Rank, Sign, and Momentum*

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Abstract

Non-parametric measures, such as rank and sign of daily returns, capture a series of information arriving continuously in small amounts while mitigating overreaction to infrequent dramatic changes in stock prices. Momentum strategies formed on the basis of rank and sign generate significant profits for short-term holding periods and exhibit no long-term return reversals. More importantly, rank and sign momentum strategies subsume traditional price momentum, but not vice versa. We further show that rank and sign momentum profits are less affected by investors' overreaction to salient price movement and are less vulnerable to crash risk.

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The search for profitable trading strategies has been a topic of enduring interest to both practitioners and academics. To date, the price momentum strategy proposed by Jegadeesh and Titman (JT) (1993) remains one of the most robust trading strategies applied to markets around the world, yet past studies have never questioned the limitations of the parametric nature of past returns in determining winners and losers. This question is critically important, because parametric statistics built on sample moments (e.g., mean and variance) are highly sensitive to the presence of extreme price movements (Wright, 2000; Gibbons and Chakraborti, 2010; Hollander, Wolfe, and Chicken, 2014). As Bordalo, Gennaioli, and Shleifer (BGS) (2012, 2013) point out, investors' reaction to payoffs of varying salience could be the cause of mispricing or price distortion. We demonstrate that the parametric nature of past and future returns simply magnifies this problem in asset valuation.

This research thus proposes that non-parametric measures (such as rank and sign of daily returns) be used to create momentum strategies to mitigate such a mispricing problem. This research further proceeds to compare rank and momentum (RSM) strategies with traditional JT price momentum strategies. RSM strategies are constructed on the basis of daily rank or sign over the formation period.[1] Our choice of these strategies is motivated by non-parametric statistics that are known to be robust to the presence of extreme price movements.[2] We believe that non-parametric performance measures, calculated based on rank and sign, weaken the impact of extreme, salient returns in the sample, thereby providing better and more stable predictability of future returns than parametric measures.

[1] The standardized rank among stocks is first averaged over a month and then over the formation period to obtain its rank measure. Similarly, the frequency of return on stocks that is positive is used to acquire its sign measure.

[2] Wright (2000) proposes alternative variance ratio tests based on ranks and signs to show that they outperform conventional parametric tests.

Our empirical results fully support our predictions. Because rank and sign suppress the impact of extreme observations, RSM profits are less affected by investors' overreaction to salient price movement. RSM strategies outperform traditional price momentum strategies for short-term holding periods and exhibit no long-term return reversals. When we simultaneously compare the competing performance of the momentum strategies, what is most amazing is that the short-term price momentum profitability widely documented by the JT (1993) price momentum completely vanishes when controlling for RSM. The profitability of RSM, in contrast, remains robust when controlling for price momentum: the average return of rank (sign) momentum after controlling for price momentum is significant at 0.438% (0.429%) per month, while that of price momentum after controlling for rank (sign) momentum is insignificant at 0.107% (0.088%) per month.

RSM profits are robust after controlling for other alternative momentum strategies. For example, Grinblatt and Moskowitz (2004) show that momentum profits are mainly driven by return consistency of past performance. Our results remain strong after return consistency is taken into account. In addition, we compare RSM with the absolute strength momentum (ASM) investigated by Gulen and Petkova (2016). They demonstrate that ASM fully explains JT momentum profits, but not vice versa. Our comparison between ASM and RSM indicates that RSM fully explains ASM profits, but not vice versa.

Why do RSM strategies work better? Over the past few decades, there has been ample evidence that investors pay attention to only a subset of available information, because they have limited information processing capacity (Hirshleifer and Teoh, 2003; Peng and Xiong, 2006) and rely heavily on rules and heuristics to make decisions (Kahneman, 2011). As a result, sometimes they either overreact or underreact as information becomes available. Kahneman and Tversky (1979) demonstrate that people tend to overweight rare events and underweight regular events

(Barberis, 2013). Daniel et al. (1998) show that investors overreact to private information, but underreact to public information due to overconfidence and biased self-attribution. BGS (2012, 2013) propose the salience theory, in which people's attention is drawn to payoffs that are most different or salient relative to others, or a benchmark such as the average of all assets in the sample. When making choices, they overweight these salient payoffs by assigning higher subjective probabilities relative to their objective counterparts.

Investor misreaction to information causes stock prices not to properly reflect the underlying fundamentals. Observations of extreme returns (positive or negative) are likely driven by investor overreaction to salient news, whereas those with small and insignificant returns are the results of investors' insensitive reaction to non-salient news. Rank and sign measures mitigate the impact of salient extreme returns while assigning higher weights to non-salient observations that are largely overlooked by investors.

The JT price momentum is by contrast constructed on the basis of average price changes; the predictability of future returns is thus obscured by extreme returns. Our empirical evidence indicates that after controlling for RSM, the price momentum only yields insignificant returns, because both price winners and price losers are vulnerable to "salient" return observations. Thus, investors in aggregate appear to overreact to extreme past asset returns, and parametric measures (mean, variance, and skewness) are sensitive to extreme observations in the sample.

We propose that if RSM profitability captures the non-salient information embedded in stock returns while mitigating salient news, then RSM should be less vulnerable to stocks with higher salient features. In contrast, the price momentum should be more susceptible to the impact of salient information. We confirm this prediction by showing that RSM profits are robust to stocks

with varying degrees of proxies on salient features, while price momentum profitability decreases with the magnitude of salience.

The cross-sectional RSM predictability leads to predictable patterns in the time series as well. In particular, Daniel and Moskowitz (2016) demonstrate that JT price momentum is vulnerable to "momentum crash" in "panic" states. Since RSM profits are less vulnerable to salient information and less sensitive to investor overreaction, they should be less susceptive to crash risk. Indeed, RSM strategies are subject to smaller losses when JT momentum experiences extreme crashes. Over the 10 worst months in which JT momentum has an average extreme loss of -44.61%, rank and sign momentum shows average returns of -29.76% and -17.78% over the same months, respectively.

Our study builds on existing studies that recognize the information embedded in the sign of past returns to construct proxies of behavioral theories. Grinblatt and Moskowitz (2004) propose the measure of return consistency based on the frequency of positive or negative sign of past return to analyze the disposition effect in explaining the JT momentum profits. Da, Gurun, and Warachka (2014) adopt the relative frictions of negative and positive daily returns to distinguish between continuous and discrete information embedded in past returns. We provide comprehensive analyses by using not only sign but also rank of daily returns as direct measures of past performance to investigate return predictability. To the best of our knowledge, the analyses based on rank- and sign-based performance are new to the momentum literature and open up a new avenue for the analyses of momentum strategies.

Our empirical results also confirm that RSM momentum captures the non-salient component of the information often neglected by investors, which has not been highlighted by past studies. Our study has important implications. As it has been well documented that stock returns tend to be

positively skewed and leptokurtic (Albuquerque, 2012), our findings indicate that parametric risk measures and moments do not adequately summarize all the information embedded in stock prices. Our results instead highlight the importance of information embedded in non-parametric measures like rank and sign to better predict future stock returns.

1. Performance of rank and sign momentum strategies

1.1. Data and non-parametric measures

Our sample consists of the ordinary common equities of all firms (with share codes of 10 and 11) listed on NYSE, AMEX, and NASDAQ for the 54-year sample period from January 1963 to December 2016. We obtain market data, including daily returns, monthly returns, share prices, and market equities, from the Center for Research in Security Prices (CRSP) database and retrieve accounting data from the COMPUSTAT database. To be included in our sample, a stock must have available market and accounting data.

We consider non-parametric measures based on ranks and signs. Let $R_{i,d}$ denote stock i's daily return on day d, and N_d denotes the number of stocks on day d. We define $y(R_{i,d})$ as the rank of $R_{i,d}$ among N_d stocks $(R_{1,d}, \dots, R_{N_d,d})$ on day d in ascending order. We assign ties with an average rank. For example, if two stocks with equal returns are ranked third and fourth, then they are both assigned an average rank of 3.5. Before calculating a firm's average rank over a formation period, we first calculate its standardized rank for each trading day, expressed as follows (Wright, 2000):

$$rank_{i,d} = \left(y(R_{i,d}) - \frac{N_d+1}{2}\right) / \sqrt{\frac{(N_d-1)(N_d+1)}{12}}. \quad (1)$$

The daily ranks are then averaged every month and summed over the p-month formation period, which gives a firm's average rank, $rank_{i,t}(p)$:[3]

$$rank_{i,t}(p) = \frac{1}{p}\sum_{j=t-p-1}^{t-2}\left(\frac{1}{D}\sum_{d=1}^{D_j} rank_{i,d}\right), \tag{2}$$

where D_j is the number of trading days in month j. The $rank_{i,t}(p)$ measure is calculated on the basis of the number of available observations. We focus on the formation period of six months, or $p = 6$.[4]

In addition to ranks we also calculate an alternative non-parametric measure based on signs. The sign measure, $sign_{i,d}$, is an indicator function that takes the value of 1 if stock i's corresponding daily return $R_{i,d}$ is positive, and zero otherwise. Once we obtain the daily sign measure for a stock, we calculate the average sign measure across trading days with non-zero daily returns in month t, $sign_{i,t}(p)$, over past p months similar to Equation (2).[5]

From a behavioral finance perspective, stock returns essentially contain two components: a "rational" component that corresponds to the fundamentals and a "behavioral" component that corresponds to either misreaction to news or adjustment to previous misreaction, or both. A better performance measure would be one that best reflects the former while suppressing the latter. The traditional mean returns used in price momentum strategies are affected by the misreaction component, thereby causing a weaker persistence in performance and stronger reversals thereafter.

[3] As a common practice to alleviate potential microstructure problems associated with the bid-ask bounce, we skip one month between the formation and holding periods when forming the portfolios.

[4] We also conduct the same analysis based on a formation period of 12 months. The results are generally similar except that the patterns and their statistical significance are slightly weaker.

[5] Rank and sign measures can also be constructed using monthly returns. In particular, the sign measure based on monthly frequency is similar to the return consistency measure of Grinblatt and Moskowitz (2004). In the internet appendix A1, we show in cross-sectional regressions that rank and sign measures based on daily returns have better explanatory power on future stock returns than those based on monthly returns, implying that non-parametric statistics embedded in daily returns contain more information than those embedded in monthly returns.

Both rank and sign suppress the impact of extreme observations, which are likely driven by investors' overreaction to salient payoffs. However, the sign measure only keeps the information on the sign of returns, thus may suppress the misreaction component at the cost of also removing the fundamental component. It would appear that the rank measure, which still retains the ordering of returns, may provide a better trade-off between the "information" and the "noise" components.[6]

1.2 Portfolio approach to rank and sign momentum strategies

We adopt JT's (1993) portfolio approach to investigate the performance of RSM strategies. After imposing a $5 price filter at the beginning of each month, we sort the remaining stocks into ten decile portfolios based on their average ranks defined in Equation (2) and construct a rank momentum strategy by buying the stocks in the top decile portfolio (referred to as rank winners) and short selling those in the bottom decile portfolio (referred to as the rank losers). A sign momentum strategy is likewise evaluated using the average sign measure. The long-short portfolio is held for up to three years. Let portfolio 1 (P1) and portfolio 10 (P10) denote the rank (or sign) loser and winner portfolios, respectively. All portfolios are constructed with equal weights and held for the subsequent K months with a one-month skip. Following JT's approach which involves an overlapping procedure, we average the portfolio return for each month across K separate positions, with each formed in one of the K consecutive prior months from $t-K-1$ to $t-2$. For comparisons, we follow JT to construct the price momentum strategy based on a stock's past 6-month average return.

[6] In unreported results, we also did some experiments by examining an alternative momentum strategy based on signed rank. Unlike rank whose values range over 1 and N, the values of signed rank range over $-N$ and N. Thus, signed rank keeps more information by allowing the sample distribution to be asymmetric, but it is also more vulnerable to noise. Indeed, we find that signed rank momentum has a similar performance to JT's price momentum by having a slightly higher short-term profit and weaker long-term reversals.

Panel A of Table 1 reports the average monthly returns of the rank, sign, and JT momentum strategies for short-term (1-, 6-, and 12-month) holding periods subsequent to portfolio formation. The performances of rank, sign, and JT momentum strategies are profitable at 1.309%, 1.038%, and 1.150% per month, respectively, for the first month and are persistent up to one year. The JT results for the 54-year period are consistent with the price momentum compiled by JT for their 25-year study period (1965-1989), exhibiting short-term return continuation for the extended sample.

[Insert Table 1]

The results in Panel B are momentum profits during non-January months. The underlying motive for showing Panel B is the tax-loss selling effect (Roll, 1983; D'Mello, Ferris, and Hwang, 2001; George and Hwang, 2004). Investors sell loser stocks to realize tax loss benefits at year-end, depressing prices of those losers, but the prices rebound in January as the selling pressure weakens. Because momentum strategies take short positions in loser stocks, the price recovery in January increases momentum losses. With January excluded, it is natural that all momentum profits should be larger than those with January included. An important finding is that RSM strategies remain more profitable than price momentum with January excluded, especially for 6- and 12-month holding periods. Specifically, rank (sign) momentum profits are uniformly positive over short holding periods following formation; the average monthly profit is 1.226% (0.981%) with a *t*-statistic of 7.19 (7.97) for the first year. The return patterns of the JT strategy outside of January are generally similar to RSM except for being slightly smaller.

1.3 Long-term profits of momentum strategies

In addition to short-term profits we observe long-term return patterns of RSM because investor overreaction to information necessarily leads to return reversals (Daniel et al., 1998) while

underreaction may not (Da et al., 2014). We calculate the average monthly returns of the three strategies for the second- and third-year holding periods. We also calculate the cumulative buy-and-hold returns for the entire three-year holding period following formation. Panel C of Table 1 reports the results for the three strategies.

We document two interesting findings. First, rank and sign momentum strategies both generate negative but insignificant returns for the second- and third-year holding periods. The JT momentum strategy, in contrast, generates significantly negative returns for corresponding holding periods. In unreported results, we find that the negative returns of RSM are concentrated in January. With January excluded, both rank and sign momentum strategies generate significantly positive returns in the second year and insignificantly positive returns in the third year, while the JT profitability still remains significantly negative in non-January periods.

Second, the cumulative profits for the entire three-year holding period are 7.451% (*t*-statistic = 2.63) for rank momentum and 7.313% (*t*-statistic = 2.95) for sign momentum. The JT momentum, by contrast, yields an insignificant profit of 0.038% (*t*-statistic = 0.02) over the entire three-year holding period. This pattern indicates that RSM strategies outperform the JT strategy in the long term and are thus beneficial for long-term investors. More importantly, these observations suggest that RSM profitability is not driven by investor overreaction, because there is no occurrence of return reversals.

1.4 Robustness of profitability to momentum strategies

In this subsection we investigate the robustness of the profitability of JT price momentum and RSM strategies, focusing on short-term and the entire three-year holding periods.[7] Four sets of

[7] The results for the second- and third-year holding periods are similar to those reported in Table 1 and thus are not reported in order to conserve space.

robustness tests are conducted. First, we construct momentum strategies based on value weights as compiled in Panel A of Table 2. Specifically, RSM and JT momentum strategies all generate positive and significant returns under the value-weighted scheme, implying that their equal-weighted profitability is not dictated by the small-firm effect. Second, we confirm persistence of the momentum profits (with equal weights) for a 90-year period, 1927-2016, as shown in Panel B. For the one-month holding period, rank, sign, and JT momentum strategies generate average profits of 1.134%, 0.897%, and 0.934% per month with *t*-statistics of 6.11, 6.91, and 5.30, respectively. The profits are smaller for the 6- and 12-month holding periods. The results indicate that all strategies are profitable for the entire 90-year period, which suggests that rank and sign momentum profitability is not limited to any specific subsample period. Third, since we exclude low-priced stocks with price below $5 in Table 1, it is critical to show that our results are not driven by this filter. We show in Panel C that RSM profits for the 1963-2016 period remain significantly positive all over the holding periods when we include low-priced stocks. The JT momentum, however, is more sensitive to this filter as its profits become insignificant for 1- and 12-month holding periods. To make the momentum profits comparable for all strategies, we adopt the sample excluding low-priced stocks for subsequent analyses. Finally, to ensure that RSM profits are not concentrated in stocks with extreme rank or sign values, we allocate individual stocks into rank or sign quintile portfolios and identify stocks classified in the top (bottom) 20% as winners (losers). We show in Panel D that RSM profits in both the short term and long term remain significantly positive when we adopt the 20% breakpoints. JT momentum profits in the short term are also robust to this criterion of a wider range in identifying winners and losers; they are, however, insignificant when the holding period is extended to the entire three years.

[Insert Table 2]

1.5 Are rank and sign momentum profits explained by risk?

In this subsection we examine whether rank and sign momentum profits can be explained by risk-based pricing models. To this end, we consider three well-known asset-pricing models that have been used in prior literature to evaluate the performance of the price momentum strategy: FF's (1993, 2015) three- and five-factor models and CRR's (1986) macroeconomic factor model. Our choice of the CRR model is motivated by Liu and Zhang (2008) who demonstrate that the growth-related macroeconomic factor on industrial production, denoted *MP*, explains more than half of price momentum profits. Their empirical results echo the findings of Chordia and Shivakumar (2002) and Cooper, Gutierrez, and Hameed (2004), who show that price momentum profits are strong in economic expansions, but not in recessions. Therefore, it is of interest to examine whether RSM profits are attributed to fundamental economic forces.[8]

We estimate the following time-series regressions:

$$MOM_t = b_0 + b_1 RMRF_t + b_2 SMB_t + b_3 HML_t + \varepsilon_t, \tag{3}$$

$$MOM_t = b_0 + b_1 RMRF_t + b_2 SMB_t + b_3 HML_t + b_4 RMW_t + b_5 CMA_t + \varepsilon_t, \tag{4}$$

$$MOM_t = b_0 + b_1 MP_t + b_2 UI_t + b_3 DEI_t + b_4 UTS_t + b_5 UPR_t + \varepsilon_t, \tag{5}$$

where MOM_t is the one-month holding period return of momentum in month *t*, in which rank (RM_t), sign (SM_t), and JT (JTM_t) momentum are considered as alternative strategies;[9] $RMRF_t$,

[8] Note, however, that the CRR model in its original form is not a pricing model, but a return generating process in the spirit of the Ross (1976) arbitrage pricing theory. To come up with a pricing formula, we need to estimate the factor risk premium associated with each of the macroeconomic factors. Following Liu and Zhang's (2008) research design, we first choose 10 size, 10 book-to-market, and 10 momentum one-way sorted portfolios as the testing assets. For each month from January 1963 to November 2016, factor loadings are estimated for each testing asset over the prior 60 months. The Fama-MacBeth (1973) cross-sectional regression of portfolio returns on the factor loadings is then estimated, which gives the estimates of factor risk premiums. The factor risk premiums are plugged back into the factors, resulting in the "estimates" of the factor portfolios.

[9] To conserve space, we do not report the results based on 6- and 12-month holding periods. They are, however, statistically similar to the results based on the one-month holding period and are available upon request.

SMB_t, and HML_t are factor returns of the FF (1993) three-factor model in month *t*; RMW_t and CMA_t are returns associated with operating profitability and investment factors that are two additional factors of the 5-factor model in month *t*; and MP_t, UI_t, DEI_t, UTS_t, and UPR_t are the CRR factors in month *t*. The CRR factors include the growth rate of industrial production (MP), unexpected inflation (UI), change in expected inflation (DEI), term premium (UTS), and default premium (UPR), respectively. In particular, if risk-based factor models explain RSM profitability, then b_0 would be insignificant. A significantly positive coefficient of b_0, by contrast, indicates that risk-based factor models do not account for rank and sign momentum profitability.

Table 3 reports estimation results of Equations (3) to (5) using rank, sign, and JT momentum profits as the dependent variables, respectively. The three momentum strategies all yield significantly positive coefficients of b_0 in all specifications, suggesting that neither model fully accounts for the profitability of the three strategies. In untabulated results, we also show that rank and sign momentum profits outside of January are robust to the three risk-based factor models. The evidence indicates that RSM profits are unlikely to be the result of exposure to common risk factors.

[Insert Table 3]

2. Comparison between momentum strategies

2.1 Time-series regressions of momentum strategies

On the basis of reported results we find strong and persistent RSM profitability that cannot be explained by common risk-based models. So far, all strategies are examined in isolation. Because the three strategies seem to share similar patterns in terms of short-term profitability and January reversals, it is important to examine the comparative performance of the momentum

strategies simultaneously. By doing so, we are able to observe whether RSM strategies play the determining role in generating momentum profits.

The main purpose of this section is to examine the relative profitability of the momentum strategies simultaneously with and without risk adjustment. To explore this issue, we first estimate the following time-series regressions where *RM*, *SM*, and *JTM* denote rank momentum, sign momentum, and JT momentum, respectively:

$$RM_t(SM_t) = b_0 + b_1 JTM_t + \varepsilon_t, \tag{6}$$

$$RM_t(SM_t) = b_0 + b_1 JTM_t + b_2 RMRF_t + b_3 SMB_t + b_4 HML_t + \varepsilon_t, \tag{7}$$

$$RM_t(SM_t) = b_0 + b_1 JTM_t + b_2 RMRF_t + b_3 SMB_t + b_4 HML_t + b_5 RMW_t + b_6 CMA_t + \varepsilon_t, \tag{8}$$

$$RM_t(SM_t) = b_0 + b_1 JTM_t + b_2 MP_t + b_3 UI_t + b_4 DEI_t + b_5 UTS_t + b_6 UPR_t + \varepsilon_t. \tag{9}$$

Equation (6) examines whether rank and sign momentum are explained by JT momentum without risk adjustment while Equations (7) through (9) examine whether JT momentum combined with factor models explains the profitability of rank or sign momentum. Analogously, significantly positive coefficients of b_0 suggest that JT momentum does not subsume the profitability of rank or sign momentum.

Table 4 reports the estimation results for Equations (6) through (9). It should also be noted that rank and sign momentum both have significantly positive loadings on JT momentum, suggesting the possibility that they are positively correlated. However, JT momentum does not fully explain rank or sign momentum profits. When JT momentum is used as the sole explanatory variable in Equation (6), the b_0 coefficient is 0.438% (*t*-statistic = 2.43) for rank momentum and is 0.429% (*t*-statistic = 3.65) for sign momentum. When different sets of factor models are combined with JT momentum, as shown in Equations (7) through (9), the b_0 coefficients still

remain positive and significant in all specifications. Thus, the results in Table 4 suggest that the profitability of RSM is not subsumed by JT momentum.

[Insert Table 4]

The next task is to investigate whether RSM accounts for the profitability of JT momentum. To this end, we perform the following regressions of Equations (10) through (13) by replacing the dependent variable with JTM_t and the independent variable JTM_t with RM_t or SM_t:

$$JTM_t = b_0 + b_1 RM_t(SM_t) + \varepsilon_t, \tag{10}$$

$$JTM_t = b_0 + b_1 RM_t(SM_t) + b_2 RMRF_t + b_3 SMB_t + b_4 HML_t + \varepsilon_t, \tag{11}$$

$$JTM_t = b_0 + b_1 RM_t(SM_t) + b_2 RMRF_t + b_3 SMB_t + b_4 HML_t + b_5 RMW_t + b_6 CMA_t + \varepsilon_t, \tag{12}$$

$$JTM_t = b_0 + b_1 RM_t(SM_t) + b_2 MP_t + b_3 UI_t + b_4 DEI_t + b_5 UTS_t + b_6 UPR_t + \varepsilon_t. \tag{13}$$

Table 5 indicates that rank or sign momentum alone fully explains JT momentum, and that the b_0 coefficients in Equation (10) are insignificant at 0.107% and 0.088% for rank and sign momentum, respectively. The results remain unchanged when controlling for risk adjustments using Equations (11) to (13). On the basis of reported findings, we find strong and persistent rank and sign momentum profitability that are independent of the JT momentum and cannot be fully explained by common risk-based models.

[Insert Table 5]

2.2 Is price momentum subsumed by rank or sign momentum?

The most intriguing observation from Table 5 is that the short-term profitability of JT momentum is fully explained by RSM. The fact that RSM explains the short-term momentum profitability suggests that these strategies are highly interrelated. Indeed, within our sample the overall correlation between past six-month returns and rank (sign) is 0.627 (0.481). Such high

correlations motivate us to investigate the proportions of price winners (losers) that overlap rank and/or sign winners (losers). For each month, we simultaneously calculate the numbers and proportions of price winner (loser) stocks that belong to rank and/or sign winners (losers). We next average the numbers and proportions over our sample period. As Panel A of Table 6 shows, on average 45.54% (32.62%) of price winners are rank (sign) winners, and 58.48% (29.09%) of price losers are rank (sign) losers as reported in Panel B. Moreover, 48.62% of price winners are either rank or sign winners, while 60.91% of price losers are either rank or sign losers. When we focus on the three strategies together, there are 29.23% (26.67%) of price winners (losers) that overlap both rank and sign winners (losers).

[Insert Table 6]

An interesting question arises: do overlapped or isolated winners and losers of price momentum behave differently in generating momentum profits? To answer this question, we break down price winners and losers into two categories: (i) one category whose membership overlaps with rank (or sign) momentum winners and losers; and (ii) the other category whose membership is unrelated to rank (or sign) winners and losers. We refer to the former as the "overlapped" category of price momentum stocks and the latter as the "isolated" category of price momentum stocks. We hold each category of stocks for subsequent 1, 6, and 12 months with component stocks invested based on equal weights.[10]

Panel A of Table 7 reports the average returns of overlapped and isolated categories consolidated by price momentum and rank momentum, denoted as R_Overlap and R_Isolate, respectively. The R_Overlap strategy generates remarkably high returns for 1-, 6-, and 12-month holding periods while the R_Isolate strategy generates insignificant returns in corresponding

[10] The results based on value-weighted returns are qualitatively and statistically similar to those based on equal-weighted returns.

holding periods. More dramatically, the profitability of the R_Overlap strategy is twice as large as that of price momentum. Taking the 1-month return for example, the R_Overlap strategy is profitable at 1.936% per month while the corresponding return of the price momentum is 1.150% per month (reported in Table 1). The R_Isolate strategy, however, generates a negative 1-month return of -0.180% per month. The evidence based on the consolidation of price momentum and sign momentum, as reported in Panel B, is virtually the same with the results documented in Panel A. The findings suggest that rank and sign measures are both effective in discriminating the component stocks that underlie the price momentum profitability.[11]

Table 6 indicates that 29% (26%) of price momentum winners (losers) overlap both rank and sign momentum winners (losers). Thus it is interesting to investigate the profitability of the overlapping components of price momentum (denoted as the RS_Overlap strategy) that interact with both rank and sign momentum and that of isolated components (denoted as the RS_Isolate strategy) that are mutually exclusive from rank or sign momentum. In particular, we construct the RS_Overlap strategy that involves buying price winners that belong to rank and sign winners simultaneously and short selling price losers that belong to rank and sign losers simultaneously. Analogously, the RS_Isolate strategy is constructed by buying price winners that do not belong to either rank or sign winners and short selling price losers that does not belong to either rank or sign losers. Panel C shows that the overall patterns are quantitatively and statistically similar to those presented in Panels A and B, suggesting that conditioning on an additional measure beyond rank or sign provides no incremental impact to discriminate price momentum profits. This evidence is

[11] In untabulated results, we show that the isolated category of rank or sign momentum that is unrelated to JT momentum winners and losers generates significant profits. For example, the 1-month return of the isolated strategy of rank (sign) momentum that is unrelated to JT momentum is 0.909% (0.710%) with a *t*-statistic of 4.27 (4.93), suggesting that past average returns do not provide incremental information to discriminate RSM profitability.

not surprising, because rank and sign have a remarkably high correlation of 0.844. It also implies that the profits to rank and sign momentum strategies are highly correlated.

We next calculate summary statistics of performances for the three alternative momentum strategies (price, rank, and sign) and all sets of overlapped and isolated categories of price momentum. We focus on 1-month holding-period returns to conserve space and to make the results comparable to Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016), who show that the JT momentum is subject to severe crashes and exhibits negative skewness. The statistics include annualized means, annualized standard deviations, and annualized Sharpe ratios, as well as minimum, maximum, and skewness of monthly returns. We document several interesting findings. First, price momentum has remarkably negative skewness and is subject to severe crashes, which is consistent with Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016); it has a skewness of -3.229 with a minimum monthly return of -78.093%. In comparison, RSM strategies are less vulnerable to momentum crashes because their maximum losses are -34.959% and -25.406% with corresponding skewness of -0.981 and -0.144, respectively. Second, the profitability of RSM strategies is relatively stable because they have lower standard deviations and higher Sharpe ratios than price momentum. Third, overlapped strategies have lower minimum monthly returns and higher maximum monthly returns, mean returns, skewness, and Sharpe ratios than the corresponding isolated strategies. Finally, overlapped strategies have the highest mean returns and Sharpe ratios compared with the original three momentum strategies. Overall, the empirical results indicate that the RSM strategies outperform the JT momentum strategy, and that rank and sign measures help discriminate momentum from reversal patterns.

[Insert Table 7]

2.3 Rank and sign momentum versus return consistency

Grinblatt and Moskowitz (2004) propose the measure of return consistency based on the sign of past returns and show that return consistency plays an important role in the predictability of past returns. They also show that consistent winners exhibit superior performance while consistent losers have little impact on future returns. We follow Grinblatt and Moskowitz (2004) to investigate the incremental impact of winner consistency on RSM and JT momentum strategies. In particular, stocks with positive returns in at least 8 out of the 11 months over months $t-12$ to $t-2$ are defined as consistent winner. We next perform the following cross-sectional regressions:

$$R_{i,t} = b_0 + b_1 RS_{i,t-2} + b_2 PR6_{i,t-2} + b_3 WC_{i,t-2} + b_4 RS_{i,t-2} \times WC_{i,t-2} + b_5 PR6_{i,t-2} \times WC_{i,t-2} + \varepsilon_{i,t}, \quad (14)$$

where $WC_{i,t-2}$ equals 1 if the stock is classified as consistent winner and zero otherwise. Panel A of Table 8 reports the estimation results with $RS_{i,t-2}$ proxied by rank and sign measures, respectively. Consistent with Grinblatt and Moskowitz (2004), we show that the coefficients b_5 are significantly positive, suggesting that winner consistency significantly enhances the momentum phenomenon. The coefficients b_4 are significantly negative, indicating that RSM profits are not positively associated with winner consistency. In addition, the coefficients on $PR6_{i,t-2}$ are insignificant when winner consistency is included in the regressions, while those on $rank_{i,t-2}$ and $sign_{i,t-2}$ remain significant. This observation suggests that RSM profitability is more robust than JT momentum profitability when controlling for the impact of winner consistency.

We next construct the momentum strategy based on return consistency and examine whether and how it interacts with RSM strategies. In addition to consistent winners, we define stocks with negative returns in at least 8 out of the 11 months over months $t-12$ to $t-2$ as consistent losers. We allocate consistent winners into the $P3$ portfolio, consistent losers into the $P1$ portfolio, and

those in between into the $P2$ portfolio. The portfolios are constructed with equal weights and are held for one month. The return consistency momentum (RCM) profit is defined as the return difference between $P3$ and $P1$ portfolios. Panel B of Table 8 shows that the average RCM profit is significant at 1.023% per month with a t-statistic of 5.79. We also show in Panel C that consistent winners have remarkably higher values of rank and sign than consistent losers, suggesting that the RCM profitability could be associated with RSM.

We thus perform the time-series regressions of Equations (6) to (9) and Equations (10) to (13) by replacing JTM with RCM, with the results reported in Panels D and E. Overall, we show that RSM strategies fully explain RCM profitability, but not vice versa.

[Insert Table 8]

2.4 Rank and sign momentum versus absolute strength momentum

Gulen and Petkova (2016) propose absolute strength momentum (ASM) strategies based on the absolute strength of recent past performance over the time series instead of in the cross section. They show that ASM fully explains JT momentum profits, but not vice versa. Because this observation is similar to our finding for RSM, we are motivated to consider a horse race between ASM and RSM.[12] To investigate this issue, we follow the Gulen and Petkova (2016) procedure to construct the ASM strategy. At the beginning of each month t, a stock's performance is computed as the 11-month cumulative return over months $t-12$ to $t-2$. This 11-month cumulative return is compared with the distribution of all non-overlapping 11-month cumulative returns up to month t. This distribution is then ranked into deciles. If a stock's recent 11-month cumulative return is

[12] In addition to the return consistency and ASM strategies, we also compare RSM strategies with the 52-week high momentum strategy of George and Hwang (2004) and George, Hwang, and Li (2018). We show that the RSM strategies outperform George and Hwang's strategy. The results are provided in the internet appendix A2.

ranked in the top (bottom) 10% of the historical distribution up to month *t*, then it is classified as an ASM winner (loser). We exclude stocks priced below $5 at the beginning of the holding period. The ASM strategy is constructed by buying ASM winners and short selling ASM losers with equal weights for the holding period of month *t*+1. This procedure is repeated every month and the historical distribution of the 11-month cumulative returns is updated continuously. Because the distribution requires sufficient observations, the return data are traced back to 1927 to determine performance breakpoints. The observation period of the strategy spans from January 1963 to December 2016, so that we can make direct comparisons with RSM profits.

We report the average monthly return of absolute strength decile portfolios and ASM based on the 1-month holding period in Panel A of Table 9. The average monthly returns of ASM winners and losers are 1.559% and 0.313%, respectively, resulting in a significant difference of 1.219% with a *t*-statistic of 5.34. The significant ASM profits are consistent with Gulen and Petkova's (2016) findings.

To examine the extent to which a stock's absolute strength is related to rank and sign measures, we calculate the average values of rank and sign as defined in Equation (2) for each ASM decile portfolio. We show in Panel B that rank and sign increase monotonically with ASM decile portfolios; the average rank ranges from -0.084 to 0.079 while the average sign ranges from 0.448 to 0.527. As a result, ASM winners exhibit significantly higher ranks and signs than ASM losers. This finding is interesting, because despite the fact that ASM winners (losers) are those with the highest (lowest) rankings in cumulative returns in the time series, they actually exhibit relatively higher ranks and signs in the cross section. This also leads to the possibility that ASM and RSM profits are related.

Motivated by this observation, we further compare ASM and RSM by performing the time-series regressions of Equations (6) to (13) by replacing JTM returns with ASM returns. We first adopt rank or sign momentum return as the dependent variable and ASM return as the independent variable and report regression results in Panel B. Regardless of risk adjustment, the results show that ASM does not fully explain rank or sign momentum profits as intercepts from the regressions that are all significantly positive. However, when we perform Equations (10) to (13) by using rank or sign momentum to explain ASM returns, as reported in Panel C, the regression results reveal no significant intercept in all model specifications - that is, either rank or sign momentum alone is effective enough in fully explaining ASM profits. The overall evidence from Table 9 suggests that ASM is related to but different from RSM, and that RSM fully explains ASM profits.

[Insert Table 9]

3. Why do rank and sign momentum perform better?

So far we have documented RSM profits that cannot be explained by well-known asset-pricing models. In this section, we investigate the advantages of RSM over price momentum. BGS (2013), for example, argue that investors' attention tends to be drawn to assets whose payoffs are most different or salient relative to an average benchmark. Their trading thus causes stocks with salient positive (negative) payoffs to be overpriced (underpriced). As non-parametric measures such as rank and sign are well-known for being less sensitive to extreme observations in stock returns, they could highlight the relatively non-salient information in stock returns while mitigating the effect of extreme price movements. Hence, RSM profits would exhibit a pattern that is less vulnerable to stocks with salient features.

The evidence that RSM profitability is robust to the salience hypothesis leads to implications in the time series. In particular, Daniel and Moskowitz (2016) demonstrate that JT price momentum is vulnerable to momentum crashes when poor market conditions ameliorate and the market starts to rebound. Since RSM profits are robust to salient information and less sensitive to investor overreaction, they should be less vulnerable to crash risk. We test the above two hypotheses for RSM profitability in this section.

3.1 The characteristics of RSM portfolios

To elucidate the nature of the RSM effect, we begin with an analysis of the characteristics of both rank- and sign-sorted portfolios. Because rank and sign are non-parametric measures, it is of interest to examine the distributional characteristics of rank- and sign-sorted portfolios. Presumably, across portfolios of different rank or sign, there should be weaker patterns in terms of higher statistics moments such as skewness and kurtosis. We also look to see whether stocks with similar rank and sign values exhibit similar firm characteristics that have been documented to be important determinants of the cross-section of stock returns.

For each month, we calculate the standardized rank and the first through fourth moments for each stock using daily returns over the previous six months. In addition to basic descriptive statistics, we also obtain maximum (*Max*) and minimum (*Min*) daily returns in the previous month. We consider market capitalization (*Size*) and book-to-market (*BM*) ratio because they are important determinants of the cross-section of stock returns suggested by FF (1992, 1993). From July of each year to June of next year, *Size* is defined as the market value of equity in million dollars at the end of June in the current year, while *BM* is defined as the ratio of book value of equity at the end of the previous year divided by market capitalization at the end of the previous year.

Following the idea of BGS (2013), we also introduce two proxies to capture salience as follows.

1. Segment-level skewness ($Skew_{SEG}$):[13] Motivated by BGS (2013), Zhang (2006), Green and Hwang (2012), and Schneider and Spalt (2016), we adopt an industry-level approximation to measure segment-level skewness. For each segment j, the measure is constructed as follows:

$$Skew_{SEG,j,t-1} = \frac{(P_{99}-P_{50})-(P_{50}-P_1)}{(P_{99}-P_1)},$$

where P_n is the nth percentile of the pooled return distribution of daily returns of all firms in the same Fama-French 48 industry classification as segment j over the past 12 months ending in month $t-1$. Similarly, because positive (negative) $Skew_{SEG}$ reflects assets with positive (negative) salient payoffs for winners (losers), we take the absolute value of the variable ($|Skew_{SEG}|$) so that a higher value of the variable signifies higher salience.[14]

2. Information discreteness (ID): This measure, proposed by Da et al. (2014), is defined as $\text{sign}(PRET_{i,t}) \times [\%_{neg_{i,t}} - \%_{pos_{i,t}}]$, where $PRET_{i,t}$ is stock i's cumulative return from $t-12$ to $t-2$; $\%_{neg_{i,t}}$ and $\%_{pos_{i,t}}$ denote the percentages of days with positive and negative returns, respectively, over the same period. The sign of $PRET_{i,t}$, $\text{sign}(PRET_{i,t})$, equals +1 when $PRET_{i,t} > 0$ and -1 when $PRET_{i,t} < 0$. Because a larger ID corresponds to situations where a few extreme positive or negative observations dominate the overall performance, ID can also serve as a proxy for salience for both winners and losers (Da et al., 2014).[15]

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[13] We do not use stock-level skewness for two reasons. First, skewness and individual stock rank show a convex relation, because (i) mean-median values have a positive relation with individual stocks' ranks; and (ii) standard deviations have a negative relation with individual stock ranks. Once they are used in the skewness measure, a convex function shows up, which distorts the regression results. Second, according to BGS (2013), the definition of salience is built based on a relative concept with a benchmark or reference point. Segment-level skewness better conforms to this requirement.

[14] In untabulated results, we show that our findings are robust without taking absolute values of the skewness variable.

[15] Da et al. (2014) and Chang, Ko, Nakano, and Rhee (2018) use this measure to detect market underreaction. Specifically, they propose a frog-in-the-pan (FIP) hypothesis and claim that ID reflects information that arrives

Each of the variables is averaged across stocks in a portfolio and then averaged over the sample period. Table 10 reports descriptive statistics and firm characteristics for stocks in the rank- and sign-sorted portfolios, with the highest 10% rank observations in the winner portfolio (P10) and the lowest 10% rank observations in the loser portfolio (P1). Panel A reports the average descriptive statistics for the ten rank-sorted portfolios. A number of interesting patterns emerge from Panel A. First, stocks with higher ranks earn higher past returns in terms of mean and median, but display a smaller standard deviation, skewness, and kurtosis, suggesting that the higher returns of higher-rank stocks are not the result of their higher risk. Lower-rank portfolios also show higher positive extreme returns *Max* and lower negative extreme returns *Min*, indicating that lower-rank stocks exhibit strong lottery-like features.[16] For example, the lowest-rank portfolio has the lowest average monthly return of -0.084% during the formation period, but the largest *Max* of 11.461% and the smallest *Min* of -9.028%. In contrast, the highest-rank portfolio's average monthly return is 0.237%, with the largest *Max* of 5.866% and the smallest *Min* of -4.398%.

Second, as *rank* increases across low-rank to high-rank portfolios, *Size* and *BM* ratios both increase, indicating that rank winners (losers) tend to be large value (small growth) stocks. This pattern implies that the rank-related return premia are not driven by the combination of small-firm and value effects. Finally, $|Skew_{SEG}|$ ($|Skew_{SEG}|$) and *ID* are concave across rank portfolios, suggesting RSM winners and losers have less discrete information. More importantly, they seem to exhibit non-salient features, because they demonstrate a higher degree of continuous (rather than discrete) information that is less salient to investors. In Panel B we repeat the same procedure

continuously in small amounts, thus capturing investor underreaction.

[16] Bali, Cakici, and Whitelaw (2011) show that stocks with higher maximum daily returns *Max* over the past month earn negative average future returns. There is also a similar inverse, but weaker, relation between the minimum daily returns *Min* and future returns, which is subsumed by the negative "maxing out" effect.

for portfolios sorted by sign. The overall patterns and statistical significance are similar to those reported in Panel A.

[Insert Table 10]

3.2 The salience hypothesis

BGS (2012, 2013) propose a salience theory to characterize investors' reaction to asset payoffs in terms of how they differ relative to the average. Basically, because investors' attention is drawn to salient payoffs, they tend to overweight such payoffs relative to their objective probabilities. As a result, stocks with salient positive (negative) payoffs are more likely to be overvalued (undervalued) and thus have lower (higher) expected returns. Da et al. (2014) also show that salient discrete information is related to investor attention and weakens JT momentum profits. Because rank and sign measures do not allocate higher weights on salient information embedded in past stock returns, we expect RSM predictability to be robust across stocks with both salient and non-salient features.

Let $Salience_{i,t}$ denote a salience measure for stock i in month t; we can perform the following cross-sectional regressions by incorporating interaction terms into rank (or sign) measures and past returns:[17]

$$R_{i,t} = b_0 + b_1 RS_{i,t-2} + b_2 PR6_{i,t-2} + b_3 Salience_{i,t-2} + b_4 RS_{i,t-2} \times Salience_{i,t-2} + b_5 PR6_{i,t-2} \times Salience_{i,t-2} + \varepsilon_{i,t}, \quad (15)$$

where $R_{i,t}$ is stock i's future return in month t; $RS_{i,t-2}$ is defined as the average of the past 6-month rank or sign measure, $rank_{i,t-2}$ or $sign_{i,t-2}$ for stock i ending in month $t-2$; $PR6_{i,t-2}$

[17] Because rank and sign are highly correlated, including the two variables in the same regression may cause a multicollinearity problem. We thus perform two separate regression models.

is defined as the average of the past 6-month returns for stock i ending in month $t-2$; and $Salience_{i,t-2}$ is stock i's salience measure calculated ending in month $t-2$. We obtain estimated coefficients every month and calculate average coefficients with corresponding t-statistics adjusted by Newey and West's (1987) robust standard errors. We hypothesize that the coefficient of the interaction between RS and Salience, b_4, is insignificantly different from zero because rank or sign momentum profits are more robust to salient features. The coefficient of the interaction between PR6 and Salience, b_5, is expected to be significantly negative because investors tend to overreact to past salient returns (Da et al., 2014).

We report the results in Table 11 with Panels A and B presenting rank and sign momentum, respectively. In Models (1) and (2), we incorporate the interaction terms for each proxy separately. We first focus on the results based on rank momentum as reported in Panel A. The coefficients of the interaction terms of *rank* and salience measures are insignificant as predicted, while the coefficients of the interaction terms of *PR6* and salience measures are both significantly negative; they are -8.368 (t-statistic = -2.03) and -0.986 (t-statistic = -1.97) in Models (1) and (2), respectively. When we consider the interaction terms associated with absolute skewness and ID simultaneously in Model (3), the results remain unchanged. This finding confirms our hypothesis that price winners (losers) are more overvalued (undervalued) if they have higher degree of salience. While rank measures present robust statistics to extreme past returns, their momentum profitability is unaffected by the salient features of stocks.

The results based on sign momentum, as reported in Panel B, are similar to those reported in Panel A. The only exception is that sign momentum is more sensitive to the ID measure. The interaction terms of *sign* and *ID* are marginally significant in Model (2), but become insignificant in Model (3) when variables associated with absolute skewness are included in the regression. We

also observe that the interaction terms of *PR6* and salience measures are significantly negative in all specifications. The overall evidence from Panel B leads us to conclude that sign momentum is less affected by the salient features of stocks than by JT momentum.

[Insert Table 11]

Another important finding from Table 11 is that when we control for the impact of salience, the average coefficients on *rank* or *sign* are significantly positive in all model specifications, while those on *PR6* are either insignificant or marginally significant. The significance of *rank* and *sign* again confirms the robustness of RSM profitability to the salience explanation.

3.3 Momentum crashes

We next examine whether RSM profits exhibit any crash risk. This analysis is motivated by Daniel and Moskowitz's (2016) observation that JT momentum exhibits extreme losses in panic states. Because RSM profitability is more robust to salient news or events and thus less subject to investor overreaction, it should not expose investors to severe crash risk. To examine this hypothesis, we report the 10 worst monthly returns of JT momentum, along with the returns of rank and sign momentum.[18] To make our results comparable to Daniel and Moskowitz (2016), we extend the sample period back to 1927. In addition to the JT strategy, we also report the corresponding returns of rank and sign momentum in the same months for comparison. The left panel of Table 12 presents the results.

[Insert Table 12]

[18] Daniel and Moskowitz (2016) use past performance from 12 to 2 months prior to portfolio formation to identify JT winners and losers, while our evaluation period is from 6 to 2 months prior to portfolio formation. Our results based on the formation period from 12 to 2 months exhibit similar patterns as what we report based on the six- to two-month formation period.

During the months in which JT momentum generates the lowest returns, we show that rank and sign momentum have smaller losses in magnitude than JT momentum. In particular, the crashes of rank momentum are smaller in magnitude than those of JT momentum in 8 out of the 10 months, while the returns of sign momentum are all higher than those of JT momentum in the 10 months. As a result, JT momentum has an average return of -44.61% over the 10 months, while the corresponding returns of rank and sign momentum strategies are -29.76% and -17.78%, respectively. Thus, RSM strategies are confirmed to be less vulnerable to momentum crashes than JT momentum.

We also observe the 10 worst monthly returns of rank momentum and corresponding returns of sign and JT strategies in the same months in the middle panel of Table 12. Even for the 10 worst losses for rank momentum, they are still smaller than the losses of JT momentum in magnitude for 5 cases. Overall, rank momentum generates an average return of -34.83% in the 10 worst cases while JT momentum has an average return of -40.16% in the corresponding periods. Sign momentum, however, has an average return of -18.23% over the same months.

When we concentrate on the 10 worst monthly returns of sign momentum as presented in the right panel of Table 12, we still find that sign momentum exhibits smaller crashes than JT momentum. Sign momentum has larger losses than JT momentum only in 2 out of the 10 months (June 1938 and June 1931). The average returns of rank, sign, and JT momentum over the 10 months in which sign momentum has severe crashes are -29.15%, -19.09%, and -37.53%, respectively. It is notable that sign momentum experiences weakest degree of momentum crash among the three strategies. As explained earlier, it is because the sign measure has a distinctive feature in that it reflects a scaled measure of mean and variance in stock returns that is proportional to the Sharpe measure.

The overall evidence from Table 12 suggests that RSM strategies are less prone to crash risk than JT momentum; sign momentum has the lowest losses among the three strategies. This observation is again consistent with our previous finding that RSM strategies outperform JT momentum, especially during periods of momentum crashes.

4. Conclusions

We propose non-parametric performance measures (ranks and signs) of past stock returns and explore whether these measures are more effective in attaining higher momentum profits than the traditional JT price momentum. Unlike parametric statistics that have been widely adopted to identify stocks' past performances, non-parametric statistics are far less vulnerable to outliers in the sample and can account for non-salient information embedded in stock prices. Because investors are limited in their attention and information-processing capacity (Hirshleifer and Teoh, 2003; Peng and Xiong, 2006), we hypothesize that non-parametric measures such as ranks and signs are likely to capture investors' underreaction to non-salient information embedded in stock returns, thus inducing subsequent return continuations.

Our empirical findings confirm this prediction. The RSM strategies of buying stocks with high average ranks (or signs) and shorting those with low average ranks (or signs) are more profitable, outperforming JT price momentum strategies for the first year following portfolio formation. The profitability of RSM strategies exhibits no long-term reversal and cannot be explained by well-known risk-based asset-pricing models. Moreover, RSM subsumes the profitability of JT momentum, but not vice versa.

We further demonstrate that RSM captures the non-salient component in stock prices that is neglected by showing that RSM profitability is robust to stocks with salient features, suggesting

that it is not driven by investor overreaction. The evidence from cross-sectional tests also suggests that RSM profitability is less prone to crash risk. Our results confirm these predictions for RSM profitability. Given the unique properties of non-parametric measures, RSM profits experience much weaker momentum crashes in panic states examined by Daniel and Moskowitz (2016). In addition, RSM momentum strategies outperform alternative momentum strategies investigated by Grinblatt and Moskowitz (2004) and Gulen and Petkova (2016). While winners and losers identified by return consistency, ASM, and RSM overlap significantly, RSM fully explains the profitability of the other two strategies, but not vice versa.

References

Albuquerque, R. A. 2012. Skewness in stock returns: Reconciling the evidence on firm versus aggregate returns. *Review of Financial Studies* 25:1630-1673.

Bali, T. G., N. Cakici, and R. F. Whitelaw. 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics* 99:427-446.

Barberis, N. C. 2013. Thirty years of prospect theory in economics: A review and assessment. *Journal of Economic Perspectives* 27:173-195.

Barroso, P., and P. Santa-Clara. 2015. Momentum has its moments. *Journal of Financial Economics* 116:111-120.

Bordalo, P., N. Gennaioli, and A. Shleifer. 2012. Salience theory of choice under risk. *Quarterly Journal of Economics* 127:1243-1285.

Bordalo, P., N. Gennaioli, and A. Shleifer. 2013. Salience and asset prices. *American Economic Review: Papers & Proceedings* 103:623-628.

Chang, R. P., K.-C. Ko, S. Nakano, and S. G. Rhee. 2018. Residual Momentum in Japan. *Journal of Empirical Finance* 45:283-299.

Chen, N.-F., R. Roll, and S. A. Ross. 1986. Economic forces and the stock market. *Journal of Business* 59:383-403.

Chordia, T., and L. Shivakumar. 2002. Momentum, business cycle and time-varying expected returns. *Journal of Finance* 57:985-1019.

Cooper, M. J., R. C. Gutierrez Jr., and A. Hameed. 2004. Market states and momentum. *Journal of Finance* 59:1345-1365.

D'Mello, R., S. P. Ferris, and C.-Y. Hwang. 2001. The tax-loss selling hypothesis, market liquidity, and price pressure around the turn-of-the-year. *Journal of Financial Markets* 6:73-98.

Da, Z., U. G. Gurun, and M. Warachka. 2014. Frog in the pan: Continuous information and momentum. *Review of Financial Studies* 27:2171-2218.

Daniel, K. D., D. Hirshleifer, and A. Subrahmanyam. 1998. Investor psychology and security market under- and over-reactions. *Journal of Finance* 53:1839-1885.

Daniel, K. D., and T. J. Moskowitz. 2016. Momentum crashes. *Journal of Financial Economics* 122:221-247.

Fama, E. F., and K. R. French. 1992. The cross-section of expected stock returns. *Journal of Finance* 47:427-465.

Fama, E. F., and K. R. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33:3-56.

Fama, E. F., and K. R. French. 2015. A five-factor asset pricing model. *Journal of Financial Economics* 116:1-22.

Fama, E. F., and J. D. MacBeth. 1973. Risk, return and equilibrium: Empirical tests. *Journal of Political Economy* 81:607-636.

George, T. J., and C.-Y. Hwang. 2004. The 52-week high and momentum investing. *Journal of Finance* 5:2145-2176.

George, T. J., C.-Y. Hwang, and Y. Li. 2018. The 52-week high, q-theory, and the cross section of stock returns. *Journal of Financial Economics* 128:148-163.

Gibbons, J. D., and S. Chakraborti. 2010. *Nonparametric Statistical Inference, Fifth Edition* (Chapman and Hall/CRC).

Green, T. C., and B.-H. Hwang. 2012. IPOs as lotteries: Expected skewness and first-day returns. *Management Science* 58:432-444.

Grinblatt, M., and T. J. Moskowitz. 2004. Predicting stock price movements from past returns: The

role of consistency and tax-loss selling. *Journal of Financial Economics* 71:541-579.

Gulen, H., and R. Petkova. 2016. Absolute strength: Exploring momentum in stock returns. Working paper.

Hirshleifer, D., and S. H. Teoh. 2003. Limited attention, financial reporting, and disclosure. *Journal of Accounting and Economics* 36:337-386.

Hollander, M., D. A. Wolfe, and E. Chicken. 2014. *Nonparametric Statistical Methods, Third Edition* (John Wiley & Sons).

Jegadeesh, N., and S. Titman. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance* 43:65-91.

Kahneman, D. 2011. *Thinking, Fast and Slow* (New York: Farrar, Straus and Giroux).

Kahneman, D., and A. Tversky. 1979. Prospect theory: An analysis of decision under risk. *Econometrica* 47:263-291.

Liu, L. X., and L. Zhang. 2008. Momentum profits, factor pricing, and macroeconomic risk. *Review of Financial Studies* 21:2417-2448.

Newey, W. K., and K. D. West. 1987. Hypothesis testing with efficient method of moments estimation. *International Economic Review* 28:777-787.

Peng, L., and W. Xiong. 2006. Investor attention, overconfidence and category learning. *Journal of Financial Economics* 80:563-602.

Roll, R. 1983. Vas ist das? The turn-of-the-year effect and the return premium of small firms. *Journal of Portfolio Management* 9:18-28.

Ross, S. A. 1976. The arbitrage theory of capital asset pricing. *Journal of Economic Theory* 13:341-360.

Schneider, C., and O. Spalt. 2016. Conglomerate investment, skewness, and the CEO long-shot

bias. *Journal of Finance* 71:635-672.

Wright, J. H. 2000. Alternative variance-ratio tests using ranks and signs. *Journal of Business and Economic Statistics* 18:1-9.

Zhang, Y. 2006. Individual skewness and the cross-section of average stock returns. Working paper, Yale University.

Table 1: Performance of momentum strategies

For each month t, we calculate individual stocks' rank or sign measure ($rank_{i,t}(P)$ or $sign_{i,t}(P)$) and classify all stocks into decile portfolios. We exclude stocks priced below $5 at the beginning of the holding period. Stocks with the largest rank (or sign) measures are placed in portfolio P10, while those with the smallest rank measures are placed in portfolio P1. All of the decile portfolios are constructed with equal weights and rebalanced monthly with holding periods of 1, 6, and 12 months, skipping one-month following portfolio formation. The rank or sign momentum profit is defined as the return difference between P10 and P1. We also follow JT to construct the alternative strategy. Panels A and B report the momentum profits for the full and non-January samples, respectively. In Panel C, we calculate monthly momentum profits for the three strategies for the second and third years, as well as their cumulative returns over the entire three-year holding period. Numbers in the parentheses are the t-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
Panel A: All months											
Rank momentum											
1 month	0.336	0.886 ***	1.002 ***	1.116 ***	1.162 ***	1.214 ***	1.265 ***	1.277 ***	1.335 ***	1.646 ***	1.309 ***
	(1.03)	(3.21)	(4.03)	(4.80)	(5.23)	(5.78)	(6.16)	(6.58)	(6.59)	(7.16)	(6.29)
6 months	0.358	0.836 ***	0.999 ***	1.081 ***	1.168 ***	1.230 ***	1.284 ***	1.326 ***	1.371 ***	1.564 ***	1.205 ***
	(1.11)	(3.07)	(4.05)	(4.66)	(5.34)	(5.88)	(6.33)	(6.69)	(6.77)	(6.80)	(6.48)
12 months	0.552 *	0.920 ***	1.049 ***	1.115 ***	1.178 ***	1.207 ***	1.259 ***	1.282 ***	1.299 ***	1.371 ***	0.819 ***
	(1.72)	(3.39)	(4.26)	(4.81)	(5.38)	(5.75)	(6.17)	(6.39)	(6.37)	(6.01)	(5.01)
Sign momentum											
1 month	0.506 *	0.825 ***	0.968 ***	1.083 ***	1.156 ***	1.204 ***	1.233 ***	1.307 ***	1.430 ***	1.543 ***	1.038 ***
	(1.84)	(3.18)	(3.87)	(4.56)	(4.93)	(5.24)	(5.64)	(6.12)	(6.76)	(7.57)	(6.61)
6 months	0.551 **	0.830 ***	0.971 ***	1.041 ***	1.121 ***	1.189 ***	1.262 ***	1.328 ***	1.412 ***	1.521 ***	0.970 ***
	(2.02)	(3.23)	(3.94)	(4.38)	(4.85)	(5.27)	(5.77)	(6.19)	(6.68)	(7.30)	(7.30)
12 months	0.703 **	0.910 ***	1.024 ***	1.081 ***	1.141 ***	1.173 ***	1.233 ***	1.271 ***	1.317 ***	1.382 ***	0.679 ***
	(2.57)	(3.52)	(4.13)	(4.52)	(4.94)	(5.19)	(5.64)	(5.92)	(6.22)	(6.64)	(5.57)
JT momentum											
1 month	0.445	0.914 ***	1.063 ***	1.098 ***	1.161 ***	1.184 ***	1.183 ***	1.263 ***	1.396 ***	1.594 ***	1.150 ***
	(1.47)	(3.61)	(4.72)	(5.19)	(5.62)	(5.89)	(5.75)	(5.79)	(5.72)	(5.28)	(5.67)
6 months	0.405	0.867 ***	1.014 ***	1.094 ***	1.155 ***	1.210 ***	1.231 ***	1.296 ***	1.369 ***	1.436 ***	1.031 ***
	(1.33)	(3.50)	(4.54)	(5.14)	(5.65)	(6.03)	(5.99)	(5.95)	(5.56)	(4.66)	(6.07)
12 months	0.565 *	0.933 ***	1.061 ***	1.130 ***	1.175 ***	1.206 ***	1.248 ***	1.264 ***	1.284 ***	1.216 ***	0.651 ***
	(1.88)	(3.79)	(4.75)	(5.31)	(5.74)	(5.96)	(6.04)	(5.77)	(5.20)	(3.95)	(4.57)

Table 1 (continued)

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
Panel B: January months excluded											
Rank momentum											
1 month	-0.066	0.552 **	0.728 ***	0.889 ***	0.962 ***	1.063 ***	1.127 ***	1.167 ***	1.259 ***	1.600 ***	1.666 ***
	(-0.19)	(1.98)	(2.91)	(3.84)	(4.33)	(5.03)	(5.45)	(5.90)	(6.05)	(6.66)	(7.06)
6 months	-0.090	0.493 *	0.714 ***	0.848 ***	0.968 ***	1.057 ***	1.137 ***	1.198 ***	1.272 ***	1.498 ***	1.587 ***
	(-0.26)	(1.79)	(2.87)	(3.64)	(4.40)	(5.02)	(5.54)	(5.96)	(6.15)	(6.30)	(7.45)
12 months	0.066	0.566 **	0.756 ***	0.871 ***	0.970 ***	1.027 ***	1.103 ***	1.144 ***	1.186 ***	1.293 ***	1.226 ***
	(0.20)	(2.07)	(3.05)	(3.75)	(4.40)	(4.85)	(5.35)	(5.63)	(5.70)	(5.47)	(7.19)
Sign momentum											
1 month	0.164	0.521 **	0.707 ***	0.848 ***	0.937 ***	1.007 ***	1.085 ***	1.185 ***	1.326 ***	1.485 ***	1.321 ***
	(0.57)	(1.99)	(2.80)	(3.55)	(3.99)	(4.38)	(4.89)	(5.50)	(6.18)	(7.03)	(7.45)
6 months	0.182	0.510 *	0.698 ***	0.790 ***	0.898 ***	0.992 ***	1.096 ***	1.187 ***	1.291 ***	1.431 ***	1.249 ***
	(0.65)	(1.96)	(2.81)	(3.30)	(3.85)	(4.36)	(4.94)	(5.46)	(6.02)	(6.71)	(8.43)
12 months	0.303	0.578 **	0.735 ***	0.821 ***	0.910 ***	0.966 ***	1.054 ***	1.120 ***	1.189 ***	1.284 ***	0.981 ***
	(1.09)	(2.23)	(2.96)	(3.41)	(3.90)	(4.23)	(4.75)	(5.13)	(5.50)	(6.00)	(7.97)
JT momentum											
1 month	0.070	0.625 **	0.820 ***	0.919 ***	0.989 ***	1.031 ***	1.050 ***	1.150 ***	1.257 ***	1.439 ***	1.369 ***
	(0.22)	(2.46)	(3.66)	(4.34)	(4.80)	(5.09)	(5.01)	(5.16)	(5.03)	(4.69)	(6.34)
6 months	-0.013	0.574 **	0.778 ***	0.902 ***	0.976 ***	1.046 ***	1.083 ***	1.148 ***	1.206 ***	1.223 ***	1.236 ***
	(-0.04)	(2.31)	(3.48)	(4.23)	(4.75)	(5.17)	(5.19)	(5.17)	(4.79)	(3.84)	(6.94)
12 months	0.137	0.641 **	0.823 ***	0.931 ***	0.990 ***	1.038 ***	1.084 ***	1.095 ***	1.097 ***	0.959 ***	0.822 ***
	(0.45)	(2.58)	(3.67)	(4.35)	(4.82)	(5.10)	(5.19)	(4.91)	(4.31)	(2.99)	(5.55)
Panel C: Long-term profits											
Rank momentum											
Year 2	1.194 ***	1.220 ***	1.222 ***	1.204 ***	1.217 ***	1.197 ***	1.202 ***	1.159 ***	1.139 ***	1.026 ***	-0.167
	(3.66)	(4.46)	(4.94)	(5.13)	(5.49)	(5.58)	(5.72)	(5.57)	(5.42)	(4.48)	(-1.05)
Year 3	1.339 ***	1.334 ***	1.296 ***	1.289 ***	1.259 ***	1.262 ***	1.223 ***	1.195 ***	1.148 ***	1.075 ***	-0.264
	(4.15)	(4.86)	(5.20)	(5.50)	(5.63)	(5.84)	(5.80)	(5.69)	(5.36)	(4.59)	(-1.64)
Years 1-3	39.225 ***	46.204 ***	48.430 ***	49.296 ***	50.535 ***	50.788 ***	51.426 ***	50.660 ***	49.721 ***	46.676 ***	7.451 ***
	(9.36)	(12.57)	(14.20)	(15.22)	(16.11)	(16.61)	(17.01)	(17.01)	(16.87)	(15.43)	(2.63)
Sign momentum											
Year 2	1.203 ***	1.201 ***	1.218 ***	1.205 ***	1.187 ***	1.177 ***	1.169 ***	1.157 ***	1.128 ***	1.116 ***	-0.087
	(4.23)	(4.55)	(4.86)	(4.98)	(5.04)	(5.15)	(5.25)	(5.33)	(5.24)	(5.33)	(-0.70)
Year 3	1.325 ***	1.325 ***	1.297 ***	1.274 ***	1.277 ***	1.227 ***	1.236 ***	1.180 ***	1.152 ***	1.110 ***	-0.215
	(4.66)	(5.05)	(5.15)	(5.23)	(5.42)	(5.35)	(5.52)	(5.38)	(5.32)	(5.15)	(-1.62)
Years 1-3	43.181 ***	46.194 ***	47.605 ***	48.121 ***	48.943 ***	48.545 ***	49.809 ***	49.329 ***	49.172 ***	50.494 ***	7.313 ***
	(11.24)	(12.91)	(14.08)	(14.71)	(15.45)	(15.80)	(16.61)	(17.02)	(17.14)	(16.28)	(2.95)
JT momentum											
Year 2	1.237 ***	1.218 ***	1.206 ***	1.209 ***	1.200 ***	1.208 ***	1.190 ***	1.180 ***	1.108 ***	0.908 ***	-0.329 ***
	(4.05)	(4.96)	(5.42)	(5.73)	(5.80)	(5.79)	(5.51)	(5.19)	(4.41)	(3.04)	(-3.20)
Year 3	1.403 ***	1.318 ***	1.268 ***	1.249 ***	1.224 ***	1.207 ***	1.215 ***	1.216 ***	1.194 ***	1.090 ***	-0.313 ***
	(4.62)	(5.38)	(5.72)	(5.83)	(5.82)	(5.71)	(5.59)	(5.29)	(4.70)	(3.63)	(-3.15)
Years 1-3	41.580 ***	46.853 ***	48.401 ***	49.566 ***	49.841 ***	50.311 ***	50.881 ***	50.896 ***	48.899 ***	41.618 ***	0.038
	(10.79)	(14.17)	(15.74)	(16.53)	(16.78)	(16.67)	(16.52)	(15.57)	(13.70)	(10.16)	(0.02)

Table 2: Robustness of momentum profits

For each month t, we calculate individual stocks' rank or sign measure ($rank_{i,t}(P)$ or $sign_{i,t}(P)$) and classify all stocks into decile portfolios. We exclude stocks priced below $5 at the beginning of the holding period. Stocks with the largest rank (or sign) measures are placed in portfolio P10, while those with the smallest rank measures are placed in portfolio P1. In Panel A (Panels B and C), all of the decile portfolios are constructed with value (equal) weights and rebalanced monthly with the holding periods of 1, 6, and 12 months, skipping one-month following portfolio formation. The rank or sign momentum profit is defined as the return difference between P10 and P1. In addition to RSM strategies, we also follow JT to construct the alternative strategy. In Panel B, we trace momentum profits to the three strategies back to 1927. In Panel C, we include stocks priced below $5 at the beginning of the holding period. In Panel D, individual stocks are classified into quintile portfolios with stocks whereby the largest values on each measure are placed in portfolio P5 and those with the smallest values on each measure are placed in portfolio P1. Numbers in the parentheses are the t-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Rank momentum			Sign momentum			JT momentum		
	P1	P10	P10-P1	P1	P10	P10-P1	P1	P10	P10-P1
Panel A: Portfolios formed on value weights									
1 month	0.426	1.178 ***	0.752 ***	0.562 **	1.166 ***	0.605 ***	0.563 *	1.376 ***	0.813 ***
	(1.36)	(5.76)	(3.20)	(2.33)	(6.34)	(3.53)	(1.86)	(4.71)	(3.20)
6 months	0.346	1.295 ***	0.948 ***	0.522 **	1.267 ***	0.746 ***	0.394	1.391 ***	0.998 ***
	(1.14)	(6.34)	(4.67)	(2.25)	(6.72)	(5.09)	(1.37)	(4.74)	(4.68)
12 months	0.504 *	1.182 ***	0.678 ***	0.644 ***	1.167 ***	0.523 ***	0.499 *	1.186 ***	0.687 ***
	(1.70)	(5.89)	(3.67)	(2.77)	(6.25)	(3.82)	(1.77)	(4.07)	(3.73)
Years 1-3	41.941 ***	48.289 ***	6.348 ***	44.950 ***	50.739 ***	5.789 ***	44.095 ***	46.485 ***	2.390
	(10.87)	(14.80)	(2.93)	(12.44)	(15.54)	(3.07)	(12.18)	(11.24)	(1.27)
Panel B: The 1927-2016 period									
1 month	0.461	1.595 ***	1.134 ***	0.592 **	1.488 ***	0.897 ***	0.597 **	1.530 ***	0.934 ***
	(1.57)	(8.57)	(6.11)	(2.37)	(8.37)	(6.91)	(2.15)	(6.22)	(5.30)
6 months	0.548 *	1.545 ***	0.997 ***	0.650 ***	1.464 ***	0.814 ***	0.576 **	1.478 ***	0.902 ***
	(1.87)	(8.00)	(6.09)	(2.60)	(7.92)	(7.26)	(2.12)	(5.68)	(6.50)
12 months	0.728 **	1.360 ***	0.631 ***	0.793 ***	1.338 ***	0.545 ***	0.708 ***	1.275 ***	0.567 ***
	(2.49)	(6.99)	(4.24)	(3.15)	(7.12)	(5.28)	(2.63)	(4.90)	(5.04)
Years 1-3	35.893 ***	42.202 ***	6.309 **	39.422 ***	42.706 ***	3.283	37.375 ***	39.120 ***	1.745
	(10.63)	(13.49)	(2.17)	(13.59)	(13.84)	(1.31)	(11.90)	(9.87)	(0.52)
Panel C: Low-priced stocks included									
1 month	0.596	1.594 ***	0.998 ***	0.770 **	1.546 ***	0.776 ***	1.172 ***	1.518 ***	0.345
	(1.45)	(6.92)	(3.57)	(2.20)	(7.27)	(3.60)	(2.83)	(4.54)	(1.41)
6 months	0.594	1.553 ***	0.960 ***	0.773 **	1.555 ***	0.782 ***	0.997 **	1.481 ***	0.484 **
	(1.46)	(6.75)	(3.64)	(2.24)	(7.16)	(3.99)	(2.47)	(4.44)	(2.32)
12 months	0.804 **	1.382 ***	0.578 **	0.957 ***	1.416 ***	0.459 **	1.116 ***	1.298 ***	0.182
	(2.02)	(6.05)	(2.41)	(2.81)	(6.55)	(2.52)	(2.86)	(3.92)	(1.08)
Years 1-3	39.225 ***	46.676 ***	7.451 ***	43.181 ***	50.494 ***	7.313 ***	41.580 ***	41.618 ***	0.038
	(9.36)	(15.43)	(2.63)	(11.24)	(16.28)	(2.95)	(10.79)	(10.16)	(0.02)
	P1	P5	P5-P1	P1	P5	P5-P1	P1	P5	P5-P1
Panel D: Quintile portfolios in identifying winner and loser portfolios									
1 month	0.611 **	1.490 ***	0.879 ***	0.666 **	1.486 ***	0.820 ***	0.679 **	1.495 ***	0.815 ***
	(2.04)	(6.95)	(5.23)	(2.51)	(7.20)	(6.53)	(2.47)	(5.52)	(4.98)
6 months	0.598 **	1.467 ***	0.869 ***	0.691 ***	1.466 ***	0.775 ***	0.667 **	1.443 ***	0.776 ***
	(2.02)	(6.83)	(5.84)	(2.61)	(7.01)	(7.06)	(2.46)	(5.31)	(5.52)
12 months	0.737 **	1.335 ***	0.598 ***	0.806 ***	1.349 ***	0.543 ***	0.783 ***	1.288 ***	0.506 ***
	(2.50)	(6.21)	(4.52)	(3.04)	(6.44)	(5.33)	(2.91)	(4.74)	(4.24)
Years 1-3	42.671 ***	48.200 ***	5.529 **	44.705 ***	49.804 ***	5.099 **	44.951 ***	46.410 ***	1.460
	(10.93)	(16.25)	(2.30)	(12.08)	(16.81)	(2.43)	(12.87)	(12.29)	(0.68)

Table 3: Risk-adjusted returns of momentum strategies

We examine whether rank, sign, and JT momentum profits are explained by several risk-based factor models by performing time-series regressions of each strategy on the other strategy and three risk-based factor models. We perform the following regressions:

$$MOM_t = b_0 + b_1 RMRF_t + b_2 SMB_t + b_3 HML_t + \varepsilon_t, \quad (3)$$

$$MOM_t = b_0 + b_1 RMRF_t + b_2 SMB_t + b_3 HML_t + b_4 RMW_t + b_5 CMA_t + \varepsilon_t, \quad (4)$$

$$MOM_t = b_0 + b_1 MP_t + b_2 UI_t + b_3 DEI_t + b_4 UTS_t + b_5 UPR_t + \varepsilon_t, \quad (5)$$

where MOM_t is the one-month holding period return of rank (RM_t), sign (SM_t), or JT (JTM_t) momentum in month t; $RMRF_t$, SMB_t, and HML_t are factor returns of FF's (1993) three-factor model in month t; RMW_t and CMA_t are returns of operating profitability and investment factors; MP_t, UI_t, DEI_t, UTS_t, and UPR_t are the CRR factors in month t. Numbers in the parentheses are the t-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Rank momentum as dependent variable			Sign momentum as dependent variable			JT momentum as dependent variable		
	FF3	FF5	CRR	FF3	FF5	CRR	FF3	FF5	CRR
Intercept	1.617 ***	1.256 ***	1.410 ***	1.268 ***	1.031 ***	1.102 ***	1.328 ***	1.224 ***	1.271 ***
	(9.21)	(5.20)	(7.03)	(9.08)	(5.36)	(7.14)	(6.73)	(4.63)	(6.46)
RMRF	-0.382 ***	-0.254 ***		-0.268 ***	-0.180 ***		-0.178 **	-0.122	
	(-5.08)	(-3.14)		(-5.05)	(-3.05)		(-2.32)	(-1.47)	
SMB	-0.362 **	-0.232		-0.251 *	-0.173		0.229	0.209	
	(-2.17)	(-1.64)		(-1.71)	(-1.58)		(1.04)	(1.29)	
HML	-0.069	-0.408 **		-0.088	-0.311 *		-0.355 *	-0.643 ***	
	(-0.37)	(-2.04)		(-0.60)	(-1.86)		(-1.76)	(-2.73)	
RMW		0.571 *			0.383			-0.010	
		(1.84)			(1.43)			(-0.03)	
CMA		0.849 ***			0.565 **			0.563	
		(2.67)			(2.36)			(1.62)	
MP			-0.088			-0.093			-0.149
			(-0.77)			(-1.07)			(-1.11)
UI			-0.769			-0.282			-0.866
			(-1.02)			(-0.58)			(-0.90)
DEI			0.612			-0.067			2.184
			(0.54)			(-0.08)			(1.52)
UTS			-0.296 ***			-0.238 ***			-0.093
			(-3.29)			(-3.91)			(-1.02)
UPR			-0.395			-0.493 **			-0.248
			(-1.23)			(-2.45)			(-0.78)

Table 4: Time-series regressions of rank and sign momentum profits

We examine whether rank and sign momentum profits are explained by JT momentum by performing the following time-series regressions:

$$RM_t(SM_t) = b_0 + b_1 JTM_t + \varepsilon_t, \quad (6)$$

$$RM_t(SM_t) = b_0 + b_1 JTM_t + b_2 RMRF_t + b_3 SMB_t + b_4 HML_t + \varepsilon_t, \quad (7)$$

$$RM_t(SM_t) = b_0 + b_1 JTM_t + b_2 RMRF_t + b_3 SMB_t + b_4 HML_t + b_5 RMW_t + b_6 CMA_t + \varepsilon_t, \quad (8)$$

$$RM_t(SM_t) = b_0 + b_1 JTM_t + b_2 MP_t + b_3 UI_t + b_4 DEI_t + b_5 UTS_t + b_6 UPR_t + \varepsilon_t, \quad (9)$$

where RM_t is the one-month holding period return of rank momentum in month t; SM_t is the one-month holding period return of sign momentum in month t; JTM_t is the one-month holding period return of JT momentum in month t; $RMRF_t$, SMB_t, and HML_t are factor returns of FF's (1993) three-factor model in month t; RMW_t and CMA_t are returns of operating profitability and investment factors; MP_t, UI_t, DEI_t, UTS_t, and UPR_t are the CRR factors in month t. We use RM_t and SM_t as the independent variable, respectively. Numbers in the parentheses are the t-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Rank momentum as dependent variable				Sign momentum as dependent variable			
	Raw returns	FF3	FF5	CRR	Raw returns	FF3	FF5	CRR
Intercept	0.438 **	0.550 ***	0.287 ***	0.465 **	0.429 ***	0.528 ***	0.358 ***	0.442 ***
	(2.43)	(4.58)	(2.78)	(2.36)	(3.65)	(5.66)	(3.72)	(3.69)
JTM	0.758 ***	0.804 ***	0.792 ***	0.743 ***	0.529 ***	0.557 ***	0.550 ***	0.519 ***
	(7.72)	(16.82)	(23.00)	(7.60)	(10.48)	(13.86)	(14.82)	(10.16)
RMRF		-0.239 ***	-0.157 ***			-0.169 ***	-0.113 ***	
		(-6.82)	(-5.06)			(-5.33)	(-3.45)	
SMB		-0.546 ***	-0.397 ***			-0.378 ***	-0.288 ***	
		(-12.64)	(-9.46)			(-7.84)	(-6.13)	
HML		0.217 ***	0.101 *			0.110 *	0.043	
		(2.74)	(1.73)			(1.70)	(0.76)	
RMW			0.579 ***				0.388 ***	
			(7.81)				(4.10)	
CMA			0.404 ***				0.255 ***	
			(4.83)				(3.45)	
MP				0.023				-0.016
				(0.28)				(-0.26)
UI				-0.126				0.168
				(-0.33)				(0.76)
DEI				-1.012				-1.201 **
				(-1.26)				(-2.06)
UTS				-0.227 ***				-0.190 ***
				(-4.74)				(-5.42)
UPR				-0.211				-0.364 ***
				(-1.09)				(-2.67)

Table 5: Time-series regressions of JT momentum profits

We examine whether JT momentum profits are explained by rank or sign momentum by performing the following time-series regressions:

$$JTM_t = b_0 + b_1 RM_t(SM_t) + \varepsilon_t, \quad (10)$$

$$JTM_t = b_0 + b_1 RM_t(SM_t) + b_2 RMRF_t + b_3 SMB_t + b_4 HML_t + \varepsilon_t, \quad (11)$$

$$JTM_t = b_0 + b_1 RM_t(SM_t) + b_2 RMRF_t + b_3 SMB_t + b_4 HML_t + b_5 RMW_t + b_6 CMA_t + \varepsilon_t, \quad (12)$$

$$JTM_t = b_0 + b_1 RM_t(SM_t) + b_2 MP_t + b_3 UI_t + b_4 DEI_t + b_5 UTS_t + b_6 UPR_t + \varepsilon_t, \quad (13)$$

where JTM_t is the one-month holding period return of JT momentum in month t; RM_t is the one-month holding period return of rank momentum in month t; SM_t is the one-month holding period return of sign momentum in month t; $RMRF_t$, SMB_t, and HML_t are factor returns of FF's (1993) three-factor model in month t; RMW_t and CMA_t are returns of operating profitability and investment factors; MP_t, UI_t, DEI_t, UTS_t, and UPR_t are risk premiums of the CRR factors in month t. We use RM_t and SM_t as the independent variable, respectively. Numbers in the parentheses are the t-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Rank momentum as independent variable				Sign momentum as independent variable			
	Raw returns	FF3	FF5	CRR	Raw returns	FF3	FF5	CRR
Intercept	0.107	-0.232 *	-0.067	0.134	0.088	-0.193	-0.075	0.118
	(0.71)	(-1.74)	(-0.58)	(0.76)	(0.48)	(-1.28)	(-0.53)	(0.59)
RM	0.796 ***	0.965 ***	1.028 ***	0.806 ***				
	(15.93)	(23.46)	(29.40)	(14.15)				
SM					1.023 ***	1.200 ***	1.260 ***	1.047 ***
					(11.07)	(19.60)	(22.10)	(10.40)
RMRF		0.191 ***	0.139 ***			0.144 ***	0.105 **	
		(5.11)	(4.15)			(2.94)	(2.22)	
SMB		0.578 ***	0.447 ***			0.530 ***	0.427 ***	
		(6.83)	(8.70)			(6.85)	(5.95)	
HML		-0.289 ***	-0.223 ***			-0.250 ***	-0.251 ***	
		(-3.58)	(-3.07)			(-3.39)	(-2.99)	
RMW			-0.597 ***				-0.493 ***	
			(-6.78)				(-5.50)	
CMA			-0.310 ***				-0.149	
			(-3.53)				(-1.35)	
MP				-0.078				-0.052
				(-0.83)				(-0.57)
UI				-0.246				-0.571
				(-0.46)				(-1.01)
DEI				1.691 *				2.254 **
				(1.74)				(2.23)
UTS				0.146 ***				0.156 ***
				(2.99)				(2.79)
UPR				0.071				0.268
				(0.37)				(1.24)

Table 6: Proportions of stocks in price momentum that overlap rank or sign momentum

This table reports the average numbers and proportions of price winners (losers) that overlap rank or sign winners (losers). Stocks with rank, sign, or past six-month average return ranked at the top 10% are placed in the rank, sign, or price winner portfolio, while those with rank, sign, or past 6-month average return ranked at the bottom 10% are placed in the rank, sign, or price loser portfolio. Panels A and B reveal the parts of winner and loser stocks, respectively. We calculate the numbers and proportions of firms for each category at the end of every formation period and average them over our sample period. {price winners} is the number of price winner stocks, and {price losers} is the number of price loser stocks. {price winners}∩{rank winners} ({price winners}∩{sign winners}) is the number of price winner stocks that overlap rank (sign) winner stocks; {price losers}∩{rank losers} ({price losers}∩{sign losers}) is the number of price loser stocks that overlap rank (sign) loser stocks; {price winners}∩{rank winners}∩{sign winners} ({price losers}∩{rank losers}∩{sign losers}) is the number of price winner (loser) stocks that overlap rank and sign winner (loser) stocks; {price winners}∩{rank or sign winners} ({price losers}∩{rank or sign losers}) is the number of price winner (loser) stocks that overlap rank or sign winner (loser) stocks.

	# of stocks	Percentage
Panel A: Winners		
{price winners}	325	100%
{price winners}∩{rank winners}	148	45.54%
{price winners}∩{sign winners}	106	32.62%
{price winners}∩{rank or sign winners}	158	48.62%
{price winners}∩{rank winners}∩{sign winners}	95	29.23%
Panel B: Losers		
{price losers}	330	100%
{price losers}∩{rank losers}	193	58.48%
{price losers}∩{sign losers}	96	29.09%
{price losers}∩{rank or sign losers}	201	60.91%
{price losers}∩{rank losers}∩{sign losers}	88	26.67%

Table 7: Performance of overlapped and isolated strategies of price momentum

This table reports the short-term performance of two strategies that contain different components of price momentum. We break down price momentum winners and losers into two categories: (i) one category whose membership overlaps with rank (or sign) momentum winners and losers; and (ii) the other category whose membership is unrelated to rank (or sign) momentum winners and losers. We refer to the former as the "overlapped" category of price momentum stocks and the latter as the "isolated" category of price momentum stocks. We hold each category of stocks for subsequent 1, 6, and 12 months with component stocks invested based on equal weights. In Panels A and B, overlapped and isolated strategies of price momentum are partitioned by rank and sign measures, respectively. In Panel C, the overlapped strategy contains price momentum winners (losers) that belong to rank and sign momentum winners (losers) simultaneously while the isolated strategy contains price momentum winners (losers) that do not belong to either rank or sign momentum winners (losers). In Panel D, we report summary statistics of 1-month holding-period returns for the three momentum strategies (price, rank, and sign) and overlapped and isolated categories of price momentum constructed in Panels A to C. We calculate minimum, maximum, mean, standard deviation, skewness, and Sharpe ratio for each strategy. Means, standard deviations, and Sharpe ratios are reported on an annual basis while minimum, maximum, and skewness are calculated based on monthly returns. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Overlapped strategy			Isolated strategy		
	1 month	6 months	12 months	1 month	6 months	12 months
Panel A: Price winners and losers partitioned by the rank measure (R_Overlap and R_Isolate)						
P1	0.099	0.027	0.284	1.464 ***	1.262 ***	1.362 ***
	(0.28)	(0.08)	(0.82)	(3.39)	(2.99)	(3.33)
P10	2.035 ***	1.836 ***	1.469 ***	1.284 ***	1.326 ***	1.212 ***
	(7.02)	(6.22)	(5.07)	(3.65)	(3.71)	(3.42)
P10-P1	1.936 ***	1.809 ***	1.186 ***	-0.180	0.064	-0.150
	(7.19)	(7.57)	(6.02)	(-0.74)	(0.32)	(-0.93)
Panel B: Price winners and losers partitioned by the sign measure (S_Overlap and S_Isolate)						
P1	0.098	0.000	0.259	1.338 ***	1.159 ***	1.266 ***
	(0.28)	(0.00)	(0.76)	(3.16)	(2.80)	(3.15)
P10	2.020 ***	1.914 ***	1.534 ***	1.409 ***	1.379 ***	1.238 ***
	(6.97)	(6.48)	(5.33)	(4.15)	(3.98)	(3.60)
P10-P1	1.922 ***	1.914 ***	1.275 ***	0.071	0.219	-0.028
	(7.06)	(7.96)	(6.37)	(0.29)	(1.09)	(-0.17)
Panel C: Price winners and losers partitioned by rank and sign measures (RS_Overlap and RS_Isolate)						
P1	0.008	-0.037	0.192	1.308 ***	1.126 ***	1.220 ***
	(0.02)	(-0.10)	(0.55)	(3.22)	(2.87)	(3.21)
P10	2.045 ***	1.915 ***	1.525 ***	1.387 ***	1.354 ***	1.228 ***
	(7.03)	(6.50)	(5.28)	(4.05)	(3.88)	(3.54)
P10-P1	2.036 ***	1.953 ***	1.332 ***	0.079	0.228	0.008
	(7.32)	(7.75)	(6.41)	(0.33)	(1.22)	(0.05)

	Minimum	Maximum	Mean (annualized)	Std. dev. (annualized)	Skewness	Sharpe ratio (annualized)
Panel D: Statistics of alternative strategies						
Price momentum	-78.093	33.021	13.796	18.989	-3.229	0.479
Rank momentum	-34.959	26.307	15.712	18.529	-0.981	0.595
Sign momentum	-25.406	21.353	12.451	13.660	-0.144	0.568
R_Overlap	-54.478	43.241	23.231	24.631	-1.110	0.753
R_Isolate	-79.616	27.744	-2.161	23.814	-3.428	-0.288
S_Overlap	-52.665	39.848	23.063	25.135	-1.052	0.731
S_Isolate	-78.985	31.172	0.850	23.911	-3.348	-0.161
RS_Overlap	-54.280	40.038	24.438	26.138	-1.122	0.755
RS_Isolate	-67.297	32.126	0.945	22.544	-2.714	-0.166

Table 8: Rank and sign momentum versus return consistency

For each month t, we identify stocks as consistent winners (losers) if their monthly returns were positive (negative) in at least eight of the past 11 months from $t-12$ to $t-2$. We exclude stocks priced below $5 at the beginning of the holding period. In Panel A, we perform the following cross-sectional regressions and report the estimated coefficients:

$$R_{i,t} = b_0 + b_1 RS_{i,t-2} + b_2 PR6_{i,t-2} + b_3 WC_{i,t-2} + b_4 RS_{i,t-2} \times WC_{i,t-2} + b_5 PR6_{i,t-2} \times WC_{i,t-2} + \varepsilon_{i,t},$$

where $WC_{i,t-2}$ equals 1 if the stock is classified as consistent winner and zero otherwise. In Panels B and C, we form three portfolios with consistent winners and losers are placed in portfolio P3 and P1, respectively, while the remaining are placed in portfolio P2. All of the portfolios are constructed with equal weights and rebalanced monthly with the holding periods of one month, skipping one month following portfolio formation. The RCM momentum profit is defined as the return difference between P3 and P1. We report average raw returns, rank, and sign values for each three portfolio and the differences between P3 and P1 in Panels B and C. In Panels D and E, we perform the time-series regressions of Equations (6) to (9) and Equations (10) to (13) by replacing JTM with RCM. We report the intercepts from the regressions. Numbers in the parentheses are the t-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Intercept	*rank*	*sign*	*PR6*	*WC*	*rank*×*WC*	*sign*×*WC*	*PR6*×*WC*
Panel A: Cross-sectional regressions on winner consistency							
0.011 ***	0.040 ***		0.004	0.003 **	-0.033 ***		0.045 ***
(4.43)	(3.65)		(0.33)	(2.35)	(-3.46)		(2.67)
-0.010		0.043 ***	0.008	0.016 ***		-0.027 **	0.043 **
(-1.38)		(3.74)	(0.67)	(2.59)		(-2.40)	(2.38)

	P1	P2	P3	P3-P1
Panel B: Portfolio returns and characteristics formed on return consistency				
Raw	0.610 **	1.170 ***	1.633 ***	1.023 ***
	(2.03)	(4.76)	(7.20)	(5.79)
Panel C: Average values of rank and sign for portfolios formed on return consistency				
rank	-0.072	0.002	0.084	0.156 ***
				(54.79)
sign	0.445	0.490	0.536	0.091 ***
				(46.57)

	Rank momentum as dependent variable				Sign momentum as dependent variable			
	Raw returns	FF3	FF5	CRR	Raw returns	FF3	FF5	CRR
Panel D: Rank or sign momentum regressing on return consistency momentum								
Intercept	0.482 ***	0.575 ***	0.425 ***	0.506 ***	0.424 ***	0.494 ***	0.410 ***	0.431 ***
	(2.96)	(4.03)	(2.96)	(3.06)	(3.69)	(4.68)	(3.69)	(3.82)

	Rank momentum as independent variable				Sign momentum as independent variable			
	Raw returns	FF3	FF5	CRR	Raw returns	FF3	FF5	CRR
Panel E: Return consistency momentum regressing on rank or sign momentum								
Intercept	0.154	0.187	0.204	0.216	0.083	0.136	0.130	0.146
	(1.01)	(1.12)	(1.19)	(1.41)	(0.55)	(0.83)	(0.76)	(1.02)

Table 9: Rank and sign momentum versus absolute strength momentum

For each month *t*, we calculate the 11-month cumulative return over months *t*−12 to *t*−2. We exclude stocks priced below $5 at the beginning of the holding period. We then compare the recent 11-month cumulative return with the distribution of all non-overlapping 11-month cumulative returns up to month *t*. This distribution is then ranked into deciles. If a stock is ranked in the top (bottom) 10% of the historical distribution up to month *t*, then it is classified as an ASM winner (loser). Stocks with the recent 11-month cumulative return ranked in the top 10% are placed in portfolio P10, while those with the recent 11-month cumulative return ranked in the bottom 10% are placed in portfolio P1. All of the decile portfolios are constructed with equal weights and rebalanced monthly with the holding periods of one month, skipping one month following portfolio formation. The ASM momentum profit is defined as the return difference between P10 and P1. Because the distribution requires sufficient observations, the return data are traced back to 1927 to determine performance breakpoints. The observation period of the strategy spans from January 1963 to December 2016. In Panels A and B, we report average raw returns, rank, and sign values for each decile portfolio and the differences between P10 and P1. In Panels C and D, we perform the time-series regressions of Equations (6) to (9) and Equations (10) to (13) by replacing JTM with ASM. We report the intercepts from the regressions. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
Panel A: Portfolio returns and characteristics formed on absolute strength											
Raw return	0.313	0.516 **	0.632 **	0.718 ***	1.088 ***	0.981 ***	1.326 ***	1.604 ***	1.694 ***	1.559 ***	1.219 ***
	(1.09)	(2.00)	(2.51)	(2.89)	(4.62)	(3.64)	(5.05)	(6.20)	(6.07)	(5.94)	(5.34)
Panel B: Average values of rank and sign for portfolios formed on absolute strength											
rank	-0.084	-0.059	-0.040	-0.023	-0.004	0.000	0.020	0.040	0.055	0.079	0.163 ***
											(51.59)
sign	0.448	0.458	0.467	0.475	0.486	0.487	0.498	0.509	0.517	0.527	0.080 ***
											(45.81)

	Rank momentum as dependent variable				Sign momentum as dependent variable			
	Raw returns	FF3	FF5	CRR	Raw returns	FF3	FF5	CRR
Panel C: Rank or sign momentum regressing on absolute momentum								
Intercept	0.886 ***	1.086 ***	0.723 ***	0.956 ***	0.713 ***	0.864 ***	0.625 ***	0.752 ***
	(4.23)	(6.33)	(3.86)	(4.60)	(4.72)	(6.60)	(4.26)	(4.89)
	Rank momentum as independent variable				Sign momentum as independent variable			
	Raw returns	FF3	FF5	CRR	Raw returns	FF3	FF5	CRR
Panel D: Absolute momentum regressing on rank or sign momentum								
Intercept	0.160	0.086	0.217	0.243	0.076	0.015	0.125	0.152
	(0.76)	(0.39)	(0.96)	(1.06)	(0.35)	(0.07)	(0.54)	(0.66)

Table 10: Descriptive statistics and firm characteristics of rank and sign decile portfolios

For each month *t*, we calculate individual stocks' rank or sign measure ($rank_{i,t}(P)$ or $sign_{i,t}(P)$) and classify all stocks into decile portfolios. Stocks with rank or sign measures ranked at the top 10% are placed in portfolio P10, while those with rank measures ranked at the bottom 10% are placed in portfolio P1. Panels A and B report the time-series average values of summary statistics and characteristics calculated on a monthly basis for stocks in rank- and sign-sorted portfolios. *rank* is defined as the average of the past 6-month rank measure; *sign* is defined as the average of the past 6-month sign measure; *Mean* is the average daily return of stocks over the past 6 months; *Median* is the medium daily return of stocks over the past 6 months; *Std. dev.* is the standard deviation of each stock computed using daily returns over the past 6 months; *Skewness* is the skewness of each stock computed using daily returns over the past 6 months; *Kurtosis* is the kurtosis of each stock computed using daily returns over the past 6 months; *Max* and *Min* are the maximum and minimum daily return for each stock in the previous month. From July of each year to June of next year, *Size* is the market value of equity (in billions of dollars) at the end of June in the current year; *BM* is the ratio of book value of equity at the end of the previous year divided by market capitalization at the end of the previous year; $Skew_{SEG}$ is the segment-level skewness calculated using data over past year ending in the previous month; $|Skew_{SEG}|$ is the absolute value of the segment-level skewness; *ID* is the information discreteness measure calculated using data over past year ending in the previous month. The last column reports the difference between P10 and P1 portfolios with *t*-statistics reported in parentheses calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10−P1
Panel A: Summary statistic of formation-period daily returns for rank-sorted portfolios											
rank	-0.164	-0.090	-0.054	-0.028	-0.006	0.015	0.036	0.059	0.088	0.146	0.310 ***
											(99.65)
Mean	-0.084	-0.006	0.028	0.051	0.071	0.090	0.107	0.129	0.159	0.237	0.321 ***
											(39.44)
Median	-0.181	-0.072	-0.040	-0.023	-0.012	-0.003	0.005	0.012	0.024	0.056	0.237 ***
											(12.38)
Std. dev.	4.813	4.075	3.722	3.460	3.238	3.054	2.877	2.746	2.635	2.684	-2.130 ***
											(-26.88)
Skewness	0.925	0.706	0.631	0.590	0.563	0.556	0.540	0.540	0.542	0.554	-0.371 ***
											(-12.74)
Kurtosis	9.379	7.903	7.735	7.650	7.652	7.671	7.546	7.430	7.253	6.884	-2.496 ***
											(-7.96)
Max	11.461	9.151	8.161	7.453	6.914	6.456	6.071	5.796	5.598	5.866	-5.596 ***
											(-19.26)
Min	-9.028	-7.506	-6.760	-6.182	-5.695	-5.290	-4.914	-4.611	-4.359	-4.398	4.630 ***
											(25.23)
Size (in millions)	0.382	0.765	1.089	1.343	1.493	1.648	1.789	1.893	1.988	1.880	1.498 ***
											(8.27)
BM	0.753	0.845	0.886	0.920	0.937	0.946	0.958	0.940	0.930	0.946	0.193 ***
											(4.95)
$Skew_{SEG}$	0.944	0.886	0.932	1.020	1.050	1.116	1.157	1.163	1.134	1.040	0.096
											(1.16)
$\|Skew_{SEG}\|$	0.950	0.895	0.942	1.032	1.063	1.128	1.169	1.175	1.147	1.051	0.101
											(1.23)
ID	-0.072	-0.044	-0.032	-0.025	-0.020	-0.019	-0.019	-0.021	-0.027	-0.043	0.029 ***
											(7.16)

Table 10 (continued)

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10−P1
Panel B: Summary statistic of formation-period daily returns for sign-sorted portfolios											
sign	0.388	0.434	0.454	0.469	0.482	0.495	0.508	0.522	0.541	0.586	0.198 ***
											(50.18)
Mean	-0.070	0.003	0.035	0.061	0.081	0.100	0.116	0.133	0.153	0.187	0.257 ***
											(34.97)
Median	-0.158	-0.079	-0.050	-0.031	-0.018	-0.006	0.005	0.016	0.030	0.056	0.214 ***
											(11.88)
Std. dev.	4.234	3.867	3.680	3.550	3.408	3.269	3.110	2.953	2.754	2.500	-1.734 ***
											(-24.37)
Skewness	0.966	0.746	0.651	0.596	0.556	0.517	0.488	0.463	0.454	0.545	-0.422 ***
											(-17.31)
Kurtosis	10.748	7.747	6.862	6.425	6.164	5.945	5.835	5.836	6.052	7.911	-2.837 ***
											(-12.58)
Max	9.803	8.820	8.223	7.819	7.421	7.040	6.643	6.269	5.832	5.414	-4.388 ***
											(-18.99)
Min	-8.005	-7.034	-6.597	-6.292	-5.987	-5.695	-5.398	-5.085	-4.720	-4.216	3.789 ***
											(25.94)
Size (in millions)	0.610	0.913	1.142	1.280	1.431	1.527	1.669	1.810	1.946	2.046	1.436 ***
											(7.56)
BM	0.819	0.859	0.869	0.896	0.905	0.900	0.915	0.909	0.916	0.968	0.149 ***
											(5.32)
$Skew_{SEG}$	0.953	0.925	0.960	0.980	1.012	1.051	1.062	1.101	1.124	1.181	0.228 **
											(2.52)
$\lvert Skew_{SEG}\rvert$	0.961	0.935	0.969	0.990	1.023	1.064	1.074	1.112	1.135	1.193	0.232 **
											(2.57)
ID	-0.068	-0.043	-0.032	-0.025	-0.021	-0.019	-0.019	-0.022	-0.029	-0.045	0.023 ***
											(5.52)

Table 11: Cross-sectional regressions on salience measures

In each month t from January 1963 to December 2016, we perform the following cross-sectional regressions:

$$R_{i,t} = b_0 + b_1 RS_{i,t-2} + b_2 PR6_{i,t-2} + b_3 Salience_{i,t-2} + b_4 RS_{i,t-2} \times Salience_{i,t-2} + b_5 PR6_{i,t-2} \times Salience_{i,t-2} + \varepsilon_{i,t}, \quad (15)$$

where $R_{i,t}$ is stock i's future return in month t; $RS_{i,t-2}$ is defined as the average of the past 6-month rank or sign measure, $rank_{i,t-2}$ or $sign_{i,t-2}$ for stock i ending in month $t-2$; $PR6_{i,t-2}$ is defined as the average of the past 6-month returns for stock i ending in month $t-2$; $Salience_{i,t-2}$ is stock i's salience measure calculated in month $t-2$. We adopt $|Skew_{SEG}|$ and ID as proxies of salience measures, where $Skew_{SEG}$ is the segment-level measure of skewness. We obtain estimated coefficients every month and report average coefficients. In Panels A and B, $RS_{i,t-2}$ is proxied by $rank_{i,t-2}$ and $sign_{i,t-2}$, respectively. Numbers in the parentheses are the t-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Model (1)	Model (2)	Model (3)
Panel A: Rank measure as the independent variable			
Intercept	0.139 ***	0.155 ***	0.141 ***
	(7.50)	(8.39)	(7.64)
rank	0.267 ***	0.253 ***	0.256 ***
	(2.78)	(3.11)	(2.89)
PR6	-0.003	-0.107	-0.033
	(-0.02)	(-1.04)	(-0.25)
$\lvert Skew_{SEG}\rvert$	0.361 *		0.350 *
	(1.75)		(1.71)
ID		0.091 ***	0.084 ***
		(3.26)	(3.02)
$rank \times \lvert Skew_{SEG}\rvert$	1.681		1.532
	(0.80)		(0.73)
rank×*ID*		-0.284	-0.172
		(-1.07)	(-0.63)
$PR6 \times \lvert Skew_{SEG}\rvert$	-8.368 **		-7.733 *
	(-2.03)		(-1.86)
PR6×*ID*		-0.986 **	-1.264 **
		(-1.97)	(-2.42)
Panel B: Sign measure as the independent variable			
Intercept	-0.026	-0.001	-0.018
	(-0.49)	(-0.02)	(-0.35)
sign	0.325 ***	0.306 ***	0.315 ***
	(3.76)	(4.33)	(3.78)
PR6	0.196	0.053	0.130
	(1.55)	(0.56)	(1.09)
$\lvert Skew_{SEG}\rvert$	-0.632		-0.679
	(-0.69)		(-0.73)
ID		0.381 **	0.334 *
		(2.2)	(1.91)
$sign \times \lvert Skew_{SEG}\rvert$	1.895		1.971
	(1.03)		(1.04)
sign×*ID*		-0.608 *	-0.530
		(-1.78)	(-1.53)
$PR6 \times \lvert Skew_{SEG}\rvert$	-8.021 **		-7.089 **
	(-2.58)		(-2.33)
PR6×*ID*		-1.775 ***	-1.875 ***
		(-3.28)	(-3.39)

Table 12: Worst monthly momentum profits

For each month *t*, we calculate individual stocks' rank, sign, or JT measure and classify all stocks into decile portfolios. We exclude stocks priced below $5 at the beginning of the holding period. Stocks with the largest values of the measure are placed in portfolio P10, while those with the smallest values of the measure are placed in portfolio P1. All of the decile portfolios are constructed with equal weights and rebalanced monthly with the holding periods of one month, skipping one month following portfolio formation. The momentum profit is defined as the return difference between P10 and P1. We report the 10 worst monthly returns (in %) of JT, rank, and sign momentum strategies in each panel, respectively. We also report the monthly returns of the other two alternative strategies in the same months as comparisons. In the bottom row, we report the averages of the 10 monthly returns for each strategy.

	Worst JT momentum returns				Worst rank momentum returns				Worst sign momentum returns			
Rank	month	rank	sign	JT	month	rank	sign	JT	month	rank	Sign	JT
1	200101	-34.35	-25.41	-78.09	193304	-46.50	-15.67	-36.92	193909	-39.27	-34.70	-69.44
2	193909	-39.27	-34.70	-69.44	193208	-43.21	-9.98	-25.81	193401	-34.36	-26.82	-31.31
3	193207	-39.93	-12.22	-47.95	193207	-39.93	-12.22	-47.95	200101	-34.35	-25.41	-78.09
4	200211	-20.55	-13.98	-44.37	193909	-39.27	-34.70	-69.44	193806	-31.12	-17.76	-15.27
5	200904	-34.96	-14.67	-39.80	200904	-34.96	-14.67	-39.80	193305	-10.35	-16.48	-33.06
6	193304	-46.50	-15.67	-36.92	193401	-34.36	-26.82	-31.31	193304	-46.50	-15.67	-36.92
7	197501	-21.61	-11.98	-35.55	200101	-34.35	-25.41	-78.09	200904	-34.96	-14.67	-39.80
8	193305	-10.35	-16.48	-33.06	193806	-31.12	-17.76	-15.27	200211	-20.55	-13.98	-44.37
9	193401	-34.36	-26.82	-31.31	197009	-23.03	-13.04	-21.49	197009	-23.03	-13.04	-21.49
10	193101	-15.75	-5.91	-29.60	197501	-21.61	-11.98	-35.55	193106	-16.98	-12.37	-5.59
Average		-29.76	-17.78	-44.61		-34.83	-18.23	-40.16		-29.15	-19.09	-37.53

Internet Appendix of Rank, Sign, and Momentum

Appendix A1. Rank and sign measures based on monthly frequencies

Throughout the paper, our rank and sign measures are constructed based on daily returns of individual stocks. An alternative way is to calculate rank and sign measures based on monthly returns. In particular, the idea of sign measure based on monthly returns is similar to the return consistency measure proposed by Grinblatt and Moskowitz (2004). Thus understanding the information content embedded in different frequencies of non-parametric statistics becomes an important issue. We replicate the identifications of rank and sign for individual stocks every month and then calculate average rank and sign over for six-month formation period.

We next perform cross-sectional regressions as follows:

$$R_{i,t} = b_0 + b_1 PR6_{i,t-2} + b_2 RS(M)_{i,t-2} + b_3 RS(D)_{i,t-2} + \varepsilon_{i,t}, \quad \text{(A1)}$$

where $RS(M)_{i,t-2}$ is defined as the average of the past 6-month rank or sign measure based on monthly returns; $RS(D)_{i,t-2}$ is defined as the average of the past 6-month rank or sign measure based on daily returns. We obtain estimated coefficients every month and test average coefficients using Newey and West's (1987) robust standard errors. Table A1 shows that when considered alone, both monthly-based rank and sign measures are positively and significantly associated with future stock returns. When daily-based rank and sign measures are included in the regressions, monthly-based measures lose their explanatory power for future returns. This finding suggests that non-parametric statistics based on daily returns contain more information about future returns than those based on monthly returns.

Table A1: Cross-sectional regressions

In each month *t* from January 1963 to December 2016, we perform the following cross-sectional regressions:

$$R_{i,t} = b_0 + b_1 PR6_{i,t-2} + b_2 RS(M)_{i,t-2} + b_3 RS(D)_{i,t-2} \varepsilon_{i,t},$$

where $R_{i,t}$ is stock *i*'s future return in month *t*; $PR6_{i,t-2}$ is defined as the average of the past 6-month returns for

stock i ending in month $t-2$; $RS(M)_{i,t-2}$ is defined as the average of the past 6-month rank or sign measure based on monthly returns; $RS(D)_{i,t-2}$ is defined as the average of the past 6-month rank or sign measure based on daily returns. We obtain estimated coefficients every month and report average coefficients. Numbers in the parentheses are the t-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Intercept	1.172 ***	1.174 ***	0.838 **	-1.002	2.310 ***
	(4.64)	(4.62)	(2.55)	(-1.41)	(3.80)
PR6	-1.731	-1.779	1.363	0.776	-2.107 *
	(-1.32)	(-1.41)	(1.19)	(0.66)	(-1.72)
rank(*M*)	0.670 ***	-0.079			0.177
	(2.73)	(-0.54)			(0.94)
rank(*D*)		4.130 ***			5.240 ***
		(3.88)			(3.25)
sign(*M*)			0.557 **	0.192	-0.295
			(2.26)	(1.05)	(-1.46)
sign(*D*)				4.083 ***	-1.905
				(4.08)	(-1.40)

Appendix A2. RSM versus 52-week high momentum

We compare RSM profitability with the 52-week high momentum profitability. We follow George and Hwang (2004) and George, Hwang, and Li (2018) by defining the 52-week high ratio as a stock's closing price in month $t-2$ divided by its highest price during the past 52-weeks ending in month $t-2$. The 52-week high momentum involves buying stocks with 52-week high ratios ranked at the top 10% and short selling those with 52-week high ratios ranked at the bottom 10%. We replicate the same analyses as in Tables 8 and 9 and report the results in Table A2. The results are summarized as follows: (i) stocks with higher 52-week high ratios have higher values of ranks and signs; (ii) 52-week high momentum cannot explain RSM profits; and (iii) rank and sign momentum strategies fully explain 52-week high momentum profits.

Table A2: Rank and sign momentum versus 52-week high momentum

For each month t, we calculate the ratio of end-of-month price to past 52-week high. We exclude stocks priced below \$5 at the beginning of the holding period. Stocks are ranked into deciles according to their values of 52-week high ratios. If a stock's 52-week high ratio is ranked in the top (bottom) 10% in month t, then it is classified as a 52WH winner (loser). All of the decile portfolios are constructed with equal weights and rebalanced monthly with the holding periods of one month, skipping one month following portfolio formation. The 52WH momentum (52WHM) profit is defined as the return difference between P10 and P1. In Panels A and B, we report average raw returns, rank, and sign

values for each decile portfolio and the differences between P10 and P1. In Panels C and D, we perform the time-series regressions of Equations (6) to (9) and Equations (10) to (13) by replacing JTM with 52WHM. We report the intercepts from the regressions. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
Panel A: Portfolio returns and characteristics formed on 52-week high ratio											
Raw return	0.469	0.640 **	0.945 ***	1.079 ***	1.227 ***	1.268 ***	1.366 ***	1.383 ***	1.405 ***	1.461 ***	1.016 ***
	(1.47)	(2.23)	(3.58)	(4.36)	(5.32)	(5.81)	(6.61)	(7.07)	(7.51)	(7.60)	(4.78)
Panel B: Average values of rank and sign for portfolios formed on 52-week high ratio											
rank	-0.090	-0.055	-0.035	-0.018	-0.002	0.014	0.029	0.045	0.058	0.067	0.156 ***
											(38.07)
sign	0.445	0.461	0.469	0.477	0.485	0.493	0.501	0.510	0.519	0.527	0.081 ***
											(41.52)

	Rank momentum as dependent variable				Sign momentum as dependent variable			
	Raw returns	FF3	FF5	CRR	Raw returns	FF3	FF5	CRR
Panel C: Rank or sign momentum regressing on 52WHM								
Intercept	0.475 ***	0.402 ***	0.396 ***	0.510 ***	0.468 ***	0.433 ***	0.441 ***	0.496 ***
	(3.92)	(2.85)	(2.74)	(4.18)	(4.38)	(3.44)	(3.35)	(4.57)
	Rank momentum as independent variable				Sign momentum as independent variable			
	Raw returns	FF3	FF5	CRR	Raw returns	FF3	FF5	CRR
Panel D: 52WHM regressing on rank or sign momentum								
Intercept	-0.194 *	0.020	-0.045	-0.203 *	-0.195	0.060	-0.044	-0.178
	(-1.71)	(0.17)	(-0.39)	(-1.72)	(-1.28)	(0.42)	(-0.34)	(-1.14)