Nonparametric Momentum Strategies

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Abstract

Nonparametric measures, such as the rank and sign of daily returns, capture investor underreaction while mitigating overreaction to extreme movements of stock prices. Alternative momentum strategies formed on the basis of such measures, or nonparametric momentum strategies, outperform both Jegadeesh and Titman's (1993) price momentum and George and Hwang's (2004) 52-week high momentum, and exhibit no long-term return reversals. The profits, however, are not fully explained by common risk-based asset pricing models, and exhibit patterns consistent with the salience theory proposed by Bordallo, Gennaioli, Shleifer (2012, 2013). In particular, the nonparametric momentum, in conjunction with the 52-week high momentum, subsumes the price momentum, thus suggesting that the price momentum is driven by investor underreaction rather than continued overreaction.

JEL Classification: G12; G14.
Keywords: Nonparametric momentum; Rank; Sign; Price momentum; 52-week high momentum.

1. Introduction

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. However, none of the past studies has questioned the weakness of the parametric nature of computing past returns in determining winners and losers. This question is critically important because parametric statistics built on sample mean and variance are highly sensitive to the presence of extreme observations or outliers (Wright, 2000; Gibbons and Chakraborti, 2010; Hollander, Wolfe, and Chicken, 2014). As Bordalo, Gennaioli, and Shleifer (BGS) (2012, 2013) point out, salient features of stock prices could be the cause of mispricing. We believe that the parametric nature of past and future returns simply magnifies this mispricing problem in asset valuation.

We propose nonparametric momentum (NPM) strategies and investigate their profitability. NPM strategies are constructed on the basis of daily rank or sign over the formation period.[1] Our choice of these strategies is motivated by the theory of nonparametric statistics, which is known to be robust to the presence of extreme observations. Nonparametric performance measures, calculated based on rank and sign, mitigate the impact of extreme returns in the sample, thereby providing better and more stable predictability of future returns than parametric measures.

Our empirical results fully support the predictions. First, NPM strategies outperform two well-known momentum strategies, namely the price momentum strategy of JT and the 52-week high (52wh) momentum strategy of George and Hwang (GH) (2004). Over the five-year holding

[1] We use the standardized rank among stocks to obtain its rank measure and the frequency of return on stock that is positive to acquire its sign measure. As the results based on rank and sign measures are quite similar, we mainly focus on rank momentum in this paper but present summary results of the sign momentum in Appendix B. Throughout this paper, we use NPM and rank momentum interchangeably.

period following formation, the NPM strategy generates an average monthly profit of 0.352% outside of January; the profits of JT's price momentum strategy and the GH's 52wh momentum strategy are statistically insignificant. Second, NPM strategies also earn significant profits for one year following formation, and the profits remain robust after returns are risk-adjusted using either the Fama and French (FF) (1993) three-factor model or the macroeconomic factor model of Chen, Roll, and Ross (CRR) (1986).

Why do NPM 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 do 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). Sometimes they overreact and sometimes they underreact. Kahneman and Tversky (1979) demonstrate that people tend to overweight rare events and underweight regular events (Barberis, 2013). Daniel, Hirshleifer, and Subrahmanyam (1998) show that investors overreact to private information but underreact to public information because of overconfidence and biased self-attribution. BGS (2012, 2013) propose the salience theory, in which people's attention is drawn to the payoffs that are most different or salient relative to the average. When making choices, they overweight these salient payoffs relative to their objective probabilities.

A consequence of investor misreaction to information is that stock prices may not properly reflect stocks' fundamentals: Observations with extreme returns (positive or negative) are likely to be driven by investor overreaction to salient news, whereas those with small and insignificant returns are likely to be driven by investor underreaction to non-salient events. Our nonparametric measures which curtail the impact of salient extreme returns while assigning a higher weight to the non-salient observations capture the non-salient information in stock prices that is largely overlooked by investors.

In contrast, JT's price momentum is constructed on the basis of average past returns; the predictability of future returns is obscured by extreme returns. Our empirical evidence indicates that after controlling for nonparametric and 52wh momentum, the price momentum only yields negative returns, because both price winners and price losers are associated with "salient" return observations. Similarly, securities with higher positive skewness and extreme positive returns tend to have lower average returns (Boyer, Mitton, and Vorkink, 2010; Bali, Cakici, and Whitelaw, 2011). Thus, investors in aggregate appear to overreact to extreme past asset returns, and parametric measures such as mean, variance, and skewness are sensitive to extreme observations in the sample.

There are at least two interesting findings associated with NPM. First, it is not associated with any long-term reversals, which thereby eliminates the well-known overreaction phenomenon. Rather, we observe that NPM profitability is an underreaction-only phenomenon. In addition, contrary to Lakonishok, Shleifer, and Vishny (1994) and Daniel et al. (1998), there is no over-extrapolation on past performance for NPM. Second, the persistence of NPM profits comes mainly from the short leg (or rank losers). This influence is not particularly surprising because it may be costly to engage in short-selling to exploit the mispricing of rank losers.

What is most amazing is that when we simultaneously compare the competing performance of the three momentum strategies, the short-term price momentum profitability widely documented in past literature completely vanishes. What remains is long-term return reversal, which nevertheless disappears under the CRR risk adjustment. The findings echo GH's (2004) claim that short-term profitability and long-term return reversals are two separate phenomena.

Moreover, NPM profitability is consistent with investor underreaction predicted by the theories of Barberis, Shleifer, and Vishny (1998) and Hong and Stein (1999), rather than by continued overreaction as suggested by Daniel et al. (1998). This issue will be examined in greater detail in Section 4.

After we confirm that neither the FF (1993) three-factor model nor the CRR (1986) macroeconomic factor model explains NPM profitability, we propose two sets of behavioral hypotheses to gain a better understanding of its profits. First, if NPM profitability captures the non-salient aspect of information embedded in stock returns, we expect it to be less prominent among stocks with higher salient features, as suggested by BGS (2013). Second, if NPM profitability is behavioral in nature, we expect it to be stronger and more persistent among stocks that are subject to higher degrees of arbitrage risk (Ali, Hwang, and Trombley, 2003; Lam and Wei, 2011). We find strong supportive evidence for the above hypotheses.

Overall, our empirical results verify that nonparametric measures capture the non-salient component of the information neglected by investors, thus contributing to the literature on momentum investment strategies. Our study has important implications. Although 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 sufficiently summarize all the information embedded in stock prices.

The remainder of this article proceeds as follows: Section 2 describes the data and construction of non-parametric momentum measures, and it presents preliminary results regarding the performance of rank-sorted portfolios. Section 3 compares the performance of three representative momentum strategies: price momentum, 52wh momentum, and NPM. Section 4 outlines two sets of behavioral hypotheses related to NPM profitability, and Section 5 presents our conclusions.

2. Performance of nonparametric momentum strategies

2.1. Data and nonparametric 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 sample period of January 1963 to December 2015. 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 a nonparametric measure based on ranks. Let $R_{i,d}$ denote stock i's daily return on day d, and N_d denote the number of stocks on day d. We define $y(R_{i,d})$ as the rank of $R_{i,d}$ among the 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, 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):

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

The daily ranks are then averaged every month and summed over the p-month formation period, which gives a firm's average rank, $rank_{i,t}(p)$:[2]

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

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.[3]

2.2. Portfolio approach to nonparametric momentum strategies

We adopt the portfolio approach used by JT and GH to investigate the performance of NPM strategies. We sort all stocks into five quintile portfolios based on their average ranks defined in Equation (2) and construct a NPM strategy by buying the stocks in top quintile portfolio (referred to as rank winners) and short selling those in the bottom portfolio (referred to as the rank losers); the long-short portfolio is held for up to five years. Let portfolio 1 (Q1) and portfolio 5 (Q5), respectively, denote the rank loser and winner portfolios. All portfolios are constructed with equal weights and held for the subsequent K months with one-month skip. Because JT's approach involves an overlapping procedure, we average the portfolio return for each month across K separate positions, each formed in one of the K consecutive prior months from $t-K$ to $t-1$. In addition to NPM, we follow JT and GH to construct the two alternative momentum strategies as comparisons.[4]

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[2] 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.

[3] 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.

[4] The JT momentum is constructed based on a stock's past 6-month average return, while the GH momentum is

With all months included, Panel A of Table 1 reports the average monthly returns of the three momentum strategies for one-year to five-year holding period subsequent to portfolio formation. The performance of both NPM and JT momentum strategies are profitable at 0.442% and 0.309% per month, respectively, for the first year, but they reverse to become negative and significant for JT momentum but negative and insignificant for NPM thereafter. This pattern is consistent with the price momentum compiled by JT, which also exhibits short-term continuation but significant long-term reversals. As comparisons, the GH strategy generates a positive but insignificant return of 0.151% per month for the first year and negative, significant returns of -0.480% and -0.397% per month for second- and third-year holding periods.

[Insert Table 1]

Panel B indicates that three momentum strategies show much larger one-year profits outside of January than those with January included. The underlying reason is obvious. 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, price recovery in January increases potential loss. With January excluded, it is natural that all three momentum profits should be larger than those with January included. The fact that NPM is subject to the tax-loss-selling effect is not surprising because the phenomenon is associated with capital losses of individual stocks and our rank measure is constructed on the basis of individual stocks. Although the three strategies all exhibit reversals in January, the NPM strategy still remains the most profitable when January observations are excluded. The most interesting finding is that the long-term reversal pattern disappears for all three momentum strategies, indicating that long-term reversals are related primarily to January seasonality. Specifically, NPM

constructed based on a stock's 52wh ratio, which is the closing price at the end of previous month divided by the highest price over past 52 weeks ending in previous month.

profits are uniformly positive over longer holding periods following formation; the average monthly profit is 1.075% (t-statistic = 5.36) for the first year. Even for the entire five-year holding period, the average monthly profit is still 0.352% (t-statistic = 2.34), suggesting that NPM profitability is not driven by investor overreaction because there is no occurrence of return reversals. The return patterns of JT and GH strategies outside of January are generally similar to NPM except for the slightly smaller profits in the first year and insignificant profits for the entire 5-year holding period.

Overall, this analysis indicates short-term performance persistence for the three momentum strategies, especially outside of January. So far, each of the three strategies is examined in isolation from other strategies. 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 three momentum strategies simultaneously by controlling for various confounding factors. By doing so, we are able to observe whether the NPM strategy plays the determinant role in generating momentum profits. We formally investigate this issue in next section.

3. Comparison of three representative momentum strategies

3.1. Price momentum, 52-week high momentum, and NPM strategies

Thus far, our empirical results show that the NPM strategy yields short-term profits, and there are no long-term reversals. The return pattern is different from that of JT's price momentum profits but is similar to that of the 52wh momentum profits reported by GH. However, it remains unclear whether the NPM outperforms the two conventional strategies in generating future return predictability. Thus, it is important to compare the relative profitability of the three strategies simultaneously. In this section, we explore how the NPM strategy contrasts with price momentum and 52wh momentum strategies. We estimate the following cross-sectional regressions:

$$R_{i,t} = b_{0j,t} + b_{1j,t}R_{i,t-1} + b_{2j,t}Size_{i,t-1} + b_{3j,t}priceW_{i,t-j} + b_{4j,t}priceL_{i,t-j}$$

$$+b_{5j,t}52whW_{i,t-j} + b_{6j,t}52whL_{i,t-j} + b_{7j,t}rankW_{i,t-j} + b_{8j,t}rankL_{i,t-j} + \varepsilon_{i,t}. \quad (3)$$

where $R_{i,t}$ is stock *i*'s return in month *t*. The variable $rankW_{i,t-j}$ ($rankL_{i,t-j}$) is the NPM winner (loser) dummy, which takes the value of 1 if stock *i*'s average rank performance is ranked in the top (bottom) 30% in month *t−j*; $priceW_{i,t-j}$ ($priceL_{i,t-j}$) is the price winner (loser) dummy, which takes the value of 1 if stock *i*'s past six-month average return is ranked in the top (bottom) 30% in month $t-j$, and 0 otherwise; $52whW_{i,t-j}$ ($52whL_{i,t-j}$) is the 52wh winner (loser) dummy, which takes the value of 1 if $\frac{price_{i,t-j}}{high_{i,t-j}}$ is ranked in the top (bottom) 30% in month *t−j*, and 0 otherwise. In addition, $R_{i,t-1}$ and $Size_{i,t-1}$ are the return and market capitalization of stock *i* in month *t*−1, which are included to control for the microstructure effect due to bid-ask bounce and the size effect.

As in Table 1, the regressions are performed over the holding periods of 12 months (*j* = 1,..., 12 to 37,..., 48) and 60 months (*j* = 1,..., 60), respectively. For instance, for the 60-month holding period, we estimate 60 cross-sectional regressions for *j* = 1 to *j* = 60 in month *t* and then average the corresponding coefficient estimates. Thus, the return of the "pure" rank winner (loser) portfolio with the 60-month holding period in month *t* is calculated as $\bar{b}_{7j,t} = \frac{1}{60}\sum_{j=1}^{60} b_{7j,t}$ (and $\bar{b}_{8j,t} = \frac{1}{60}\sum_{j=1}^{60} b_{8j,t}$), and the difference between $\bar{b}_{7j,t}$ and $\bar{b}_{8j,t}$ is the profit of the NPM strategy. The t-statistics of the coefficient estimates are adjusted using the Newey-West (1987) robust standard errors.

Note that unlike common Fama-MacBeth regression applications where variables of interest normally take the form of continuous variables, dummy variables are used in this regression. As a result, the coefficients of dummy variables capture the "net" return of the portfolio related to that particular dummy variable. For example, $b_{0j,t}$ captures the average return of the rest of the sample stocks (i.e., the "medium" portfolio) that are neither winners nor losers, which are formed in month $t{-}j$ and held in month t. Thus, $b_{7j,t}$ and $b_{8j,t}$ capture the *incremental* returns of rank winner and loser portfolios, respectively, over the medium portfolio. A major advantage of the regression approach over the traditional portfolio formation method as used in JT is that it can filter out the confounding effects such as the size effect and the bid-ask bounce. A second advantage of this method, as we demonstrate later, is that we can compare the performances of various holding periods simultaneously. The regression results in Table 2 indicate that: (i) the NPM strategy has the strongest performance persistence among the three strategies; and (ii) the 52wh momentum strategy exhibits short-term persistence, but the price momentum totally disappears.

[Insert Table 2]

1. *NPM*: The most notable finding is that outside of January, NPM profitability is even stronger and more persistent after controlling for the effects of the other two momentum strategies. When January observations are excluded, the NPM strategy yields an average return of 0.640% (t-statistic = 5.04) per month for the first year and 0.332% (t-statistic = 2.93) per month for the entire five-year holding period. More importantly, profits persist across the entire five-year holding period. NPM profits outside of January for the holding period from the first to the fourth year are 0.640%, 0.305%, 0.273%, and 0.270%, respectively; all are statistically significant. In addition, profitability mainly comes from the persistent underperformance of the rank losers.

2. *52wh momentum*: The 52wh momentum strategy yields a short-term profit of 0.398% (t-statistic =2.41) per month in non-January observations, and no long-term reversals occur. The return patterns are consistent with the findings of GH except that the profitability of the 52wh momentum strategy is slightly weaker after controlling for the NPM effect.

3. *Price momentum*: Perhaps the most striking finding is that by controlling for the other two strategies, price momentum completely disappears, regardless of the inclusion of January observations. The price momentum profit (excluding January) is 0.094% (-0.023%) for the first year; both are statistically insignificant. What remains is a long-term reversal pattern: Outside of January, price momentum yields an average negative return of -0.194% (t-statistic = -1.66) per month for the entire five-year holding period; the returns of price momentum from the second to the fourth year are -0.296%, -0.245%, and -0.204%, respectively, and all are statistically significant. Although we are not yet aware why NPM momentum and 52wh momentum in combination explain the short-term price momentum, our empirical results support GH's (2004) argument that short-term momentum and long-term reversals are two separate phenomena.

Figure 1 presents the cumulative returns over a 60-month holding period for price momentum, 52wh, and NPM strategies based on the estimates from Equation (3). To avoid January seasonality, we exclude January observations in calculating the cumulative returns. As seen from Figure 1, NPM outperforms the other strategies over the entire five-year holding period, followed by the 52wh momentum; price momentum displays the worst performance of the three.

[Insert Figure 1]

3.2. Disappearing price momentum?

The most intriguing observation from Table 2 is that the short-term profitability of price momentum is fully explained jointly by NPM and 52wh momentum. An immediate question to be resolved is what happens to the short-term profitability of price momentum when we consider only either 52wh momentum or NPM, but not both?

To address this question, we follow the following step-by-step approach. First, we perform the cross-sectional regression of Equation (3) by including $R_{i,t-1}$, $Size_{i,t-1}$, and dummies of price momentum only. This model specification is similar to that of JT (1993, 2001), but our model specifically controls for bid-ask bounce effect and the size effect. As Panel A of Table 3 indicates, price momentum generates significantly positive profits in the first year following formation regardless of the inclusion of January months. Its profitability reverses to become significantly negative with January included in the second, third, and the entire five-year period following formation. The results are consistent with those of JT, which is expected.

[Insert Table 3]

Second, we introduce both dummies of price momentum and 52wh momentum simultaneously in Equation (3). This model specification is similar to that introduced by GH, but differs from theirs in that we do not control for the effect of industry momentum proposed by Moskowitz and Grinblatt (1999). However, our specification allows us to assess the impact of 52wh momentum on price momentum. Consistent with the results of GH, Panel B of Table 3 shows that 52wh momentum dominates price momentum in the short term when January seasonality is removed. The profit of price momentum declines to 0.269% from 0.566% in the absence of 52wh momentum. Nevertheless, 52wh momentum alone does not fully explain the short-term profitability of price momentum.

In the third step, we assess the impact of NPM alone on price momentum. Panel C of Table 3 shows that the short-term profitability of price momentum disappears: the profit of price momentum declines to 0.050% (with all months included) and 0.041% (without January excluded), but both of these figures are insignificant. Moreover, the long-term reversals of price momentum outside of January are enhanced by the inclusion of NPM. This observation highlights that importance of the nonparametric measure in isolating short-term momentum from long-term reversals.[5] More importantly, we only need to rely on NPM to explain the return patterns of price momentum.

The fact that NPM and 52wh momentum in combination explain the short-term momentum profitability suggests that the three strategies are highly interrelated. Indeed, within our sample, the overall correlation between past six-month returns and rank is 0.634 and is 0.500 between past 6-month returns and 52wh ratios.[6] Such high correlations motivate us to investigate the proportions of price winners (losers) that overlap 52wh and/or rank winners (losers). As Panel A of Table 4 shows, on average 62.29% of price winners are rank winners, and 72.68% of price winners are either rank winners or 52wh winners. Results for price losers are reported in Panel B; 66.87% of price losers are rank losers, and up to 79.65% of price losers are either rank losers or 52wh losers.

[Insert Table 4]

An interesting question arises: do overlapped or isolated winners and losers of price momentum behave differently in generating momentum profitability? To answer this question, we break down price momentum stocks into two categories: (i) one category whose membership

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[5] Because the 52wh measure is constructed based on the highest price over past 52 weeks, which is the maximum in essence, the information embedded in this measure is more likely to be parametric-based.

[6] Analogously, the average correlation between 52wh ratios and rank is 0.609. The correlations are first calculated across all stocks in a month, and then averaged over the entire sample.

overlaps with rank or 52wh momentum stocks; and (ii) the other category whose membership is unrelated to rank or 52wh momentum stocks. We refer to the former as the "overlapped" category of price momentum stocks and the latter as the "isolated" category of price momentum stocks. In Figure 2, we plot the cumulative returns of the two categories of stocks relative to the entire price momentum stocks.

[Insert Figure 2]

The most intriguing finding is that the "isolated" category of price momentum stocks experiences downward performance from the beginning of the five-year horizon of the holding period. This category of price momentum stocks do not show a long-term reversal pattern that starts after one or two years following formation as compiled by Jegadeesh and Titman (2001). In contrast, the "overlapped" category of price momentum stocks shows superior and more persistent profitability than the isolated category and the standard price momentum. In particular, this category of price momentum stocks experiences upward performance up to four years, followed by slight reversal in the 5th year after the portfolio formation.[7]

Overall, the empirical results indicate that the NPM outperforms the other two forms of momentum strategies, and that rank measure helps discriminate momentum from reversal patterns implied by past six-month returns.

3.3. Can nonparametric momentum profits be explained by risk?

In this subsection, we examine whether NPM profits can be explained by risk-based theories. To this end, we consider two well-known asset-pricing models that have been used in prior

[7] Taking a closer look at winner and loser stocks of "overlapped" and "isolated" categories, we find that "overlapped" winners consistently outperform price momentum winners and "isolated" winners while "overlapped" losers consistently underperform price momentum losers and "isolated" losers, generating the return difference between "overlapped" and "isolated" categories of price momentum stocks.

literature to evaluate the performance of the price momentum strategy: FF's (1993) three-factor model and CRR's (1986) macroeconomic factor model (the CRR model).[8]

Our use of the CRR model is justified because Liu and Zhang (2008) demonstrate that the growth-related macroeconomic factor on industrial production, denoted *MP*, explains more than half of price momentum profit. 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 NPM profits can be attributed to fundamental economic forces.[9]

We estimate the risk-adjusted portfolio returns using the intercepts from time series regressions of monthly returns of the portfolios (the average coefficient of the corresponding dummy variable) on the contemporaneous factors. The empirical results are reported in Table 5. Panel A reports the results based on the FF risk adjustment; Panel B reports the results based on the CRR risk adjustment.[10]

[Insert Table 5]

Panel A of Table 5 shows that the NPM profitability remains mostly intact under the FF risk adjustment. We observe that NPM profits are even stronger for all holding period horizons. Panel B reveals several interesting features under the CRR adjustment. First, NPM profits remain highly

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[8] When the FF (2015) five-factor model is used, the results are similar to the results in Table 6.

[9] Note, however, that the CRR model in its original form is not a pricing model, but a return generating process in the spirit of Ross's (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 2015, factor loadings are estimated for each testing asset over the prior 60 months. Fama-MacBeth 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.

[10] The data for the FF three factors are obtained from Kenneth French's data library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/. The data for CRR factors are downloaded from Xiaolei Liu's website at http://www.bm.ust.hk/~fnliu/research.html. To conserve space, we report the coefficients of NPM only.

significant throughout the five-year holding period, but the CRR model explains approximately half of NPM profits. For example, the non-January raw NPM profit reported in Table 2 is 0.640% for the first year but drops to 0.298% for the first year under the CRR risk adjustment. For the entire 5-year holding period, the risk-adjustment non-January profit is 0.127%, which is only approximately one-third of the original profit (which is 0.332%, see Table 2).

On the basis of reported findings, we find strong and persistent NPM profitability that is independent of existing momentum strategies and cannot be fully explained by common risk-based models. In the following section, we apply behavioral perspectives.

4. Sources of nonparametric momentum profits: Tests of behavioral hypotheses

So far, we have documented strong and persistent NPM profits that cannot be fully explained by well-known asset-pricing models; we have also shown that rank losers experience stronger return persistence than rank winners. In this section, we investigate the sources of NPM profitability from a behavioral perspective. Nonparametric measures, such as ranks and signs, are well-known for being less sensitive to the presence of extreme observations in the sample. 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). This is where the unique property of NPM measures plays a unique role in assessing momentum strategies: rank measures highlight the relatively non-salient information in the sample while mitigating the effect of salient features of stock price movements. Moreover, because NPM profitability can not be explained by risk-based theories, it seems plausible that such profitability is the result of investors' neglect and is therefore underreaction to non-salient information embedded in stock prices.

If NPM profits are truly behavioral, there are at least two dimensions that can be examined empirically. First, rank-related performance persistence should be more prominent for stocks with weaker salience features. Second, if the source of the profitability is behavioral in nature, performance persistence should also be stronger for stocks that are subject to a higher degree of arbitrage risk (e.g., Ali et al., 2003; Lam and Wei, 2013).

We test the above two behavioral hypotheses. To elucidate the nature of the NPM effect, however, we begin with a preliminary analysis of the characteristics of rank-sorted portfolios. Because rank is a nonparametric measure, it is interesting to understand whether and how it relates to distribution of returns. Also, we observe whether stocks with similar rank values exhibit similar firm characteristics that have been documented to be important determinants of momentum and the cross-section of stock returns.

4.1. The characteristics of rank-sorted portfolios

Table 6 reports descriptive statistics and firm characteristics for stocks in the rank-sorted quintile portfolios, with the highest rank observations in portfolio Q5 and the lowest rank observations in portfolio Q1. In Panel A, we report the average descriptive statistics for the rank quintile portfolios. For each month, we calculate the standardized rank and the first to the fourth moments for each stock in a quintile portfolio using daily returns over the previous six months. Each of the descriptive statistics is averaged across stocks in a quintile portfolio and then averaged over the sample period. In addition to basic descriptive statistics, we also report the average maximum (*Max*) and minimum (*Min*) daily return in the previous month.

Panel A reveals a number of interesting patterns across stocks with different ranks. First, stocks with higher ranks earn higher past returns in terms of mean and median but display a smaller standard deviation and kurtosis, suggesting that the higher returns of higher-rank stocks are not the result of their higher risk. Similar to the negative rank-kurtosis relation, lower-rank portfolios also have higher positive extreme returns *Max* and lower negative extreme returns *Min*, indicating that lower-rank stocks exhibit stronger lottery-like features.[11] For example, the lowest- rank portfolio Q1 has the lowest average monthly return of -0.126% during the formation period, but the largest *Max* of 10.252% and the smallest *Min* of -8.230%.

[Insert Table 6]

Second, there is a U-shaped pattern between skewness and ranks. The average skewness is smaller for Q3 (0.462) but larger in Q1 (0.697) and Q5 (0.514). This U-shaped relation suggests that the rank-related return patterns are not simply the result of investors' preferences for stocks with positive skewness (Kraus and Litzenberger, 1976; Mitton and Vorkink, 2007).

Panel B reports the average values for market capitalization (*Size*), book-to-market (*BM*) ratio, idiosyncratic risk (*Ivolatility*), illiquidity measure (*Illiq*) of Amihud (2002),[12] number of analysts following (*Analyst*), percentage of institutional ownership (*Inst%*), and information discreteness (*ID*). Detailed variable definitions are given in Appendix A. We use the measures of *Ivolatility*, *Illiq*, *Analyst*, and *Inst%* to proxy for arbitrage risk (Ali et al., 2003; Li and Zhang, 2010; Lam and Wei, 2011). The *ID* measure is a proxy for limited investor attention and thus captures the degree of investor underreaction (Da, Gurun and Warachka, 2014).

[11] 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, relationship between the minimum daily returns *Min* and future returns, which is subsumed by the negative "maxing out" effect.

[12] In addition to the Amihud (2002) measure, we also replicate our analyses using the frequency of zero daily return and obtain similar results. Thus, our results are not sensitive to the use of the illiquidity measure.

Several interesting patterns emerge in Panel B. First, as *rank* increases across low-rank to high-rank portfolios, *Size* increases but *BM* ratios decrease, indicating that rank winners (losers) tend to be large growth (small value) stocks. This pattern implies that the rank-related return premium is not driven by either the small-firm effect or the value effect. Second, higher-rank portfolios are characteristics of lower idiosyncratic risk *Ivolatility*, higher analyst coverage *Analyst*, and higher institutional ownership *Inst%*. In comparison, lower rank portfolios seem to be more exposed to arbitrage risk than higher rank portfolios.

Third, we observe a concave pattern of *Illiq* across rank portfolios. This observation suggests that rank winners and losers are less prone to the illiquidity problem, and that the profitability of NPM is unlikely to be the result of market fraction. Despite the inverted-U relation between *Illiq* and rank measure, rank losers (Q1) have significantly higher values of *Illiq* than rank winners (Q5), implying that rank losers are more exposed to arbitrage risk than rank winners. Finally, *ID* is also concave across rank portfolios, suggesting rank winners and losers have less discrete information. More importantly, they seem to exhibit non-salient feature because they demonstrate higher degree of continuous information that is less salient to investors.

As illustrated by Figure 2 in Section 3.2, the overlapped strategy shows superior and more persistent profitability while the isolated strategy exhibits downward performance from the beginning of the 5-year horizon of the holding period. It is possible that the two categories of stocks exhibit different salient features. In particular, as the overlapped category contains NPM stocks, this category should demonstrate lower degrees of salient features. The isolated category, however, is expected to exhibit higher degrees of salient features because this category includes only pure price momentum stocks. We verify this prediction by reporting descriptive statistics and firm characteristics for stocks in overlapped and isolated strategies in Table 7.

We focus on several salience-related variables. First, isolated winners have higher *Skewness* than overlapped winners (1.464 vs. 0.912), indicating that isolated winners are more prone to positively salient returns. Isolated losers, however, have an average *Skewness* of -0.380 while overlapped losers have an average *Skewness* of 0.184. This evidence suggests that isolated losers are more prone to negatively salient returns than overlapped losers. Second, the average *ID* values are -0.029 and -0.016 for overlapped and isolated winners, respectively. The corresponding *ID* values are -0.051 and -0.023 for overlapped and isolated losers, respectively. The observation of lower values of *ID* for overlapped components signifies the fact that they are less subject to investor attention and thus are less salient to investors. The two important findings confirm our conjecture that salient features are the underlying reason that explains the divergence in return performance between overlapped and isolated strategies.

[Insert Table 7]

Overall, preliminary results indicate that high rank portfolios exhibit high average returns, low total volatility, and relatively non-salient features in the past, whereas low-rank portfolios present high degrees of arbitrage risk. Next, we formally examine the performance of the NPM strategy by controlling for various confounding factors and explore how various behavioral hypotheses compete with each other to explain rank-based performance.

4.2. The salience hypothesis

If NPM profitability is driven by investor underreactions to non-salient information embedded in past stock returns, we expect rank-return predictability to exhibit a salience-related pattern. In other words, we expect NPM profits to be smaller and weaker for stocks with higher salience features.

Empirically, let $Pos\_Salience_{it}$ ($Neg\_Salience_{it}$) denote a salience measure for a rank winner (loser) such that a larger value of $Pos\_Salience_{it}$ ($Neg\_Salience_{it}$) is associated with stronger salience; we can perform the following cross-sectional regressions by incorporating interaction terms into the dummies on rank winners and rank losers:

$$R_{i,t} = b_{0j,t} + b_{1j,t}R_{i,t-1} + b_{2j,t}Size_{i,t-1} + b_{3j,t}priceW_{i,t-j} + b_{4j,t}priceL_{i,t-j}$$
$$+b_{6j,t}52whL_{i,t-j} + b_{7j,t}rankW_{i,t-j} + b_{8j,t}rankL_{i,t-j} + b_{9j,t}rankW_{i,t-j}$$
$$\times Pos\_Salience_{i,t-j} + b_{10j,t}rankL_{i,t-j} \times Neg\_Salience_{i,t-j} + \varepsilon_{i,t}. \tag{4}$$

We expect the average estimate of b_9 to be negative and the average estimate of b_{10} to be positive. Based on BGS's (2013) idea, we propose three proxies to capture salience:

1. Mean-minus-median. When a winner stock has more observations with positive extreme payoffs, its mean is greater than its median. Therefore, mean-minus-median serves as a natural proxy for positive salience $Pos\_Salience_{it}$. Likewise, the negative salience measure $Neg\_Salience_{i,t-j}$ for loser stocks is defined similar to median-minus-mean.
2. Skewness. Positive (negative) skewness reflects assets with positive (negative) salient payoffs for winners (losers).[13] This measure is conceptually similar to the mean-minus-median measure, except it is deflated by standard deviation.
3. Information discreteness (ID). This measure, proposed by Da et al. (2014), is defined in Appendix A. 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.[14]

[13] Empirically, at the beginning of each holding month t, we calculate the mean, median and skewness for each stock using data from the past year ending in month t−1.

[14] Da et al. (2014) actually 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 continuously in small amounts, thus capturing investor underreaction.

We report the results in Table 8 for holding periods of the first year and the entire five years. Panel A presents the results based on the positive and negative mean-minus-median measures. Consistent with the prediction of the salience theory, the coefficient of the interaction term on rank winner (loser) dummy and salience measure is negative (positive), especially outside of January. For example, the coefficient of $rankW \times Pos\_Salience$ outside of January observations is -0.297 (t-statistic = -1.30) for the first year and -0.594 (t-statistic = -3.35) for the entire five years; the coefficient of $rankL \times Neg\_Salience$ is 0.503 (t-statistic = 3.14) for the first year and 0.474 (t-statistic = 4.46) for the entire five years.

[Insert Table 8]

Panel B reports the results based on skewness; the results are similar to those reported in Panel A. The only difference is that the interaction term on rank loser is statistically significant for the entire 5 years only and not for the first year holding period. Results based on ID reported in Panel C of Table 8 also support our salience hypothesis and are consistent with the FIP hypothesis, thus strengthening our claim that NPM profits are driven by investor underreactions.

4.3. The limits-of-arbitrage hypothesis

Given that our empirical evidence (Table 2) indicates that NPM profitability is primarily derived from the persistent underperformance of the short leg (i.e., rank losers), a natural emerging question is why? One good possibility is that the presence of arbitrage limits prevents asset prices of rank losers from quickly adjusting to their fundamental values.

We can classify such arbitrage limits, or arbitrage risk, into three types: fundamental risk, noise trader risk, and implementation risk (Barberis and Thaler, 2003). Fundamental risk implies that investors are uncertain about the true values of the asset (Zhang, 2006). Noise trader risk is present when the market of the asset is populated with irrational traders, whose trading drives an asset's price away from its fundamental value (De Long, Shleifer, Summers, and Waldmann, 1990). Finally, implementation risk pertains to the transaction costs and short-sale restrictions associated with arbitrage activities.

Empirically, we use analysts' coverage (*Analyst*) to proxy the fundamental risk, idiosyncratic risk (*Ivolatility*) to proxy noise trader risk, the Amihud measure (*Illiq*) to proxy potential transaction costs, and institutional ownership (*Inst%*) to capture short-sale constraints. Table 9 reports the overall correlations among rank measure and the arbitrage risk proxies. Specifically, in each month, we first calculate the cross-sectional correlation coefficients for all variables; we next average the monthly correlation coefficients over the entire sample period. Table 9 shows that *rank* is inversely correlated with *Ivolatility* and *Illiq* but positively correlated with *Analyst* and *Inst%*.

Next, we perform regressions as in Equation (3) by incorporating the interaction terms of rank winners/losers and each of the four arbitrage risk measures. If arbitrage risk plays a role in driving NPM, the interaction terms should be significant, especially for rank losers, because arbitrage risks such as short-sale restrictions are more binding on the short leg.

[Insert Table 9]

To discuss the relation between NPM and arbitrage risk, we invert two variables, *Analyst* and *Inst%*, in the regression model, such that larger variables are associated with a higher arbitrage limit (Ali, Hwang, and Trombley, 2003). As in Table 8, we focus our analyses on the holding periods of the first year and the entire five years following formation, as reported in Table 10.

We first focus on the results based on the holding period of the entire five years, as shown in the right-hand four columns of Table 10. Coefficients on $rankL \times Ivolatility$ and $rankL \times Analyst^{-1}$ (Panels A and C) are significantly negative when January observations are excluded. Another striking observation is that coefficients on the interaction terms associated with *Illiq* (Panel B) are not significant but with expected signs, confirming our previous argument that NPM momentum profitability is not induced by the illiquidity problem. In addition, the significance of rank losers completely disappears or even becomes significantly positive when arbitrage risk is taken into account, regardless of the inclusion of January observations and price momentum and 52wh strategies. Again confirming our conjecture, Panel D indicates that coefficients on $rankL \times Inst\%^{-1}$ are also all significantly negative. The evidence suggests that the performance persistence of rank losers is highly related to arbitrage risk and that fundamental risk and noise trader risk are major sources of risk underpinning the long-term persistence of the NPM.

[Insert Table 10]

Results of the first-year holding period are generally similar to those of the entire five-year holding period. Coefficients on interaction terms between rank winners and arbitrage risk measures are insignificant; coefficients on $rankL \times Inst\%^{-1}$ are significantly negative. Coefficients on $rankL \times Ivolatility$ and $rankL \times Analyst^{-1}$ are also significantly negative when January observations are excluded. These results again confirm that fundamental risk and noise trader risk play important roles in explaining the return persistence of rank losers.

Overall, the evidence in Table 10 clearly shows that the return persistence of rank losers can be attributed to arbitrage risk, but this is not the case for rank winners, which is consistent with the limits-of-arbitrage argument. It also indicates that stock prices continuously deviate from their fundamental values because of the existence of limits-to-arbitrage, which impedes arbitrageurs in engaging in arbitrage activities to correct for rank-related mispricing. This further leads to the long-term persistence of NPM profits.

5. Conclusions

We propose nonparametric performance measures (ranks and signs) of past stock returns and explore whether the measures are associated with future stock returns. Unlike parametric statistics that have been widely adopted to identify stocks' past performances, nonparametric statistics are robust to the presence of outliers in the sample and can account for the 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 they tend to underreact to information embedded in nonparametric measures, further inducing subsequent return continuations.

Our empirical findings generally confirm this prediction. The NPM strategies of buying stocks with high average ranks (or signs) and shorting those with low average ranks (or signs) are more profitable, outperforming price momentum and 52wh momentum strategies for the first year following portfolio formation. When January months are excluded, the profitability of NPM strategies persists for up to five years and cannot be explained by well-known asset-pricing models.

We further test two sets of behavioral hypotheses to demonstrate that nonparametric measures, such as rank and sign, capture the non-salient component in stock prices neglected by investors. First, we show that NPM profitability is weaker among stocks with salient features, suggesting that NPM is driven by investor underreaction rather than overreaction. Second, the return persistence of NPM is induced by the higher arbitrage risk of losers, which is consistent with the limits-of-arbitrage argument.

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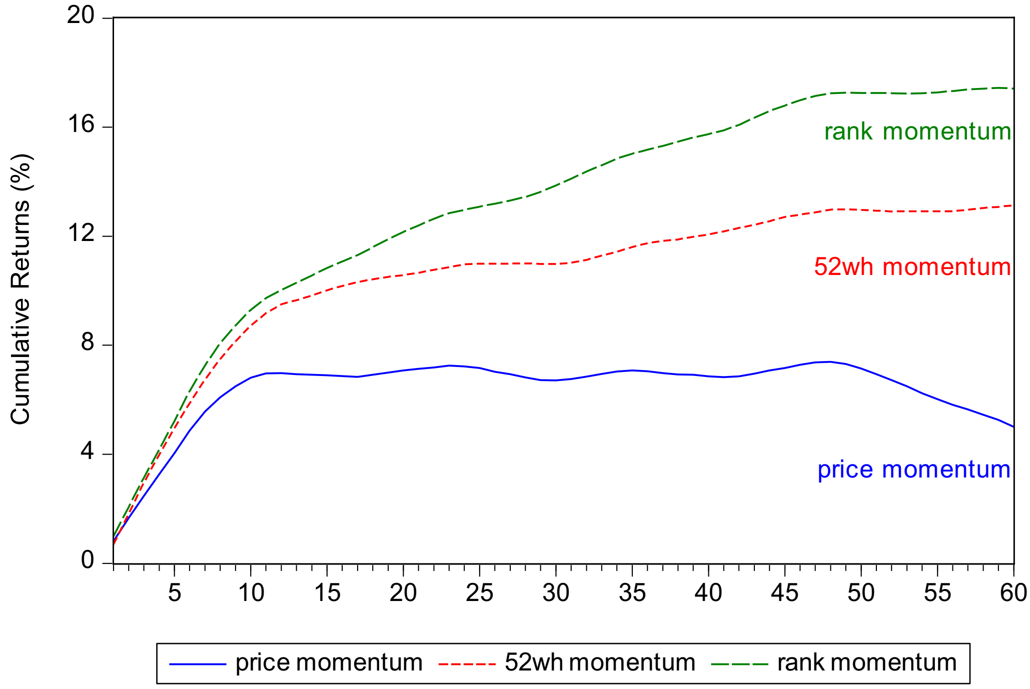

Figure 1: Cumulative monthly returns on price momentum, 52-week high momentum, and rank momentum strategies: Excluding January seasonality

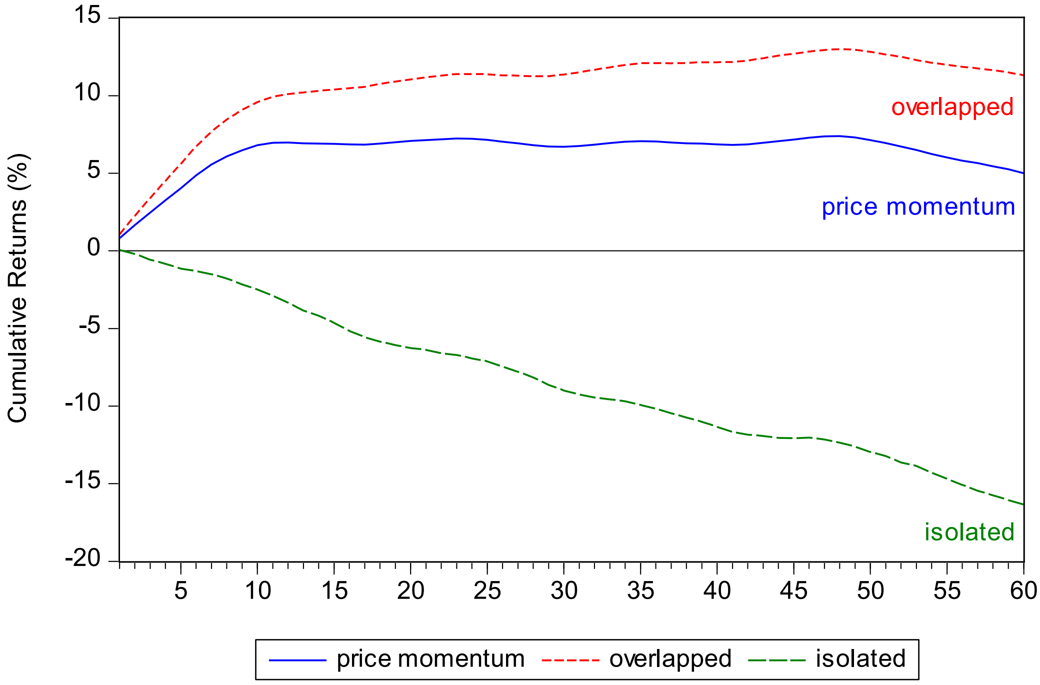

Figure 2: Cumulative monthly returns on price momentum, overlapped, and isolated strategies: Excluding January seasonality

Table 1: Performance of momentum strategies

For each month t, we calculate individual stocks' rank measure ($rank_{i,t}(P)$) and classify all stocks into quintile portfolios. Stocks with the largest rank measures are placed in portfolio Q5, while those with the smallest rank measures are placed in portfolio Q1. We also follow JT and GH to construct the two alternative strategies. All of the quintile portfolios are rebalanced monthly with the holding period ranging from one year to five years following portfolio formation. Panels A and B report the momentum profits for the full and non-January samples, 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.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1	
Panel A: All months							
NPM							
1-12 months	0.943	1.244	1.317	1.346	1.385	0.442 **	(2.20)
13-24 months	1.404	1.397	1.332	1.260	1.107	-0.297	(-1.54)
25-36 months	1.437	1.416	1.341	1.281	1.142	-0.295	(-1.62)
37-48 months	1.387	1.374	1.328	1.272	1.206	-0.181	(-1.21)
1-60 months	1.322	1.369	1.330	1.281	1.192	-0.130	(-0.83)
JT momentum							
1-12 months	1.089	1.123	1.225	1.319	1.398	0.309 **	(2.16)
13-24 months	1.542	1.302	1.266	1.245	1.118	-0.424 ***	(-3.65)
25-36 months	1.522	1.342	1.266	1.259	1.199	-0.323 ***	(-2.92)
37-48 months	1.442	1.300	1.259	1.269	1.288	-0.153 *	(-1.82)
1-60 months	1.420	1.288	1.257	1.261	1.235	-0.185 ***	(-2.78)
52wh momentum							
1-12 months	1.193	1.117	1.201	1.293	1.344	0.151	(0.63)
13-24 months	1.577	1.347	1.247	1.175	1.098	-0.480 **	(-2.24)
25-36 months	1.531	1.436	1.294	1.207	1.134	-0.397 **	(-2.02)
37-48 months	1.440	1.406	1.314	1.238	1.178	-0.261	(-1.64)
1-60 months	1.444	1.341	1.275	1.232	1.181	-0.263	(-1.49)
Panel B: January months excluded							
NPM							
1-12 months	0.156	0.737	0.957	1.098	1.231	1.075 ***	(5.36)
13-24 months	0.659	0.905	0.976	1.001	0.929	0.270	(1.52)
25-36 months	0.748	0.941	0.985	1.013	0.939	0.191	(1.09)
37-48 months	0.768	0.927	0.981	0.998	0.973	0.205	(1.36)
1-60 months	0.640	0.901	0.979	1.017	0.992	0.352 **	(2.34)
JT momentum							
1-12 months	0.333	0.729	0.938	1.048	1.036	0.703 ***	(5.04)
13-24 months	0.834	0.912	0.977	0.973	0.734	-0.100	(-0.97)
25-36 months	0.897	0.957	0.973	0.986	0.787	-0.110	(-1.06)
37-48 months	0.880	0.946	0.972	0.985	0.867	-0.012	(-0.14)
1-60 months	0.788	0.916	0.970	0.986	0.835	0.048	(0.81)
52wh momentum							
1-12 months	0.332	0.596	0.863	1.079	1.203	0.871 ***	(3.68)
13-24 months	0.802	0.821	0.898	0.938	0.919	0.118	(0.60)
25-36 months	0.852	0.916	0.922	0.949	0.940	0.089	(0.47)
37-48 months	0.815	0.922	0.952	0.973	0.949	0.134	(0.82)
1-60 months	0.743	0.838	0.921	0.983	0.985	0.242	(1.42)

Table 2: Comparison of three representative momentum strategies

In each month t from January 1963 to December 2015, we perform the following cross-sectional regressions for (j = 1,..., 12 to j = 1,..., 60):

$$R_{i,t} = b_{0j,t} + b_{1j,t}R_{i,t-1} + b_{2j,t}Size_{i,t-1} + b_{3j,t}priceW_{i,t-j} + b_{4j,t}priceL_{i,t-j} + b_{5j,t}52whW_{i,t-j} + b_{6j,t}52whL_{i,t-j} + b_{7j,t}rankW_{i,t-j} + b_{8j,t}rankL_{i,t-j} + \varepsilon_{i,t},$$

where $R_{i,t}$ is the return of stock i in month t; $Size_{i,t-1}$ is the natural logarithm of stock i's market capitalization at the end of previous month; $priceW_{i,t-j}$ ($priceL_{i,t-j}$) is a dummy variable that equals 1 if stock i's past 6-month average return is ranked at the top (bottom) 30% at the end of month $t-j$, and zero otherwise; $52whW_{i,t-j}$ ($52whL_{i,t-j}$) is a dummy variable that equals 1 if stock i's 52-week high measure is ranked at the top (bottom) 30% at the end of month $t-j$, and zero otherwise; $rankW_{i,t-j}$ ($rankL_{i,t-j}$) is a dummy variable that equals 1 if stock i's past 6-month rank measure is ranked at the top (bottom) 30% at the end of month $t-j$, and zero otherwise. In each month t, we estimate the cross-sectional regressions for j = 1,..., 12 to j = 1,..., 60 and average the corresponding coefficient estimates. 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.

	Monthly return (1,12)		Monthly return (13,24)		Monthly return (25,36)		Monthly return (37,48)		Monthly return (1,60)	
	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.
Intercept	1.319 ***	1.025 ***	1.329 ***	1.017 ***	1.338 ***	1.010 ***	1.307 ***	0.984 ***	1.338 ***	1.024 ***
	(5.35)	(4.19)	(5.32)	(4.12)	(5.27)	(4.03)	(5.10)	(3.90)	(5.49)	(4.26)
$R_{i,t-1}$	-0.055 ***	-0.045 ***	-0.056 ***	-0.044 ***	-0.056 ***	-0.044 ***	-0.056 ***	-0.044 ***	-0.056 ***	-0.045 ***
	(-13.84)	(-12.70)	(-13.60)	(-12.54)	(-13.50)	(-12.40)	(-13.15)	(-12.00)	(-13.98)	(-12.87)
Size	-3.399 ***	-1.401	-2.820 **	-0.710	-2.892 **	-0.739	-2.586 **	-0.459	-2.858 ***	-0.776
	(-2.95)	(-1.33)	(-2.48)	(-0.68)	(-2.56)	(-0.72)	(-2.35)	(-0.46)	(-2.63)	(-0.79)
priceW	0.074	-0.064	-0.077	-0.217 **	-0.027	-0.178 *	0.019	-0.136	0.006	-0.142
	(0.67)	(-0.56)	(-0.79)	(-2.09)	(-0.28)	(-1.80)	(0.19)	(-1.40)	(0.06)	(-1.46)
priceL	-0.020	-0.041	0.088 **	0.079 **	0.062 *	0.067 *	0.049	0.068 **	0.050 *	0.053 *
	(-0.47)	(-0.91)	(2.41)	(2.07)	(1.75)	(1.88)	(1.43)	(2.00)	(1.85)	(1.89)
52whW	0.027	0.134 **	-0.050	0.047	-0.078	0.025	-0.064	0.020	-0.047	0.044
	(0.45)	(2.25)	(-0.95)	(0.95)	(-1.50)	(0.49)	(-1.33)	(0.42)	(-1.02)	(0.96)
52wh L	0.028	-0.264 **	0.190 *	-0.054	0.153	-0.025	0.095	-0.066	0.103	-0.100
	(0.24)	(-2.33)	(1.81)	(-0.54)	(1.63)	(-0.27)	(1.16)	(-0.81)	(1.19)	(-1.20)
rankW	0.037	0.167 ***	-0.073	0.062	-0.066	0.060	-0.030	0.077	-0.046	0.075
	(0.67)	(3.14)	(-1.27)	(1.13)	(-1.19)	(1.10)	(-0.58)	(1.53)	(-0.94)	(1.60)
rankL	-0.307 ***	-0.473 ***	-0.074	-0.244 ***	-0.052	-0.213 ***	-0.057	-0.193 ***	-0.109	-0.257 ***
	(-3.79)	(-5.81)	(-0.88)	(-2.94)	(-0.66)	(-2.69)	(-0.78)	(-2.68)	(-1.54)	(-3.64)
price momentum	0.094	-0.023	-0.165	-0.296 **	-0.089	-0.245 **	-0.031	-0.204 *	-0.044	-0.194 *
	(0.67)	(-0.16)	(-1.36)	(-2.27)	(-0.74)	(-1.98)	(-0.26)	(-1.75)	(-0.39)	(-1.66)
52wh momentum	-0.001	0.398 **	-0.239	0.101	-0.231	0.050	-0.159	0.086	-0.150	0.144
	(-0.01)	(2.41)	(-1.58)	(0.71)	(-1.64)	(0.36)	(-1.29)	(0.70)	(-1.16)	(1.15)
NPM	0.344 ***	0.640 ***	0.001	0.305 **	-0.014	0.273 **	0.026	0.270 **	0.063	0.332 ***
	(2.69)	(5.04)	(0.01)	(2.33)	(-0.11)	(2.15)	(0.22)	(2.33)	(0.54)	(2.93)

Table 3: Pairwise comparisons of the momentum strategies

In each month t from January 1963 to December 2015, we perform the following cross-sectional regressions for (j = 1,..., 12 to j = 1,..., 60):

$$R_{i,t} = b_{0j,t} + b_{1j,t}R_{i,t-1} + b_{2j,t}Size_{i,t-1} + b_{3j,t}priceW_{i,t-j} + b_{4j,t}priceL_{i,t-j} + b_{5j,t}52whW_{i,t-j} + b_{6j,t}52whL_{i,t-j} + b_{7j,t}rankW_{i,t-j} + b_{8j,t}rankL_{i,t-j} + \varepsilon_{i,t},$$

where $R_{i,t}$ is the return of stock i in month t; $Size_{i,t-1}$ is the natural logarithm of stock i's market capitalization at the end of previous month; $priceW_{i,t-j}$ ($priceL_{i,t-j}$) is a dummy variable that equals 1 if stock i's past 6-month average return is ranked at the top (bottom) 30% at the end of month $t-j$, and zero otherwise; $52whW_{i,t-j}$ ($52whL_{i,t-j}$) is a dummy variable that equals 1 if stock i's 52-week high measure is ranked at the top (bottom) 30% at the end of month $t-j$, and zero otherwise; $rankW_{i,t-j}$ ($rankL_{i,t-j}$) is a dummy variable that equals 1 if stock i's past 6-month rank measure is ranked at the top (bottom) 30% at the end of month $t-j$, and zero otherwise. In each month t, we estimate the cross-sectional regressions for j = 1,..., 12 to j = 1,..., 60 and average the corresponding coefficient estimates. 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.

	Monthly return (1,12)		Monthly return (13,24)		Monthly return (25,36)		Monthly return (37,48)		Monthly return (1,60)	
	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.
Panel A: Price momentum strategy only										
priceW	0.123	0.084	-0.114 *	-0.151 **	-0.062	-0.116	0.010	-0.061	-0.032	-0.088
	(1.44)	(0.92)	(-1.69)	(-2.03)	(-0.89)	(-1.62)	(0.15)	(-0.91)	(-0.52)	(-1.33)
priceL	-0.183	-0.481 ***	0.177 *	-0.091	0.161 *	-0.055	0.102	-0.066	0.086	-0.132
	(-1.62)	(-4.30)	(1.70)	(-0.96)	(1.67)	(-0.60)	(1.22)	(-0.77)	(1.01)	(-1.60)
price momentum	0.306 ***	0.566 ***	-0.291 ***	-0.059	-0.223 **	-0.061	-0.092	0.005	-0.118 **	0.044
	(2.65)	(4.86)	(-3.19)	(-0.74)	(-2.45)	(-0.71)	(-1.32)	(0.06)	(-2.26)	(0.91)
Panel B: Price and 52wh momentum strategies										
priceW	0.111	0.020	-0.097	-0.186 **	-0.051	-0.155 *	0.025	-0.088	-0.004	-0.106
	(1.13)	(0.19)	(-1.18)	(-2.08)	(-0.61)	(-1.81)	(0.31)	(-1.06)	(-0.05)	(-1.30)
priceL	-0.145 ***	-0.249 ***	0.073 *	-0.028	0.048	-0.036	0.036	-0.018	0.023	-0.053 *
	(-3.29)	(-5.54)	(1.66)	(-0.72)	(1.17)	(-0.92)	(0.94)	(-0.46)	(0.80)	(-1.91)
52whW	0.067	0.232 ***	-0.068	0.089	-0.084	0.076	-0.078	0.054	-0.055	0.089
	(0.84)	(2.91)	(-0.91)	(1.25)	(-1.16)	(1.08)	(-1.15)	(0.80)	(-0.83)	(1.37)
52wh L	-0.023	-0.366 ***	0.184	-0.104	0.143	-0.076	0.097	-0.098	0.098	-0.143
	(-0.17)	(-2.69)	(1.47)	(-0.86)	(1.29)	(-0.68)	(1.01)	(-1.02)	(0.95)	(-1.42)
price momentum	0.255 **	0.269 **	-0.170 **	-0.158 *	-0.099	-0.119	-0.011	-0.070	-0.027	-0.053
	(2.43)	(2.40)	(-2.03)	(-1.73)	(-1.16)	(-1.36)	(-0.14)	(-0.89)	(-0.40)	(-0.73)
52wh momentum	0.091	0.598 ***	-0.252	0.193	-0.228	0.152	-0.175	0.152	-0.153	0.232
	(0.43)	(2.88)	(-1.30)	(1.04)	(-1.27)	(0.86)	(-1.11)	(0.98)	(-0.92)	(1.43)

Table 3 continued

	Monthly return (1,12)		Monthly return (13,24)		Monthly return (25,36)		Monthly return (37,48)		Monthly return (1,60)	
	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.
Panel C: Price and NPM strategies										
priceW	0.057	-0.076	-0.092	-0.226 **	-0.045	-0.193 *	0.027	-0.126	-0.009	-0.153
	(0.51)	(-0.65)	(-0.93)	(-2.16)	(-0.46)	(-1.94)	(0.27)	(-1.28)	(-0.10)	(-1.57)
priceL	0.007	-0.117 *	0.158 ***	0.056	0.127 ***	0.062	0.092 **	0.053	0.105 ***	0.034
	(0.12)	(-1.94)	(3.19)	(1.29)	(2.88)	(1.54)	(2.20)	(1.26)	(3.26)	(1.12)
rankW	0.044	0.231 ***	-0.100	0.082	-0.084	0.089	-0.059	0.087	-0.068	0.097
	(0.57)	(3.08)	(-1.30)	(1.12)	(-1.15)	(1.24)	(-0.86)	(1.31)	(-1.01)	(1.50)
rankL	-0.316 ***	-0.575 ***	-0.023	-0.268 **	-0.022	-0.246 **	-0.022	-0.214 **	-0.076	-0.290 ***
	(-2.69)	(-4.81)	(-0.20)	(-2.31)	(-0.20)	(-2.26)	(-0.22)	(-2.23)	(-0.76)	(-2.92)
price momentum	0.050	0.041	-0.249 **	-0.282 **	-0.171 *	-0.255 **	-0.065	-0.179 *	-0.114	-0.187 **
	(0.40)	(0.31)	(-2.43)	(-2.56)	(-1.69)	(-2.48)	(-0.65)	(-1.81)	(-1.29)	(-2.01)
NPM	0.360 *	0.806 ***	-0.077	0.350 *	-0.063	0.335 *	-0.037	0.301 *	0.008	0.387 **
	(1.92)	(4.30)	(-0.41)	(1.91)	(-0.35)	(1.92)	(-0.23)	(1.93)	(0.05)	(2.42)

Table 4: Proportions of stocks in price momentum overlapping rank and 52-week high momentum

This table reports the average numbers and proportions of price winners (losers) that overlap rank and 52-week high winners (losers). 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 then 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} is the number of price winner stocks that overlap rank winner stocks; {price losers}∩{rank losers} is the number of price loser stocks that overlap rank loser stocks. {price winners}∩{rank winners or 52wh winners} is the number of price winner stocks that overlap rank or 52 week-high winner stocks; {price losers}∩{rank losers or 52wh losers} is the number of price loser stocks that overlap rank or 52 week-high loser stocks.

	# of stocks	Percentage
Panel A: Winners		
{price winners}	1,388	100%
{price winners}∩{rank winners}	865	62.29%
{price winners}∩{rank winners or 52wh winners}	1,009	72.68%
Panel B: Losers		
{price losers}	1,388	100%
{price losers}∩{rank losers}	928	66.87%
{price losers}∩{rank losers or 52wh losers}	1,106	79.65%

Table 5: Performance of profits from price, 52-week high, and NPM strategies under risk adjustments

In each month t from January 1963 to December 2015, we perform the following cross-sectional regressions for (j = 1,..., 12 to j = 1,..., 60):

$$R_{i,t} = b_{0j,t} + b_{1j,t}R_{i,t-1} + b_{2j,t}Size_{i,t-1} + b_{3j,t}priceW_{i,t-j} + b_{4j,t}priceL_{i,t-j} + b_{5j,t}52whW_{i,t-j} + b_{6j,t}52whL_{i,t-j} + b_{7j,t}rankW_{i,t-j} + b_{8j,t}rankL_{i,t-j} + \varepsilon_{i,t},$$

where $R_{i,t}$ is the return of stock i in month t; $Size_{i,t-1}$ is the natural logarithm of stock i's market capitalization at the end of previous month; $priceW_{i,t-j}$ ($priceL_{i,t-j}$) is a dummy variable that equals 1 if stock i's past 6-month average return is ranked at the top (bottom) 30% at the end of month $t-j$, and zero otherwise; $52whW_{i,t-j}$ ($52whL_{i,t-j}$) is a dummy variable that equals 1 if stock i's 52-week high measure is ranked at the top (bottom) 30% at the end of month $t-j$, and zero otherwise; $rankW_{i,t-j}$ ($rankL_{i,t-j}$) is a dummy variable that equals 1 if stock i's past 6-month rank measure is ranked at the top (bottom) 30% at the end of month $t-j$, and zero otherwise. In each month t, we estimate the cross-sectional regressions for j = 1,..., 12 to j = 1,..., 60 and average the corresponding coefficient estimates. To obtain risk-adjusted returns, we perform time-series regressions of these averages (one for each average) on the contemporaneous FF's three factors (Panel A) and CRR's five factors (Panel B) to hedge out the risk exposure. 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.

	Monthly return (1,12)		Monthly return (13,24)		Monthly return (25,36)		Monthly return (37,48)		Monthly return (1,60)	
	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.
Panel A: Risk-adjusted returns using the FF three-factor model										
rankW	0.110 ***	0.195 ***	-0.023	0.074 **	-0.011	0.076 **	0.018	0.085 ***	0.007	0.088 ***
	(2.95)	(5.47)	(-0.59)	(2.06)	(-0.30)	(2.25)	(0.52)	(2.60)	(0.22)	(3.12)
rankL	-0.400 ***	-0.535 ***	-0.157 ***	-0.287 ***	-0.127 **	-0.248 ***	-0.118 **	-0.219 ***	-0.186 ***	-0.298 ***
	(-7.33)	(-10.94)	(-2.88)	(-5.72)	(-2.53)	(-5.48)	(-2.51)	(-5.21)	(-4.3)	(-7.68)
NPM	0.511 ***	0.730 ***	0.134	0.361 ***	0.116	0.324 ***	0.136 *	0.304 ***	0.193 ***	0.386 ***
	(6.12)	(9.57)	(1.54)	(4.59)	(1.46)	(4.55)	(1.84)	(4.55)	(2.77)	(6.18)
Panel B: Risk-adjusted returns using the CRR five-factor model										
rankW	0.069 **	0.043	0.001	0.014	0.021	0.032	0.052 *	0.024	0.027	0.017
	(2.21)	(1.36)	(0.04)	(0.44)	(0.70)	(1.06)	(1.67)	(0.80)	(1.24)	(0.81)
rankL	-0.256 ***	-0.255 ***	-0.058	-0.060	-0.089 **	-0.093 **	-0.094 **	-0.084 **	-0.12 ***	-0.110 ***
	(-6.01)	(-6.05)	(-1.29)	(-1.39)	(-2.13)	(-2.32)	(-2.29)	(-2.24)	(-3.71)	(-3.64)
NPM	0.326 ***	0.298 ***	0.059	0.073	0.110 *	0.125 **	0.146 **	0.108 *	0.147 ***	0.127 ***
	(5.07)	(4.66)	(0.91)	(1.15)	(1.78)	(2.12)	(2.34)	(1.92)	(3.02)	(2.79)

Table 6: Descriptive statistics and firm characteristics of rank quintile portfolios

For each month t, we calculate individual stocks' rank measure ($rank_{i,t}(P)$) and classify all stocks into quintile portfolios. Stocks with the largest rank measures are placed in portfolio Q5, while those with the smallest rank measures are placed in portfolio Q1. Panels A and B report the time-series average values of summary statistics and characteristics calculated on a monthly basis for stocks in rank-sorted quintile portfolios. *rank* is defined as the average of the past 6-month rank 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 millions 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; *Ivolatility* is the variance of residuals obtained from regressing individual stocks' daily returns on the value-weighted market index over the past year ending in the previous month with a minimum of 250 trading days; *Illiq* is the Amihud measure calculated over the past year ending in the previous month; *Analyst* is defined as the number of analysts following the firm at end of June in the current year, and is set to be zero if a firm is not included in the database; *Inst%* is defined as the percentage of common stocks owned by institutions at end of June in the current year; *ID* is the information discreteness measure calculated using data over past year ending in the previous month. The last column reports the difference between Q5 and Q1 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.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Panel A: Summary statistic of daily returns over the formation period						
rank	-0.126	-0.041	0.004	0.047	0.116	0.243 ***
						(36.36)
Mean	-0.150	0.008	0.087	0.159	0.297	0.446 ***
						(19.42)
Median	-0.201	-0.049	-0.011	0.017	0.092	0.293 ***
						(4.22)
Std. dev.	4.497	3.581	3.109	2.757	2.597	-1.901 ***
						(-8.69)
Skewness	0.697	0.494	0.462	0.482	0.514	-0.183 ***
						(-2.74)
Kurtosis	6.324	5.782	5.804	5.673	5.254	-1.069 ***
						(-2.93)
Max	10.252	7.812	6.692	5.943	5.732	-4.520 ***
						(-7.24)
Min	-8.230	-6.470	-5.497	-4.765	-4.375	3.854 ***
						(9.40)
Panel B: Firm characteristics						
Size (in millions)	555.735	1,138.754	1,455.674	1,736.385	1,838.918	1,283.183 ***
						(2.98)
BM	0.997	0.972	0.919	0.838	0.685	-0.313 ***
						(-6.17)
Ivolatility	4.220	3.437	3.012	2.683	2.517	-1.703 ***
						(-9.58)
ILLIQ	7.176	9.110	8.993	7.309	4.740	-2.436 ***
						(-3.68)
Analyst	4.689	5.525	6.010	6.661	7.290	2.601 ***
						(5.51)
Inst%	0.260	0.311	0.332	0.353	0.380	0.120 ***
						(7.74)
ID	-0.056	-0.027	-0.019	-0.021	-0.040	0.016 **
						(2.46)

Table 7: Descriptive statistics and firm characteristics of overlapped and isolated strategies

For each month *t*, we calculate individual stocks' past 6-month average return, rank measure, and 52-week high. We classify all stocks into quintile portfolios for the three measures. Stocks with the largest values on each measure are placed in portfolio Q5, while those with the smallest values on each measure are placed in portfolio Q1. We define stocks belonging to price momentum Q5 (Q1) portfolio that overlap with rank or 52wh momentum Q5 (Q1) portfolios as overlapped winners (losers). Stocks belonging to price momentum Q5 (Q1) portfolio that are unrelated to rank or 52wh momentum Q5 (Q1) portfolios are defined as isolated winners (losers). Panels A and B report the time-series average values of summary statistics and characteristics calculated on a monthly basis for stocks in rank-sorted quintile portfolios. *rank* is defined as the average of the past 6-month rank 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 millions 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; *Ivolatility* is the variance of residuals obtained from regressing individual stocks' daily returns on the value-weighted market index over the past year ending in the previous month with a minimum of 250 trading days; *Illiq* is the Amihud measure calculated over the past year ending in the previous month; *Analyst* is defined as the number of analysts following the firm at end of June in the current year, and is set to be zero if a firm is not included in the database; *Inst%* is defined as the percentage of common stocks owned by institutions at end of June in the current year; *ID* is the information discreteness measure calculated using data over past year ending in the previous month. The last column reports the difference between Q5 and Q1 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.

	Winner portfolio		Loser portfolio	
	Overlapped	Isolated	Overlapped	Isolated
Panel A: Summary statistic of daily returns over the formation period				
Mean	0.348	0.371	-0.193	-0.078
Median	0.068	-0.055	-0.141	-0.012
Std. dev.	3.075	5.348	4.053	2.442
Skewness	0.912	1.464	0.184	-0.380
Kurtosis	6.236	8.458	5.879	6.134
Max	7.261	12.004	8.856	4.809
Min	-4.789	-7.851	-8.214	-5.110
Panel B: Firm characteristics				
Size (in millions)	1,901.225	501.853	1,064.259	1,869.815
BM	0.594	0.738	0.971	0.873
Ivolatility	3.191	5.590	4.294	2.666
ILLIQ	6.216	17.348	10.037	5.859
Analyst	6.456	3.633	5.006	5.506
Inst%	0.355	0.215	0.282	0.305
ID	-0.029	-0.016	-0.051	-0.023

Table 8: Performance of NPM profits conditional on salience

In each month t from January 1963 to December 2015, we perform the following cross-sectional regressions for (j = 1,..., 12 to j = 1,..., 60):

$$R_{i,t} = b_{0j,t} + b_{1j,t}R_{i,t-1} + b_{2j,t}Size_{i,t-1} + b_{3j,t}priceW_{i,t-j} + b_{4j,t}priceL_{i,t-j} + b_{5j,t}52whW_{i,t-j} + b_{6j,t}52whL_{i,t-j} + b_{7j,t}rankW_{i,t-j} + b_{8j,t}rankL_{i,t-j} + b_{9j,t}rankW_{i,t-j} \times Pos\_Salience_{i,t-j} + b_{10j,t}rankL_{i,t-j} \times Neg\_Salience_{i,t-j} + \varepsilon_{i,t},$$

where $R_{i,t}$ is the return of stock i in month t; $Size_{i,t-1}$ is the natural logarithm of stock i's market capitalization at the end of previous month; $priceW_{i,t-j}$ ($priceL_{i,t-j}$) is a dummy variable that equals 1 if stock i's past 6-month average return is ranked at the top (bottom) 30% at the end of month $t-j$, and zero otherwise; $52whW_{i,t-j}$ ($52whL_{i,t-j}$) is a dummy variable that equals 1 if stock i's 52-week high measure is ranked at the top (bottom) 30% at the end of month $t-j$, and zero otherwise; $rankW_{i,t-j}$ ($rankL_{i,t-j}$) is a dummy variable that equals 1 if stock i's past 6-month rank measure is ranked at the top (bottom) 30% at the end of month $t-j$, and zero otherwise. In each month t, we estimate the cross-sectional regressions for j = 1,..., 12 to j = 1,..., 60 and average the corresponding coefficient estimates. $Pos\_Salience_{i,t-j}$ and $Neg\_Salience_{i,t-j}$ are stock i's salience measure taking positive and negative signs, respectively. In Panels A, B, and C, $Pos\_Salience_{i,t-j}$ and ($Neg\_Salience_{i,t-j}$) are measured by mean-minus-median (median-minus-mean), skewness (negative skewness), and ID, 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.

	Monthly return (1,12)				Monthly return (1,60)			
	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.
Panel A: Salience defined by the difference between mean and medium								
priceW			0.068	-0.065			0.022	-0.112
			(0.69)	(-0.64)			(0.26)	(-1.29)
priceL			-0.053	-0.075 *			0.038	0.038
			(-1.30)	(-1.79)			(1.55)	(1.53)
52whW			0.006	0.112 *			-0.061	0.028
			(0.11)	(1.91)			(-1.34)	(0.63)
52wh L			0.080	-0.204 *			0.115	-0.082
			(0.68)	(-1.80)			(1.34)	(-0.99)
rankW	0.102	0.300 ***	0.069	0.220 ***	-0.039	0.137 **	-0.005	0.148 **
	(1.24)	(3.75)	(0.92)	(2.96)	(-0.55)	(1.99)	(-0.07)	(2.18)
rankL	-0.198 *	-0.471 ***	-0.191 ***	-0.336 ***	0.042	-0.164 *	-0.032	-0.159 ***
	(-1.80)	(-4.43)	(-2.65)	(-4.96)	(0.48)	(-1.95)	(-0.52)	(-2.62)
rankW × *Pos_Salience*	-0.305	-0.442	-0.260	-0.297	-0.390	-0.719 ***	-0.390 **	-0.594 ***
	(-0.98)	(-1.40)	(-1.15)	(-1.30)	(-1.53)	(-2.77)	(-2.23)	(-3.35)
rankL × *Neg_Salience*	0.477 ***	0.406 **	0.537 ***	0.503 ***	0.452 ***	0.513 ***	0.397 ***	0.474 ***
	(2.60)	(2.14)	(3.44)	(3.14)	(3.79)	(4.12)	(3.92)	(4.46)

Table 8 continued

	Monthly return (1,12)				Monthly return (1,60)			
	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.
Panel B: Salience defined by skewness								
priceW			0.042	-0.079			-0.006	-0.145
			(0.39)	(-0.7)			(-0.06)	(-1.51)
priceL			-0.070 *	-0.092 **			0.033	0.027
			(-1.74)	(-2.19)			(1.28)	(1.02)
52whW			0.022	0.130 **			-0.052	0.037
			(0.38)	(2.25)			(-1.13)	(0.82)
52wh L			-0.171 *	-0.416 ***			0.043	-0.145 *
			(-1.67)	(-4.06)			(0.53)	(-1.81)
rankW	0.093 *	0.242 ***	0.053	0.181 ***	-0.078 *	0.040	-0.044	0.078
	(1.68)	(4.56)	(0.93)	(3.34)	(-1.87)	(1.05)	(-0.87)	(1.59)
rankL	-0.432 ***	-0.655 ***	-0.301 ***	-0.403 ***	-0.052	-0.236 ***	-0.094	-0.198 ***
	(-4.21)	(-6.33)	(-4.35)	(-5.79)	(-0.62)	(-2.87)	(-1.53)	(-3.21)
$rankW \times Pos\_Skewness$	0.034	0.005	0.023	-0.002	0.022	-0.007	0.022	0.004
	(1.43)	(0.21)	(1.28)	(-0.10)	(1.05)	(-0.35)	(1.53)	(0.26)
$rankL \times Neg\_Skewness$	-0.035	0.026	-0.018	0.047 *	0.001	0.055 ***	-0.004	0.050 ***
	(-1.18)	(0.84)	(-0.67)	(1.81)	(0.04)	(2.61)	(-0.21)	(2.58)
Panel C: Salience defined by information discreteness								
priceW			0.075	-0.063			0.002	-0.141
			(0.70)	(-0.57)			(0.02)	(-1.52)
priceL			-0.009	-0.025			0.051 **	0.055 **
			(-0.23)	(-0.60)			(2.04)	(2.11)
52whW			0.018	0.124 **			-0.043	0.047
			(0.31)	(2.13)			(-0.95)	(1.05)
52wh L			0.052	-0.226 **			0.094	-0.097
			(0.46)	(-2.08)			(1.14)	(-1.22)
rankW	0.038	0.174 ***	0.032	0.159 ***	-0.074 **	0.027	-0.039	0.080 *
	(0.73)	(3.38)	(0.61)	(3.16)	(-2.24)	(0.90)	(-0.82)	(1.76)
rankL	-0.273 ***	-0.501 ***	-0.262 ***	-0.390 ***	-0.051	-0.239 ***	-0.103	-0.231 ***
	(-2.69)	(-4.84)	(-3.42)	(-5.07)	(-0.61)	(-2.85)	(-1.59)	(-3.51)
$rankW \times ID$	-0.704 **	-1.150 ***	-0.311	-0.421	0.246	-0.110	0.132	0.096
	(-2.04)	(-3.39)	(-1.15)	(-1.56)	(1.25)	(-0.59)	(0.85)	(0.62)
$rankL \times ID$	1.512 **	2.759 ***	1.571 ***	2.258 ***	-0.106	0.569 **	0.246	0.562 **
	(2.55)	(4.64)	(3.47)	(4.98)	(-0.34)	(1.98)	(1.02)	(2.43)

Table 9: Correlations between rank and proxies of arbitrage risk

This table reports the averages of cross-sectional correlations between rank and proxies of arbitrage risk. *rank* is defined as the average of past 6-month rank measure. From July of each year to June of next year, *Ivolatility* is the variance of residuals obtained from regressing individual stocks' daily returns on the value-weighted market index over the past year ending in the previous month with a minimum of 250 trading days; *Illiq* is the Amihud measure calculated over the past year ending in the previous month; *Analyst* is defined as the number of analysts following the firm at end of June in the current year, and is set to be zero if a firm is not included in the database; *Inst%* is defined as the percentage of common stocks owned by institutions at end of June in the current year.

	rank	*Ivolatility*	*Illiq*	*Analyst*	*Inst%*
rank	1.000	-0.324	-0.044	0.096	0.162
Ivolatility		1.000	0.423	-0.292	-0.385
Illiq			1.000	-0.117	-0.167
Analyst				1.000	0.450
Inst%					1.000

Table 10: Performance of NPM profits conditional on arbitrage risk

In each month t from January 1963 to December 2015, we perform the following cross-sectional regressions for (j = 1,..., 12 to j = 1,..., 60):

$$R_{i,t} = b_{0j,t} + b_{1j,t}R_{i,t-1} + b_{2j,t}Size_{i,t-1} + b_{3j,t}priceW_{i,t-j} + b_{4j,t}priceL_{i,t-j} + b_{5j,t}52whW_{i,t-j} + b_{6j,t}52whL_{i,t-j} + b_{7j,t}rankW_{i,t-j} + b_{8j,t}rankL_{i,t-j} + b_{9j,t}rankW_{i,t-j} \times Arbitrage_{i,t-j} + b_{10j,t}rankL_{i,t-j} \times Arbitrage_{i,t-j} + \varepsilon_{i,t},$$

where $R_{i,t}$ is the return of stock i in month t; $Size_{i,t-1}$ is the natural logarithm of stock i's market capitalization at the end of previous month; $priceW_{i,t-j}$ ($priceL_{i,t-j}$), $52whW_{i,t-j}$ ($52whL_{i,t-j}$), and $rankW_{i,t-j}$ ($rankL_{i,t-j}$) are dummy variables that equals 1 if stock i's past 6-month average return, 52-week high measure, and past 6-month rank measure is ranked at the top (bottom) 30% at the end of month $t-j$, and zero otherwise; $Arbitrage_{i,t-j}$ is stock i's arbitrage risk measure calculated in month $t-j$. In Panels A to D, the arbitrage risk measure is proxied by $Ivolatility_{i,t-j}$, $Illiq_{i,t-j}$, $Analyst_{i,t-j}$, and $Inst\%_{i,t-j}$, respectively. In each month t, we estimate the cross-sectional regressions for j = 1,..., 12 to j = 1,..., 60 and average the corresponding coefficient estimates. 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.

	Monthly return (1,12)				Monthly return (1,60)			
	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.
Panel A: *Ivolatility* as the arbitrage risk measure								
priceW			0.035	-0.028			-0.023	-0.101
			(0.42)	(-0.31)			(-0.33)	(-1.39)
priceL			-0.110 ***	-0.149 ***			0.033	0.008
			(-2.94)	(-3.80)			(1.55)	(0.38)
52whW			0.058	0.143 ***			-0.027	0.036
			(1.27)	(3.12)			(-0.79)	(1.09)
52wh L			-0.209 ***	-0.333 ***			0.002	-0.096 *
			(-2.82)	(-4.30)			(0.01)	(-1.72)
rankW	0.111	0.478 ***	0.008	0.297 *	-0.088	0.277 *	-0.069	0.245 *
	(0.60)	(2.60)	(0.05)	(1.85)	(-0.52)	(1.68)	(-0.46)	(1.66)
rankL	-0.084	0.194	0.017	0.328 ***	-0.033	0.249 **	-0.069	0.226 **
	(-0.65)	(1.50)	(0.15)	(2.88)	(-0.30)	(2.30)	(-0.70)	(2.36)
rankW× Ivolatility	0.020	-0.082	0.033	-0.048	0.016	-0.105	0.018	-0.082
	(0.29)	(-1.16)	(0.59)	(-0.85)	(0.23)	(-1.60)	(0.34)	(-1.57)
rankL× Ivolatility	-0.096	-0.248 ***	-0.082 *	-0.220 ***	0.005	-0.145 ***	0.008	-0.129 ***
	(-1.64)	(-5.23)	(-1.67)	(-4.55)	(0.08)	(-3.20)	(0.16)	(-2.72)

Table 10 continued

	Monthly return (1,12)				Monthly return (1,60)			
	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.
Panel B: *Illiq* as the arbitrage risk measure								
priceW			0.024	-0.081			-0.065	-0.189 *
			(0.22)	(-0.72)			(-0.69)	(-1.91)
priceL			-0.081 *	-0.090 *			0.044	0.048
			(-1.86)	(-1.93)			(1.53)	(1.60)
52whW			0.049	0.146 ***			-0.02	0.061
			(0.88)	(2.60)			(-0.44)	(1.32)
52wh L			-0.239 ***	-0.418 ***			-0.018	-0.166 **
			(-2.68)	(-4.54)			(-0.24)	(-2.23)
rankW	0.103 *	0.253 ***	0.053	0.191 ***	-0.077 *	0.046	-0.011	0.124 **
	(1.76)	(4.44)	(0.90)	(3.36)	(-1.85)	(1.20)	(-0.20)	(2.43)
rankL	-0.487 ***	-0.673 ***	-0.337 ***	-0.439 ***	-0.089	-0.255 ***	-0.131 *	-0.239 ***
	(-4.58)	(-6.03)	(-4.29)	(-5.34)	(-1.02)	(-2.89)	(-1.79)	(-3.16)
rankW × *Illiq*	0.014	-0.003	0.013	-0.003	0.008	-0.009	0.006	-0.012
	(1.54)	(-0.34)	(1.57)	(-0.37)	(1.11)	(-1.31)	(0.75)	(-1.55)
rankL × *Illiq*	0.028 ***	0.008	0.030 ***	0.010	0.012	-0.005	0.011	-0.005
	(2.65)	(0.79)	(3.03)	(1.07)	(1.56)	(-0.58)	(1.40)	(-0.64)
Panel C: *Analyst*$^{-1}$ as the arbitrage risk measure								
priceW			0.054	-0.068			-0.005	-0.122
			(0.38)	(-0.45)			(-0.04)	(-0.99)
priceL			-0.095 *	-0.124 **			0.013	-0.019
			(-1.73)	(-2.13)			(0.35)	(-0.49)
52whW			0.058	0.133 *			0.002	0.074
			(0.77)	(1.68)			(0.04)	(1.27)
52wh L			-0.085	-0.372 **			0.002	-0.197 *
			(-0.52)	(-2.28)			(0.02)	(-1.84)
rankW	0.125	0.257 ***	0.066	0.195 ***	0.026	0.135 **	0.042	0.155 **
	(1.61)	(3.08)	(0.93)	(2.77)	(0.46)	(2.51)	(0.62)	(2.25)
rankL	-0.271	-0.436 **	-0.187 *	-0.224 *	-0.047	-0.168	-0.064	-0.092
	(-1.53)	(-2.34)	(-1.65)	(-1.86)	(-0.46)	(-1.64)	(-0.72)	(-1.00)
rankW × *Analyst*$^{-1}$	0.106	-0.027	0.126	-0.007	-0.041	-0.150	-0.038	-0.139
	(0.81)	(-0.19)	(0.96)	(-0.05)	(-0.36)	(-1.26)	(-0.33)	(-1.14)
rankL × *Analyst*$^{-1}$	-0.284	-0.796 ***	-0.246	-0.723 ***	-0.151	-0.541 ***	-0.151	-0.521 ***
	(-1.31)	(-3.72)	(-1.17)	(-3.47)	(-0.88)	(-3.40)	(-0.95)	(-3.30)

Table 10 continued

	Monthly return (1,12)				Monthly return (1,60)			
	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.
Panel D: *Inst%*$^{-1}$ as the arbitrage risk measure								
priceW			-0.036	-0.178			-0.094	-0.228 *
			(-0.26)	(-1.19)			(-0.80)	(-1.86)
priceL			0.008	-0.020			0.082 ***	0.071 **
			(0.16)	(-0.35)			(2.65)	(2.17)
52whW			0.081	0.169 **			0.008	0.086
			(1.08)	(2.15)			(0.14)	(1.47)
52wh L			-0.012	-0.325 **			0.013	-0.190 *
			(-0.08)	(-2.06)			(0.11)	(-1.73)
rankW	-0.561	-0.496	0.113 *	0.228 ***	-0.138	-0.047	0.035	0.144 **
	(-0.82)	(-0.66)	(1.77)	(3.62)	(-1.12)	(-0.36)	(0.63)	(2.58)
rankL	-1.033	-1.411 *	-0.343 ***	-0.512 ***	-0.214	-0.454 ***	-0.154 *	-0.295 ***
	(-1.48)	(-1.87)	(-3.20)	(-4.72)	(-1.35)	(-2.82)	(-1.68)	(-3.20)
rankW × *Inst%*$^{-1}$	-0.024	-0.033	-0.050	-0.061	0.020	-0.001	-0.046	-0.071
	(-1.01)	(-1.31)	(-1.08)	(-1.19)	(0.27)	(-0.02)	(-0.86)	(-1.22)
rankL × *Inst%*$^{-1}$	-0.019 ***	-0.026 ***	-0.028 **	-0.036 **	-0.103 ***	-0.122 ***	-0.127 *	-0.146 *
	(-2.71)	(-3.55)	(-1.98)	(-2.33)	(-2.84)	(-3.12)	(-1.80)	(-1.92)

Appendix A: Variable definitions

These variables are defined as follows. As in FF (1992, 1993), from July of each year to June of next year,

1. *Size* is defined as the market value of equity in million dollars at the end of June in the current year;
2. *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;
3. *Ivolatility* is the variance of residuals obtained from regressing individual stocks' daily returns on the value-weighted market index over the past year ending in the previous month with a minimum of 250 trading days;
4. *Illiq* is the average value of daily illiquidity measure over the past year ending in the previous month, where the daily illiquidity measure is calculated as $|R_{i,d}|/(P_{i,d} \times N_{i,d})$ with $|R_{i,d}|$ representing the absolute value of stock *i*'s return on day *d*, $P_{i,d}$ representing stock *i*'s closing price on day *d*, and $N_{i,d}$ representing stock *i*'s number of shares traded on day *d*;
5. *Analyst* is defined as the number of analysts following the firm at end of June in the current year;
6. *Inst%* is defined as the percentage of the firm's common stocks owned by institutions at end of June in the current year;
7. *ID* 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 $t-1$; $\%_{neg_{i,t}}$ 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 $PRET_{i,t} < 0$.

The data of *Analyst* are recorded from the Institutional Brokers' Estimate System (I/B/E/S) database for the period from 1980 to 2015. Note that *Analyst* equals 0 if the stock is not included in the database, as suggested by Bhushan (1994). The data of *Inst%* are obtained from the Spectrum/CDA quarterly database, which is available from 1980 to 2015.

Appendix B: Sign momentum strategies

In addition to ranks, we also calculate an alternative nonparametric measure based on signs. The sign measure, $sign_{i,d}$, is an indicator function which takes the value of 1 if stock i's corresponding daily return $R_{i,d}$ is positive, and zero otherwise. The average sign measure in month t, $sign_{i,t}(p)$, is calculated in a similar way.

We identify several interesting results, which are reported in Table A, and are summarized in the following.

1. Compared with Table 3, although the profits of the sign momentum are smaller in magnitude than those of the NPM, they are significant in both short and long terms. In Panel A, the "pure" sign momentum profit controlling for the price momentum and the 52wh momentum is 0.272% with a t-statistic of 3.78 (which is 0.344% for the NPM) for the first year with January observations and 0.446% with a t-statistic of 6.32 (which is 0.640% for the NPM) for the first year without January observations. For the entire 5-year holding period with January excluded, the profits are 0.204% (t-statistic = 3.01) for the sign momentum versus 0.332% (t-statistic = 2.92) for the NPM. The significance of the positive profits remains when the CRR risk adjustment is taken into account, as presented in Panel B.
2. The 52wh momentum strategy yields a short-term profit of 0.519% (t-statistic = 2.75) for the first year in non-January observations, and display no long-term continuation or reversal patterns. Consistent with Panel B of Table 6, the profitability of the 52wh momentum disappears under the CRR adjustment.
3. The only difference between Tables 3 and A is the short-term profit of the price momentum. Recalling from Table 3, the price momentum effect totally disappears when the 52wh momentum and the NPM are incorporated in the regressions. In Table A, the price losers

yields significantly negative returns of -0.096% (t-statistic = -2.43) with January months included and -0.164% (t-statistic = -3.98) with January months excluded, respectively. This result suggests that the 52wh momentum and the sign momentum cannot totally eliminate the price momentum effect. However, consistent with Table 6, Panel B of Table A indicates that the long-term return reversals of the price momentum can be explained by the CRR five-factor model. This finding again confirms that long-term return reversals are fully resolved by the CRR model, and that inclusion of the sign momentum does not account for the reversal patterns.

Overall, Table A confirms our conjecture that the soundness of the sign momentum is not special to the nonparametric measure, but is also robust to the sign measure. This evidence indicates that we need not to rely on a particular nonparametric approach to generate momentum profits. Nevertheless, we still observe slight difference between the NPM and the sign momentum in explaining the price momentum effect, suggesting that the information contents behind signs may be partly distinct from those behind ranks.

Table A: Performance of profits from price, 52-week high, and sign momentum strategies

In each month *t* from January 1963 to December 2015, we perform the following cross-sectional regressions for (*j* = 1,..., 12 to *j* = 1,..., 60):

$$R_{i,t} = b_{0j,t} + b_{1j,t}R_{i,t-1} + b_{2j,t}Size_{i,t-1} + b_{3j,t}priceW_{i,t-j} + b_{4j,t}priceL_{i,t-j} + b_{5j,t}52whW_{i,t-j} + b_{6j,t}52whL_{i,t-j} + b_{7j,t}signW_{i,t-j} + b_{8j,t}signL_{i,t-j} + \varepsilon_{i,t},$$

where $R_{i,t}$ is the return of stock i in month *t*; $Size_{i,t-1}$ is the natural logarithm of stock *i*'s market capitalization at the end of previous month; $priceW_{i,t-j}$ ($priceL_{i,t-j}$), $52whW_{i,t-j}$ ($52whL_{i,t-j}$), and $signW_{i,t-j}$ ($signL_{i,t-j}$) are dummy variables that equals 1 if stock *i*'s past 6-month average return, 52-week high measure, and past 6-month sign measure is ranked at the top (bottom) 30% at the end of month *t−j*, and zero otherwise. In each month *t*, we estimate the cross-sectional regressions for *j* = 1,..., 12 to *j* = 1,..., 60 and average the corresponding coefficient estimates. In Panel A, we report the raw return, while in Panel B, we perform time-series regressions of these averages (one for each average) on the contemporaneous CRR's five factors to hedge out the risk exposure. 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.

	Monthly return (1,12)		Monthly return (13,24)		Monthly return (25,36)		Monthly return (37,48)		Monthly return (1,60)	
	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.
Panel A: Raw returns										
priceW	0.039	0.169 **	-0.057	0.065	-0.077	0.049	-0.058	0.047	-0.046	0.067
	(0.57)	(2.45)	(-0.92)	(1.10)	(-1.28)	(0.84)	(-1.04)	(0.84)	(-0.85)	(1.25)
priceL	-0.035	-0.350 ***	0.174	-0.090	0.142	-0.056	0.083	-0.096	0.082	-0.140
	(-0.27)	(-2.75)	(1.51)	(-0.81)	(1.37)	(-0.55)	(0.93)	(-1.08)	(0.86)	(-1.50)
52whW	0.072	-0.038	-0.096	-0.211 **	-0.037	-0.162 *	0.022	-0.112	-0.004	-0.126
	(0.69)	(-0.35)	(-1.07)	(-2.17)	(-0.41)	(-1.75)	(0.25)	(-1.23)	(-0.04)	(-1.41)
52wh L	-0.096 **	-0.164 ***	0.077 **	0.018	0.047	0.002	0.026	0.002	0.024	-0.018
	(-2.43)	(-3.98)	(2.16)	(0.54)	(1.42)	(0.06)	(0.81)	(0.05)	(1.11)	(-0.84)
signW	0.085 **	0.174 ***	-0.017	0.077 *	-0.048	0.043	-0.040	0.039	-0.023	0.063 *
	(2.14)	(4.45)	(-0.40)	(1.83)	(-1.07)	(0.98)	(-0.95)	(0.95)	(-0.59)	(1.69)
signL	-0.186 ***	-0.273 ***	-0.040	-0.132 ***	-0.019	-0.102 **	-0.005	-0.071 *	-0.064 *	-0.140 ***
	(-4.57)	(-6.79)	(-0.90)	(-3.09)	(-0.42)	(-2.26)	(-0.14)	(-1.85)	(-1.83)	(-4.02)
price momentum	0.168	0.127	-0.173 *	-0.228 **	-0.084	-0.164	-0.003	-0.113	-0.028	-0.109
	(1.43)	(1.01)	(-1.76)	(-2.14)	(-0.85)	(-1.63)	(-0.04)	(-1.21)	(-0.32)	(-1.18)
52wh momentum	0.074	0.519 ***	-0.231	0.155	-0.219	0.106	-0.141	0.143	-0.128	0.207
	(0.39)	(2.75)	(-1.35)	(0.94)	(-1.38)	(0.68)	(-1.02)	(1.04)	(-0.87)	(1.44)
sign momentum	0.272 ***	0.446 ***	0.023	0.209 ***	-0.029	0.145 *	-0.034	0.110	0.041	0.204 ***
	(3.78)	(6.32)	(0.28)	(2.67)	(-0.35)	(1.78)	(-0.47)	(1.51)	(0.60)	(3.01)

Table A continued

	Monthly return (1,12)		Monthly return (13,24)		Monthly return (25,36)		Monthly return (37,48)		Monthly return (1,60)	
	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.	Jan. Inc.	Jan. Exc.
Panel B: Risk-adjusted returns using the CRR five-factor returns										
priceW	-0.084 **	-0.017	0.000	0.041	0.035	0.081 *	0.054	0.102 **	-0.001	0.049
	(-2.06)	(-0.41)	(0.01)	(0.99)	(0.77)	(1.83)	(1.21)	(2.40)	(-0.02)	(1.56)
priceL	0.027	0.013	-0.016	-0.007	-0.034	-0.042	-0.006	-0.006	0.007	0.007
	(0.96)	(0.46)	(-0.50)	(-0.22)	(-1.15)	(-1.42)	(-0.21)	(-0.18)	(0.41)	(0.40)
52whW	0.018	-0.036	-0.006	-0.041	-0.021	-0.035	-0.019	-0.036	-0.012	-0.041 *
	(0.53)	(-1.13)	(-0.18)	(-1.34)	(-0.72)	(-1.22)	(-0.64)	(-1.23)	(-0.50)	(-1.91)
52wh L	0.054	0.113 ***	0.163 ***	0.228 ***	0.126 ***	0.180 ***	0.068	0.086 **	0.083 **	0.124 ***
	(1.21)	(2.59)	(3.16)	(4.48)	(2.67)	(3.77)	(1.60)	(1.98)	(2.40)	(3.63)
signW	0.130 ***	0.121 ***	0.028	0.047 *	0.031	0.043	0.042	0.025	0.045 **	0.041 **
	(4.77)	(4.41)	(1.03)	(1.72)	(1.15)	(1.57)	(1.64)	(1.03)	(2.30)	(2.11)
signL	-0.172 ***	-0.184 ***	-0.021	-0.035	-0.050 *	-0.045	-0.023	-0.028	-0.070 ***	-0.072 ***
	(-5.42)	(-6.03)	(-0.65)	(-1.13)	(-1.67)	(-1.50)	(-0.78)	(-0.98)	(-3.23)	(-3.42)
price momentum	-0.111 *	-0.030	0.017	0.047	0.070	0.123 **	0.061	0.107 *	-0.008	0.042
	(-1.94)	(-0.51)	(0.27)	(0.78)	(1.09)	(1.99)	(1.00)	(1.85)	(-0.18)	(1.04)
52wh momentum	-0.036	-0.149 **	-0.169 **	-0.269 ***	-0.147 **	-0.215 ***	-0.087	-0.122 **	-0.095 *	-0.165 ***
	(-0.54)	(-2.44)	(-2.36)	(-3.89)	(-2.30)	(-3.35)	(-1.47)	(-2.04)	(-1.83)	(-3.34)
sign momentum	0.302 ***	0.305 ***	0.048	0.082 *	0.082 *	0.088 **	0.066	0.054	0.115 ***	0.113 ***
	(6.89)	(6.93)	(1.05)	(1.82)	(1.92)	(2.11)	(1.57)	(1.38)	(3.81)	(3.85)