Nearness to the 52-week high and low prices, past returns, and average stock returns

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Abstract

This study examines the interactions between trading strategies based on the nearness to the 52-week high, the nearness to the 52-week low, and past returns. We offer evidence that the nearness to the 52-week low has predictive power for future average returns. Our results also reveal that the nearness to the 52-week high as well as to the 52-week low and past returns each have certain exclusive unpriced information content in the cross-sectional pricing of stocks. Moreover, a trading strategy based on the nearness to the 52-week low provides an excellent hedge for the momentum strategy, thereby nearly doubling the Sharpe ratio of the momentum strategy.

Keywords: 52-week high, 52-week low, past returns, momentum

1. Introduction

Price levels are the most accessible information for investors. Nearly every newspaper that publishes stock prices also identifies the stocks' 52-week high and low prices. For example, The Wall Street Journal, Investors Business Daily, and Financial Times all print lists of the stocks hitting 52-week high and low prices each day, and Barron's Magazine prints a comprehensive weekly list of such stocks. A growing body of research is focusing on the 52-week high and low prices in the cross-sectional pricing of stocks as well as the association between these two variables and momentum (e.g., George and Hwang, 2004; Huddart, Lang, and Yetman, 2009). This study examines whether extreme price levels have predictive power for future average returns, and whether the predictive power of extreme price levels on average stock returns can subsume or be subsumed by momentum. Unlike past studies, our empirical results reveal that the nearness to the 52-week high, the nearness to the 52-week low, and past returns each contain certain exclusive unpriced information content in the cross-sectional pricing of stocks. Moreover, the trading strategy based on the nearness to the 52-week low provides a hedge for the momentum strategy, thereby nearly doubling the Sharpe ratio of the momentum strategy.

Previous studies have empirically found that past returns as well as approaching or hitting the 52-week high or low price affect future average returns (e.g., Jegadeesh and Titman, 1993, 2001; Barroso and Santa-Clara, 2015; George and Hwang, 2004; Huddart, Lang, and Yetman, 2009; Liu, Liu, and Ma, 2011; Li and Yu, 2012; Bhootra and Hur, 2013; Driessen, Lin, and Hemert, 2013; George, Hwang, and Li, 2014; Hong, Jordan, and Liu, 2015). Based on the adjustment and anchoring bias surveyed by Kahneman, Slovic, and Tversky (1982), George and Hwang (2004) present a pioneering study that links the nearness to the 52-week high and momentum investing. They report that the nearness to the 52-week high explains a large portion of the profits that are derived from momentum investing, because traders use the 52-week high as a reference for evaluating the potential impact of news. However, they do not find any predictive power from the nearness to the 52-week low. George and Hwang (2004) argue that the absence of the predictability of the nearness to the 52-week low is due to tax distortion.

Whereas George and Hwang (2004) measure the nearness to the 52-week high and low prices for every stock, Huddart, Lang, and Yetman (2009) focus on stocks that cross either high or low prices. They report that stocks with prices that rise above previous high prices as well as those with prices that fall below previous low prices generate a larger volume and higher risk-adjusted average returns compared with other stocks. More important, their results are not driven purely by the predictability of past returns, because the results are still supported even when the control for past returns is included in the analyses¹. Yates (2007) presents evidence

¹ The major variables used by George and Hwang (2004) and Huddart, Lang, and Yetman (2009) differ only

showing that investors at a brokerage firm tend to purchase shares when a stock's price exceeds its prior trading range and documents a positive 1-day return.

The findings on 52-week low prices in previous studies are conflicting. A major overlap exists empirically between the sorting group including stocks hitting the 52-week lows and the sorting group including stocks that are the closest to their 52-week highs. However, George and Hwang (2004) and Huddart, Lang, and Yetman (2009) obtain significantly different empirical results concerning whether approaching or hitting the 52-week low contains of unpriced information. Moreover, George and Hwang (2004) and Huddart, Lang, and Yetman (2009) produce inconsistent results on whether the unpriced information contained in approaching or hitting the 52-week high and low prices can or cannot be explained by momentum. George and Hwang (2004) assert that the nearness to the 52-week high explains a large portion of the momentum profit, whereas Huddart, Lang, and Yetman (2009) obtain conflicting results. Such inconsistency in the literature motivates us to investigate whether the three price-related variables-the 52-week high, 52-week low, and past returns-each carry exclusive unpriced information content in the cross-sectional pricing of stocks.

Our sample includes all common nonfinancial stocks in NYSE/Amex and Nasdaq for the

slightly. George and Hwang (2004) use continuous variables to measure the nearness to 52-week high and low price. Huddart, Lang, and Yetman (2009) use the dummy variable MAX (MIN), which is equal to 1 if the closing stock price for the observation week is above (below) the highest (lowest) price attained in the 48-week period that ends 20 trading days before the last day of the observation week. Although the variables used in the two studies differ, they are highly correlated.

period spanning July 1962 to December 2014. We construct two variables (i.e., *HIGH* and *LOW*) to capture the nearness to the 52-week high and low prices, respectively. Next, we sort the stocks by *HIGH* or *LOW* to quintiles in the end of the previous month, and examine the monthly returns of the portfolios over the sample period. We emphasize the right (left) tail of the variable *HIGH* (*LOW*), because the tail is more relevant to investors (i.e., attracts more investor attention) (Huddart, Lang, and Yetman, 2009). Hence, for the 52-week high strategy, we purchase a value-weighted portfolio of the top *n*% stocks, and sell a value weighted portfolio of the bottom (*1-n*)% stocks based on the sorting of *HIGH*. Conversely, for the 52-week low strategy, we purchase a value-weighted portfolio of the bottom *n*% stocks, and sell a value weighted portfolio of the top for the bottom *n*% stocks, and sell a value weighted portfolio of the bottom *n*% stocks, and sell a value weighted portfolio of the portfolio of the bottom *n*% stocks, and sell a value weighted portfolio of the bottom *n*% stocks, and sell a value weighted portfolio of the portfolio of the bottom *n*% stocks, and sell a value weighted portfolio of the bottom *n*% stocks, and sell a value weighted portfolio of the bottom *n*% stocks, and sell a value weighted portfolio of the portfolio of the bottom *n*% stocks, and sell a value weighted portfolio of the bottom *n*% stocks, and sell a value weighted portfolio of the bottom *n*% stocks, and sell a value weighted portfolio of the portfolio of the bottom *n*% stocks, and sell a value weighted portfolio of the portfolio of the bottom *n*% stocks, and sell a value weighted portfolio of the bottom *n*% stocks, and sell a value weighted portfolio of the bottom *n*% stocks, and sell a value weighted portfolio of the bottom portfolio of the bottom *n*% stocks, and sell a value weighted portfolio of the bottom *n*% stocks, and sell a value weighted portfolio of the bottom *n*% stocks, and sell a value weig

Based on the univariate sorts analysis, two features are obvious. First, consistent with the findings of Huddart, Lang, and Yetman (2009), we observe that the nearness to the 52-week low and the future average return are positively correlated. The raw return of the 52-week low strategy is 40.71 basis points in the first month, and becomes negative in the third month. Second, the empirical findings reveal that the 52-week high strategy, the 52-week low strategy, and the momentum strategy are separate phenomena, and contain exclusive information regarding the cross-sectional pricing of stocks. The return correlations between the 52-week high and low strategies as well as between the momentum strategy and the 52-week low strategy are negative.

Specifically, the profitability of the three strategies is in adherence to their respective patterns. The raw return of the 52-week high strategy in the first month is -16.51 basis points, and generates a positive return only when the long–short portfolio is held for more than 3 months. However, the 52-week low strategy and the momentum strategy are profitable in the first month. For a robustness check, we divide the entire sample along the time-series horizon. The empirical evidence reveals that the three strategies exhibit diverse return patterns in magnitude and significance under different market states.

We then use the bivariate sorts and the firm-level cross-sectional Fama–Macbeth regressions for investigating the relation among the 52-week high, 52-week low, and momentum strategies after controlling for various other firm-level characteristics. The empirical results reveal that the nearness to 52-week high as well as to the 52-week low and past returns each exhibit substantial predictive power on future average returns in firm-level cross-sectional regressions, even after controlling for various other firm-level variables, including the size, book-to-market ratio, illiquidity, and lagged 1-month return. Moreover, we regress the returns of a test strategy on those of explanatory strategies to determine whether the trading strategy based on one variable can generate a significant alpha relative to the other two strategies. Significant abnormal returns imply that an investor already trading the explanatory strategies can realize significant gains by trading the test strategy. The results suggest that the 52-week low and the

momentum strategies, except for the 52-week high, have significant alphas in time-series regressions.

Because of the negative return correlation between the momentum strategy and the 52-week low strategy, we further examine whether the 52-week low strategy provides a hedge for the momentum strategy, thus improving a momentum investor's investment opportunity set. The 52-week low strategy, despite generating significant returns on its own, provides insurance for the momentum strategy. Diversifying into the momentum strategy and the 52-week low strategy leads to a reduction in overall volatility and an increase in the Sharpe ratio. The annualized Sharpe ratio of the diversified strategy is 0.98, which is marginally higher than that of the risk-managed momentum strategy used by Barroso and Santa-Clara (2015). Moreover, our result cannot be explained by the risk-managed momentum strategy proposed by Barroso and Santa-Clara (2015). Through diversification, momentum investors can avoid the momentum crashes and secure the momentum profit without exposing themselves to additional risk.

This study contributes to the finance literature by focusing on the inconsistencies found in previous studies. First, we identify the profitability of the 52-week low strategy. Second, we report the absence of a dominating strategy among the three trading strategies. Each of them contains exclusive unpriced information content in the cross-sectional pricing of stocks. This result implies that the anchoring bias discussed by George and Hwang (2004) is not a dominant driving force for momentum; hence, the explanation for momentum cannot be found here. This finding may present a venue for tracking the sources of price momentum. Third, the 52-week low strategy provides an excellent hedge for the momentum strategy. The hedge eliminates momentum crashes and nearly doubles the Sharpe ratio of the momentum strategy. This makes the momentum a greater puzzle than the original version. Momentum investors should consequently focus on the nearness to the 52-week low when selecting their portfolio holdings, because adding the 52-week low strategy increases the performance of momentum investing considerably. Aside from academic interest, this finding can be used as a useful guide for asset managers seeking profitable investment strategies.

The remainder of this study is organized as follows. Section 2 presents an outline of the data and provides various tests for examining the relation among the 52-week high, 52-week low, and momentum strategies. Section 3 discusses the diversification between various strategies. Section 4 offers a conclusion.

2. Nearness to the 52-week high and low prices and the cross-section of expected returns

2.1 Data

Our sample includes all common nonfinancial stocks listed in the NYSE, Amex, and Nasdaq. The sample period is from January 1962 to December 2014. The return data are collected from the Center for Research in Security Prices (CRSP) daily and monthly files. The monthly return data are used to calculate the portfolio returns, whereas the daily return data are used to calculate the variables as idiosyncratic volatility and illiquidity for regression analysis. We also retrieve accounting data from COMPUSTAT to calculate the book-to-market ratios and other variables for regression analysis. Stocks with prices under US\$5 are removed, because such stocks incur large transaction costs because of their poor market liquidity (thin trading and large bid-ask spreads), which can distort the results. Throughout our analysis, we employ the corrections proposed by Shumway (1997) for the delisting bias; however, this adjustment does not affect our results.

The nearness to the 52-week high (hereafter denoted as *HIGH*) is measured as $\frac{P_{i,t-1}}{high_{i,t-1}}$, where $P_{i,t-1}$ denotes the price of stock *i* at the end of month t - 1, and $high_{i,t-1}$ denotes the highest price of stock *i* during the past 12-month period ending on the last day of month t - 1. The nearness to the 52-week low (hereafter denoted as *LOW*) is measured as $\frac{P_{i,t-1}}{low_{i,t-1}}$, where $low_{i,t-1}$ represents the lowest price of stock *i* over the past 12-month period ending on the last day of month t - 1. The maximum value of the variable *HIGH* is 1, because when a stock price crosses it 52-week high, its price at the end of month t - 1 is the highest price of stock *i* over the past 12-month period ending on the last day of month t - 1. In a similar manner, the minimum value of the variable *LOW* is also 1.

Table 1 lists the descriptive statistics for *HIGH*, *LOW*, and other firm characteristics. The table shows that the correlation between *HIGH* and *LOW* is 0.07, which cannot be regarded as high. This result implies that it is unnecessary for a stock approaching its 52-week high to concurrently be far from its 52-week low. Moreover, the correlations between *HIGH* and the past 1-year return ($R_{(2,13)}$) and between *LOW* and the past 1-year return ($R_{(2,13)}$) are both positive (0.24 and 0.20, respectively). The two positive correlations imply that stocks approaching the 52-week high or low both generate higher returns.

2.2 Univariate portfolio-level analysis

Table 2 presents the average monthly raw returns and risk-adjusted returns according to the results of univariate portfolio-level analysis. The portfolios are formed by sorting the NYSE/Amex/Nasdaq stocks based on *HIGH*, *LOW*, or past returns at the end of the previous month. Throughout this paper, the 52-week high strategy is to buy stocks in the top n% based on the variable *HIGH* (i.e., buying stocks nearest to their 52-week highs) and sell the others, and it is labeled n/1-n in Panel A. Conversely, the 52-week low strategy is to buy stocks in the bottom

n% based on the variable *LOW* (i.e., buying stocks nearest to their 52-week lows) and sell the others, and it is also labeled n/1-n in Panel B. The momentum strategy is to buy n% winners and sell the bottom m% losers based on the sorting of the past 12-month returns, and is labeled n/m in Panel C. We skip one full month between the formation period and the holding period in the construction of the momentum portfolio to avoid the microstructure issues (Jegadeesh and Titman, 1993; Chan, Jegadeesh, and Lakonishok, 1996). Each portfolio is value-weighted and held for 1 month. The *t* values are corrected through the Newey–West procedure. The factor data are collected from Kenneth R. French's website.

For brevity, our following discussion focuses on the 10/90 case for the 52-week high and low strategies and on the 10/10 case for the momentum strategy. Two features are obvious. First, the 52-week low strategy (Panel B) generates significant risk-adjusted returns for every instance in various factor models. Its monthly raw return is 42.80 basis points, approximately 5.26% annually. Its monthly three- and five-factor adjusted returns are 45.14 and 43.43 basis points, respectively. The results suggest that the 52-week low strategy cannot be fully captured by Fama and French's three and five risk factors. This finding is closer to that presented by Huddart, Lang, and Yetman (2009), which reveals that stock returns are positive after a stock crosses either limit of its trading range. Second, converse to the 52-week low strategy, the 52-week high strategy (Panel A) does not generate significant returns in each factor model. Instead, the 52-week high strategy produces a negative return in every factor model. However, if we are to construct equal-weighted portfolios, a positive return can be found for the 52-week high strategy. Table A1 in the Appendix lists the profitability of the equal-weighted 52-week high strategy.

[Table 2 here]

We also investigate the profitability of the three strategies with an extended holding period. We use overlapping portfolios, in accordance with Jegadeesh and Titman (1993), to recalculate the monthly return for each strategy in the Kth month, where K ranges from 1 to 36. Figure 1 displays the results. For brevity, our following discussion focuses on the 10/90 case for the HIGH and LOW strategies and the 10/10 case for the momentum strategy. We confirm a decline in profit for the momentum strategy. The monthly momentum profit turns negative (-16.40 basis points) in the 10th holding month. Compared with the momentum strategy, the profit of the 52-week low strategy turns negative faster. The profit from investing the 52-week low strategy is only 4.42 basis points in the second month, and -26.37 basis points in the third month. By contrast, the profitability of the 52-week high strategy is negative in the first holding month (-15.94 basis points, t = -1.48) (see Table 2), and turns positive from the second holding month (12.18, 5.21, 9.54, 18.86, and 28.99 basis points in the second, third, fourth, fifth, and sixth holding months, respectively). The return pattern of this strategy obviously differs from those of the other two strategies.

[Figure 1 here]

This finding can also be confirmed by the return correlation. If the three strategies carry similar unpriced information content, they should share a similar return pattern. Conversely, if the three strategies each contain exclusive unpriced information content, they should have distinct return patterns. To test this hypothesis, we examine the correlation matrix of returns for the three strategies and the profitability of these strategies under different market states.

[Table 3 here]

The correlation matrix of returns for the three strategies is reported in Table 3. Panel A reports the return correlation under a 1-month holding period. The return correlation is negative between the momentum strategy and the 52-week low strategy (-0.44) as well as between the 52-week high strategy and the 52-week low strategy (-0.33). However, the return correlation is positive between the momentum strategy and the 52-week high strategy (0.38). The results do

not change materially when the holding period is extended to 6 months in Panel B. Figure 2 displays the time-series return under the 1-month holding period over the past 5 years. It shows that the momentum strategy performs poorly between 2003 and 2007, whereas the 52-week low strategy performs well in this period. The reverse is true for the 1990–1995 period.

Collectively, from the viewpoint of return patterns, the 52-week low strategy is distinct from the other two strategies. The negative return correlation between any two strategies possibly provides an advantage for diversification. We discuss this possibility in a later subsection.

[Figure 2 here]

Table 4 presents the profitability of the three strategies under different market states. According to Cooper, Gutierrez, and Hameed (2004), an up market is when the market return over the past 24 months is nonnegative, whereas a down market occurs when the market return over the past 24 months is negative. Consistent with the results reported by Cooper, Gutierrez, and Hameed (2004), we report that the profitability of the momentum strategy is significant in the up market but insignificant in the down market. Conversely, the 52-week low strategy performs better in a down market, although this strategy is profitable in both up and down markets. In addition, the 52-week high strategy performs better in an up market only under certain specifications. If any two of the three strategies overlap each other, we should not observe such a different performance in up and down markets.

[Table 4 here]

2.3 Bivariate portfolio-level analysis

This section presents our examination of the relation between one variable and future stock returns after controlling for other variables. For example, we control for past returns first by sorting stocks into quintiles based on the past 12-month returns at the beginning of each month t. Afterward, within each past return quintile, we further sort the stocks into quintile portfolios based on the nearness to the 52-week low, so that Quintile 1 (Quintile 5) contains stocks with the lowest (highest) *LOW*. We ultimately obtain 25 portfolios. Each portfolio is value-weighted and held for 1 month. Table 5 shows the results. For brevity, this study does not provide the returns for all 25 portfolios. Instead, each cell of Table 5 reports the long–short raw returns or the long-short risk-adjusted returns for a strategy. We focus on the 10/90 case for the 52-week high and low strategies and on the 10/10 case for the momentum strategy. The t values are adjusted

using the Newey-West procedure.

Several key features stand out. First, we observe that the momentum profit prevails in each HIGH-quintile portfolio in Panel A as well as in each LOW-quintile portfolio in Panel B. The untabulated results reveal that the finding is robust in various ranking and holding periods up to 1 year. When we construct equal-weighted portfolios, the 52-week high and low strategies still cannot fully subsume the momentum strategy. Hence, the empirical results provide sufficient support for the hypothesis that information contained in past returns differs from that contained in 52-week high and low prices. Second, the 52-week low strategy in Panel B is profitable only in the first, second, and third HIGH-sorted portfolios (i.e., portfolios including stocks far from their 52-week highs). In the fourth and fifth quintiles, sorted by the nearness to the 52-week high, the 52-week low strategy no longer generates significant returns. This finding reveals that the nearness to the 52-week low contains exclusive unpriced information in stocks that are not that close to their 52-week high. Third, after controlling for the nearness to the 52-week low or past returns, the 52-week high strategy produces negative returns for both Panels B and C. This finding implies that compared with the nearness to the 52-week high, the nearness to the 52-week low is a more significant return-predictive stock characteristic. Moreover, the negative returns of the 52-week high strategy in most cells in Panel C also show the following: Being closer to the 52-week high generates lower future returns for stocks that share a similar degree of nearness to their 52-week lows.

[Table 5 here]

Overall, the bivariate sorts here suggest that the nearness to the 52-week high, the nearness to the 52-week low, and past returns each contain exclusive unpriced information in the cross-sectional pricing of stocks, especially the nearness to the 52-week low and past returns. However, the one concern with dependent bivariate sorts on correlated variables is that they do not sufficiently control for the control variable. In other words, there can be some residual variations in the nearness to the 52-week high across the past return portfolios. We address this concern by using the independent bivariate sorts on the two variables; such sorts produce similar results.

2.4 Fama–Macbeth regression and time-series regression

Although the bivariate sorts reveal that the three trading strategies cannot be used to explain each other, one trading strategy may incidentally capture the predictability of other return determinants. Hence, we run the Fama-MacBeth regression to assess whether our results still hold after controlling for certain firm characteristics, and to simultaneously isolate the returns contributed by the nearness to the 52-week high and low prices and past return.

$$R_{i,t} = \alpha_{i,t} + \beta_{1it}HIGH_D_{i,t-1} + \beta_{2it}LOW_D_{i,t-1} + \beta_{3it}Winner_{i,t-1} + \beta_{4it}Loser_{i,t-1} + \beta_{5it}ln(size)_{i,t-1} + \beta_{6it}ln(bm)_{i,t-1} + \beta_{7it}R_{(1,2)i,t-1} + \beta_{8it}Turnover_{i,t-1} + \beta_{9it}IVol_{i,t-1} + \beta_{10it}Illiq_{i,t-1} + \varepsilon_{it}$$
(1)

The dependent variable in these regressions is the month *t* return to stock *i*, $R_{i,t}$. Because we focus more on the tails of the two variables *HIGH* and *LOW*, we convert the two variables to dummies in the Fama–MacBeth regression. The dummy $HIGH_D_{i,t-1}$ ($LOW_D_{i,t-1}$) is assigned a value of 1 if the nearness to the 52-week high (low) price measure for stock *i* is ranked in the top (bottom) 10% in month t - 1. The dummy $Winner_{i,t-1}$ ($Loser_{i,t-1}$) indicates whether firm *i* is included in the top (bottom) 10% portfolio based on the past 12-month returns. The control variables include the log of firm size in millions in the month ($ln(size)_{i,t-1}$) and the log of the book-to-market ratio ($ln(bm)_{i,t-1}$). Some may be concerned that the nearness to the 52-week low is simply a manifestation of the monthly reversals presented by Jegadeesh (1990), because a stock approaching its 52-week low in the last month is possibly a loser before reversing to achieve a high return as a winner this month. Hence, the lagged 1-month return from t - 1 to t - 2 $(R_{(1,2)i,t-1})$ is included to show that the risk-adjusted return earned by sorting by the nearness to the 52-week low is not a simple manifestation of the monthly reversals, and to mitigate the impact of the bid-ask bounce. We also include the total turnover for the month (*Turnover*_{i,t-1}), idiosyncratic volatility in the month (*IVol*_{i,t-1}), and the Amihud (2002) illiquidity measure (*Illiq*_{i,t-1}). To reduce the influence of outliers, the independent variables, except for the dummies, are trimmed at the 2.5% and 97.5% percentiles, because these variables have less meaning in the lower (upper) bound. The *t* values are corrected using the Newey–West procedure. For ease of exposition, we scale up the illiquidity measure by 10³.

Table 6 presents the results. Overall, the results of the Fama–MacBeth regressions suggest that the explanatory power of the nearness to the 52-week high, of the nearness to the 52-week low, and of past returns on the cross-section of returns is separate and cannot be subsumed by other return determinants. Column (4) shows that the dummies *LOW_D*, *Winner*, and *Loser* are all significant with *t*-statistics as 4.34, 3.84, and -10.01, respectively. After including other return predictors in Column (6), the significance of the nearness to the 52-week low and past returns in the cross-section of returns is not jeopardized considerably. In addition, the dummy *HIGH_D* is significantly positive only in Column (6) (*t*-statistics = 2.63), under which all return predictors are included. This implies that the predictability of the nearness to the 52-week high on the cross-section of returns is only conditional on other control variables. Overall, we cannot regard

the three trading strategies as analogues.

[Table 6 here]

Even when we extend the holding period to 6 months, instead of 1 month, the regression results do not change. In line with the method employed by George and Hwang (2004), the coefficient estimate of a variable in month t is averaged over the past 6 months. The reported coefficients are the time-series averages of these averages. The numbers are listed in Table A2 in the Appendix.

Next we show that one trading strategy cannot fully capture another trading strategy in time-series regressions. Time-series regression does not require parametric assumptions on the functional form of the relation between expected returns and predictive variables, and avoids the measurement error in cross-sectional regressions. These time-series regressions are used for identifying the strategy that generates significant abnormal returns relative to others. We regress the returns of a test strategy on those of explanatory strategies, as follows:

$$y_t = \alpha + \boldsymbol{\beta}' \boldsymbol{X}_t + \varepsilon_t \tag{2}$$

where y_t represents the monthly excess returns of one test strategy (i.e., the 52-week high, 52-week low, or momentum strategy). The explanatory strategies include the Fama and French factors (i.e., MKT, SMB, HML, RMW, and CMA), downloaded from Kenneth R. French's website and the other two test strategies. A significant alpha indicates that an investor already trading the explanatory strategies can realize significant gains by trading the test strategy.

Table 7 lists the results. The argument that the three strategies each contain exclusive unpriced information in the cross-sectional pricing of stocks is partly confirmed by our results. First, the profit of the 52-week low strategy shown in Panel B cannot be explained by the 52-week high and momentum strategies. For example, the monthly profit of the 52-week low strategy is 75.86 basis points (t = 6.62) with the five risk factors plus the momentum factor. The coefficient of the momentum factor in Column (1) is -0.20 (t = -13.16), implying that the profit of the 52-week low strategy is negatively correlated with that of the momentum strategy. Second, the momentum strategy in Panel C has large, highly significant alphas compared with the 52-week high and low strategies. Hence, the 52-week low and momentum strategies are least likely to proxy for the same unpriced information. Panels A and C collectively imply that an investor who has already traded the momentum strategy will obtain profit by trading the 52-week low strategy, and vice versa. However, Panel B shows that the alpha of the 52-week high strategy is negative in Column (1), and insignificant in Column (2). This finding suggests that the abnormal return of the 52-week high strategy, if any, is fully captured by the 52-week low and momentum strategies. An investor who trades the momentum or 52-week low strategy will lose nothing by dismissing the 52-week high strategy completely.

[Table 7 here]

3. Diversification between two strategies

The performance of momentum comes with occasional large crashes. In January 2001, the momentum strategy delivered a -41.52% return in only one month. In April 2009, the momentum strategy also experienced a crash of -35.22% in a month. Even the large returns of momentum do not compensate an investor with reasonable risk aversion for these sudden crashes that take decades to recover from. A negative return correlation presents an advantage for diversification. One explanation for this pattern is the time-varying systematic risk of the momentum strategy. Grundy and Martin (2001) show that momentum has significant negative beta following bear markets. They argue that hedging this time-varying market exposure produces stable momentum returns, but Daniel and Moskowitz (2013) show that using betas in real time does not avoid the crashes. Barroso and Santa-Clara (2015) find the risk of momentum is predictable. Managing the

risk of momentum by using the realized variance of daily returns can eliminates exposure to crashes and increases the Sharpe ratio of the strategy substantially.

Since Table 3 shows that the correlations between the momentum and 52-week low strategies and between the 52-week high and low strategies are negative, it is possible that the 52-week low strategy can provide a hedge for the momentum strategy and thereby avoid the large crashes of momentum. Therefore, we diversify into any two of the three strategies to observe whether the Sharpe ratio is significantly enhanced. We equally invest our capital into two strategies m and n, denoted (m, n), and hold the diversified strategy for 1 month.

Table 8 lists the results, and Panel A shows the return volatility. In brief, we can reduce volatility through diversification. The return volatility of the 52-week high, 52-week low, and momentum strategies is 0.03, 0.03, and 0.07, respectively. When we diversify into the momentum and 52-week low strategies, the volatility of the diversified strategy becomes 0.04. Using the F-test to test equality of variances, we observe that the reduction in volatility under diversification is significant at the 1% level compared with the volatility of the momentum strategies, the volatility turns to 0.02. Compared with the volatility of the 52-week high or low strategy (i.e., investing in a single strategy), the volatility decreases significantly. The F-values are 2.69 and 3.28, respectively, for the test of variance equality. However, diversifying into the

52-week high and momentum strategies does not lead to a reduction in the volatility of investing in a single strategy. The volatility of the diversified strategy is 0.06. Compared with the 52-week high, the volatility of the diversified strategy is significantly enhanced by 0.03 (F value = 3.41).

Panel B lists the results for the monthly Sharpe ratio and shows that certain diversified strategies generate significantly higher Sharpe ratios. Because the momentum and 52-weel low strategies' return are negatively correlated, the two strategies work extremely well together. The monthly Sharpe ratios of the 52-week high, 52-week low, and momentum strategies are -0.06, 0.14, and 0.19, respectively. Their annualized Sharpe ratios are respectively -0.21, 0.48, and 0.66. The negative monthly Sharpe ratio of the 52-week high strategy reflects the numbers shown in Table 2, indicating that the 52-week high strategy does not generate a positive return in the first month. In the diversified strategies, the highest monthly Sharpe ratio is 0.28 when we diversify into the momentum and 52-week low strategies, denoted as (momentum strategy, 52-week low strategy). Based on the monthly Sharpe ratio, its annualized Sharpe ratio is 0.98, which is marginally higher than that of the risk-managed momentum strategy used by Barroso and Santa-Clara (2015). The monthly Sharpe ratio of this diversified strategy is significantly higher than those of the single momentum and 52-week low strategies (t = 39.41 and 60.78,

[Table 8 here]

However, the significant enhancement of the Sharpe ratio is only one-sided for the other two diversified strategies; that is, (momentum strategy, 52-week high strategy) and (52-week high strategy, 52-week low strategy). For example, diversifying into the 52-week high and low strategies enhances the Sharpe ratio compared with the 52-week high strategy (t = 62.07), but reduces the Sharpe ratio compared with the 52-week low strategy (t = -27.35). Based on the Sharpe ratio, the diversified strategy (momentum strategy, 52-week high strategy) produces the weakest hedge portfolio. Table A3 in the Appendix lists the results we obtain after extending the

² For conducting the mean difference test of the Sharpe ratios, we follow the procedures presented by Jobson and Korkie (1981) and their corrected version presented by Memmel (2003) to derive the moments, asymptotic distributions, and propose test statistics of the Sharpe ratios. The test originally proposed by Jobson and Korkie (1981) and corrected by Memmel (2003) (referred to as the JKM test) is the most frequently used test for the equality of the Sharpe ratios of two investment strategies. Its null hypothesis is formally expressed as follows: $H_0: \Delta = \eta_i - \eta_j = 0$, where $\eta_i = \mu_i/\sigma_i$ and $\eta_j = \mu_j/\sigma_j$ are the Sharpe ratios of two investment strategies with mean excess returns μ_i and j and the standard deviations of excess returns σ_i and σ_j , respectively. At a nominal level of α , this null hypothesis is rejected if the hypothetical value of zero for the Sharpe ratio difference is outside the confidence region $\hat{\Delta} \pm z_{1-\frac{\alpha}{2}} \hat{s}(\hat{\Delta})$, where $\hat{\Delta} = \hat{\eta}_i - \hat{\eta}_j$, $\hat{s}(\hat{\Delta}) = \{T^{-1}(2 - 2\hat{\rho}_{ij} + \frac{1}{2}(\hat{\eta}_i^2 + \hat{\eta}_j^2 - 2\hat{\eta}_i\hat{\eta}_j\hat{\rho}_{ij}))\}^{0.5}$, $\hat{\eta}_i$, $\hat{\eta}_j$, and $\hat{\rho}_{ij}$ are estimators of the Sharpe ratio difference, the standard error of the difference estimator, the Sharpe ratios, and the correlation between the excess returns of strategy *i* and *j*, respectively. *T* denotes the number of excess return observations for each strategy. Moreover, $z_{1-\frac{\alpha}{2}}$ represents the $(1-\frac{\alpha}{2})$ quantile of the standard normal distribution. Rejecting the null hypothesis of equal risk-adjusted performance suggests that one of the investment strategies outperforms the other. Jorion (1992) notes that the statistical power of the test is low, especially for small samples. Thus, a significant test result can be regarded as strong evidence for a difference in risk-adjusted performance.

holding period to 6 months. Once the holding period is extended, the monthly Sharpe ratio of the 52-week high strategy becomes 0.05. The other major results do not change materially.

Figure 3 (a) displays the annualized Sharpe ratio and Figure 3 (b) displays the time-series return under the 1-month holding period over the preceding 5 years for three strategies – the momentum strategy (dashed line), the 52-week low strategy (dotted line) and an equal mix of the two strategies (solid line). We can observe that regardless of the Sharpe ratio or the raw return, the momentum strategy (dashed line) typically performs well during the period when the 52-week low strategy (dotted line) performs poorly, and vice versa. For example, the momentum strategy performs well in 1993 and 1999, whereas the 52-week low strategy performs poorly that same year. For 2004, the opposite is observed. Moreover, the diversified strategy (solid line) never has a negative raw return and a negative Sharpe ratio over the sample period. The lowest Sharpe ratio of the diversified strategy is 0.01 (in 2009), whereas the highest is 2.04 (in 1965).

[Figure 3 here]

Since our diversified strategy (momentum strategy, 52-week low strategy) never generates a negative raw return and a negative Sharpe ratio over the sample period, it can certainly avoid the momentum cashes and obtain a higher Sharpe ratio, as the risk-managed momentum strategy

proposed by Barroso and Santa-Clara (2015) does. Thus, we next control for the risk-managed momentum strategy to observe whether the diversified strategy, which equally invests in the momentum and 52-week low strategies, would be subsumed by the risk-managed momentum strategy. The risk-managed momentum is constructed following the procedures in Barroso and Santa-Clara (2015). Table 9 reports the results for the time-series regressions. We can observe that the returns of the diversified strategy cannot be fully captured by these explanatory strategies. The risk-adjusted return is 41.28 (t = 3.12) in Column (1). After controlling the risk-managed momentum strategy, the risk-adjusted return is 40.75 (t = 3.28) in Column (2), which means that the diversified strategy proposed in this paper and the risk-managed momentum strategy are separate strategies. They are not the two sides of the same coin.

[Table 9 here]

Collectively, diversifying into the momentum and 52-week low strategies improves the Sharpe ratio the most among the three diversified strategies. The presented empirical evidence not only shows that the pricing information contained in the 52-week low strategy differs from that contained in the momentum strategy but also reveals that the 52-week low strategy is an excellent hedge for the momentum strategy.

To investigate whether our findings are conditional on different specifications, we repeat all tests by considering additional filter criteria, for example, (1) by implementing the strategies with the midpoints of bid-ask quotes to ensure that our results are not driven by the bid-ask bounce ³; (2) without skipping a month between the ranking and holding periods for the momentum strategy; (3) without removing stocks with prices below US\$5; (4) deleting stocks with market capitalizations that are in the smallest NYSE/Amex/Nasdaq decile; and (5) ensuring different exchanges. All of these findings remain robust in relation to various data filters and specifications.

4. Conclusion

Price levels are the most accessible information for investors. Nearly every newspaper that publishes stock prices also identifies their 52-week high and low prices. However, past studies present mixed empirical results on whether the 52-week low contains unpriced information, and whether the unpriced information contained in the 52-week high or low prices subsumes or is subsumed by the information contained in past returns.

³ We repeat all the tests by replacing closing prices with the midpoints of the closing bid and ask quotes, as obtained from CRSP. Because CRSP begins reporting the closing quotes only in the early 1990s, this analysis pertains specifically to the period spanning 1994 to 2014.

This study presents empirical evidence showing that each of the three variables (i.e., the nearness to the 52-week high, nearness to the 52-week low, and past returns) contain exclusive unpriced information in the cross-sectional pricing of stocks. Based on the results of univariate portfolio-level analysis, the zero-investment strategy based on the sorting of past returns (i.e., the momentum strategy) and the nearness to the 52-week low (i.e., the 52-week low strategy) can generate significant risk-adjusted returns in the first holding month. However, the zero-investment strategy based on the sorting of the nearness to the 52-week high (i.e., the 52-week high strategy) cannot generate significant risk-adjusted returns in the first holding month, but can produce significant risk-adjusted returns when the strategy is held for more than 3 months. Moreover, the returns of the three strategies are negatively correlated, and exhibit significantly different patterns under different market states. Bivariate portfolio-level analysis and the Fama-Macbeth regression further confirm that the pricing information embedded in past returns, the 52-week high, and the 52-week low differs. The coefficients of past returns and the nearness to the 52-week low are always significant after controlling for each other and other firm characteristics. However, we do not find any evidence showing that the 52-week high or low strategy can explain the momentum strategy. Based on these findings, we further show that the 52-week low strategy can act as a hedge for the momentum strategy. Diversifying into the momentum strategy and the 52-week strategy significantly enhances the annualized Sharpe ratio, to 0.98.

Overall, our results reveal that the nearness to extreme prices, especially the nearness to the 52-week low, provides predictive power for future returns, and that their predictive power is separate from that of past returns. This finding supports the results presented by Huddart, Lang, and Yetman (2009), who report that extreme prices in a stock's past price path affect investors' trading decisions in equity markets. Moreover, the 52-week low strategy provides an excellent hedge for the momentum strategy. Given the nearly doubled Sharpe ratio of the hedged strategy, the momentum becomes a greater puzzle than the original version. Momentum investors should consequently focus on the nearness to the 52-week low when selecting their portfolio holdings, The Although this study does not provide an exact explanation for momentum, the finding that the nearness to the 52-week high and to the 52-week low as well as past returns each contain exclusive unpriced information in the cross-sectional pricing of stocks implies that momentum is not best characterized as an anchoring bias; hence, the explanation for momentum is to be found elsewhere. Because the nearness to the 52-week extreme prices is public information, our findings present a serious challenge to the notion that markets are semi-strong form efficient.

Table 1 Descriptive statistics of the 52-week high, 52-week low, and firm characteristics

This table lists the summary statistics. The sample includes all NYSE-, Amex-, and Nasdaq-listed nonfinancial common stocks (share codes 10 or 11) for the period spanning January 1962 to December 2014. Panel A lists the summary statistics of the variables HIGH, LOW, and other firm characteristics. The nearness to the 52-week high (*HIGH*) or low price (*LOW*) is measured as $\frac{P_{i,t}}{high_{i,t}}$ or $\frac{P_{i,t}}{low_{i,t}}$, respectively, where $P_{i,t}$ denotes the price of stock *i* at the end of month t, and $high_{i,t}$ and $low_{i,t}$ are the highest and the lowest prices of stock i, respectively, in the past 52 weeks. Size denotes the market value of equity, and B/M represents the book-to-market ratio. The turnover rate (Turnover) is defined as the shares traded divided by outstanding shares. Monthly idiosyncratic volatility (IVol) is defined as the standard deviation of the regression residuals of the Fama and French (1993) three-factor model. At the beginning of each month t, the daily excess returns of stock i in month t-1 are regressed on the daily three Fama and French (1993) factors for obtaining the residuals. Illiq is the Amihud (2002) illiquidity measure, which is defined as the time-series average of absolute daily returns divided by the daily dollar trading volume. The Illiq variable is scaled up by 10^6 . Standardized unexpected earnings (SUE) for stock *i* in each month are computed as the most recently announced earnings minus the earnings from four quarters ago. This earnings change is standardized by its standard deviation estimated over the prior eight quarters. $R_{(1,2)}$ and $R_{(2,13)}$ represent the cumulative returns from months t - 1 to t - 2 and t - 2 to t - 13, respectively. Panel B shows the correlation matrix between these variables.

	Panel A. Descriptive statistics									
	HIGH	LOW	Size (\$10 ⁶)	BM	Turnover	IVol	Illiq	SUE	R _(1,2)	R _(2,13)
Mean	0.74	1.54	1552.83	0.88	0.06	0.03	0.01	0.36	0.01	0.23
Median	0.79	1.28	58.63	0.69	0.03	0.02	0.00	0.22	0.00	0.13
Standard Devitation	0.21	2.25	11162.03	3.48	0.15	0.02	0.14	1.47	0.16	0.64
Maximum	1.00	450.62	697505.40	154.40	58.40	2.35	67.72	47.11	24.00	46.00
Minimum	0.00	1.00	0.00	-906.64	0.00	0.00	0.00	-7.74	-0.98	-0.99
			Panel B. (Correlatio	n matrix					
	HIGH	LOW	Size	BM	Turnover	IVol	Illiq	SUE	R _(1,2)	R _(2,13)
HIGH	1.00									
LOW	0.07	1.00								
Size	0.05	-0.01	1.00							
BM	0.10	-0.02	-0.10	1.00						
Turnover	-0.06	0.12	0.05	-0.11	1.00					
IVol	-0.29	0.11	-0.10	0.04	0.26	1.00				
Illiq	-0.05	0.00	-0.03	0.11	-0.06	0.17	1.00			
SUE	0.13	0.02	0.04	-0.08	-0.02	-0.08	-0.04	1.00		
R _(1,2)	0.31	0.10	0.00	0.04	0.11	0.21	0.01	0.05	1.00	
$R_{(2,13)}$	0.24	0.20	0.00	0.06	0.15	0.06	-0.04	0.20	0.00	1.00

Table 2 Performance of trading strategies estimated with simple raw returns and risk-adjusted returns: Value-weighted

This table reports the average monthly raw returns, *t* values, and monthly risk-adjusted returns for three trading strategies from the period spanning January 1962 to December 2014. The sample includes all nonfinancial common stocks listed in NYSE, Amex, and Nasdaq. The 52-week high strategy involves buying stocks in the top *n*% based on the variable *HIGH*, and selling the other (*1-n*)% stocks, which are labeled *n/1-n* in Panel A. Conversely, the 52-week low strategy involves buying stocks in the bottom *n*% based on the variable *LOW*, and selling the other (*1-n*)% stocks, which are also labeled *n/1-n* in Panel B. The nearness to the 52-week high (*HIGH*) or low price (*LOW*) is measured as $\frac{P_{tx}}{high_{tx}}$ or $\frac{P_{tx}}{tow_{tx}}$, respectively, where P_{tx} denotes the price of stock *i* at the end of month *t*, and *high_{tx}* and *low_{tx}* respectively represent the highest and the lowest prices of stock *i* in the past 52 weeks. The momentum strategy involves buying *n*% winners and selling the bottom *m*% losers based on the sorting of the past 12-month returns, which are labeled *n/m* in Panel C. We skip one full month between the formation period and the holding period in the construction of the momentum portfolio. Each portfolio is value-weighted and held for 1 month. The *t*-statistics in parentheses are adjusted for autocorrelation by using the Newey–West covariance matrix. Asterisks * and ** indicate significance at the 5% and 1% levels, respectively. The factor data are collected from Kenneth R. French's website.

				Panel	A. The 52-we	ek high str	ategy						
		phas and b	oeta coefficie	Alp	has and thre	e-factor loa	dings		Alph	as and five	-factor load	lings	
Long-short strategy (n/1-n)	Raw return	α	MKT	α	MKT	SMB	HML	α	MKT	SMB	HML	RMW	CMA
05/95	-30.48	-18.29	-0.24	-22.24	-0.22	0.02	0.08	-33.55	-0.20	0.08	-0.03	0.19	0.22
	(-2.65)**	(-1.69)	(-9.74)**	(-2.03)*	(-8.61)**	(0.57)	(1.95)	(-2.97)**	(-7.24)**	(2.06)*	(-0.50)	(3.29)**	(2.74)**
10/90	-15.94	-2.08	-0.27	-5.96	-0.24	-0.06	0.10	-18.15	-0.21	0.01	0.00	0.23	0.23
	(-1.48)	(-0.21)	(-12.26)**	(-0.61)	(-10.09)**	(-1.71)	(2.71)**	(-1.80)	(-8.52)**	(0.22)	(-0.03)	(4.54)**	(3.18)**
20/80	-0.48	13.70	-0.27	11.20	-0.24	-0.09	0.08	-1.32	-0.21	-0.04	-0.04	0.20	0.28
	(-0.05)	(1.48)	(-13.23)**	(1.20)	(-10.79)**	(-2.95)**	(2.30)*	(-0.14)	(-8.93)**	(-1.19)	(-0.87)	(4.25)**	(4.10)**
30/70	3.68	18.16	-0.28	14.64	-0.23	-0.12	0.11	2.46	-0.20	-0.08	-0.01	0.18	0.30
	(0.35)	(1.92)	(-13.18)**	(1.55)	(-10.34)**	(-3.90)**	(3.13)**	(0.25)	(-8.43)**	(-2.29)*	(-0.32)	(3.77)**	(4.36)**
				Panel	B. The 52-w	eek low stra	itegy						
		phas and b	oeta coefficie	Alp	has and thre	e-factor loa	dings		Alph	as and five	-factor load	lings	
Long-short strategy (n/1-n)	Raw return	α	MKT	α	MKT	SMB	HML	α	MKT	SMB	HML	RMW	CMA
05/95	61.74	58.37	0.07	58.27	0.05	0.05	-0.01	63.17	0.05	0.03	0.00	-0.08	-0.04
	(4.67)**	(4.40)**	(2.19)*	(4.32)**	(1.59)	(1.20)	(-0.25)	(4.51)**	(1.39)	(0.53)	(0.01)	(-1.17)	(-0.37)
10/90	42.80	44.77	-0.04	45.14	-0.04	-0.01	-0.01	43.43	-0.02	-0.02	-0.06	-0.01	0.12
	(3.60)**	(3.74)**	(-1.42)	(3.70)**	(-1.30)	(-0.16)	(-0.14)	(3.43)**	(-0.80)	(-0.56)	(-0.96)	(-0.16)	(1.25)
20/80	20.97	26.01	-0.10	23.84	-0.07	-0.09	0.07	22.23	-0.06	-0.09	0.08	0.03	0.00
	(1.94)	(2.42)*	(-4.05)**	(2.20)*	(-2.54)*	(-2.38)*	(1.75)	(1.97)*	(-2.30)*	(-2.34)*	(1.40)	(0.46)	(0.05)
30/70	11.32	17.42	-0.12	13.76	-0.07	-0.13	0.11	11.49	-0.06	-0.12	0.13	0.07	-0.01
	(1.10)	(1.72)	(-5.20)**	(1.36)	(-2.84)**	(-3.87)**	(3.06)**	(1.10)	(-2.49)*	(-3.44)**	(2.62)**	(1.29)	(-0.10)
				Panel	C. The mon	entum strat	tegy						
		phas and b	oeta coefficie	Alp	has and thre	e-factor loa	dings		Alph	as and five	-factor load	lings	
Long-short strategy (n/m)	Raw return	α	MKT	α	MKT	SMB	HML	α	MKT	SMB	HML	RMW	CMA
10/10	135.52	141.15	-0.11	166.61	-0.25	0.14	-0.58	158.23	-0.22	0.13	-0.79	-0.03	0.42
	(4.81)**	(4.99)**	(-1.74)	(5.95)**	(-3.74)**	(1.46)	(-5.68)**	(5.44)**	(-3.05)**	(1.28)	(-5.69)**	(-0.20)	(2.01)*
20/20	78.53	82.66	-0.08	101.37	-0.20	0.17	-0.44	95.68	-0.17	0.16	-0.61	-0.04	0.32
	(3.29)**	(3.44)**	(-1.50)	(4.26)**	(-3.55)**	(2.12)*	(-5.12)**	(3.87)**	(-2.91)**	(1.86)	(-5.15)**	(-0.28)	(1.77)

Table 3 Correlation matrix of the performance of trading strategies estimated with simple raw returns

This table reports the correlation matrix of raw returns for three trading strategies used from January 1962 to December 2014. The sample includes all nonfinancial common stocks listed in NYSE, Amex, and Nasdaq. The 52-week high strategy involves buying stocks in the top 10% based on the variable *HIGH*, and selling the other 90% of stocks. Conversely, the 52-week low strategy involves buying stocks in the bottom 10% based on the variable *LOW*, and selling the other 90% of stocks, which are also labeled *n/1-n*. The nearness to the 52-week high (*HIGH*) or low price (*LOW*) is measured as $\frac{P_{i,t}}{high_{i,t}}$ or $\frac{P_{i,t}}{low_{i,t}}$, respectively, where $P_{i,t}$ denotes the price of stock *i* at the end of month *t*, and *high_{i,t}* and *low_{i,t}* represent the highest and the lowest prices of stock *i* in the past 52 weeks, respectively. The momentum strategy involves buying 10% of winners and selling the bottom 10% of losers based on the sorting of the past 12-month returns. We skip one full month between the formation period and the holding period in the construction of the momentum portfolio. Each portfolio is value-weighted and held for 1 month in Panel A and for 6 months in Panel B.

Panel A. Holding for one month								
The momentum strategy The 52-week high strategy The 52-week low								
The momentum strategy	1.00							
The 52-week high strategy	0.38	1.00						
The 52-week low strategy	-0.44	-0.33	1.00					
	Panel B. Holdir	ng for six months						
	The momentum strategy	The HIGH strategy	The LOW strategy					
The momentum strategy	1.00							
The 52-week high strategy	0.47	1.00						
The 52-week low strategy	-0.53	-0.47	1.00					

Table 4 Performance of trading strategies conditional on market state

This table reports the average monthly raw returns, *t* values, and monthly risk-adjusted returns for three trading strategies used from January 1962 to December 2014 under different market states. The sample includes all nonfinancial common stocks listed in NYSE, Amex, and Nasdaq. An up market occurs when the market return in the past 24 months is nonnegative, whereas a down market occurs when the market return over the past 24 months is nonnegative, whereas a down market occurs when the market return over the past 24 months is negative. The 52-week high strategy involves buying stocks in the top *n*% based on the variable *HIGH* and selling the other (*1-n*)% stocks, and is labeled *n/1-n* in Panel A. Conversely, the 52-week low strategy involves buying stocks in the bottom *n*% based on the variable *LOW* and selling the other (*1-n*)% stocks, and is also labeled *n/1-n* in Panel B. The nearness to the 52-week high (*HIGH*) or low price (*LOW*) is measured as $\frac{P_{i,t}}{high_{i,t}}$ or $\frac{P_{i,t}}{low_{i,t}}$, respectively, where $P_{i,t}$ denotes the price of stock *i* at the end of month *t*, and $high_{i,t}$ and $low_{i,t}$ are the highest and the lowest prices of stock *i* in the past 52 weeks, respectively. The momentum strategy is to purchase of *n*% winners and sell the bottom *m*% losers based on the sorting of the past 12-month return, which is labeled *n/m* in Panel C. We skip one full month between the formation period and the holding period in the construction of the momentum portfolio. Each portfolio is value-weighted and held for 1 month. The *t*-statistics in parentheses are adjusted for autocorrelation by using the Newey–West covariance matrix. Asterisks * and ** indicate significance at the 5% and 1% levels, respectively. The factor data are collected from Kenneth R. French's website.

					Panel A. The 52-	week high	strategy					
		UP	market			DOW	N market		Mean com	parison (UI	P market - DOW	'N market)
Long-short strategy	Raw return	CAPM	Three-factor	Five-factor	Raw return	CAPM	Three-factor	Five-factor	Raw return	CAPM	Three-factor	Five-factor
05/95	-22.56	-12.49	-19.49	-27.26	-76.88	-57.98	-56.79	-76.05	54.32	45.49	37.30	48.79
	(-1.90)	(-1.09)	(-1.68)	(-2.30)*	(-2.06)*	(-1.88)	(-1.81)	(-2.13)*	(1.39)	(1.38)	(1.11)	(1.30)
10/90	-7.93	3.69	-2.34	-10.07	-62.87	-41.86	-40.92	-63.66	54.93	45.55	38.58	53.59
	(-0.72)	(0.36)	(-0.22)	(-0.95)	(-1.71)	(-1.49)	(-1.48)	(-2.08)*	(1.43)	(1.52)	(1.30)	(1.65)
20/80	12.87	24.55	18.02	11.55	-78.65	-56.61	-49.61	-87.19	91.52	81.16	67.63	98.74
	(1.24)	(2.55)*	(1.85)	(1.17)	(-2.16)*	(-2.12)*	(-1.90)	(-3.14)**	(2.42)*	(2.86)**	(2.43)*	(3.35)**
30/70	19.06	31.20	22.28	15.96	-86.40	-64.50	-53.42	-86.46	105.46	95.70	75.70	102.42
	(1.80)	(3.18)**	(2.28)*	(1.61)	(-2.32)*	(-2.30)*	(-2.01)*	(-3.01)**	(2.73)**	(3.23)**	(2.67)**	(3.37)**
					Panel A. The 52	-week low s	trategy					
		UP	market			DOW	N market		Mean com	parison (UI	P market - DOW	'N market)
Long-short strategy	Raw return	CAPM	Three-factor	Five-factor	Raw return	CAPM	Three-factor	Five-factor	Raw return	CAPM	Three-factor	Five-factor
05/95	50.55	47.06	43.97	46.71	127.27	124.11	119.48	152.16	-76.72	-77.05	-75.52	-105.45
	(3.72)**	(3.45)**	(3.14)**	(3.26)**	(2.96)**	(2.87)**	(2.82)**	(3.18)**	(-1.70)	(-1.70)	(-1.69)	(-2.11)*
10/90	30.53	33.10	29.47	27.63	114.69	115.13	122.64	124.84	-84.16	-82.03	-93.17	-97.20
	(2.46)*	(2.65)**	(2.31)*	(2.11)*	(3.13)**	(3.11)**	(3.34)**	(2.99)**	(-2.18)*	(-2.10)*	(-2.40)*	(-2.22)*
20/80	8.94	15.13	9.77	7.85	91.46	93.63	97.98	105.81	-82.53	-78.50	-88.21	-97.96
	(0.80)	(1.37)	(0.87)	(0.68)	(2.71)**	(2.76)**	(2.84)**	(2.66)**	(-2.32)*	(-2.20)*	(-2.43)*	(-2.37)*
30/70	0.44	7.49	1.21	-0.12	75.03	78.90	80.08	76.76	-74.59	-71.41	-78.86	-76.88
	(0.04)	(0.69)	(0.11)	(-0.01)	(2.67)**	(2.81)**	(2.78)**	(2.32)*	(-2.47)*	(-2.38)*	(-2.57)*	(-2.21)*
					Panel A. The m	omentum st	rategy					
		UP	market			DOW	N market		Mean com	parison (UI	P market - DOW	'N market)
Long-short strategy	Raw return	CAPM	Three-factor	Five-factor	Raw return	CAPM	Three-factor	Five-factor	Raw return	CAPM	Three-factor	Five-factor
10/10	168.59	160.75	191.75	203.46	-57.85	-13.39	1.25	-138.20	226.44	174.14	190.50	341.66
	(5.89)**	(5.59)**	(6.76)**	(7.04)**	(-0.62)	(-0.17)	(0.02)	(-1.63)	(2.31)*	(2.06)*	(2.25)*	(3.81)**
20/20	106.80	99.17	122.81	132.83	-86.74	-48.78	-43.86	-137.98	193.54	147.95	166.67	270.81
	(4.37)**	(4.04)**	(5.07)**	(5.38)**	(-1.12)	(-0.75)	(-0.67)	(-1.94)	(2.38)*	(2.13)*	(2.39)*	(3.60)**

Table 5 Performance of trading strategies under bivariate sorts

This table reports the average monthly raw returns, t values, and monthly risk-adjusted returns for three trading strategies under bivariate sorts. The sample includes all nonfinancial common stocks listed in NYSE, Amex, and Nasdaq. For Panel A, we first sort the stocks to quintiles based on the variable *HIGH*, measured as $\frac{P_{i,t}}{high_{i,t}}$, where $P_{i,t}$ denotes the price of stock i at the end of month t, and $high_{i,t}$ represents the highest price of stock i over the past 52 weeks. For each *HIGH* quintile, we compute the raw return and the monthly risk-adjusted return of the momentum strategy and the 52-week low strategy. The other two panels are devised in a similar manner. We skip one full month between the formation period and the holding period in the construction of the momentum portfolio. Each portfolio is value-weighted and held for 1 month. The *t*-statistics in parentheses are adjusted for autocorrelation by using the Newey-West covariance matrix. Asterisks * and ** indicate significance at the 5% and 1% levels, respectively. The factor data are collected from Kenneth R. French's website.

	F	Panel A. Cor	trolled for the	nearness to th	e 52-week high (H	-IIGH)		
		The mome	ntumstrategy			The 52-wee	k low strategy	
HIGH quintile	Raw return	CAPM	Three-factor	Five-factor	Raw return	CAPM	Three-factor	Five-factor
1 (low)	197.92	211.12	241.01	222.95	93.13	89.45	80.05	85.60
	(5.74)**	(6.13)**	(7.01)**	(6.24)**	(4.96)**	(4.74)**	(4.19)**	(4.30)**
2	114.66	101.91	121.13	128.84	88.79	100.25	88.32	80.30
	(3.98)**	(3.56)**	(4.27)**	(4.38)**	(5.12)**	(5.89)**	(5.19)**	(4.54)**
3	130.02	111.96	130.10	150.21	45.73	61.55	55.39	47.70
	(4.55)**	(3.99)**	(4.92)**	(5.50)**	(2.90)**	(4.13)**	(3.73)**	(3.11)**
4	152.88	128.42	147.41	165.77	-1.22	11.92	3.17	-2.43
	(5.53)**	(4.85)**	(5.97)**	(6.51)**	(-0.09)	(0.92)	(0.25)	(-0.18)
5 (high)	107.31	87.07	111.59	134.53	-1.42	9.11	-0.73	-4.99
	(4.03)**	(3.37)**	(4.65)**	(5.48)**	(-0.11)	(0.74)	(-0.06)	(-0.39)
]	Panel B. Cor	ntrolled for the	nearness to th	e 52-week low (L	(WC		
		The 52-weel	k high strategy			The moment	ntum strategy	
LOW quintile	Raw return	CAPM	Three-factor	Five-factor	Raw return	CAPM	Three-factor	Five-factor
1 (low)	-35.14	-15.68	-19.97	-38.24	190.83	183.29	217.43	224.53
	(-2.09)*	(-1.01)	(-1.29)	(-2.41)*	(5.56)**	(5.32)**	(6.34)**	(6.30)**
2	-24.11	-5.99	-10.87	-26.29	190.64	200.38	218.19	196.97
	(-1.75)	(-0.48)	(-0.88)	(-2.09)*	(7.10)**	(7.47)**	(8.09)**	(7.07)**
3	-7.79	11.34	5.43	-10.63	134.42	150.02	172.47	163.48
	(-0.61)	(1.02)	(0.50)	(-0.96)	(4.84)**	(5.47)**	(6.32)**	(5.77)**
4	5.90	23.16	16.75	9.64	109.68	123.73	147.56	126.42
	(0.46)	(2.01)*	(1.47)	(0.82)	(3.97)**	(4.51)**	(5.47)**	(4.54)**
5 (high)	-15.15	1.89	-6.25	-17.88	44.75	74.63	91.09	66.73
	(-1.05)	(0.14)	(-0.47)	(-1.30)	(1.47)	(2.60)**	(3.18)**	(2.26)*
			Panel C. Con	trolled for pas	t return			
		The 52-weel	k high strategy			The 52-wee	k low strategy	
Past return quintile	Raw return	CAPM	Three-factor	Five-factor	Raw return	CAPM	Three-factor	Five-factor
1 (loser)	-11.37	1.26	-3.95	-20.09	137.82	134.95	127.74	125.00
	(-0.67)	(0.08)	(-0.24)	(-1.17)	(7.92)**	(7.71)**	(7.20)**	(6.79)**
2	-40.41	-33.11	-31.52	-37.27	87.11	85.56	93.78	101.49
	(-3.01)**	(-2.49)*	(-2.33)*	(-2.66)**	(6.06)**	(5.91)**	(6.44)**	(6.74)**
3	-42.45	-31.56	-33.34	-36.03	74.16	74.31	74.14	65.91
	(-3.29)**	(-2.54)*	(-2.63)**	(-2.76)**	(5.74)**	(5.71)**	(5.60)**	(4.81)**
4	-38.77	-28.00	-32.40	-39.31	27.37	25.52	29.96	34.66
	(-3.27)**	(-2.47)*	(-2.82)**	(-3.31)**	(2.10)*	(1.94)	(2.26)*	(2.51)*
5 (winner)	-39.00	-26.60	-33.69	-44.93	2.16	1.54	2.44	0.01
	(-2.66)**	(-1.88)	(-2.36)*	(-3.04)**	(0.14)	(0.10)	(0.16)	(0.00)

Table 6 Fama–Macbeth regressions for controlling for other return determinants

This table presents the results of the Fama–Macbeth regression using all nonfinancial common stocks listed in NYSE, Amex, and Nasdaq from January 1962 to December 2014. Each month, we cross-sectionally regress the returns on various variables, as follows: The dummy *HIGH_D* (*LOW_D*) is assigned a value of 1 if the nearness to the 52-week high (low) price measure for a stock is ranked in the top (bottom) 10% at the beginning of month *t*. The dummy *Winner* (*Loser*) denotes whether a firm is included in the top (bottom) 10% portfolio based on the past 12-month returns. Ln(Size) represents the natural log of firm capitalization, whereas *Ln(BM)* denotes the natural log of the book-to-market ratio. $R_{(1,2)}$ denotes the cumulative returns from month t - 1 to month t - 2. The turnover rate (*Turnover*) is defined as the shares traded within 1 month divided by outstanding shares. Monthly idiosyncratic volatility (*IVol*) is defined as the standard deviation of regression residuals of the Fama and French (1993) three-factor model. At the beginning of each month *t*, the daily excess returns of stock *i* in month *t*-*1* are regressed on the daily three Fama and French (1993) factors for obtaining the residuals. The monthly illiquidity measure (*Illiq*) for each stock is computed by dividing the daily absolute return by the daily trading volume, and then averaging this daily quantity over the month. The *Illiq* variable is scaled up by 10³. The *t*-statistics (in parentheses) are calculated from the times series and adjusted for autocorrelation by using the Newey–West covariance matrix. Asterisks * and ** indicate significance at the 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.0127	0.0126	0.0131	0.0127	0.0171	0	0.025
	(4.97)**	(4.98)**	(5.31)**	(4.98)**	(4.72)**		(9.47)**
HIGH_D	0.0001			-0.0005	-0.0009	0	0.0019
	(0.08)			(-0.37)	(-0.90)		(2.63)**
LOW_D		0.0027		0.0044	0.007	0	0.0027
		(2.53)*		(4.34)**	(8.30)**		(4.20)**
Winner			0.0049	0.0057	0.0073	0	0.0063
			(3.02)**	(3.84)**	(5.12)**		(5.80)**
Loser			-0.011	-0.0115	-0.009	0	-0.0068
			(-9.12)**	(-10.01)**	(-8.69)**		(-7.27)**
ln(Size)					-0.0009	0	-0.0016
					(-2.00)**		(-4.56)**
ln(BM)					0.003	0	0.0033
					(4.25)**		(6.05)**
R (1, 2)						0	-0.0537
							(-12.95)**
Turnover							0.0682
							(5.07)**
IVol							-0.2876
							(-7.70)**
Illiq							0.6946
							(2.65)**
Average R-square	0.00	0.00	0.01	0.01	0.03		0.05

Table 7 Time-series regressions of trading strategies

This table reports the monthly risk-adjusted returns in basis points and its *t*-value under time-series regressions for three trading strategies: the 52-week high strategy (Panel A), 52-week low strategy (Panel B), and momentum strategy (Panel C). All nonfinancial common stocks listed in NYSE, Amex, and Nasdaq from January 1962 to December 2014 are included. We regress the returns of a test strategy on those of explanatory strategies, as follows: $y_t = \alpha + \beta' X_t + \varepsilon_t$, where y_t denotes the monthly excess returns for three testing strategies: the 52-week high strategy, 52-week low strategy (Panel B), and momentum strategy (Panel C). The supplementary explanatory factors are the returns to the Fama and French five factors (i.e., MKT, SMB, HML, RMW, and CMA) as well as the monthly excess returns of the other two testing strategies, which are not regarded as the dependent variable. Each portfolio is held for 1 month. The *t*-statistics (in parentheses) are calculated from the times series and adjusted for autocorrelation by using the Newey–West covariance matrix. Asterisks * and ** indicate significance at the 5% and 1% levels, respectively.

Panel A. $y =$ The 52-week high strategy								
		(1)		(2)				
~ _	-42.49	(-4.60)**	-3.93	(-0.42)				
β_{MKT}	-0.18	(-7.93)**	-0.22	(-9.70)**				
β_{SMB}	-0.01	(-0.39)	0.00	(-0.01)				
β_{HML}	0.12	(2.72)**	-0.02	(-0.46)				
β_{RMW}	0.23	(5.17)**	0.23	(4.91)**				
β_{CMA}	0.17	(2.54)*	0.27	(4.05)**				
β_{MOM}	0.15	(12.27)**						
β_{LOW}			-0.33	(-11.20)**				
Average R-square		0.38		0.36				
	Panel B.	y = The 52-week le	ow strategy					
		(1)		(2)				
~ _	75.86	(6.62)**	34.00	(2.93)**				
β_{MKT}	-0.07	(-2.51)*	-0.13	(-4.48)**				
β_{SMB}	0.00	(0.05)	-0.02	(-0.51)				
β_{HML}	-0.22	(-4.00)**	-0.06	(-1.06)				
β_{RMW}	-0.02	(-0.29)	0.11	(1.85)				
β_{CMA}	0.20	(2.48)*	0.24	(2.79)**				
_{Вмом}	-0.20	(-13.16)**						
β_{HIGH}			-0.52	(-11.20)**				
Average R-square		0.22		0.17				
	Panel C.	y = The momentu	ımstrategy					
_		(1)		(2)				
~ _	181.55	(6.95)**	205.05	(7.91)**				
β_{MKT}	0.05	(0.78)	-0.24	(-3.88)**				
β_{SMB}	0.12	(1.32)	0.10	(1.16)				
β_{HML}	-0.78	(-6.33)**	-0.85	(-6.94)**				
β_{RMW}	-0.32	(-2.44)*	-0.04	(-0.32)				
β_{CMA}	0.13	(0.66)	0.55	(2.94)**				
β_{HIGH}	1.28	(12.27)**						
β_{LOW}			-1.08	(-13.16)**				
Average R-square	0.25 0.27			0.27				

Table 8 Volatility and Sharpe ratio of diversified strategies

This table presents the volatility (Panel A) and Sharpe ratios (Panel B) of a single trading strategy and three diversified trading strategies. The single trading strategy includes the 52-week high strategy, 52-week low strategy, and momentum strategy. All single strategies are value-weighted. For diversification, we choose two strategies from the three single strategies, and equally invest our capital into the two strategies, denoted as (m, n). We hold the single and diversified strategies for 1 month. Volatility is computed as the standard deviation of the monthly raw returns. The Sharpe ratio is defined as dividing the alpha under alternative factor models by the idiosyncratic volatility of the portfolio returns. Asterisks * and ** indicate significance at the 5% and 1% levels, respectively.

	Panel A. Vola	tility	
		Single strategy	
	(52-week high strategy)	(52-week low strategy)	(momentum strategy)
Volatility	0.03	0.03	0.07
		Diversified into two strategies (m,n)	
	(52-week high strategy, 52-week low strategy)	(momentum strategy, 52-week low strategy)	(momentum strategy, 52-week high strategy)
Volatility	0.02	0.03	0.06
		F-test for equality of variances	
	(52-week high strategy, 52-week low strategy)	(momentum strategy, 52-week low strategy)	(momentum strategy, 52-week high strategy)
Diversified strategy (m, n) - the momentum strategy		-0.04	-0.01
		[4.97]**	[1.78]
Diversified strategy (m, n) - the 52-week high strategy	-0.01		0.03
	[2.69]**		[3.41]**
Diversified strategy (m,n) - the 52-week low strategy	-0.01	0.002	
	[3.28]**	[0.89]	
	Panel B. Sharpe	e ratio	
		Single strategy	
	(52-week high strategy)	(52-week low strategy)	(momentum strategy)
Sharpe ratio	-0.06	0.14	0.19
		Diversified into two strategies (m,n)	
	(52-week high strategy, 52-week low strategy)	(momentum strategy, 52-week low strategy)	(momentum strategy, 52-week high strategy)
Sharpe ratio	0.14	0.28	0.08
		T-test for mean difference	
	(52-week high strategy, 52-week low strategy)	(momentum strategy, 52-week low strategy)	(momentum strategy, 52-week high strategy)
Diversified strategy (m,n) - the momentum strategy		0.09	-0.05
		(39.41)**	(-22.51)**
Diversified strategy (m,n) - the 52-week high strategy	0.14		0.20
	(62.07)**		(88.18)**
Diversified strategy (m, n) - the 52-week low strategy	-0.06	0.14	
	(-27.35)**	(60.78)**	

Table 9 Time-series regressions of the diversified strategy

This table reports the monthly risk-adjusted returns in basis points and its *t*-value under time-series regressions for the diversified strategy which equally invest in the momentum and 52-week low strategies at the beginning of each month. All nonfinancial common stocks listed in NYSE, Amex, and Nasdaq from January 1962 to December 2014 are included. We regress the returns of the diversified strategy on various explanatory strategies. The supplementary explanatory factors are the returns to the Fama and French five factors (i.e., MKT, SMB, HML, RMW, and CMA) as well as the risk-managed momentum strategy (RISK-MOM). The risk-managed momentum strategy is constructed following the procedures in Barroso and Santa-Clara (2015). Each portfolio is held for 1 month. The *t*-statistics (in parentheses) are calculated from the times series and adjusted for autocorrelation by using the Newey–West covariance matrix. Asterisks * and ** indicate significance at the 5% and 1% levels, respectively.

Diversified s	Diversified strategy: (momentum strategy, 52-week low strategy)							
		(1)		(2)				
~ _	41.28	(3.12)**	40.75	(3.28)**				
β_{MKT}	0.02	(1.29)	0.14	(1.59)				
β_{SMB}	0.28	(2.14)*	0.31	(2.08)*				
β_{HML}	-0.46	(3.52)**	-0.37	(2.75)**				
β_{RMW}	0.15	(0.98)	0.25	(1.99)*				
β_{CMA}	0.27	(2.56)*	0.31	(3.03)**				
$\beta_{RISK-MOM}$			0.12	(1.37)				
Average R-square		0.19	(0.21				



Figure 1 Monthly raw return in the *K***th month after portfolio construction.** This graph plots the average monthly raw returns of overlapping portfolios for the 52-week high strategy, 52-week low strategy, and momentum strategy in the *K*th month. The sample excludes financial firms and spans January 1962 to December 2014.



Figure 2 Time-series monthly raw return of trading strategies. This graph shows the average monthly raw returns of the 52-week high strategy, 52-week low strategy, and momentum strategy over the past 5 years at the end of each month between December 1967 and December 2014. The sample excludes financial firms.



(a) Annualized Sharpe ratio



(b) Monthly raw return

Figure 3 Time-series Sharpe ratio of various trading strategies. This graph shows the annualized Sharpe ratio and the monthly raw return of the momentum strategy, 52-week low strategy, and diversified strategy over the past 5 years at the end of each month between December of 1967 and 2014. The diversified strategy is to equally invest in the momentum strategy and the 52-week low strategy. The sample excludes financial firms.

Appendix tables

Table A1 Performance of trading strategies estimated by simple raw returns and risk-adjusted returns: Equal-weighted

This table lists the average monthly raw returns, *t* values, and monthly risk-adjusted returns for three trading strategies used from January 1962 to December 2014. The sample includes all nonfinancial common stocks listed in NYSE, Amex, and Nasdaq. The 52-week high strategy involves buying stocks in the top *n*% based on the variable *HIGH* and selling the other (*1-n*)% stocks, and is labeled *n/1-n* in Panel A. Conversely, the 52-week low strategy involves buying stocks in the bottom *n*% based on the variable *LOW* and selling the other (*1-n*)% stocks, and is also labeled *n/1-n* in Panel B. The nearness to the 52-week high (*HIGH*) or low price (*LOW*) is measured as $\frac{P_{i,t}}{high_{i,t}}$ or $\frac{P_{i,t}}{low_{i,t}}$, respectively, where $P_{i,t}$ denotes the price of stock *i* at the end of month *t*, and *high_{i,t}* and *low_{i,t}* respectively represent the highest and the lowest prices of stock *i* in the past 52 weeks. The momentum strategy involves buying *n*% winners and selling the bottom *m*% losers based on the sorting of the past 12-month returns, and is labeled *n/m* in Panel C. We skip one full month between the formation period and the holding period in the construction of the momentum portfolio. Each portfolio is equal-weighted and held for 1 month. The *t*-statistics in parentheses are adjusted for autocorrelation by using the Newey–West covariance matrix. Asterisks * and ** indicate significance at the 5% and 1% levels, respectively. The

factor data are collected from Kenneth R. French's website.

				Panel	A. The 52-w	eek high stı	rategy						
		phas and b	oeta coefficie	Alp	has and thre	e-factor loa	dings		Alph	as and five-	-factor load	ings	
Long-short strategy (n/1-n)	Raw return	α	MKT	α	MKT	SMB	HML	α	MKT	SMB	HML	RMW	CMA
05/95	14.99	32.25	-0.33	40.06	-0.30	-0.25	-0.10	29.11	-0.27	-0.21	-0.20	0.14	0.30
	(1.28)	(3.16)**	(-14.60)**	(4.03)**	(-12.60)**	(-7.44)**	(-2.72)**	(2.85)**	(-10.75)**	(-5.95)**	(-4.14)**	(2.73)**	(4.03)**
10/90	19.61	36.70	-0.33	43.26	-0.28	-0.28	-0.06	30.51	-0.25	-0.23	-0.16	0.19	0.30
	(1.74)	(3.78)**	(-15.20)**	(4.66)**	(-12.69)**	(-9.10)**	(-1.85)	(3.22)**	(-10.64)**	(-7.19)**	(-3.64)**	(4.02)**	(4.42)**
20/80	25.69	42.94	-0.33	47.83	-0.27	-0.30	-0.02	33.31	-0.23	-0.24	-0.15	0.21	0.36
	(2.31)*	(4.52)**	(-15.66)**	(5.31)**	(-12.76)**	(-9.75)**	(-0.74)	(3.65)**	(-10.46)**	(-7.81)**	(-3.44)**	(4.51)**	(5.44)**
30/70	30.09	47.48	-0.34	51.06	-0.27	-0.29	0.00	35.60	-0.23	-0.24	-0.13	0.22	0.38
	(2.66)**	(4.91)**	(-15.51)**	(5.56)**	(-12.41)**	(-9.52)**	(0.09)	(3.84)**	(-10.04)**	(-7.58)**	(-3.02)**	(4.70)**	(5.71)**
				Panel	B. The 52-w	eek low stra	ategy						
		phas and b	oeta coefficie	Alp	has and thre	e-factor loa	dings		Alph	as and five-	-factor load	ings	
Long-short strategy (n/1-n)	Raw return	α	MKT	α	MKT	SMB	HML	α	MKT	SMB	HML	RMW	CMA
05/95	51.14	52.10	-0.02	53.44	0.01	-0.13	0.01	55.19	0.01	-0.15	0.03	-0.05	-0.01
	(5.04)**	(5.10)**	(-0.81)	(5.20)**	(0.46)	(-3.86)**	(0.20)	(5.18)**	(0.44)	(-4.18)**	(0.58)	(-0.90)	(-0.14)
10/90	45.69	49.43	-0.07	49.18	-0.03	-0.16	0.05	49.55	-0.03	-0.17	0.09	0.01	-0.05
	(4.85)**	(5.26)**	(-3.43)**	(5.26)**	(-1.28)	(-5.12)**	(1.42)	(5.11)**	(-1.26)	(-5.00)**	(1.91)	(0.23)	(-0.66)
20/80	31.19	36.98	-0.11	34.31	-0.05	-0.21	0.11	32.64	-0.05	-0.19	0.16	0.07	-0.04
	(3.41)**	(4.11)**	(-5.56)**	(3.95)**	(-2.25)*	(-7.04)**	(3.53)**	(3.63)**	(-2.08)*	(-6.26)**	(3.65)**	(1.59)	(-0.69)
30/70	22.10	28.79	-0.13	24.38	-0.05	-0.24	0.16	20.90	-0.05	-0.21	0.20	0.12	-0.05
	(2.35)*	(3.13)**	(-6.28)**	(2.81)**	(-2.36)*	(-8.11)**	(4.96)**	(2.33)*	(-2.09)*	(-6.83)**	(4.81)**	(2.70)**	(-0.71)
				Pane	l C. The mon	nentum stra	tegy						
		phas and b	oeta coefficie	Alp	has and thre	e-factor loa	dings		Alph	as and five-	-factor load	ings	
Long-short strategy (n/m)	Raw return	α	MKT	α	MKT	SMB	HML	α	MKT	SMB	HML	RMW	CMA
10/10	158.48	160.74	-0.04	184.79	-0.16	0.08	-0.53	174.87	-0.12	0.06	-0.75	0.00	0.46
	(7.00)**	(7.05)**	(-0.86)	(8.25)**	(-3.04)**	(1.04)	(-6.54)**	(7.55)**	(-2.15)*	(0.78)	(-6.81)**	(-0.03)	(2.73)**
20/20	117.55	119.13	-0.03	139.54	-0.14	0.10	-0.46	130.81	-0.10	0.09	-0.66	0.00	0.41
	(6.18)**	(6.22)**	(-0.72)	(7.45)**	(-3.14)**	(1.60)	(-6.77)**	(6.76)**	(-2.17)*	(1.29)	(-7.17)**	(-0.04)	(2.95)**

Table A2 Fama–Macbeth regressions for controlling for other return determinants under a 6-month holding period

This table lists the results of Fama-Macbeth regression obtained using all nonfinancial common stocks listed in NYSE, Amex, and Nasdaq from January 1962 to December 2014. Each month, we cross-sectionally regress returns on various variables, as follows: The dummy HIGH_D (LOW_D) is assigned a value of 1 if the nearness to the 52-week high (low) price measure for a stock is ranked in the top (bottom) 10% at the beginning of month t. The dummy Winner (Loser) denotes whether a firm is included in the top (bottom) 10% portfolio based on the past 12-month return lagged 1 month. Ln(Size) represents the natural log of firm capitalization, whereas Ln(BM) denotes the natural log of the book-to-market ratio. $R_{(1,2)}$ represents the cumulative returns from months t - 1 to t - 2. The turnover rate (Turnover) is defined as the shares traded within 1 month divided by outstanding shares. Monthly idiosyncratic volatility (IVol) is defined as the standard deviation of regression residuals of the Fama and French (1993) three-factor model. At the beginning of each month t, the daily excess returns of stock i in month t-1 are regressed on the daily three Fama and French (1993) factors for obtaining the residuals. The monthly illiquidity measure (*Illiq*) for each stock is computed by dividing the daily absolute return by the daily trading volume and then averaging this daily quantity over the month. The *Illiq* variable is scaled up by 10^3 . Parallel with the method employed by George and Hwang (2004), the coefficient estimate of a variable in month t is averaged over the past 6 months. The coefficients reported are the time-series averages of these averages. The t-statistics (in parentheses) are calculated from the times series and adjusted for autocorrelation by using the Newey-West covariance matrix. Asterisks * and ** indicate significance at the 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.0125	0.0129	0.0130	0.0131	0.0171	0	0.0253
	(4.88)	(5.09)**	(5.27)**	(5.14)**	(4.71)**		(9.63)**
HIGH_D	0.0017			0.0012	0.0021	0	0.0022
	(1.34)			(1.04)	(2.84)**		(3.73)**
LOW_D		-0.0046		-0.0037	-0.0011	0	-0.0020
		(-5.28)**		(-4.31)**	(-1.65)		(-4.17)**
Winner			0.0015	0.0016	0.0038	0	0.0028
			(1.10)	(1.25)	(3.16)**		(3.15)**
Loser			-0.0072	-0.0066	-0.0045	0	-0.0043
			(-6.49)**	(-6.33)**	(-4.67)**		(-5.34)**
ln(Size)					-0.0008	0	-0.0015
					(-1.82)		(-4.42)**
ln(BM)					0.0031	0	0.0034
					(4.50)**		(6.29)**
R (1, 2)						0	-0.0547
							(-13.18)**
Turnover							0.0725
							(5.42)**
IVol							-0.3008
							(-8.00)**
Illiq							0.7105
							(2.72)**
Average R-square	0.00	0.00	0.00	0.01	0.03		0.05

Table A3 Volatility and Sharpe ratio of diversified strategies under a 6-month holding period

This table reports the volatility (Panel A) and Sharpe ratios (Panel B) of a single trading strategy and three diversified trading strategies. The single trading strategy includes the 52-week high strategy, 52-week low strategy, and momentum strategy. All single strategies are value-weighted. For diversification, we choose two strategies from the three single strategies, and equally invest our capital into the two strategies, denoted as (m, n). We hold and maintain the single and diversified strategies for 6 months. Volatility is computed as the standard deviation of monthly raw returns. The Sharpe ratio is defined as dividing the alpha under alternative factor models by the idiosyncratic volatility of the portfolio returns. Asterisks * and ** indicate significance at the 5% and 1% levels, respectively.

	Panel A. Volati	lity	
		Single strategy	
	(52-week high strategy)	(52-week low strategy)	(momentum strategy)
Volatility	0.02	0.02	0.06
		Diversified into two strategies (m,n)	
	(52-week high strategy, 52-week low strategy)	(momentum strategy, 52-week low strategy)	(momentum strategy, 52-week high strategy)
Volatility	0.01	0.03	0.04
		F-test for equality of variances	
	(52-week high strategy, 52-week low strategy)	(momentum strategy, 52-week low strategy)	(momentum strategy, 52-week high strategy)
Diversified strategy (m, n) - the momentum strategy		-0.03	-0.03
		[5.26]**	[2.84]**
Diversified strategy (m,n) - the 52-week high strategy	-0.01		0.02
	[3.71]**		[0.29]**
Diversified strategy (m,n) - the 52-week low strategy	-0.01	0.01	
	[3.83]**	[0.56]**	
	Panel B. Sharpe	ratio	
		Single strategy	
	(52-week high strategy)	(52-week low strategy)	(momentum strategy)
Sharpe ratio	0.05	-0.04	0.16
		Diversified into two strategies (m,n)	
	(52-week high strategy, 52-week low strategy)	(momentum strategy, 52-week low strategy)	(momentum strategy, 52-week high strategy)
Sharpe ratio	0.01	0.17	0.15
		T-test for mean difference	
	(52-week high strategy, 52-week low strategy)	(momentum strategy, 52-week low strategy)	(momentum strategy, 52-week high strategy)
Diversified strategy (m, n) - the momentum strategy		0.01	-0.01
		(3.94)**	(-5.00)**
Diversified strategy (m, n) - the 52-week high strategy	-0.04		0.10
	(-18.36)**		(42.25)**
Diversified strategy (m,n) - the 52-week low strategy	0.05	0.21	
	(22.38)**	(91.79)**	

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