}$	-0.11	-0.13	-0.20	-0.08	-0.10	-0.08	-0.20	-0.10
	(-1.99)	(-2.20)	(-3.16)	(-2.53)	(-1.47)	(-1.07)	(-2.56)	(-1.72)
Model 2								
$\hat{\alpha_0}$	0.55%	0.46%	0.39%	-0.16%	0.49%	0.44%	0.41%	-0.08%
	(2.22)	(1.80)	(1.44)	(-1.04)	(1.66)	(1.44)	(1.27)	(-0.30)
$\hat{\beta_0}$	0.14	0.13	0.08	-0.06	0.19	0.22	0.19	-0.01
	(2.02)	(1.86)	(1.07)	(-1.39)	(2.34)	(2.52)	(2.05)	(-0.10)
$\hat{\beta_B}$	-0.64	-0.67	-0.70	-0.06	-0.74	-0.74	-0.96	-0.23
	(-5.85)	(-5.85)	(-5.86)	(-0.92)	(-5.65)	(-5.41)	(-6.70)	(-1.99)
Model 3								
$\hat{\alpha_0}$	0.55%	0.55%	0.56%	0.01%	0.44%	0.42%	0.61%	0.17%
	(2.03)	(1.97)	(1.90)	(0.07)	(1.37)	(1.27)	(1.72)	(0.60)
$\hat{\beta_0}$	0.14	0.13	0.07	-0.07	0.19	0.22	0.18	-0.02
	(2.02)	(1.80)	(0.97)	(-1.57)	(2.36)	(2.52)	(1.96)	(-0.25)
$\hat{\beta_B}$	-0.64	-0.60	-0.56	0.08	-0.77	-0.75	-0.80	-0.03
	(-4.54)	(-4.05)	(-3.67)	(0.89)	(-4.62)	(-4.28)	(-4.35)	(-0.18)
$\hat{\beta_{B,U}}$	-0.00	-0.16	-0.29	-0.29	0.08	0.03	-0.34	-0.42
	(-0.01)	(-0.80)	(-1.45)	(-2.58)	(0.37)	(0.12)	(-1.40)	(-2.21)

Table VII: Size/$RET_{T-12,T-7}$/RNS triple sorted Portfolio Optionality in Bear Market. At the end of each calendar month, we independently sort firms by Market Capitalization, $RET_{T-12,T-7}$ and RNS into terciles. In each Size/RNS group, we regress the equally- and value-weighted WML portfolio returns on the time series model: $\tilde{R}_{WML,t} = \alpha_0 + (\beta_0 + I_{B,t-1}(\beta_B + \tilde{I}_{U,t}\beta_{B,U}))\tilde{R}_{m,t} + \tilde{\epsilon_t}$ and report the regression results on left and right panels, respectively.

	EW				VW			
	RNS Tercile				RNS Tercile			
	L	M	H	H-L	L	M	H	H-L
Size Tercile 1								
	0.71%	0.67%	0.63%	-0.08%	0.55%	0.63%	0.44%	-0.11%
$\hat{\alpha_0}$	(2.47)	(2.23)	(2.05)	(-0.32)	(1.87)	(2.02)	(1.43)	(-0.42)
	0.18	0.20	0.14	-0.05	0.26	0.18	0.18	-0.08
$\hat{\beta_0}$	(2.49)	(2.56)	(1.74)	(-0.70)	(3.48)	(2.27)	(2.32)	(-1.14)
	-0.25	-0.43	-0.42	-0.17	-0.38	-0.36	-0.54	-0.16
$\hat{\beta_B}$	(-1.67)	(-2.76)	(-2.60)	(-1.22)	(-2.44)	(-2.19)	(-3.35)	(-1.11)
	-0.35	-0.24	-0.19	0.16	-0.36	-0.19	-0.04	0.33
$\hat{\beta_{B,U}}$	(-1.77)	(-1.16)	(-0.90)	(0.90)	(-1.78)	(-0.86)	(-0.18)	(1.70)
Size Tercile 2								
	0.25%	0.45%	0.40%	0.15%	0.23%	0.45%	0.43%	0.21%
$\hat{\alpha_0}$	(0.85)	(1.46)	(1.27)	(0.67)	(0.75)	(1.43)	(1.33)	(0.84)
	0.13	0.14	0.10	-0.03	0.14	0.15	0.08	-0.06
$\hat{\beta_0}$	(1.76)	(1.73)	(1.27)	(-0.50)	(1.79)	(1.82)	(0.94)	(-0.95)
	-0.66	-0.55	-0.67	-0.01	-0.67	-0.59	-0.67	-0.00
$\hat{\beta_B}$	(-4.32)	(-3.44)	(-4.03)	(-0.05)	(-4.23)	(-3.61)	(-3.94)	(-0.03)
	0.07	-0.35	-0.50	-0.57	0.05	-0.27	-0.49	-0.54
$\hat{\beta_{B,U}}$	(0.34)	(-1.65)	(-2.27)	(-3.56)	(0.24)	(-1.26)	(-2.15)	(-3.15)
Size Tercile 3								
	0.56%	0.42%	0.80%	0.24%	0.44%	0.40%	0.80%	0.36%
$\hat{\alpha_0}$	(1.82)	(1.25)	(2.34)	(1.02)	(1.33)	(1.17)	(1.95)	(1.01)
	0.18	0.18	0.20	0.02	0.19	0.23	0.25	0.06
$\hat{\beta_0}$	(2.29)	(2.09)	(2.26)	(0.29)	(2.18)	(2.55)	(2.34)	(0.66)
	-0.74	-0.76	-0.88	-0.14	-0.76	-0.75	-0.92	-0.16
$\hat{\beta_B}$	(-4.62)	(-4.26)	(-4.91)	(-1.11)	(-4.36)	(-4.16)	(-4.30)	(-0.88)
	0.03	0.04	-0.50	-0.53	0.07	0.04	-0.41	-0.49
$\hat{\beta_{B,U}}$	(0.14)	(0.16)	(-2.09)	(-3.23)	(0.32)	(0.18)	(-1.45)	(-1.97)

Table VIII: Institutional Ownership/$RET_{T-12,T-7}$/RNS triple sorted Portfolio Optionality in Bear Market. At the end of each calendar month, we independently sort firms by Institutional Ownership, $RET_{T-12,T-7}$ and RNS into terciles. In each Size/RNS group, we regress the equally- and value-weighted WML portfolio returns on the time series model: $\tilde{R}_{WML,t} = \alpha_0 + (\beta_0 + I_{B,t-1}(\beta_B + \tilde{I}_{U,t}\beta_{B,U}))\tilde{R}_{m,t} + \tilde{\epsilon}_t$ and report the regression results on left and right panels, respectively.

	EW				VW			
	RNS Tercile				RNS Tercile			
	L	M	H	H-L	L	M	H	H-L
Inst Own Tercile 1								
	1.26%	1.48%	0.94%	-0.32%	0.82%	1.24%	1.17%	0.35%
$\hat{\alpha_0}$	(3.81)	(4.51)	(2.72)	(-1.30)	(1.97)	(2.77)	(2.39)	(0.78)
	0.12	0.10	0.12	-0.00	0.12	0.10	0.22	0.10
$\hat{\beta_0}$	(1.42)	(1.19)	(1.36)	(-0.01)	(1.10)	(0.91)	(1.77)	(0.92)
	-0.72	-0.62	-0.70	0.02	-0.87	-0.67	-1.16	-0.29
$\hat{\beta_B}$	(-4.21)	(-3.68)	(-3.93)	(0.14)	(-4.08)	(-2.90)	(-4.61)	(-1.25)
	-0.00	-0.23	-0.08	-0.08	0.26	0.20	-0.32	-0.59
$\hat{\beta_{B,U}}$	(-0.01)	(-1.01)	(-0.35)	(-0.47)	(0.92)	(0.65)	(-0.97)	(-1.91)
Inst Own Tercile 2								
	0.13%	0.11%	-0.06%	-0.19%	0.21%	-0.04%	0.19%	-0.02%
$\hat{\alpha_0}$	(0.44)	(0.34)	(-0.18)	(-0.75)	(0.57)	(-0.10)	(0.47)	(-0.05)
	0.15	0.14	0.06	-0.09	0.16	0.24	0.15	-0.01
$\hat{\beta_0}$	(2.09)	(1.78)	(0.73)	(-1.46)	(1.73)	(2.64)	(1.47)	(-0.12)
	-0.62	-0.63	-0.48	0.15	-0.61	-0.86	-0.58	0.03
$\hat{\beta_B}$	(-4.18)	(-3.89)	(-2.77)	(1.14)	(-3.16)	(-4.56)	(-2.75)	(0.16)
	-0.01	-0.14	-0.45	-0.44	-0.12	0.06	-0.36	-0.24
$\hat{\beta_{B,U}}$	(-0.05)	(-0.64)	(-1.98)	(-2.61)	(-0.48)	(0.25)	(-1.30)	(-0.85)
Inst Own Tercile 3								
	0.26%	0.09%	0.19%	-0.07%	0.17%	-0.00%	-0.01%	-0.18%
$\hat{\alpha_0}$	(0.93)	(0.31)	(0.63)	(-0.30)	(0.53)	(-0.00)	(-0.02)	(-0.54)
	0.17	0.21	0.07	-0.10	0.34	0.24	0.11	-0.23
$\hat{\beta_0}$	(2.39)	(2.78)	(0.90)	(-1.70)	(4.24)	(2.74)	(1.19)	(-2.82)
	-0.63	-0.64	-0.48	0.15	-0.82	-0.79	-0.59	0.23
$\hat{\beta_B}$	(-4.38)	(-4.12)	(-3.07)	(1.23)	(-5.05)	(-4.46)	(-3.24)	(1.38)
	0.03	-0.03	-0.31	-0.34	0.24	0.12	-0.27	-0.51
$\hat{\beta_{B,U}}$	(0.18)	(-0.15)	(-1.47)	(-2.16)	(1.12)	(0.53)	(-1.11)	(-2.28)

Table IX: WML Portfolio Returns and Estimated Market Variance. At the end of each calendar month, we independently sort firms by $RET_{T-12,T-7}$ and RNS into terciles. In each RNS tercile, the equally- and value-weighted WML portfolio returns are regressed on a set of time series models and reported on left and right panels, respectively. Model 1 regresses the WML portfolios as well as a long-short portfolio on the bear market indicator $I_{B,t-1}$: $\tilde{R}_{WML,t} = \gamma_0 + \gamma_0 I_{B,t-1} + \tilde{\epsilon_t}$. Model 2 regresses the WML portfolios on the market variance $\sigma^2_{m,t-1}$: $\tilde{R}_{WML,t} = \gamma_0 + \gamma_{\sigma^2_{m,t-1}} \sigma^2_{m,t-1} + \tilde{\epsilon_t}$. Model 3 fits the model: $\tilde{R}_{WML,t} = \gamma_0 + \gamma_0 I_{B,t-1} + \gamma_{\sigma^2_{m,t-1}} \sigma^2_{m,t-1} + \tilde{\epsilon_t}$. Model 4 runs the WML portfolio returns on the interaction of the bear market indicator and market variance: $\tilde{R}_{WML,t} = \gamma_0 + \gamma_{int} I_{B,t-1} \sigma^2_{m,t-1} + \tilde{\epsilon_t}$. Left and right panels present regression results of the equally- and value-weighted portfolios, respectively.

	EW				VW			
	RNS Tercile				RNS Tercile			
	L	M	H	H-L	L	M	H	H-L
Model 1								
	0.60%	0.59%	0.56%	-0.04%	0.54%	0.53%	0.55%	0.01%
$\hat{\gamma_0}$	(2.03)	(1.89)	(1.71)	(-0.25)	(1.53)	(1.45)	(1.37)	(0.04)
	0.06%	-0.26%	-0.61%	-0.68%	0.22%	0.12%	-0.21%	-0.43%
$\hat{\gamma_B}$	(0.10)	(-0.39)	(-0.88)	(-1.86)	(0.29)	(0.15)	(-0.25)	(-0.70)
Model 2								
	0.97%	1.04%	1.24%	0.27%	0.77%	0.86%	1.11%	0.34%
$\hat{\gamma_0}$	(2.90)	(2.97)	(3.40)	(1.40)	(1.94)	(2.09)	(2.48)	(1.05)
	-0.23	-0.33	-0.54	-0.30	-0.12	-0.20	-0.40	-0.28
$\hat{\gamma_{\sigma^2_m}}$	(-1.68)	(-2.30)	(-3.56)	(-3.85)	(-0.74)	(-1.19)	(-2.17)	(-2.08)
Model 3								
	0.93%	1.00%	1.19%	0.26%	0.74%	0.82%	1.06%	0.33%
$\hat{\gamma_0}$	(2.76)	(2.85)	(3.27)	(1.38)	(1.84)	(1.99)	(2.36)	(0.99)
	0.83%	0.71%	0.87%	0.04%	0.69%	0.81%	0.99%	0.31%
$\hat{\gamma_B}$	(1.13)	(0.93)	(1.09)	(0.10)	(0.79)	(0.90)	(1.01)	(0.43)
	-0.33	-0.42	-0.64	-0.31	-0.20	-0.30	-0.52	-0.32
$\hat{\gamma_{\sigma^2_m}}$	(-2.02)	(-2.45)	(-3.61)	(-3.34)	(-1.04)	(-1.48)	(-2.38)	(-2.01)
Model 4								
	0.76%	0.76%	0.80%	0.04%	0.62%	0.68%	0.78%	0.15%
$\hat{\gamma_0}$	(2.73)	(2.62)	(2.65)	(0.25)	(1.90)	(1.98)	(2.09)	(0.56)
	-0.19	-0.31	-0.51	-0.32	-0.05	-0.17	-0.37	-0.32
$\hat{\gamma_{int}}$	(-1.48)	(-2.30)	(-3.61)	(-4.33)	(-0.34)	(-1.06)	(-2.16)	(-2.56)

Table X: Triple Sorted Portfolio Returns and Estimated Market Variance. In Panel A, at the end of each calendar month, we independently sort firms by Market Capitalization, $RET_{T-12,T-7}$ and RNS into terciles. In each Size/RNS group, the equally- and value-weighted WML portfolio returns are regressed on the interaction of the bear market indicator and the estimated market variance: $\tilde{R}_{WML,t} = \gamma_0 + \gamma_{int} I_{B,t-1}\sigma^2_{m,t-1} + \tilde{\epsilon}_t$ and reported on left and right panels, respectively. In Panel B, at the end of each calendar month, we independently sort firms by Institutional Ownership, $RET_{T-12,T-7}$ and RNS into terciles. In each Institutional Ownership/RNS group, the equally- and value-weighted WML portfolio returns are regressed on the interaction of the bear market indicator and the estimated market variance: $\tilde{R}_{WML,t} = \gamma_0 + \gamma_{int} I_{B,t-1}\sigma^2_{m,t-1} + \tilde{\epsilon}_t$ and reported on left and right panels, respectively.

	EW				VW			
	RNS Tercile				RNS Tercile			
	L	M	H	H-L	L	M	H	H-L
Panel A: Triple Sorts by Size/$RET_{T-12,T-7}$/RNS								
Size Tercile 1								
$\hat{\gamma_0}$	0.87%	0.96%	0.94%	0.07%	0.80%	0.93%	0.79%	-0.01%
	(3.11)	(3.23)	(3.16)	(0.28)	(2.73)	(3.05)	(2.60)	(-0.04)
$\hat{\gamma_{int}}$	-0.36	-0.43	-0.48	-0.12	-0.42	-0.41	-0.37	0.04
	(-2.71)	(-3.12)	(-3.43)	(-1.05)	(-3.07)	(-2.88)	(-2.65)	(0.36)
Size Tercile 2								
$\hat{\gamma_0}$	0.48%	0.56%	0.60%	0.12%	0.45%	0.59%	0.59%	0.14%
	(1.61)	(1.77)	(1.78)	(0.52)	(1.48)	(1.83)	(1.70)	(0.55)
$\hat{\gamma_{int}}$	-0.17	-0.33	-0.58	-0.41	-0.18	-0.30	-0.54	-0.37
	(-1.23)	(-2.22)	(-3.72)	(-3.90)	(-1.22)	(-2.03)	(-3.34)	(-3.21)
Size Tercile 3								
$\hat{\gamma_0}$	0.77%	0.73%	0.94%	0.17%	0.61%	0.66%	0.95%	0.34%
	(2.44)	(2.10)	(2.50)	(0.70)	(1.79)	(1.90)	(2.19)	(0.97)
$\hat{\gamma_{int}}$	-0.14	-0.26	-0.44	-0.29	-0.04	-0.16	-0.34	-0.30
	(-0.95)	(-1.59)	(-2.48)	(-2.65)	(-0.25)	(-0.98)	(-1.70)	(-1.86)
Panel B: Triple Sorts by Institutional Ownership/$RET_{T-12,T-7}$/RNS								
Inst Own Tercile 1								
$\hat{\gamma_0}$	1.43%	1.64%	1.25%	-0.18%	0.93%	1.37%	1.34%	0.41%
	(4.20)	(4.87)	(3.57)	(-0.76)	(2.21)	(3.11)	(2.58)	(0.94)
$\hat{\gamma_{int}}$	-0.16	-0.34	-0.41	-0.25	0.12	0.04	-0.35	-0.47
	(-0.99)	(-2.18)	(-2.50)	(-2.32)	(0.63)	(0.19)	(-1.44)	(-2.32)
Inst Own Tercile 2								
$\hat{\gamma_0}$	0.33%	0.35%	0.11%	-0.22%	0.41%	0.27%	0.29%	-0.12%
	(1.14)	(1.12)	(0.34)	(-0.93)	(1.08)	(0.72)	(0.70)	(-0.31)
$\hat{\gamma_{int}}$	-0.19	-0.35	-0.55	-0.36	-0.25	-0.20	-0.31	-0.06
	(-1.38)	(-2.37)	(-3.51)	(-3.27)	(-1.44)	(-1.14)	(-1.63)	(-0.33)
Inst Own Tercile 3								
$\hat{\gamma_0}$	0.50%	0.35%	0.45%	-0.06%	0.54%	0.29%	0.32%	-0.22%
	(1.78)	(1.14)	(1.47)	(-0.25)	(1.68)	(0.82)	(0.93)	(-0.69)
$\hat{\gamma_{int}}$	-0.19	-0.22	-0.54	-0.35	-0.08	-0.13	-0.59	-0.50
	(-1.47)	(-1.58)	(-3.85)	(-3.45)	(-0.57)	(-0.81)	(-3.62)	(-3.44)

Table XI: Portfolio Sorted by Factor Loadings on Risk-Neutral Skewness Factor (β_{SKEW}) and Momentum ($RET_{T-12,T-7}$). At the end of each calendar month, we rank stocks into five portfolios according to their risk neutral skewness measure (RNS) and construct the risk-neutral skewness factor (SKEW) as the equally-weighted return of the portfolio that long the portfolio with highest RNS and short the portfolio with lowest RNS. We run the rolling window regression: $Exret = \alpha + \beta_M Mktrf + \beta_{SKEW} SKEW$ over the past 60 months and β_{SKEW} is the factor loading on the SKEW. Each calendar month, we rank stocks in ascending order by their β_{SKEW} and intermediate horizon past performance and assign the ranked stocks to one of five groups, respectively. Panel A, Panel B and Panel C present the excess return, Carhart four-factor α and Carhart four factors with Pastor and Stambaugh (2005) liquidity factor α for the twenty-five value-weighted portfolios. The rightmost column presents characteristics of a self-financing portfolio that long the past winner and short the past loser. The t-statistics are reported in parentheses and adjusted following Newey and West (1987) with a lag of 6 months.

	Panel A: Excess Return Momentum Decile										
	1	2	3	4	5	6	7	8	9	10	H-L
β_{SKEW}											
	-0.33%	0.44%	0.49%	0.52%	0.59%	0.65%	0.48%	1.01%	0.63%	1.30%	1.63%
1	(-0.46)	(0.86)	(1.20)	(1.26)	(1.54)	(2.08)	(1.47)	(3.38)	(2.07)	(2.76)	(2.71)
	0.70%	0.34%	0.68%	0.51%	0.70%	0.66%	0.67%	0.92%	0.83%	1.16%	0.46%
2	(1.23)	(0.64)	(1.68)	(1.29)	(1.98)	(2.16)	(2.39)	(3.49)	(2.57)	(3.08)	(0.84)
	0.57%	0.32%	0.61%	0.73%	0.77%	0.51%	0.83%	0.65%	0.96%	0.63%	0.07%
3	(0.95)	(0.68)	(1.42)	(1.91)	(2.15)	(1.45)	(2.72)	(2.23)	(2.52)	(1.16)	(0.12)
	0.46%	0.44%	0.32%	0.72%	0.49%	0.74%	0.32%	0.57%	0.67%	1.09%	0.63%
4	(0.78)	(0.85)	(0.66)	(1.67)	(1.30)	(1.72)	(0.77)	(1.47)	(1.41)	(1.98)	(1.25)
	0.59%	0.36%	0.52%	0.57%	0.99%	1.21%	1.57%	1.16%	0.82%	0.83%	0.24%
5	(0.80)	(0.59)	(0.89)	(0.78)	(1.46)	(1.99)	(2.23)	(2.06)	(1.33)	(1.18)	(0.49)
	0.93%	-0.08%	0.04%	0.05%	0.40%	0.56%	1.09%	0.16%	0.19%	-0.46%	-1.39%
H-L	(1.74)	(-0.17)	(0.07)	(0.07)	(0.63)	(1.11)	(1.63)	(0.37)	(0.40)	(-1.02)	(-3.12)
WML[-12,-7]	0.16%	0.31%	0.54%	0.52%	0.62%	0.64%	0.62%	0.85%	0.75%	1.00%	0.84%
All	(0.28)	(0.66)	(1.35)	(1.43)	(2.04)	(2.09)	(2.20)	(3.06)	(2.23)	(2.07)	(1.71)

	Panel B: Carhart α Momentum Decile										
	1	2	3	4	5	6	7	8	9	10	H-L
β_{SKEW}											
	-0.85%	-0.01%	-0.01%	0.08%	0.07%	0.15%	-0.07%	0.36%	0.02%	0.54%	1.38%
1	(-2.35)	(-0.03)	(-0.09)	(0.34)	(0.27)	(0.78)	(-0.44)	(2.07)	(0.09)	(2.13)	(3.49)
	0.24%	-0.12%	0.19%	-0.00%	0.15%	0.13%	0.08%	0.38%	0.13%	0.30%	0.06%
2	(0.84)	(-0.44)	(1.14)	(-0.01)	(0.79)	(0.88)	(0.57)	(2.33)	(0.66)	(1.41)	(0.16)
	0.05%	-0.19%	0.11%	0.19%	0.21%	-0.07%	0.31%	0.07%	0.37%	-0.14%	-0.19%
3	(0.16)	(-0.89)	(0.59)	(0.86)	(0.94)	(-0.34)	(1.51)	(0.46)	(1.84)	(-0.49)	(-0.50)
	-0.08%	-0.14%	-0.17%	0.10%	-0.10%	0.17%	-0.26%	-0.04%	0.01%	0.35%	0.42%
4	(-0.25)	(-0.54)	(-0.75)	(0.40)	(-0.33)	(0.68)	(-1.25)	(-0.21)	(0.06)	(1.23)	(1.30)
	-0.12%	-0.42%	-0.09%	-0.20%	0.32%	0.64%	0.88%	0.56%	0.05%	-0.10%	0.02%
5	(-0.30)	(-1.23)	(-0.30)	(-0.35)	(0.60)	(1.77)	(2.09)	(1.52)	(0.15)	(-0.27)	(0.06)
	0.73%	-0.41%	-0.08%	-0.28%	0.25%	0.50%	0.95%	0.19%	0.04%	-0.63%	-1.36%
H-L	(1.47)	(-0.94)	(-0.24)	(-0.41)	(0.37)	(1.04)	(1.81)	(0.52)	(0.09)	(-1.47)	(-3.20)
WML[-12,-7]	-0.36%	-0.14%	0.06%	0.01%	0.07%	0.11%	0.06%	0.26%	0.10%	0.20%	0.56%
All	(-1.58)	(-0.81)	(0.45)	(0.09)	(0.72)	(0.95)	(0.69)	(2.27)	(0.79)	(1.14)	(1.93)

	Panel C: Carhart + Liq α Momentum Decile										
	1	2	3	4	5	6	7	8	9	10	H-L
β_{SKEW}											
	-0.96%	-0.08%	-0.04%	0.02%	0.06%	0.10%	-0.10%	0.34%	0.02%	0.56%	1.52%
1	(-2.74)	(-0.30)	(-0.23)	(0.09)	(0.23)	(0.55)	(-0.66)	(2.03)	(0.12)	(2.19)	(4.04)
	0.16%	-0.13%	0.15%	-0.03%	0.15%	0.14%	0.03%	0.42%	0.11%	0.33%	0.17%
2	(0.55)	(-0.46)	(0.92)	(-0.16)	(0.75)	(0.93)	(0.23)	(2.61)	(0.54)	(1.48)	(0.46)
	-0.01%	-0.19%	0.07%	0.14%	0.21%	-0.05%	0.32%	0.08%	0.40%	-0.09%	-0.08%
3	(-0.03)	(-0.86)	(0.37)	(0.63)	(0.95)	(-0.24)	(1.52)	(0.53)	(1.97)	(-0.32)	(-0.21)
	-0.05%	-0.11%	-0.16%	0.11%	-0.06%	0.18%	-0.21%	-0.01%	0.06%	0.38%	0.44%
4	(-0.18)	(-0.41)	(-0.66)	(0.40)	(-0.19)	(0.72)	(-0.97)	(-0.05)	(0.25)	(1.33)	(1.30)
	-0.26%	-0.44%	-0.09%	-0.14%	0.36%	0.70%	0.89%	0.54%	0.13%	-0.06%	0.21%
5	(-0.69)	(-1.23)	(-0.29)	(-0.25)	(0.64)	(1.86)	(2.10)	(1.46)	(0.36)	(-0.15)	(0.63)
	0.70%	-0.36%	-0.06%	-0.16%	0.30%	0.60%	1.00%	0.19%	0.11%	-0.62%	-1.31%
H-L	(1.38)	(-0.79)	(-0.17)	(-0.24)	(0.42)	(1.22)	(1.92)	(0.50)	(0.25)	(-1.38)	(-3.01)
WML[-12,-7]	-0.45%	-0.17%	0.03%	-0.02%	0.08%	0.12%	0.05%	0.26%	0.13%	0.24%	0.69%
All	(-2.03)	(-0.91)	(0.26)	(-0.16)	(0.77)	(0.97)	(0.59)	(2.24)	(0.97)	(1.40)	(2.52)

Table XII: Portfolio Sorted by Factor Loadings on Risk-Neutral Skewness Factor (β_{SKEW}) and Momentum ($RET_{T-12,T-7}$) In Different Economic Conditions. We define recessions as the periods when the cumulative CRSP VW index return in the past 24 months is negative and other periods as expansions. At the end of each calendar month, we rank stocks into five portfolios according to their risk neutral skewness measure (RNS) and construct the risk-neutral skewness factor (SKEW) as the equally-weighted return of the portfolio that long the portfolio with highest RNS and short the portfolio with lowest RNS. We run the rolling window regression: $Exret = \alpha + \beta_M Mktrf + \beta_{SKEW} SKEW$ over the past 60 months and β_{SKEW} is the factor loading on the SKEW. Each calendar month, we rank stocks in ascending order by their β_{SKEW} and intermediate horizon past performance and assign the ranked stocks to one of five groups, respectively. Panel A and Panel B present the Carhart + Liq α for the twenty-five value-weighted portfolios in recessions and expansions, respectively. The rightmost column presents characteristics of a self-financing portfolio that long the past winner and short the past loser. The t-statistics are reported in parentheses and adjusted following Newey and West (1987) with a lag of 6 months.

Panel A: Recessions

	Momentum Decile										
β_{SKEW}	1	2	3	4	5	6	7	8	9	10	H-L
	-1.34%	0.53%	-0.48%	0.55%	0.69%	0.76%	0.30%	0.46%	-0.15%	0.63%	1.97%
1	(-1.84)	(0.98)	(-1.16)	(1.63)	(2.08)	(1.81)	(0.87)	(1.41)	(-0.39)	(1.28)	(2.25)
	0.52%	-0.47%	0.16%	0.32%	-0.01%	0.45%	0.41%	0.82%	0.58%	1.18%	0.66%
2	(1.17)	(-0.71)	(0.44)	(1.27)	(-0.01)	(1.66)	(1.29)	(2.29)	(1.52)	(2.17)	(1.03)
	0.18%	-0.95%	-0.05%	0.08%	0.36%	0.91%	0.85%	0.01%	0.85%	0.69%	0.51%
3	(0.34)	(-2.50)	(-0.15)	(0.13)	(0.87)	(1.74)	(1.80)	(0.04)	(2.35)	(1.57)	(0.85)
	-0.39%	-0.72%	-0.91%	-0.26%	1.18%	0.26%	-0.44%	0.50%	0.11%	0.63%	1.03%
4	(-0.76)	(-1.47)	(-2.34)	(-0.59)	(1.88)	(0.56)	(-0.71)	(1.10)	(0.28)	(0.90)	(1.15)
	-0.20%	-0.02%	-0.00%	-1.53%	0.84%	0.57%	0.50%	0.10%	0.24%	-0.41%	-0.21%
5	(-0.27)	(-0.02)	(-0.01)	(-2.49)	(0.68)	(0.91)	(0.72)	(0.16)	(0.44)	(-1.06)	(-0.22)
	1.14%	-0.54%	0.48%	-2.09%	0.15%	-0.20%	0.20%	-0.36%	0.40%	-1.04%	-2.18%
H-L	(1.26)	(-0.54)	(0.66)	(-2.76)	(0.11)	(-0.26)	(0.25)	(-0.54)	(0.62)	(-2.42)	(-2.32)
WML[-12,-7]	-0.59%	-0.41%	-0.27%	0.16%	0.51%	0.76%	0.33%	0.65%	0.22%	0.73%	1.32%
All	(-1.38)	(-1.44)	(-0.96)	(0.66)	(2.45)	(3.30)	(1.70)	(3.12)	(0.91)	(2.19)	(2.24)

Panel B: Expansions

	Momentum Decile										
β_{SKEW}	1	2	3	4	5	6	7	8	9	10	H-L
	-0.84%	-0.29%	0.12%	-0.29%	-0.23%	-0.26%	-0.28%	0.19%	-0.01%	0.47%	1.31%
1	(-2.37)	(-1.01)	(0.62)	(-1.09)	(-0.76)	(-1.31)	(-1.66)	(0.87)	(-0.06)	(1.63)	(3.16)
	-0.18%	0.15%	0.14%	-0.24%	0.25%	-0.13%	-0.10%	0.20%	-0.07%	-0.01%	0.17%
2	(-0.50)	(0.43)	(0.74)	(-1.06)	(1.04)	(-1.00)	(-0.61)	(1.27)	(-0.33)	(-0.07)	(0.35)
	-0.04%	0.01%	0.19%	0.10%	0.27%	-0.47%	0.03%	0.10%	0.20%	-0.32%	-0.28%
3	(-0.10)	(0.04)	(0.98)	(0.50)	(0.81)	(-2.51)	(0.15)	(0.52)	(0.83)	(-1.03)	(-0.64)
	0.24%	0.25%	-0.12%	0.12%	-0.47%	0.25%	0.03%	-0.09%	0.07%	0.33%	0.09%
4	(0.82)	(0.84)	(-0.43)	(0.41)	(-1.48)	(0.81)	(0.18)	(-0.34)	(0.24)	(0.95)	(0.28)
	0.14%	-0.23%	0.05%	0.55%	0.60%	0.95%	1.00%	0.52%	0.18%	0.13%	-0.01%
5	(0.27)	(-0.60)	(0.14)	(0.76)	(0.98)	(2.05)	(2.18)	(1.11)	(0.33)	(0.27)	(-0.03)
	0.98%	0.06%	-0.07%	0.84%	0.83%	1.21%	1.28%	0.33%	0.19%	-0.34%	-1.32%
H-L	(1.40)	(0.12)	(-0.18)	(1.08)	(1.13)	(1.97)	(2.19)	(0.65)	(0.33)	(-0.64)	(-2.59)
WML[-12,-7]	-0.31%	0.04%	0.15%	-0.15%	0.04%	-0.17%	-0.08%	0.12%	0.08%	0.11%	0.42%
All	(-1.27)	(0.19)	(1.07)	(-0.99)	(0.30)	(-1.59)	(-0.85)	(0.98)	(0.60)	(0.53)	(1.41)

Table XIII: Low Momentum Crash Factor Loading WML Portfolio Performance. This table presents the economic performance of the risk managed momentum strategy in Barroso and Santa-Clara (2015), the Novy-Marx (2012) momentum strategy constructed by stocks in β_{SKEW} quintile 1, and the Novy-Marx (2012) momentum strategy constructed by all stocks over the available sample periods. The mean, the standard deviation, the Sharpe ratio, and the information ratio are annualized.

Portfolio	Max	Min	Mean	Standard Deviation	Kurt	Skew	Sharpe Ratio	Information Ratio	Corr
1998.04 - 2011.12									
WML[-12,-2] *	14.45	-13.65	9.23	14.76	1.04	-0.10	0.63	-	-
WML[-12,-7] β_{SKEW} Q1	33.49	-30.33	23.64	28.74	3.28	-0.25	0.82	0.21	0.56
1998.10 - 2011.12									
WML[-12,-2] *	13.75	-13.65	7.33	14.19	0.92	-0.29	0.52	-	-
WML[-12,-7] β_{SKEW} Q1*	19.36	-10.77	21.07	18.12	0.36	0.08	1.16	0.79	0.67
1998.10 - 2016.06									
WML[-12,-7] β_{SKEW} Q1	33.49	-30.33	18.71	26.96	3.50	-0.16	0.69	-	-
WML[-12,-7] β_{SKEW} Q1*	19.36	-12.34	17.95	18.66	0.48	0.12	0.96	0.59	0.90

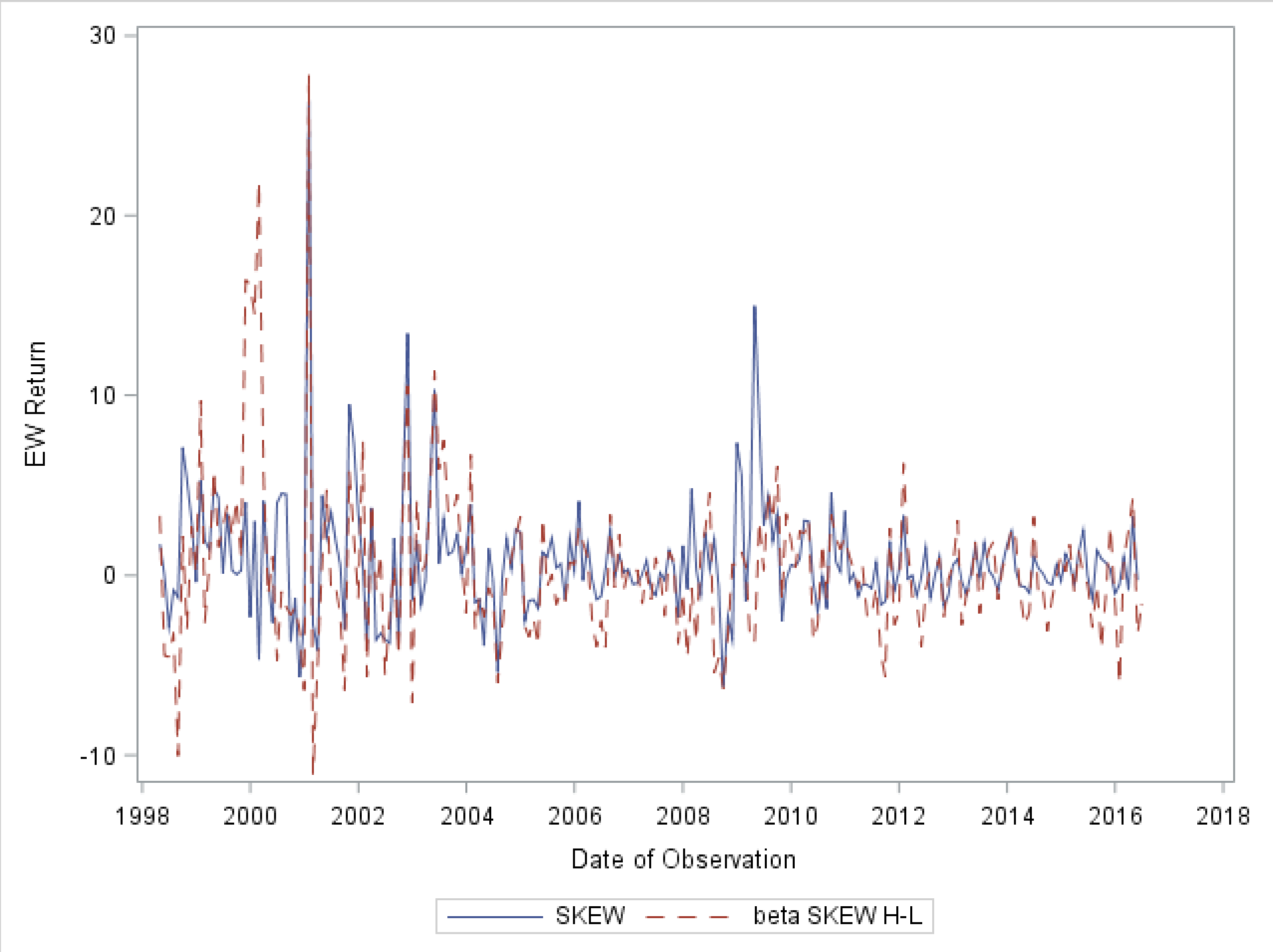
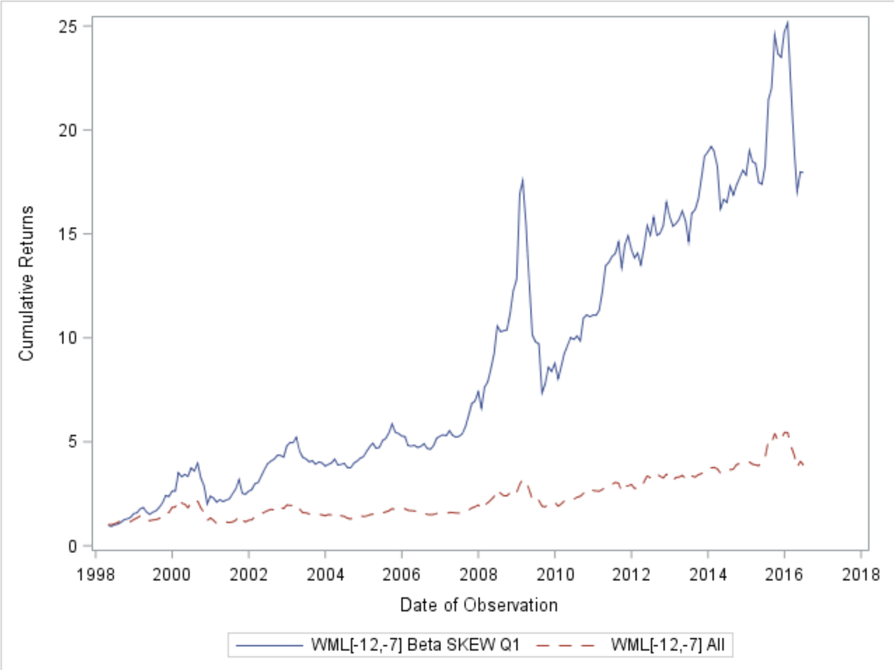
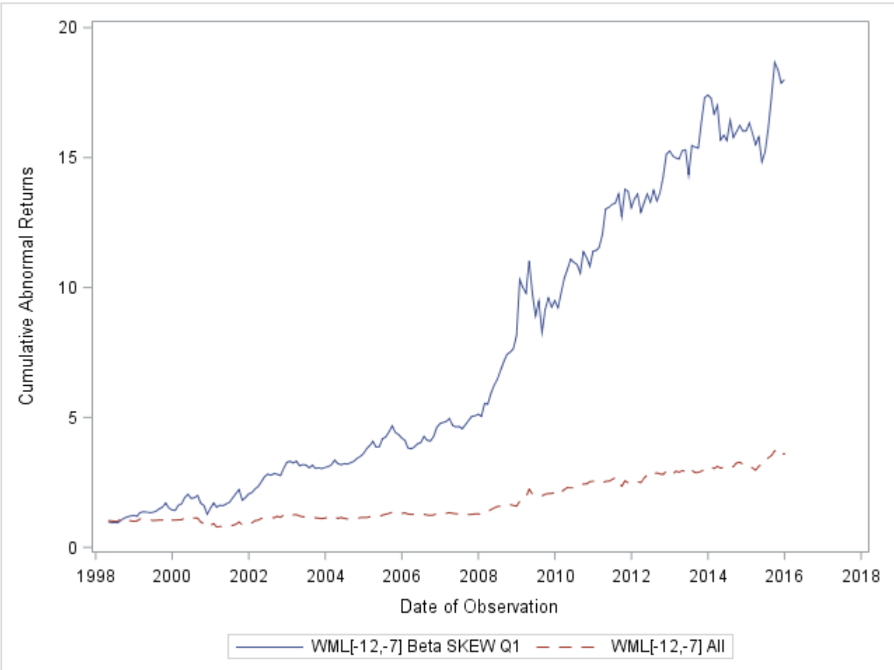


Figure 1: Comparison of Momentum Crash Factor SKEW and H-L β_{SKEW} Portfolio Return. Each calendar month, we rank stocks in ascending order by their loadings on the momentum crash factor SKEW β_{SKEW} and assign the ranked stocks to one of five groups. Then we find out the equally-weighted returns of the portfolio that long the stocks with highest β_{SKEW} and short the lowest β_{SKEW}. We plot the momentum crash factor SKEW (the H-L portfolio traded on risk neutral skewness) and the H-L portfolio returns through April 1998 to June 2016.



(a) Cumulative Returns



(b) Cumulative Abnormal Returns

Figure 2: Cumulative Returns and Cumulative Abnormal Returns of the Novy-Marx (2012) Winner minus Loser Strategies Constructed by Stocks in the First β_{SKEW} Quintile and by All Stocks. Panel A plots the cumulative monthly returns to two portfolios: (1) the Novy-Marx (2012) winner-minus-loser strategy constructed by stocks in the first β_{SKEW} quintile, and (2) the Novy-Marx (2012) winner-minus loser strategy constructed by all stocks available over the period from April, 1998 through June, 2016. Panel B plots the cumulative monthly abnormal returns benchmarked by five factor model (Carhart (1997) four factors with Pastor and Stambaugh (2005) liquidity factor) to two portfolios: (1) the Novy-Marx (2012) winner-minus-loser strategy constructed by stocks in the first β_{SKEW} quintile, and (2) the Novy-Marx (2012) winner-minus loser strategy constructed by all stocks available over the period from April, 1998 through Dec, 2015.

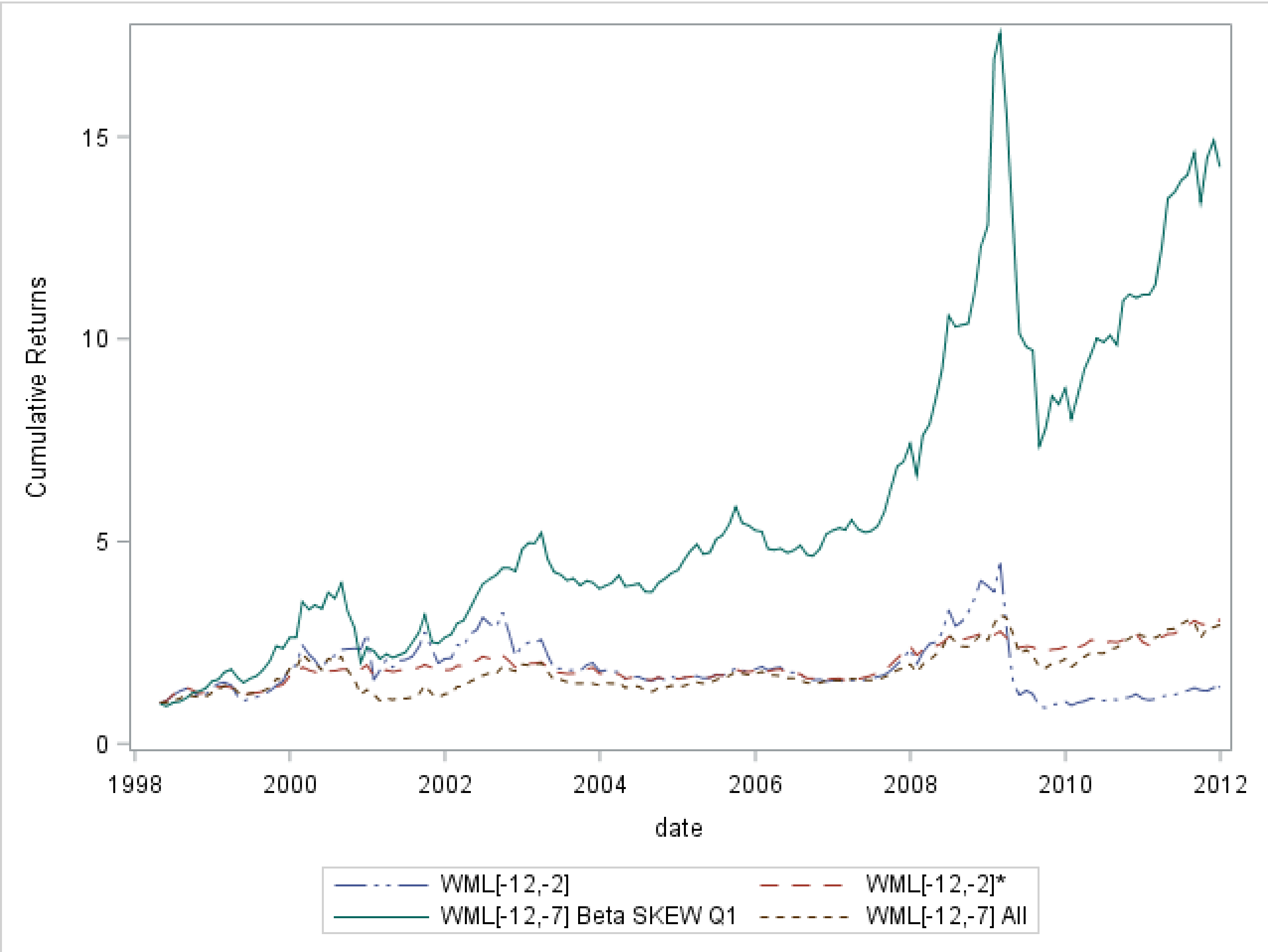
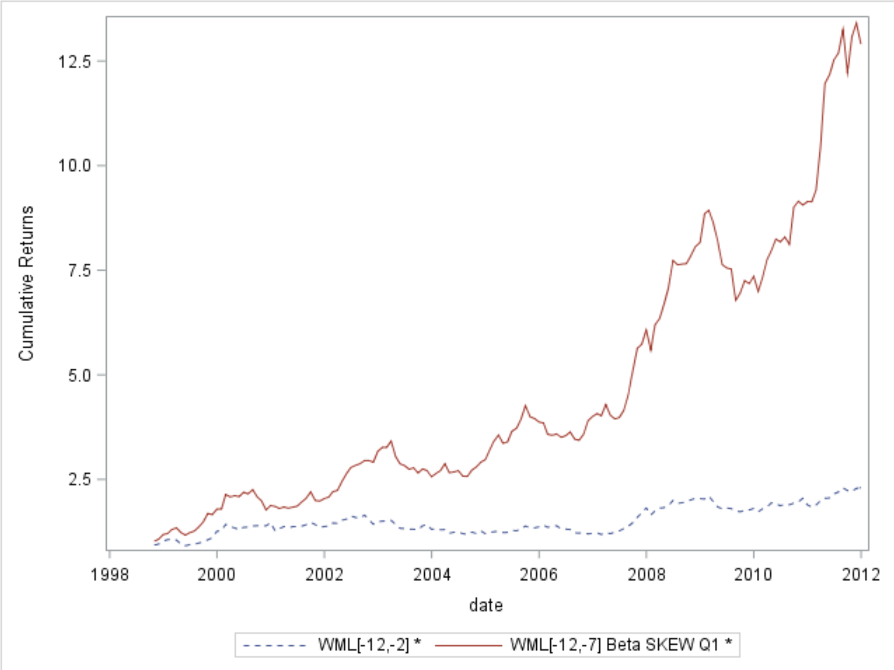
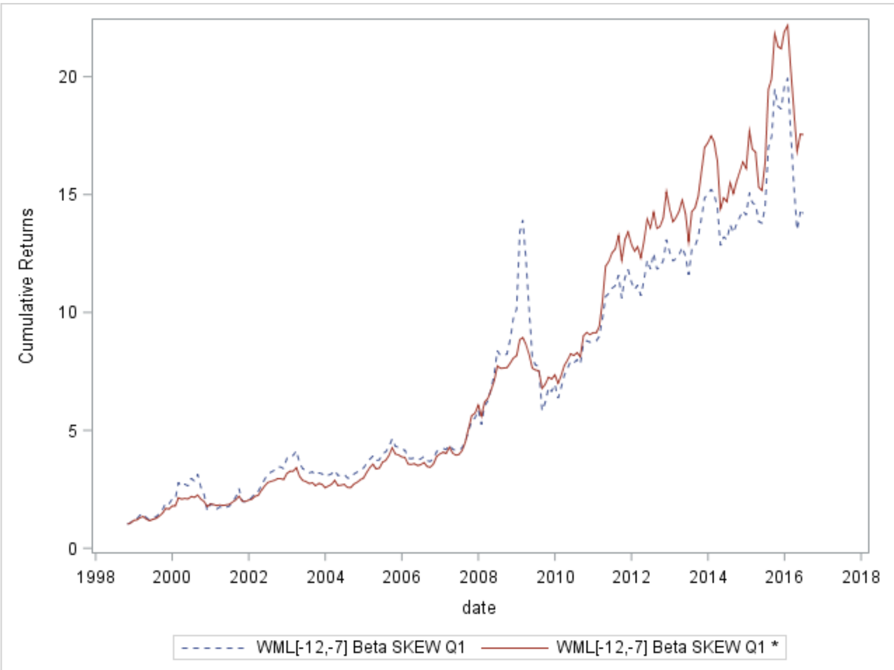


Figure 3: Low Momentum Crash Factor Loading WML Portfolio Performance. This figure plots the cumulative monthly returns to the baseline Winner-minus-Loser Strategy, the risk managed momentum strategy in Barroso and Santa-Clara (2015), the Novy-Marx (2012) momentum strategy constructed by stocks in β_{SKEW} quintile 1, and the Novy-Marx (2012) momentum strategy constructed by all stocks over the period from April, 1998 through December, 2011.



(a) The risk managed, low momentum crash factor loading WML portfolio performance and the risk managed momentum strategy in Barroso and Santa-Clara (2015).



(b) The risk managed, low momentum crash factor loading WML portfolio performance and the momentum crash factor hedged WML portfolio.

Figure 4: The Risk Managed, Low Momentum Crash Factor Loading WML Portfolio Performance. Panel A plots the cumulative monthly returns to the risk managed momentum strategy in Barroso and Santa-Clara (2015) and the risk managed, Novy-Marx (2012) momentum strategy constructed by stocks in β_{SKEW} quintile 1 over the period from October, 1998 through December, 2011. Panel B plots the cumulative monthly returns to the Novy-Marx (2012) momentum strategy constructed by stocks in β_{SKEW} quintile 1 and the risk managed, Novy-Marx (2012) momentum strategy constructed by stocks in β_{SKEW} quintile 1 over the period from October, 1998 through June, 2016.