Investor Attention, Visual Price Pattern, and Momentum Investing

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Abstract

As a visual mode of analysis is more intuitive to human cognition than algebraic numbers, we propose that the visual pattern of historical prices is a salient signal that attracts attention; thereby inducing overreaction. We construct a long-short portfolio, including the stocks that are more likely to grab attention, and create an illusion through their discernible visual patterns of historical prices. The newly-developed portfolio commands an annual risk-adjusted return of 23.1% and dominates momentum investing. The outperformance holds under various specifications and asset pricing models. We provide support that momentum is induced by visually psychological biases.

Keywords: Momentum; Technical Analysis; Limited Attention; Visual; Illusion

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Traditional asset-pricing models are based typically on the assumption that new information diffuses efficiently; therefore, the market can provide the best possible estimate of all asset values. In reality, such diffusion and estimation requires the close attention of investors to processing information and incorporating this into asset prices (Barber and Odean, 2008; Hou, Peng, and Xiong, 2009; Li and Yu, 2012). This paper studies empirically how *visual* attention induces overreaction-driven momentum investing.

Various models and theories have been proposed to explain the co-existence of intermediate-term momentum and long-term reversal. The related literature is voluminous. Intermediate-term (3-12 months) momentum is documented by Jegadeesh and Titman (1993 and 2001, hereafter JT), while short-term (weekly) and long-term (3-5 years) reversals are documented respectively by Lehmann (1990) and Jegadeesh (1990), and DeBondt and Thaler (1985). Researchers have explored explanations for these phenomena via the behavioral route; for example, Chan, Jegadeesh, and Lakonishok (1996), Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998); Hong and Stein (1999), Hong, Lim, and Stein (2000), and George and Hwang (2004). The linkage between momentum and various firm characteristics is also explored (for example, Avramov, Chordia, Jostova, and Philipov, 2007; Wei and Yang, 2012).

Based on the theory proposed by Daniel, Hirshleifer and Subrahmanyam (1998),

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short-term momentum is caused by investor overconfidence and variations in confidence arising from biased self-attribution. An overconfident investor would overestimate the precision of his private information signal, but not of information signals received publicly and universally. The overweight of private signals causes the stock price to overreact. Investor confidence is strengthened when confirming public information is received; conversely, it is weakened only modestly when disconfirming information is received. Such biased self-attribution behavior suggests that public information can trigger further overreaction to a preceding private signal; thereby causing short-term momentum.

We argue that attention is a necessary condition for overreaction because investors can only overreact to information to which they are paying attention (Hou, Peng, and Xiong, 2009). The most common public information noticed by the overwhelming majority of investors is price itself. Investors are the least likely group to ignore such public information, not only because historical prices and immediate quotes are reported in various financial websites, media, and trading tools, but also because they are usually reported via the use of charts. Based on psychology, picture stimuli have an advantage over word stimuli. Hence, historical prices and immediate quotes are presented frequently in charts because visual information is understood more easily and more eye-catching than raw numbers.

Unfortunately, when investors are attracted by the charts of historical prices, they are easily misled by their presentation. According to the law of continuity outlined in Gestalt psychology[1], humans have an innate tendency to continue contours whenever the elements of the pattern establish an implied direction. In other words, the stocks whose historical prices increase acceleratively will provide the investor with the illusion that the prices will continue to soar in the future prices. Thus, these stocks seem to confirm the validity of private positive information at a larger magnitude and induce stronger overreaction than for stocks whose historical prices increase at a slower pace. Similarly, stocks whose historical prices decrease at an accelerative speed would also provide the illusion that private negative information is confirmed more significantly.

To verify our argument, we construct several zero-investment portfolios that buy and sell stocks with different patterns of historical prices. The sample covers all common stocks listed in the NYSE, AMEX, and Nasdaq from January 1962 to December 2011. Paralleling the procedure in JT (1993), we first sort stocks into quintiles based on past J months' returns to identify winners and losers. Secondly, in order to identify the visual pattern of historical prices, we regress previous daily prices in past J months on time dummy and the square of

[1] Gestalt psychology will be introduced in the later section. A detailed introduction can be found in Kohler (1970) and Wagemans et al. (2012).

time dummy for each stock. The winners and losers are further sorted into quintiles based on the square of time dummy. We conjecture that investors will flock to the winner and loser stocks whose visual charting of historical prices confirms their private information and attract their attention more significantly.

We design nine trading strategies and compare the returns of different trading strategies. Each strategy buys and short-sells stocks with different patterns regarding historical prices. For the case of a 6-month holding based on the past 12-month returns, the plain momentum strategy (buy winners and sell losers) produces a profit of 83.22 basis points per month. However, the acceleration strategy, which buys winners whose historical prices increase acceleratively and sells losers whose historical prices decrease acceleratively, can generate 132.46 basis points per month; approximately 17.11% annually. Meanwhile, the opposing trading strategy, which buys and sells stocks whose patterns of historical prices trigger the least overreaction, produces the lowest return;46.80 basis points per month. The findings are robust to sample division into sub-periods and exchanges, replacing the daily closing prices with the midpoints of bid and ask quotes, removing January returns, and various holding/ranking periods. Moreover, we find steeper reversals for the stocks whose prices increase or decrease acceleratively. The reversals confirm the overreaction hypothesis.

We further examine whether the acceleration strategy represents the core of momentum investing. The answer is yes. Accompanying the Fama-French three-factor model with various zero-investment portfolios, we find that the returns of the acceleration strategy developed in this paper cannot be subsumed by the plain momentum strategy and the 52-week high strategy[2]. Conversely, the acceleration strategy offers explanatory power to the profit earned by the plain momentum strategy and the 52-week high strategy.

Our findings are important not only for researchers in asset pricing, but also for practitioners with an interest in asset management and the performance evaluation of portfolios. For practitioners, we propose an extremely promising trading strategy with which to distill new information from the visual patterns of past returns that should be attractive to a wide range of investors, especially hedge funds. This new strategy is feasible and easy to implement, given the sheer size of the new portfolio. For researchers, we provide empirical evidence of the theory proposed by Daniel, Hirshleifer, and Subrahmanyam (1998) and the implications of a well-established psychological visual

[2] George and Hwang (2004) suggests that traders might use the 52-week high as an anchor when assessing the increment in stock value implied by new information. They argue that a stock whose price is at or near its 52-week high is one for which good news has recently arrived, and that this maybe precisely the time when traders' underreaction to good news is at its peak. Hence, nearness to the 52-week high is positively associated with expected returns in the cross section.

illusion. Such visual illusion generated by historical prices triggers overreaction and offers a parsimonious explanation for the momentum profit.

The remainder of this paper is organized as follows. Section II outlines the motivation for the study, while Section III presents the data and proposes new trading strategies. Section IV reports the empirical findings and demonstrates that the visual attraction is the core of momentum investing. Section V presents some auxiliary tests and, finally, Section VI provides the conclusion of the study.

II. Motivation

The phenomena of momentum and reversal, which are taken for granted by all technical analysts, have been discussed in numerous studies[3]. Various models and theories have proposed explanations for the co-existence of intermediate-term momentum and long-term reversal. Some of these are consistent with the efficient market hypothesis; for instance, those provided by Berk, Green, and Naik (1999), Conrad and Kaul (1998), and

[3] For example, cross-sectional predictability based on past returns appears to be prevalent in different markets (Rouwenhorst, 1998; Doukas and McKnight, 2005) and different asset classes (Asness, Moskowitz, and Pedersen, 2013). It also exists between and within industries (Moskowitz and Grinblatt, 1999; and Hameed, Huang, and Mian, 2010).

Chordia and Shivakumar (2002). However, alternative explanations attribute momentum and reversals to systematic violations of rational behavior by investors. In Barberis, Shleifer, and Vishny (1998) and Hong and Stein (1999), fundamental investors tend to underreact to new information, while momentum traders arbitrage away the profit that fundamental investors leave behind; thereby resulting in intermediate-term momentum. However, these momentum traders subsequently overcorrect and push the price away from fundamentals. In Daniel, Hirshleifer, and Subrahmanyam (1998), momentum is a consequence of investors' tendency to overreact to private information as a result of self-attribution and overconfidence, while reversals occur when such mispricing is corrected. If the theory proposed by Daniel, Hirshleifer, and Subrahmanyam (1998) is true, the stocks that most attract investor attention should generate the strongest overreaction, as investors can only overreact to information of which they are aware.

Hence, the empirical question turns to: Which information attracts investor attention more easily and thereby induces overreaction? Our argument relies on two psychological regularities: visual attraction and continuity. Attention is the cognitive process of concentrating selectively on one aspect of the environment while ignoring other factors (Kahneman, 1973; Anderson, 2004). Although there is a variety of noisy public information, the most attractive public information should be the security price itself. Prices are provided commonly by almost all broker software and financial websites. Moreover, the historical prices are reported frequently in chart form because images attract more attention than words. According to dual-coding theory, picture stimuli have an advantage over word stimuli as they are dually encoded (Paivio, 1971, 1986; Shepard, 1967; McBride and Dosher, 2002; Whitehouse et al., 2006; Defetyer, Russo, and McPartlin, 2009; Ally, Gold, and Budson, 2009; Curran and Doyle, 2011). Pictures generate a verbal and image code, whereas word stimuli generate only a verbal code. Hence, concepts that are learned by viewing pictures are recalled more easily and frequently than those learned by viewing written words from counterparts. Therefore, compared with other public information, price is noticed more easily.

The second aspect of our argument is based on the law of continuity; specifically, one type of visual illusion. It is common to have visual illusion, which uses color, light, and patterns to create images that can deceive or mislead our brains. Psychological evidence indicates that humans have an innate tendency to group and organize lines or curves that follow an established direction over those defined by abrupt changes in direction. In other words, people like to perceive a line as continuing its established direction[4]. For example, people incline to conjecture that branch A is the possible direction of the first segment of the line rather than branch B in Figure 1. If the X-axis in Figure 1 is set to time and the Y-axis to price, we can imagine that when an investor's private information suggests a positive stock return, he is easily attracted by A rather than B in Figure 1 (a). This is because the former generates an illusion that future prices will continue to increase based on the law of continuity. Given that investors can overreact to information only when they are aware of it, stocks whose historical prices resemble branch A in Figure 1 (a) will induce stronger overreaction. Similarly, when an investor's private information suggests a negative stock return, he is easily attracted by A rather than B in Figure 1 (b), because the former is viewed generally as greater confirmation of the validity of the private signal.

[4] The law of continuity belongs to the Gestalt principles, which are a set of principles in the field of psychology. They are first proposed by Gestalt psychologists who aim to formulate the regularities according to which the perceptual input is organized into unitary forms. These principles apply mainly to vision. Gestalt psychologists argue that humans naturally perceive objects as organized patterns and objects. In the visual field, some portions are perceived as grouped or joined together, and are thus segregated from the rest of the visual field. These principles are organized into six categories: Proximity, Similarity, Closure, Continuation, Common Fate, and Good Form. The Gestalt principles were introduced in a seminal paper by Wertheimer (1923, 1938), and were further developed by many scholars. Palmer (1999) introduces more recent contributions.

Based on visual attraction and continuity, we can construct several trading strategies that buy and sell stocks using different visual patterns of historical prices. When an investor's private information suggests the price will rise, the winner's stock, which increases its prices acceleratively, would attract attention and create an illusion that future prices will continue to increase, eventually inducing a stronger overreaction. Conversely, the winner's stock, whose increasing speed of prices slows down, would be less attractive to investors. The loser's stocks also follow a similar concept.

Some may argue that analyzing the patterns of historical prices is just one form of technical analysis. Technical analysis has been criticized by academic finance from the outset. One reason for this is the subjective and impenetrable jargon used by technical analysts[5]. The major difference between academic finance and technical analysis is that the latter is "primarily *visual*, whereas quantitative finance is primarily algebraic and numerical" (Lo, Mamaysky, and Wang, 2000, [1706]). The main task of technical analysis is to predict how investors as a whole will react *ex post* when the specific charts are observed *ex ante*;

[5]Although technical analysis is known as "voodoo finance", Lo, Mamaysky, and Wang (2000) employ a systematic and automatic approach to technical pattern recognition and find that several technical indicators do provide incremental information and may have some practical value. Lo and MacKinlay (1988, 2001) have also shown that past prices may be used to forecast future returns to some degree, a fact that all technical analysts take for granted.

therefore, one can profit from the other’s behavior. However, this study begins with the assumption that some investors are not entirely rational; rather, they are psychologically biased. Thus, they will be attracted by specific visual modes of historical prices. We use an objective regression to describe the visual pattern of a stock’s historical prices and select stocks that are more likely to grab investor attention and induce overreaction by their conspicuous patterns. The concept of this study is simple: if the visual mode of analysis is more intuitive to human cognition and induces overreaction more easily, analyzing the visual patterns of previous data should provide incremental value to the momentum strategy.

III. Data and Trading Strategies

A. Data

All common stocks (share codes 10 and 11) listed in the NYSE, AMEX, and Nasdaq are included in our sample. The data are collected from CRSP daily and monthly files. The monthly data are used to calculate portfolio returns, while daily data are used in the regression and calculation of firm characteristics during the later stages. The sample period spans from January 1962 to December 2011. We filter out the stocks whose prices are below 5 dollars on the portfolio formation date[6]. We also retrieve accounting data from COMPUSTAT to calculate book-to-market ratios and other variables for our regression analyses. Throughout our analysis, we employ the corrections suggested in Shumway (1997) for the de-listing bias; however, these adjustments have no effect on our results.

B. Visual Pattern of Historical Prices and the Trading Strategies

We identify the visual pattern of historical prices using an objective method, which is very easy to implement. First, we sort stocks into quintiles based on past returns, as in JT (1993). At the beginning of each month *t*, we sort stocks into quintiles based on the returns of the previous *J* months. In order to avoid the microstructure issues identified by previous researchers (e.g. JT, 1993; Chan, Jegadeesh, and Lakonishok, 1996), we skip one full month between the formation period and the holding period. When *J* is equal to 12, at month *t* we sort stocks based on their returns from month *t-13* to month *t-2*.

Secondly, the stocks in each quintile are further sorted into quintiles based on the visual patterns of historical prices. The visual pattern of historical prices is defined as γ in

[6]We also use all common stocks listed in the NYSE, AMEX, and Nasdaq without any data filter to perform the analysis. All empirical results remain unchanged.

equation (1), which is run for each stock using daily data to increase the power of the tests.

$$P_{i,t} = \alpha + \beta t + \gamma t^2 \quad (1)$$

where $P_{i,t}$ denotes the daily price of stock *i* at day *t*, and *t* is an arithmetic sequence, which is equal to 1, 2, 3… or *n* for the indication of the past *n*, …, 3, 2, or 1 day respectively. At the beginning of each month, the daily returns in the previous *J* months (lagged one month) are used to run the equation (1) and determine the sign of the coefficients. We further sort stocks in each return group into quintiles based on their convexity, the value of γ. Finally, we have 5×5 portfolios. Some suggest that we can also use β in equation (1) to sort stocks. Interestingly, we find the sorting result based on β is similar to that based on past returns. This finding implies that being a winner stock is important, but how to become a winner stock is also vital for investors.

If the coefficient of γ is positive (negative), the price of the stock is a convex (concave) function of time in the past *J* months. We define the stocks whose γ are in the top 20% of the winner groups as having a convex-shaped pattern of historical prices. This means that their prices increase at an accelerated rate. Conversely, the stocks whose γ are in the bottom 20% of the winner group have a concave-shaped pattern of historical prices; thereby illustrating that the increasing speed of price rises gradually slows down. Based on the law of continuity, the winner stocks, whose historical prices increases at an accelerated rate, would create an illusion of increasing on a continuous basis. If the investor's private information suggests a price is moving upwards, these accelerative winners are more attention-grabbing and, thus, induce stronger overreaction.

Similarly, the stocks whose γ are in the bottom 20% of the loser group have a concave-shaped pattern of historical prices, which means that their prices decrease at an accelerated rate, whereas a convex-shaped pattern of historical prices, i.e. the stocks whose γ are in the top 20% of the loser group, illustrates that the speed of the price decrease gradually slows down. When an investor's private information suggests a price is moving downwards, the loser stock whose historical prices decrease at an accelerated rate is more attractive because investors will have a visual image of future prices following the established downward direction based on the law of continuity. Consequently, stronger overreaction to the private information emerges.

To examine our conjecture, several trading strategies can be constructed as follows to enhance momentum profit. The first strategy is the plain momentum strategy documented in JT (1993).

Strategy 1: Buy winners and sell losers.

Strategy 2: Buy winners and sell losers whose decreasing speed of the historical prices gradually slows (i.e. stocks whose γ are in the top 20% of the loser group).

Strategy 3: Buy winners and sell losers whose prices decrease acceleratively (i.e. stocks whose γ are in the bottom 20% of the loser group).

Strategy 4: Buy winners whose increasing speed of the historical prices gradually slows (i.e. stocks whose γ are in the bottom 20% of the winner group) and sell losers.

Strategy 5: Buy winners whose prices increase acceleratively (i.e. stocks whose γ are in the top 20% of the winner group) and sell losers.

Strategy 6: Buy winners whose prices increase acceleratively and sell losers whose prices decrease acceleratively. This is referred to hereafter as the acceleration strategy.

Strategy 7: The opposite of Strategy 6. Buy winners and sell losers whose increasing or decreasing speed of historical prices slows. This is referred to hereafter as the deceleration strategy.

Strategy 8: Buy winners whose historical prices increase acceleratively and sell losers whose decreasing speed of the historical prices decelerates.

Strategy 9: Buy winners whose increasing speed of the historical price decelerates and sell losers whose prices decrease acceleratively.

In accordance with JT (1993), we hold overlapping portfolios for all strategies.

Specifically, the sorting and portfolio formation procedure is repeated each month, and the returns of the long-short portfolio are equally weighted averages of the monthly returns on the overlapping portfolios. Each zero-investment portfolio will be held for K months. The t-values for the portfolio returns are corrected for serial correlations using the Newey-West adjustment.

Based on the psychological biases introduced above, several conjectures can be made. First, the profit of Strategy 3 is greater than that of Strategies 1 and 2. In a similar vein, we also anticipate that the profit of Strategy 5 will be higher than that of Strategies 1 and 4. Strategy 6, the acceleration strategy, should achieve the highest returns among the nine strategies. In contrast to Strategy 6, we expect that the return of Strategy 7, the deceleration strategy, will yield the lowest returns of all the strategies. The Fama-French three-factor model is used to measure the risk-adjusted returns of the nine strategies. The factor data are collected from Kenneth R. French's website.

IV. The Empirical Evidence

A. The Profits of the New Strategies

Before presenting the profits of the nine trading strategies introduced above, we first uncover the descriptive statistics of the key variable γ. For ease of interpretation, the value of γ is scaled up by 10^3. Table 1 illustrates that the means of γ in the three panels are near to zero, which suggests that the charts of historical prices for most stocks do not exhibit obvious patterns. However, the means of γ in the top and bottom groups are 5 to 6 times greater than those in the middle groups. Some stocks have extreme values of γ. The deletion of outliers does not change materially our conclusion.

[INSERT TABLE 1 HERE]

Next, we attempt to discern whether the visual pattern of historical prices can further distinguish the best (worst) from the better (worse). First, we sort stocks based on their past *J*-month returns lagged one month, and then sort the stocks in each return group on the coefficient γ. Each cell in Table 2 reports the monthly raw return of buying the stocks whose γ are the top 20% and selling the stocks whose γ are the bottom 20%, under the alternative ranking (*J*) and holding (*K*) periods in the winner (Panel A) and loser groups (Panel B).

In Panel A, we observe that the raw returns of the winners whose prices increase acceleratively (top 20% γ) are significantly higher than the winners, whose speed of price decreasing decelerates (bottom 20% γ) under most of (*J, K*). However, such outperformance is less significant in Panel B, although it can still be seen in some (*J, K*) combinations. This finding implies that investors are more likely to overreact to stocks whose prices increase acceleratively than to those whose prices decrease acceleratively. This is due, in part, to the fact that most individual investors sell only stocks that they already own (Barber and Odean, 2008).

[INSERT TABLE 2 HERE]

In order to explore the practical implications of the visual pattern analysis, we examine the performance of the nine zero-investment trading strategies. For brevity, hereafter we focus our attention on the case (*J, K*) = (12, 6) for the remainder of this paper. Panel A of Table 3 presents the raw and risk-adjusted returns under the Fama-French three-factor model for the nine trading strategies. The monthly return of the plain momentum strategy (Strategy 1) is 83.22 basis points (all months included) and 105.89 basis points (excluding January).

Compared with the plain momentum strategy, three features stand out. First and foremost, the acceleration strategy outperforms all other strategies. Its monthly raw return is 132.46 basis points; approximately 17.11% annually. Moreover, the Sharpe ratio is higher than the plain momentum strategy. Secondly, contrary to the acceleration strategy, the performance of the deceleration strategy, which buys and shorts stocks whose prices change at a slowing speed in the winner and loser groups, is 46.8 basis points per month; thereby achieving the least profit among all strategies. Both the outperformance of the acceleration strategy and the underperformance of the deceleration strategy correspond with our conjecture.

Thirdly, if we unilaterally buy or sell stocks whose historical prices increase or decrease acceleratively, for example Strategy 5, we can still obtain returns that are higher than the momentum profit but lower than that of the acceleration strategy. The monthly raw return of Strategy 5 is 103.35 basis points, which is higher than the plain momentum profit (Strategy 1) and the Strategy 4 profit, but lower than that of the acceleration strategy. Similarly, in Strategy 3 we buy all winner stocks and short loser stocks whose historical prices decrease acceleratively. The raw return of Strategy 3 is 112.32 basis points, which is greater than Strategies 1 and 2. In a nutshell, selecting stocks based on the visual patterns of their historical prices is helpful for profit enhancement, even if it is one-sided.

[INSERT TABLE 3 HERE]

In Panel B of Table 3, we conduct the mean difference tests and report the *t*-values in order to observe whether the average returns of these new strategies outperform significantly the plain momentum strategy. The results are overwhelming. With the exception of Strategies 2, 4, 7, and 9, which long-short the stocks with the "wrong" visual patterns, the other strategies all outperform significantly the momentum strategy, despite the inclusion or exclusion of January.

In the untabulated results, we use alternative combinations of (J, K). The main results remain similar quantitatively and qualitatively within alternative combinations. Appendix 1 repeats Table 3 under (J, K)=(24, 6). In fact, when the ranking period is longer (i.e. J is larger), the raw and risk-adjusted returns are higher. In addition to the high profit of the acceleration strategy, the Sharpe ratio of the acceleration strategy (0.210) is double the ratio of the plain momentum strategy (0.095). However, when J is smaller than 3, the profit difference between Strategies 1 and 6 becomes insignificant. This finding suggests that investors are more likely to refer to the visual pattern of stock prices over a long period.

In summary, our conjectures are all supported by the empirical evidence. However, some may argue that the acceleration strategy is simply a manifestation of the plain momentum strategy with finer partition, as it further ranks stocks in the winner and loser groups to quintile based on convexity. To examine this argument, we construct another zero-investment portfolio, which divides the stocks based on past returns to 25 groups. Thus, the number of stocks in this extreme momentum portfolio is equal to the acceleration strategy. Then, we compute the overlap percentage of stocks and the performance difference between the extreme momentum strategy and the acceleration strategy.

If the sorting result based on convexity of historical prices is similar to that based on past returns, we should obtain insignificant performance difference and high overlap percentage of stocks between the extreme momentum strategy and the acceleration strategy. However, we observe that regardless of combination of (*J, K*), the overlap percentage of stocks remains stable at 20-25% each month during the sample period. In addition, by maintaining a constant holding period (*K*), as long as the ranking period (*J*) is above 9 months, the acceleration strategy always outperforms the extreme momentum strategy. These two findings suggest that the acceleration strategy further selects a group of winners that cannot be recognized by using solely past returns. This issue is further investigated using Fama-Macbeth regression in the following section.

B. Fama-Macbeth Regression

We have already demonstrated that, in relation to time-series, the returns yielded from the new strategies cannot be subsumed by traditional risk factors. Insofar as momentum is a cross-sectional phenomenon, we run Fama-MacBeth regressions using dummy variables to assess whether our results still hold after controlling for certain firm characteristics.

The dependent variable in these regressions is the month *t* return to stock *i*, $R_{i,t}$.The control variables include firm size in the month (*Size*, in billion dollars), the book-to-market ratio (*BM*), total turnover for the month (*Turnover*), volatility in the month (*Vol*), and Amihud's illiquidity measure (*Illiq*) (Amihud, 2002). In order to obtain monthly Amihud's illiquidity for each stock, we first calculate the daily illiquidity measure – dividing the absolute return by the trading volume – and then average this daily quantity over the month (Amihud, 2002). Moreover, we include the lagged monthly return (R_{t-1}) by skipping a month between ranking and holding periods. This demonstrates that our results are not a simple manifestation of the monthly reversals presented by Jegadeesh (1990), and to mitigate the impact of bid-ask bounce.

We also include dummies that indicate whether stock *i* is held (either long or short) in month *t* as part of the plain momentum strategy, the acceleration strategy, and the 52-week high strategy. George and Hwang (2004) find that nearness to the 52-week high price dominates and improves the profits gained using the momentum strategy[7,8]. The premise of their argument is that investors will pay more attention to whether a stock's price is near or far from its 52-week high. When investors are attracted by a stock's nearness to its 52-week high, they are more likely to ignore the firm's fundamentals; therefore, anchoring bias occurs. The failure of instantaneously incorporating the news into prices leads to underreaction and return predictability. Namely, nearness to the 52-week high can be regarded as a numerical attraction. By including these dummies, we are able to examine the return to a single strategy in isolation and which attraction – numerical or visual – dominates the profits from momentum investing. The following regression is estimated.

[7] According to George and Hwang's argument, when good news has pushed a stock's price near or to a new 52-week high, traders are reluctant to bid the price of the stock higher even though the information guarantees it. The information finally prevails and the price moves up, resulting in a continuation. Similarly, when bad news pushes a stock's price far from its 52-week high, traders are unwilling initially to sell the stock at prices that are as low as the information suggests. The information eventually prevails and the price falls. In this respect, investors underreact to the stock's 52-week high, the so-called anchoring bias.

[8] We first construct the 52-week high strategy and find that the monthly raw return from January 1962 through December 2011 is 55.53 basis points. The winner (loser) portfolio for the 52-week high strategy is the equally weighted portfolio of the 20% of stocks with the highest (lowest) ratio of current price to 52-week high. The ranking period for the 52-week high strategy is 12 months and the holding period is 6 months .In George and Hwang (2004), the monthly portfolio return from July 1963 through December 2001 is 45 basis points. Note that we remove the stocks whose prices are under $5 when the portfolios are constructed, while George and Hwang (2004) do not.

$$R_{i,t} = \beta_{0jt} + \beta_{1jt} Size_{i,t-1} + \beta_{2jt} BM_{i,t-1} + \beta_{3jt} Turnover_{i,t-1} + \beta_{4jt} Vol_{i,t-1} + \beta_{5jt} Illiq_{i,t-1} + \beta_{6jt} R_{i,t-1} + \\ \beta_{7jt} Winner_{i,t-j} + \beta_{8jt} Loser_{i,t-j} + \beta_{9jt} FHH_{i,t-j} + \beta_{10jt} FHL_{i,t-j} + \beta_{11jt} AcWinner_{i,t-j} + \\ \beta_{12jt} DeWinner_{i,t-j} + \beta_{13jt} AcLoser_{i,t-j} + \beta_{14jt} DeLoser_{i,t-j} \quad (2)$$

where $Winner_{i,t-j}$ equals one if stock *i*'s past performance over the 12-month period (*t* – *j* – *12, t* – *j*) is in the top group when measured by JT's performance criterion, and is zero otherwise; $Loser_{i,t-j}$ equals one if stock *i*'s past performance over the period (*t* – *j* –*12, t* – *j*) is in the bottom group when measured by JT's performance criterion, and is zero otherwise. The variables *FHH* and *FHL* are defined similarly for the 52-week high strategy in George and Hwang (2004). $FHH_{i,t-j}$ ($FHL_{i,t-j}$) is the 52-week high winner (loser) dummy that equals 1 if the 52-week high measure[9] for stock *i* is ranked in the top (bottom) 30% in month *t* – *j*, and zero otherwise. We further define four dummies: *AcWinner, DeWinner*, *AcLoser*, and *DeLoser*. *Ac* refers to an acceleration of price increase or decrease, while *De* refers to a deceleration of price increase or decrease. *AcWinner* (*AcLoser*) equals one if a winner (*loser*) stock sorted to the top (*bottom*) 20% based on the coefficient γ in equation (1) over the period (*t* – *j* –*12, t* – *j*), and is zero otherwise. The other two dummies are defined analogously.

[9] Following George and Hwang (2004), the 52-week high measure in month *t* – *j* is the ratio of price level in month *t* – *j* to the highest price achieved in months *t* – *j* – *12* to *t* – *j*.

We parallel the method in George and Hwang (2004): for a (12, 6) strategy, the total return in month t (as a monthly return) of the set of pure winner or pure loser portfolios can be expressed as the equation: $\frac{1}{6}(\sum_{j=2}^{7}\beta_{7jt}+\sum_{j=2}^{7}\beta_{8jt}+...+\sum_{j=2}^{7}\beta_{14jt})$, where the individual coefficients are computed from separate cross-sectional regressions for each j = 2, …, 7.

Table 4 illustrates the time-series averages of the month-by-month coefficients from the cross-section regressions and the t-values with the Newey-West adjustment. For brevity, we report the results of a (12, 6) strategy in Table 4 and leave the results of a (12, 12) strategy for Appendix 2[10]. To explore whether the acceleration strategy is a manifestation of the plain momentum strategy with finer partition, the dummy $Winner_{i,t-j}$ ($Loser_{i,t-j}$) equals 1 if stock i's past performance over the 12-month period is in the top (bottom) 20% in Panel A and 4% in Panel B, and is zero otherwise. For ease of exposition, we scale up the illiquidity measure by 10^3.

Firstly, irrespective of the strong effects of all the control variables, the dummy *AcWinner* is significantly positive, while the dummy *DeWinner* is significantly negative in Panels A and B. Meanwhile, the dummies *Winner* and *FHH* are barely significant. For

[10] The analysis is performed for various ranking and holding periods in addition to the (12, 6) and (12, 12) strategies. The results are all similar.

example, after including for all control variables, the coefficient of the dummy *AcWinner* is 0.0013 (t = 2.30) in Panel B, while the coefficients of the dummies *Winner* and *FHH* are -0.0009 (t = –0.92) and 0.0006 (t = –0.81) respectively. This finding suggests that the predictive power of the dummies *Winner* and *FHH* are subsumed by *AcWinner* and *DeWinner*. In addition, the opposite signs of the coefficients of *AcWinner* and *DeWinner* indicate that the pattern of historical prices can further identify the best stocks from a group of winners.

Moreover, the dummy *AcLoser* dominates the dummy *DeLoser* in terms of magnitude and statistical significance in Panels A and B. This means that the returns of loser stocks, whose prices decrease acceleratively, will decrease more significantly in the future. In other words, it will be more profitable for short-sellers. The average slopes for the dummy *AcLoser* range from -0.0021 (t=-4.05) to -0.0060 (t=0.6.94) across different specifications in Panel B. The major results are also confirmed by a (12, 12) strategy in Appendix 2.

In brief, the results from the portfolio construction and the regressions both indicate that visual pattern of historical prices is a better predictor of future returns than measures of past price changes and the nearness of the current price to the 52-week high. The acceleration strategy is not merely a manifestation of the plain momentum strategy or the 52-week high strategy with finer partition. This finding suggests that the overreaction theory, especially the overreaction induced by visual illusion, plays an important role in short-term return autocorrelation.

[INSERT TABLE 4 HERE]

C. Factor Models

In addition to portfolio construction and the Fama-Macbeth regression, this section further adopts the factor models to investigate which attraction – numerical or visual– dominates the profits of momentum investing. Four models are adopted: (i) the Fama-French three-factor model; (ii) the three-factor model with the plain momentum strategy[11]; (iii) the three-factor model with the 52-week high strategy; and (iv) the three-factor model with the acceleration strategy. The three-factor model with the 52-week high strategy includes the market factor, size factor, book-to-market factor, and the monthly return of

[11]The calculation of the plain momentum strategy is identical to Strategy 1 outlined in Table 3. We sort stocks into quintiles based on the past returns from month *t-13* to *t-2* and hold the zero-investment portfolio for 6 months. Note that the momentum factor is calculated differently in JT (1993), Carhart (1997), and Kenneth R. French's website. We also use the methods in Carhart (1997) and French's website to compute the momentum factor and repeat the tests in Table 5. The conclusion is not materially changed.

long-short portfolio based on nearness to the 52-week high[12]. The three-factor factor model with the acceleration strategy is defined analogously. In this context, we do not regard the 52-week high and the acceleration strategy as risk factors but rather as candidates. This may explain a portion of the returns earned by other trading strategies.

Table 5 presents the results and three stand-out features are observed. First and foremost, all models outlined in Table 5 cannot explain the profit of the acceleration strategy. For example, under the three-factor model with the 52-week high strategy, the acceleration strategy continues to generate 80.57 basis points per month. Secondly, when the acceleration strategy is introduced, the monthly risk-adjusted returns of the 52-week high strategy and the plain momentum strategy are no longer significant. Thirdly, the plain momentum strategy cannot be explained by the model with the 52-week high strategy. The plain momentum strategy remains profitable; 58.67 basis points per month under the three-factor model with the 52-week high strategy. Conversely, the 52-week high strategy can be explained by the model with the JT momentum strategy. These results can be interpreted as suggestive evidence in favor of the notion that the acceleration strategy is closer to the fundamentals of the momentum strategy than the 52-week high strategy.

[12] See Note 8 for the construction of the long-short portfolio based on nearness to the 52-week high.

[INSERT TABLE 5 HERE]

D. Reversals under Longer Holding Periods

If the spectacular return of the acceleration strategy results from intense investor attention, i.e. psychological bias, this should be reversed afterwards. Moreover, if stocks whose historical prices follow an accelerative increasing or decreasing speed play at the core of momentum investing, we should observe that their returns are reversed on a larger scale. We use overlapping portfolios, in accordance with JT (1993), to recalculate the monthly return for each strategy in the K^{th} month, where K is equal to 1, 12, 24, 36, 48, or, 60. In order to conserve space, the ranking period (J) is set at 12. Essentially, we would like to observe whether the monthly returns reduce substantially if the holding period is extended.

Table 6 presents the results and three regularities are notable. First, we can confirm the existence of reversals for a holding period of 24 months or longer. In the 24^{th} month of implementing these strategies, the profits of most strategies significantly turn to negative. Secondly, compared with the plain momentum strategy, the reversals occur sooner on a larger scale, provided we focus on buying the winners whose historical prices increase acceleratively; i.e. Strategies 5, 6 (the acceleration strategy), and 8. This finding suggests that the reversals are caused mainly by winners rather than losers. This complements the results yielded from the Fama-Macbeth regressions. If the dummy measuring whether the historical prices increase acceleratively represents the highest and positive explanatory power of future returns along the winner horizon, it is natural to observe that the reversals are found largely in these stocks. Finally, but significantly, Panel B illustrates that the profit made from the acceleration strategy is significantly lower than that of plain momentum strategy after the 24th month. This supports the notion that the returns of stocks whose historical prices follow an accelerative increasing or decreasing speed reverse on a larger scale.

[INSERT TABLE 6 HERE]

V. Auxiliary Tests

A. Descriptive Characteristics of Stocks with Specific Visual Patterns of Historical Prices

In addition to returns, Table 7 outlines the main firm characteristics of the stocks in different groups. Panel A presents the statistics for the stocks that are sorted in the top 20% based on past returns (winners), while Panel B presents the bottom 20% (losers). In the winner and loser groups, we further sort stocks by the visual patterns of historical prices. To calculate the average size, we first gauge the cross-sectional mean for each month, and then average the means across time. The other characteristics are calculated analogously. Size (in thousands) is defined as the product of beginning-of-the-month share price multiplied by the number of shares outstanding; volatility for each stock is calculated using the standard deviation of daily returns within the current month. We compute the daily bid-ask spread using only non-missing observations, and then average the daily spread to become the monthly spread[13]. Monthly Amihud's illiquidity for each stock is computed daily and then average this daily quantity over the month (Amihud, 2002).

In the winner group, the stocks with accelerative historical price increase are, on average, the least volatile and the most liquid within the market, in relation to the smallest volatility, the lowest bid-ask spread, and the lowest Amihud's illiquidity. Meanwhile, these stocks are larger than the universe; for example, the size of the winner stocks whose historical prices increase acceleratively is 2,264,826, and the average size for all winner

[13] Since the spread data are extracted from ISSM/TAQ, hence available starting in 1983, the bid-ask spread is only included in the regressions for 1984–2011.

stocks is 1,442,020. The *t*-value for the mean difference test between the two groups is 17.82. This finding provides evidence that the outperformance of the stocks with accelerative historical price increase is not due to liquidity, volatility, and size premium. However, the differences in book-to-market ratio are immaterial.

On the loser horizon, the stocks with accelerative speed of historical price decreasing are smaller, have higher book-to-market ratio, more volatile, and less liquid than those whose decreasing speed of historical prices gradually slows. However, compared with the whole universe, the stocks whose historical prices decrease acceleratively are bigger, more volatile, and more liquid. Significant differences are found across various ranking and holding periods (untabulated). Furthermore, we conduct tests of median difference for these firm characteristics using various combinations of ranking and holding periods. Our findings still hold firm within all of these alternative specifications.

[INSERT TABLE 7 HERE]

B. Time Partition

Cooper, Gutierrez, and Hameed (2004) find that the historical mean return to an equal-weighted momentum strategy has been 0.93% per month in up markets and -0.37%per month in down markets. To investigate whether our findings are conditional on time, we examine the performance of the nine strategies in three equal and non-overlapping sub-periods. Table 8 presents the average monthly returns for the nine trading strategies.

[INSERT TABLE 8 HERE]

The evidence indicates that the acceleration strategy always outperforms, and the deceleration strategy always underperforms, other strategies in all sub-periods. In the last two decades, the profit of the acceleration strategy achieves 98.53 basis points per month; approximately 12.49% annually. Although the profit of the acceleration strategy remains significant, it is obvious that the profits of the other eight strategies have become insignificant in the last two decades. Given the dotcom bubble and the subprime mortgage crisis over the last 10 years, we follow Chordia and Shivakumar (2002) to analyze whether the profitability of these strategies is related to business cycles. Like Chordia and Shivakumar (2002), our sample is divided into two economic environments: expansionary and recessionary periods, based on the definition provided by NBER[14]. The returns of all strategies are examined in each of these environments.

The results in Table 8 corroborate the findings of Chordia and Shivakumar (2002), Cooper, Gutierrez, and Hameed (2004), and Daniel and Moskowitz (2013). The profitability of all strategies is significantly positive during the expansionary period, but insignificant during the recessionary period. As Daniel and Moskowitz (2013) indicate, the momentum strategy experiences negative return following market declines, but positive return in line with market rebounds. During the expansionary period, the acceleration strategy earns a significant profit of 154.83 basis points, but yields only an insignificant profit of 49 basis points during the recessionary period. Moreover, the profits of the remaining eight strategies are significant only during the expansionary period.

C. Implementing the Strategies with Midpoints of Bid-Ask Quotes

Our main results are based on the one-month gap between the ranking and the holding periods. Therefore, potential micro-structure issues are largely avoided. Nevertheless, to

[14]See http://www.nber.org/cycles.html

ensure that our results are not driven by bid-ask bounce, we repeat the analysis by replacing closing prices with the midpoints of closing bid and ask quotes, obtained from CRSP. Since CRSP only began reporting the closing quotes in the early 90s, this analysis relates specifically to the period 1994–2011.

[INSERT TABLE 9 HERE]

Table 9 illustrates that our results are not driven by bid-ask bounce. The acceleration strategy continues to outperform the plain momentum strategy (Strategy 1) by 56.45 basis points per month. The profit of the deceleration strategy is also lower than the plain momentum strategy by 41.85 basis points per month. Furthermore, we repeat the analysis in Table 6 and discover that the outperformance of the acceleration strategy obtained using midpoints is not sensitive to time period either.

D. Lagged One month, Data Filter, and Outliers

Further to the tests described above, we have calculated the profits for all strategies: (1) without skipping a month between the ranking and holding periods; (2) without removing stocks whose prices are below 5 dollars; (3) after deleting stocks whose market capitalizations are in the smallest NYSE/AMEX/Nasdaq decile; and (4) in different exchanges.

We find that the profits are higher without skipping one month, especially when the ranking period is long (e.g. J>12) and the holding period is short (e.g. K<6). Furthermore, the returns will be made more significant by deleting stocks priced below 5 dollars or whose market capitalizations are small at the beginning of the holding period. Moreover, the R^2 increases marginally for the Fama-Macbeth regression. Additionally, Nasdaq stocks exhibit a much more impressive performance when we implement the acceleration strategy. The acceleration strategy, constructed by using stocks listed in NYSE/AMEX (Nasdaq), can yield 114.43 (152.21) basis points per month. One may infer that the better performance of Nasdaq stocks is due to their smaller size. The untabulated results do not support this inference, because the three-factor risk-adjusted return of the acceleration strategy in the Nasdaq subsample remains significantly higher than in the NYSE/AMEX subsample (t=3.86). This finding is not sensitive to the length of ranking and holding periods. The results are illustrated in Appendix 3. To conclude, our findings remain robust in relation to all of the data winsorization, alternative specifications, and various ranking/holding periods.

VI. Conclusion

This study provides fresh insight into stock return predictability by considering momentum portfolios from the perspective of investor visual attention. If the visual mode of analysis is more intuitive to human cognition and induces overreaction more easily, analyzing the visual patterns of historical prices should provide incremental value to the momentum strategy. We design several alternative momentum strategies that transact in only a subset of the stocks contained in the winner and loser portfolios. Our conjecture is substantiated by the empirical results. . The acceleration strategy, i.e. buying winner stocks whose historical prices increase acceleratively and shorting loser stocks whose historical prices decrease acceleratively, produces the highest return. For example, the acceleration strategy generates an annual raw return of 17.11% (132.46 basis points) and a Sharpe ratio of 0.26 for the period 1962 to 2011.The corresponding momentum strategy generates an annual raw return of 10.46% and a Sharpe ratio of 0.204. The new strategy can enhance the profit by 64%. Furthermore, our findings are robust to sample division into sub-periods, different ranking and holding periods. Closing prices are replaced with the midpoints of closing bid and ask quotes, removing January returns, and various exchanges.

The vastly improved profits and Sharpe ratios are not the sole features of the improved strategies. The acceleration strategy shrinks the number of stocks required by an investor, while increasing simultaneously the expected returns. The new strategy calls for transactions in only approximately 200 stocks, in contrast to the 1000-2000 required by the plain momentum strategy. Our new strategy is feasible and easy to implement. Therefore, our study has immediate and profound investment implications for practice, especially in terms of hedge funds.

More importantly, our study makes a conceptual contribution. We find that the acceleration strategy can explain the returns earned by the 52-week high strategy developed by George and Hwang (2004) and the plain momentum strategy, while the reverse does not hold true. This suggests that the acceleration strategy based on visual attraction dominates and improves the forecasting power of past returns and nearness to the 52-week high for future returns.

Momentum and reversals in stock returns contradict directly the market efficiency hypothesis. Consequently, researchers have developed various theories to explain this anomaly. The profession is far from reaching a consensus on whether the cross-sectional return predictability is a violation of market efficiency, or simply a manifestation of certain rational valuation mechanisms that have eluded all to date. The fact that selecting stocks that contain special visual patterns of historical prices that can generate higher returns appears to fuel much of the market efficiency debate and poses a further challenge to any attempt to rationalize the phenomenon.

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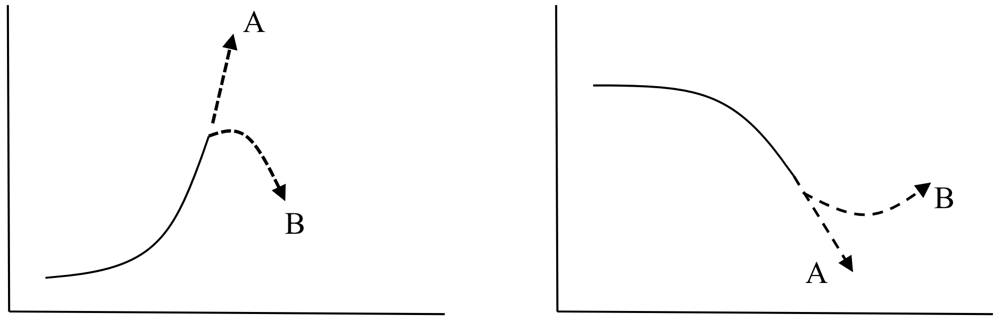

(a) (b)

Figure 1 Law of Continuity

Table 1 Descriptive Statistics of Convexity

This table reports the descriptive statistics of the convexity of stock historical prices from January 1962 to December 2011. The convexity of a stock's historical prices is computed by regressing the daily prices in the past *J* months on the variable *t* and the square of *t*, where *t* is an arithmetic sequence, which is equal to 1, 2, 3… or *n* for the indication of the past *n*, …, 3, 2, or 1 day respectively. For ease of illustration, the value of γ is scaled up by 10^3.

Rank by convexity	Mean	Median	Std	Min	Max	Observations
1 (Low)	-0.6037	-0.3103	9.2377	-1659.4009	0.2453	364292
2	-0.0906	-0.0745	0.1517	-4.5172	0.3971	364534
3	0.0127	0.0108	0.1289	-1.3913	4.0320	364544
4	0.1136	0.0926	0.2307	-0.9109	11.7783	364534
5 (High)	0.5719	0.3074	8.8040	-0.4983	2006.6398	364782
All	0.0009	0.0129	5.7209	-1659.4009	2006.6398	1822686

Table 2 The Zero-investment Portfolios of Stocks Sorted by Convexity in the Winner and Loser Groups

This table reports the average monthly returns in basis points of portfolios from January 1962 to December 2011. Stocks are first sorted into quintiles based on the past *J*-month returns lagged one month. Then, we regress the daily prices in the past *J* months on the variable *t* and the square of *t* for each stock, where *t* is an arithmetic sequence, which is equal to 1, 2, 3… or *n* for the indication of the past *n*, …, 3, 2, or 1 day respectively. In the winner group (top 20%) and loser group (bottom 20%), the stocks are sorted into quintiles based on convexity of historical prices; i.e. the coefficients of the square of *t* in equation (1). All equally-weighted portfolios are held for *K* months. Each cell in this table reports the monthly raw return of buying the stocks whose coefficients of the square of *t* are in the top 20% and selling the stocks whose coefficients of the square of *t* are in the bottom 20% under alternative ranking (*J*) and holding (*K*) periods in the winner (Panel A) and loser groups (Panel B). The sample includes all common stocks listed in NYSE, AMEX, and Nasdaq. At the time of sorting and portfolio formation, stocks with a share price of $5 or lower are deleted. The *t*-statistics in parentheses are corrected for autocorrelation by the Newey-West procedure. Bold *t*-values correspond to a significance level of 5% or higher.

		Panel A. Winner group						Panel B. Loser group					
J	K=	1	2	3	6	9	12	1	2	3	6	9	12
3		14.06	18.17	10.68	8.73	6.66	7.98	-8.09	6.98	0.66	4.27	-1.09	4.84
		(1.21)	**(2.53)**	**(2.04)**	**(3.00)**	**(2.60)**	**(3.71)**	(-0.61)	(0.86)	(0.11)	(1.27)	(-0.38)	**(1.96)**
6		10.12	4.53	5.38	8.90	18.33	17.16	-9.00	-4.07	3.37	2.11	11.40	12.62
		(0.90)	(0.49)	(0.71)	(1.63)	**(3.94)**	**(4.95)**	(-0.63)	(-0.29)	(0.31)	(0.39)	**(2.80)**	**(3.55)**
9		16.81	19.92	16.95	28.75	33.07	27.61	9.19	18.76	13.99	13.52	27.21	23.37
		(1.45)	(1.74)	(1.55)	**(3.31)**	**(4.96)**	**(5.35)**	(0.81)	(1.83)	(1.48)	(1.81)	**(4.65)**	**(4.77)**
12		47.39	44.78	49.29	54.44	50.08	37.37	-8.47	0.98	11.88	31.22	39.03	34.57
		(3.67)	**(3.57)**	**(4.11)**	**(5.49)**	**(6.26)**	**(5.59)**	(-0.67)	(0.08)	(1.03)	**(3.22)**	**(5.24)**	**(5.72)**
24		87.56	83.03	76.71	63.09	49.97	38.50	69.99	76.81	75.10	69.14	60.65	49.63
		(5.45)	**(5.22)**	**(4.97)**	**(4.18)**	**(3.45)**	**(2.94)**	**(4.64)**	**(5.19)**	**(5.12)**	**(5.13)**	**(4.95)**	**(4.66)**
36		68.16	61.24	57.91	48.85	40.65	31.92	75.95	73.05	68.48	54.28	40.03	29.44
		(3.63)	**(3.31)**	**(3.17)**	**(2.88)**	**(2.64)**	**(2.31)**	**(4.31)**	**(4.53)**	**(4.33)**	**(3.83)**	**(3.15)**	**(2.55)**
48		60.10	56.08	51.53	39.76	32.49	26.64	43.78	39.15	32.97	18.91	9.90	6.00
		(3.57)	**(3.36)**	**(3.10)**	**(2.54)**	**(2.31)**	**(2.09)**	**(2.45)**	**(2.26)**	(1.90)	(1.13)	(0.64)	(0.41)
60		42.40	43.09	39.53	30.56	22.93	16.71	26.63	18.34	14.70	10.89	5.39	4.34
		(2.40)	**(2.62)**	**(2.43)**	**(2.06)**	(1.66)	(1.30)	(1.57)	(1.13)	(0.95)	(0.74)	(0.39)	(0.33)

Table 3 Performance of Trading Strategies Estimated by Simple Raw Returns and Risk-Adjusted Returns

This table reports the average monthly returns, the *t*-values, and the Sharpe ratios for nine trading strategies from January 1962 to December 2011. The sample includes all common stocks listed in NYSE, AMEX, and Nasdaq. At the time of sorting and portfolio formation, stocks with a share price of $5 or lower are deleted. For brevity, stocks are sorted into quintiles based on the past 12-month returns lagged one month. All equally-weighted portfolios are held for 6 months. The convexity for each stock is defined by regressing the daily prices in the past 12 months on the variable *t* and the square of *t* for each stock, where *t* is an arithmetic sequence, which is equal to 1, 2, 3… or *n* for the indication of the past *n*, …, 3, 2, or 1 day respectively. Stocks whose coefficients of the square of *t* are in the top 20% are those with an accelerative speed of price increase; conversely, stocks whose coefficients of the square of *t* are in the bottom 20% are those whose decreasing speed of historical prices slows. The nine trading strategies are constructed by buying and selling stocks with different visual patterns of historical prices. Panel A presents the returns in basis points, the *t*-values, and the Sharpe ratios of the nine trading strategies. The Sharpe ratio in brackets is defined as dividing the excess return of a portfolio by the standard deviation of this excess return. The Sharpe ratio is actually the appraisal ratio: alpha divided by the idiosyncratic volatility of the portfolio returns. The *t*-statistics in parentheses are adjusted for autocorrelation using the Newey-West covariance matrix. For Panel B, the *t*-statistics in parentheses examine whether the performance difference between two portfolios is significantly different from zero, and bold *t*-values correspond to a significance level of 5% or higher.

Panel A. Portfolio return							
		Raw return			Alphas from the Fama-French three-factor model		
Trading strategy		All months	January only	January excluded	All months	January only	January excluded
1. Long (Winner)	Return (bp)	83.22	-171.39	105.89	123.14	-52.23	139.62
Short (Loser)	T-value	**(4.77)**	**(-2.44)**	**(5.65)**	**(7.55)**	(-0.70)	**(8.17)**
	Sharpe ratio	[0.204]	[-0.375]	[0.268]	[0.204]	[-0.375]	[0.268]
2. Long (Winner)	Return (bp)	81.12	-134.44	100.31	117.21	-40.30	131.85
Short (Highly convex in loser)	T-value	**(4.43)**	(-1.78)	**(5.27)**	**(6.63)**	(-0.48)	**(7.46)**
	Sharpe ratio	[0.197]	[-0.296]	[0.249]	[0.197]	[-0.296]	[0.249]
3. Long (Winner)	Return (bp)	112.32	-72.17	128.75	146.09	27.96	160.03
Short (Highly concave in loser)	T-value	**(6.35)**	(-1.08)	**(6.69)**	**(8.30)**	(0.39)	**(8.70)**
	Sharpe ratio	[0.252]	[-0.126]	[0.299]	[0.252]	[-0.126]	[0.299]
4. Long (Highly concave in winner)	Return (bp)	48.90	-241.21	74.73	93.45	-123.93	110.78
Short (Loser)	T-value	**(2.66)**	**(-3.14)**	**(3.68)**	**(5.97)**	(-1.53)	**(6.81)**
	Sharpe ratio	[0.121]	[-0.517]	[0.193]	[0.121]	[-0.517]	[0.193]
5. Long (Highly convex in winner)	Return (bp)	103.35	-232.74	133.28	151.75	-70.63	173.09
Short (Loser)	T-value	**(5.29)**	**(-3.22)**	**(6.37)**	**(7.91)**	(-0.92)	**(8.53)**
	Sharpe ratio	[0.221]	[-0.434]	[0.297]	[0.221]	[-0.434]	[0.297]
6. Long (Highly convex in winner)	Return (bp)	132.46	-133.52	156.14	174.70	9.56	193.50
Short (Highly Concave in Loser)	T-value	**(6.56)**	(-1.88)	**(6.99)**	**(8.44)**	(0.12)	**(8.80)**
	Sharpe ratio	[0.260]	[-0.198]	[0.321]	[0.260]	[-0.198]	[0.321]
7. Long (Highly Concave in Winner)	Return (bp)	46.80	-204.27	69.16	87.52	-112.00	103.00
Short (Highly Convex in Loser)	T-value	**(2.46)**	**(-2.50)**	**(3.37)**	**(5.00)**	(-1.21)	**(5.92)**
	Sharpe ratio	[0.114]	[-0.443]	[0.174]	[0.114]	[-0.443]	[0.174]
8. Long (Highly Convex in Winner)	Return (bp)	101.25	-195.80	127.71	145.82	-58.70	165.32
Short (Highly Convex in Loser)	T-value	**(5.12)**	**(-2.63)**	**(6.18)**	**(7.41)**	(-0.71)	**(8.25)**
	Sharpe ratio	[0.221]	[-0.381]	[0.288]	[0.221]	[-0.381]	[0.288]
9. Long (Highly Concave in Winner)	Return (bp)	78.00	-141.99	97.59	116.40	-43.74	131.18
Short (Highly Concave in Loser)	T-value	**(4.49)**	**(-2.16)**	**(5.25)**	**(7.23)**	(-0.59)	**(7.99)**
	Sharpe ratio	[0.191]	[-0.265]	[0.250]	[0.191]	[-0.265]	[0.250]

Panel B. Mean Comparison							
		Raw return			Alphas from the Fama-French three-factor model		
Trading strategy comparison		All months	January only	January excluded	All months	January only	January excluded
2-1	Return (bp)	-2.12	36.95	-5.60	-5.49	8.79	-7.18
	T-value	(-0.36)	**(2.00)**	(-0.99)	(-1.08)	(0.56)	(-1.38)
3-1	Return (bp)	29.12	99.22	22.88	22.97	68.48	20.51
	T-value	**(4.65)**	**(2.40)**	**(2.66)**	**(3.93)**	**(2.35)**	**(2.96)**
4-1	Return (bp)	-34.31	-69.83	-31.15	-28.53	-41.74	-28.73
	T-value	**(-5.62)**	**(-3.46)**	**(-4.45)**	**(-5.69)**	(-1.78)	**(-5.05)**
5-1	Return (bp)	20.14	-61.36	27.40	23.54	-32.91	29.04
	T-value	**(3.39)**	**(-2.65)**	**(4.30)**	**(3.75)**	(-1.53)	**(4.39)**
6-1	Return (bp)	49.26	37.86	50.27	46.51	35.57	49.54
	T-value	**(5.15)**	(0.75)	**(4.01)**	**(4.98)**	(0.84)	**(4.41)**
7-1	Return (bp)	-36.43	-32.88	-36.75	-34.02	-32.95	-35.91
	T-value	**(-4.54)**	(-1.21)	**(-4.15)**	**(-4.43)**	(-1.03)	**(-4.24)**
8-1	Return (bp)	18.01	-24.41	21.79	18.05	-24.12	21.86
	T-value	**(2.61)**	(-1.18)	**(3.02)**	**(2.60)**	(-1.23)	**(3.15)**
9-1	Return (bp)	-5.19	29.39	-8.27	-5.56	26.74	-8.22
	T-value	(-0.90)	(0.91)	(-1.36)	(-0.90)	(0.93)	(-1.30)
3-2	Return (bp)	31.24	62.27	28.48	28.46	59.69	27.68
	T-value	**(3.22)**	(1.33)	**(2.50)**	**(3.01)**	(1.50)	**(2.65)**
5-4	Return (bp)	54.45	8.47	58.54	52.06	8.83	57.77
	T-value	**(5.47)**	(0.24)	**(5.05)**	**(5.28)**	(0.22)	**(5.24)**

Table 4 Fama-MacBeth Regressions to Control for Other Return Determinants: (12, 6) Strategy

This table presents the results of the following Fama-MacBeth regression using all common stocks listed in NYSE, AMEX, and Nasdaq from January 1962 to December 2011. Stocks with a share price of \$5 or lower at the time of portfolio construction are deleted. A month is skipped between ranking and holding periods.

$$R_{i,t} = \beta_{0jt} + \beta_{1jt}Size_{i,t-1} + \beta_{2jt}BM_{i,t-1} + \beta_{3jt}Turnover_{i,t-1} + \beta_{4jt}Vol_{i,t-1} + \beta_{5jt}Illiq_{i,t-1} + \beta_{6jt}R_{i,t-1} + \beta_{7jt}Winner_{i,t-j} + \beta_{8jt}Loser_{i,t-j} + \beta_{9jt}FHH_{i,t-j} + \beta_{10jt}FHL_{i,t-j} + \beta_{11jt}AcWinner_{i,t-j} + \beta_{12jt}DeWinner_{i,t-j} + \beta_{13jt}AcLoser_{i,t-j} + \beta_{14jt}DeLoser_{i,t-j}$$

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ach month, we regress cross-sectionally returns on the various dummies and control variables, including firm size (*Size*), book-to-market ratio (*BM*), volatility (*Vol*), turnover (*Turnover*), Amihud's illiquidity measure (*Illiq*), and past 1-month return (R_{t-1}). The illiquidity measure is scaled up by 10^3 and firm size is in billion dollars. The dummies are defined as follows. $Winner_{i,t-j}$ equals one if stock *i*'s past performance over the 12-month period ($t-j-12,\ t-j$) is in the top 20% (Panel A) or top 4% (Panel B). $Loser_{i,t-j}$ is defined similarly. $FHH_{i,t-j}$ ($FHL_{i,t-j}$) takes the value of 1 if the 52-week high measure for stock *i* is ranked in the top (bottom) 30% in month $t-j$, and zero otherwise. The 52-week high measure in month $t-j$ is the ratio of price level in month *t-j* to the highest price achieved in months $t-j-12$ to $t-j$. The variable $AcWinner_{i,t-j}$ ($DeWinner_{i,t-j}$) equals one if the stock is classified into the top (bottom) 20% based on the coefficients of the square of *t* in the winner group in month $t-j$ and zero otherwise. The coefficient of the square of *t* is obtained by regressing the daily price over the period ($t-j-12,\ t-j$) on an arithmetic sequence variable *t*, which is equal to 1, 2, 3… or *n* for the indication of the past *n*, …, 3, 2, or 1 day and the square of *t*. By the same token, the variable $AcLoser_{i,t-j}$ ($Deloser_{i,t-j}$) is equal to one if the stock is ranked into the bottom (top) 20% based on the coefficients of the square of *t* in the loser group and zero otherwise. The coefficient estimates of a given independent variable are averaged over $j = 2, \ldots, 13$ for the (12, 6) strategy. The *t*-statistics (in parentheses) are calculated from the times series and adjusted for autocorrelation using the Newey-West covariance matrix. Bold t-values correspond to a significance level of 5% or higher.

Panel A. The Dummies *Winner* and *Loser* are the top and bottom 20% respectively					
	(1)	(2)	(3)	(4)	(5)
Intercept	0.0112	0.0116	0.0135	0.0130	0.0144
	(3.89)	**(4.04)**	**(4.36)**	**(5.74)**	**(5.84)**
Size	-0.2690	-0.2675	-0.3060	-0.2569	-0.2971
	(-1.74)	(-1.81)	**(-2.68)**	**(-2.50)**	**(-3.34)**
BM	0.0022	0.0021	0.0017	0.0015	0.0013
	(3.72)	**(3.70)**	**(3.22)**	**(3.30)**	**(2.90)**
Turnover				0.0000	-0.0001
				(0.00)	(-0.01)
Vol				-0.0577	-0.0566
				(-1.19)	(-1.24)
Illiq				0.0256	0.0264
				(2.01)	**(2.02)**
R_{t-1}				-0.0001	-0.0008
				(-0.03)	(-0.25)
Winner			-0.0008		-0.0005
			(-0.58)		(-0.52)
Loser			-0.0038		-0.0041
			(-3.83)		**(-4.94)**
FHH			0.0021	0.0020	0.0025
			(1.95)	(1.72)	**(2.70)**
FHL			-0.0035	-0.0047	-0.0031
			(-4.18)	**(-6.29)**	**(-4.25)**
AcWinner		0.0036	0.0021	0.0022	0.0023
		(2.30)	**(2.65)**	**(2.98)**	**(3.16)**
DeWinner		-0.0013	-0.0020	-0.0027	-0.0018
		(-0.92)	**(-2.94)**	**(-3.53)**	**(-2.63)**
AcLoser		-0.0077	-0.0018	-0.0026	-0.0017
		(-7.97)	**(-2.47)**	**(-3.77)**	**(-2.59)**
DeLoser		-0.0055	-0.0005	-0.0002	-0.0001
		(-5.14)	(-0.69)	(-0.34)	(-0.23)
Average R-square	0.00	0.01	0.02	0.04	0.04

Panel B. The Dummies *Winner* and *Loser* are the top and bottom 4% respectively					
	(1)	(2)	(3)	(4)	(5)
Intercept	0.0112	0.0117	0.0137	0.0130	0.0146
	(3.89)	**(4.02)**	**(4.37)**	**(5.71)**	**(5.86)**
Size	-0.2690	-0.2804	-0.3216	-0.2611	-0.3066
	(-1.74)	(-1.89)	**(-2.80)**	**(-2.53)**	**(-3.45)**
BM	0.0022	0.0021	0.0017	0.0015	0.0013
	(3.72)	**(3.70)**	**(3.25)**	**(3.26)**	**(2.88)**
Turnover				0.0018	0.0017
				(0.23)	(0.21)
Vol				-0.0553	-0.0554
				(-1.13)	(-1.20)
Illiq				0.0261	0.0268
				(2.04)	**(2.05)**
R_{t-1}				-0.0001	-0.0007
				(-0.02)	(-0.21)
Winner			-0.0011		-0.0009
			(-0.79)		(-0.90)
Loser			-0.0035		-0.0037
			(-3.79)		**(-4.86)**
FHH			0.0004	-0.0001	0.0006
			(0.40)	(-0.05)	(0.81)
FHL			-0.0021	-0.0029	-0.0017
			(-2.75)	**(-4.34)**	**(-2.59)**
AcWinner		0.0008	0.0010	0.0012	0.0013
		(0.67)	(1.60)	**(2.21)**	**(2.30)**
DeWinner		-0.0024	-0.0015	-0.0020	-0.0013
		(-2.24)	**(-2.61)**	**(-3.63)**	**(-2.62)**
AcLoser		-0.0060	-0.0021	-0.0028	-0.0021
		(-6.94)	**(-4.05)**	**(-5.94)**	**(-4.36)**
DeLoser		-0.0031	0.0001	0.0003	0.0004
		(-3.34)	(0.23)	(0.51)	(0.66)
Average R-square	0.00	0.01	0.02	0.04	0.04

Table 5 Performance of Trading Strategies under Various Factor Models

This table presents the monthly risk-adjusted returns in basis points, its *t*-value, and the Sharpe ratio for three trading strategies – the JT momentum strategy, the 52-week high strategy, and the acceleration strategy – under various factor models. All common stocks listed in NYSE, AMEX, and Nasdaq from January 1962 to December 2011 are included. However, stocks whose share prices are lower than $5 at the time of sorting and portfolio formation are deleted. All strategies are for a ranking period of 12 months lagged 1 month and a holding period of 6 months. To construct the momentum strategy, stocks are sorted into quintiles based on the past 12-month returns lagged 1 month and held for 6 months. In the 52-week high strategy, stocks are ranked into quintiles according to the ratio of the price of stock *i* at the end of month *t-1* to its highest price during the 12-month period that ends on the last day of month *t-1*. The Sharpe ratio in brackets is defined as dividing the monthly portfolio excess return by the standard deviation of excess returns. Bold *t*-values correspond to a significance level of 5% or higher.

		Plain momentum strategy			52-week high strategy			Illusion-based strategy		
		Return (bp)	T-value	Sharpe ratio	Return (bp)	T-value	Sharpe ratio	Return (bp)	T-value	Sharpe ratio
The three-factor model	All months	106.84	**(7.06)**	[0.204]	67.19	**(6.16)**	[0.176]	174.70	**(8.44)**	[0.260]
	January only	-58.58	(-0.91)	[-0.375]	-100.73	(-2.53)	[-0.344]	9.56	(0.12)	[-0.198]
	January excluded	123.54	**(7.73)**	[0.268]	81.90	**(6.09)**	[0.246]	193.50	**(8.80)**	[0.321]
Three-factor model with the momentum strategy	All months	--	--	--	20.51	(1.76)	[0.176]	29.13	**(3.01)**	[0.260]
	January only	--	--	--	-80.37	(-1.94)	[-0.344]	47.40	(1.10)	[-0.198]
	January excluded	--	--	--	29.54	(1.76)	[0.246]	31.54	**(2.61)**	[0.321]
Three-factor model with the 52-week high strategy	All months	58.67	**(3.70)**	[0.204]	--	--	--	80.57	**(4.01)**	[0.260]
	January only	-9.18	(-0.17)	[-0.375]	--	--	--	88.12	(1.41)	[-0.198]
	January excluded	64.76	**(3.46)**	[0.268]	--	--	--	87.22	**(3.82)**	[0.321]
Three-factor model with the illusion-based strategy	All months	1.29	(0.15)	[0.204]	7.09	(0.63)	[0.176]	--	--	--
	January only	-46.06	(-1.15)	[-0.375]	-92.45	**(-2.26)**	[-0.344]	--	--	--
	January excluded	1.04	(0.15)	[0.268]	15.49	(1.20)	[0.246]	--	--	--

Table 6 Performance of Trading Strategies under Longer Holding Periods

This table outlines the profit, its *t*-value, and the Sharpe ratio for nine trading strategies with longer holding periods. All common stocks listed in NYSE, AMEX, and Nasdaq from January 1962 to December 2010 are included. At the time of sorting and portfolio formation, we filter out the stocks whose share prices are lower than $5.The sorting and portfolio construction procedures are identical to those presented in Table 3. All the panels are for a ranking period of 12 months lagged 1 month. The only difference refers to the holding period. Unlike the 6-month holding period outlined in Table 3, we hold the nine strategies for 1, 12, 24, 36, 48, and 60 months respectively. The reported profits (in basis points) are average monthly returns of the overlapping portfolios in the K^{th} month. All *t*-values are corrected for potential autocorrelation with the Newey-West adjustment. Bold *t*-values correspond to a significance level of 5% or higher.

Panel A. Raw return							
		1st month	12th month	24th month	36th month	48th month	60th month
1. Long (Winner)	Return (bp)	121.36	-23.60	-31.15	-23.36	-31.39	-34.34
Short (Loser)	T-value	**(6.14)**	(-1.73)	**(-2.05)**	(-1.83)	**(-2.29)**	**(-2.76)**
	Sharpe ratio	[0.260]	[-0.066]	[-0.103]	[-0.084]	[-0.126]	[-0.155]
2. Long (Winner)	Return (bp)	141.12	-16.36	-26.94	-13.78	-28.29	-30.70
Short (Highly convex in loser)	T-value	**(6.65)**	(-1.01)	(-1.71)	(-0.89)	(-1.73)	**(-2.27)**
	Sharpe ratio	[0.287]	[-0.042]	[-0.082]	[-0.043]	[-0.094]	[-0.111]
3. Long (Winner)	Return (bp)	132.78	-13.27	-32.29	-28.47	-25.31	-25.46
Short (Highly concave in loser)	T-value	**(6.52)**	(-0.78)	**(-1.97)**	**(-2.13)**	(-1.88)	(-1.73)
	Sharpe ratio	[0.248]	[-0.033]	[-0.097]	[-0.088]	[-0.096]	[-0.092]
4. Long (Highly concave in winner)	Return (bp)	86.10	-20.43	-17.98	-14.93	-31.02	-26.66
Short (Loser)	T-value	**(3.95)**	(-1.42)	(-1.16)	(-1.16)	**(-2.19)**	(-1.91)
	Sharpe ratio	[0.192]	[-0.052]	[-0.052]	[-0.048]	[-0.108]	[-0.100]
5. Long (Highly convex in winner)	Return (bp)	132.59	-32.55	-56.53	-38.84	-38.68	-36.04
Short (Loser)	T-value	**(6.02)**	**(-1.98)**	**(-3.09)**	**(-2.40)**	**(-2.62)**	**(-2.32)**
	Sharpe ratio	[0.246]	[-0.074]	[-0.149]	[-0.112]	[-0.137]	[-0.126]
6. Long (Highly convex in winner)	Return (bp)	144.01	-22.22	-57.67	-43.95	-32.59	-27.16
Short (Highly Concave in Loser)	T-value	**(6.18)**	(-1.12)	**(-3.02)**	**(-2.65)**	**(-2.20)**	(-1.50)
	Sharpe ratio	[0.236]	[-0.046]	[-0.141]	[-0.115]	[-0.108]	[-0.078]
7. Long (Highly Concave in Winner)	Return (bp)	105.86	-13.20	-13.77	-5.35	-27.91	-23.02
Short (Highly Convex in Loser)	T-value	**(4.60)**	(-0.79)	(-0.82)	(-0.35)	(-1.64)	(-1.51)
	Sharpe ratio	[0.219]	[-0.031]	[-0.037]	[-0.016]	[-0.083]	[-0.072]
8. Long (Highly Convex in Winner)	Return (bp)	152.34	-25.31	-52.33	-29.26	-35.57	-32.40
Short (Highly Convex in Loser)	T-value	**(6.70)**	(-1.44)	**(-2.94)**	(-1.69)	**(-2.19)**	**(-2.09)**
	Sharpe ratio	[0.280]	[-0.057]	[-0.136]	[-0.080]	[-0.116]	[-0.106]
9. Long (Highly Concave in Winner)	Return (bp)	97.52	-10.10	-19.11	-20.04	-24.94	-17.79
Short (Highly Concave in Loser)	T-value	**(4.73)**	(-0.62)	(-1.20)	(-1.56)	(-1.90)	(-1.20)
	Sharpe ratio	[0.205]	[-0.025]	[-0.055]	[-0.059]	[-0.088]	[-0.061]

Panel B. Mean Comparison							
Trading strategy comparison		1st month	12th month	24th month	36th month	48th month	60th month
2-1	Return (bp)	19.75	7.24	4.21	9.58	3.11	3.64
	T-value	**(2.74)**	(0.87)	(0.56)	(1.07)	(0.37)	(0.54)
3-1	Return (bp)	11.42	10.34	-1.14	-5.11	6.09	8.87
	T-value	(1.34)	(1.41)	(-0.16)	(-0.73)	(0.87)	(1.03)
4-1	Return (bp)	-35.26	3.17	13.17	8.43	0.37	7.68
	T-value	**(-4.50)**	(0.47)	(1.86)	(1.46)	(0.06)	(1.17)
5-1	Return (bp)	11.23	-8.95	-25.38	-15.48	-7.29	-1.70
	T-value	(1.43)	(-1.21)	**(-3.67)**	**(-2.01)**	(-1.08)	(-0.23)
6-1	Return (bp)	22.64	1.39	-26.52	-20.58	-1.20	7.17
	T-value	(1.74)	(0.12)	**(-2.73)**	**(-1.99)**	(-0.12)	(0.58)
7-1	Return (bp)	-15.51	10.41	17.38	18.01	3.48	11.32
	T-value	(-1.50)	(0.98)	(1.55)	(1.71)	(0.32)	(1.14)
8-1	Return (bp)	30.98	-1.71	-21.18	-5.90	-4.18	1.94
	T-value	**(3.34)**	(-0.18)	**(-2.56)**	(-0.59)	(-0.46)	(0.23)
9-1	Return (bp)	-23.84	13.51	12.04	3.33	6.46	16.55
	T-value	**(-3.07)**	(1.85)	(1.38)	(0.40)	(0.81)	(1.86)
3-2	Return (bp)	-8.34	3.10	-5.34	-14.69	2.98	5.23
	T-value	(-0.67)	(0.25)	(-0.47)	(-1.21)	(0.24)	(0.43)
5-4	Return (bp)	46.49	-12.12	-38.56	-23.91	-7.66	-9.38
	T-value	**(3.62)**	(-1.19)	**(-3.44)**	**(-2.26)**	(-0.82)	(-0.88)

Table 7 Firm Characteristics of Stocks in Different Return and Convexity Quintiles

This table presents the firm characteristics of the stocks under the double partition of past returns and the convexity of historical prices. The sample covers all common stocks listed in NYSE, AMEX, and Nasdaq from January 1962 to December 2011. At the time of sorting and portfolio formation, stocks with a share price of $5 or lower are deleted. We first sort stocks into quintiles based on the past 12-month returns. In each return quintile, stocks are sorted into quintiles based on the coefficients of the square of t obtained by regressing the daily prices in the past 12 months on the variable t and the square of t for each stock. In total, there are 25 portfolios. Panel A presents the average firm size, book-to-market ratios, volatility, bid-ask spread and Amihud's illiquidity measure for the winners in different convexity groups, while Panel B presents the losers in different convexity groups. For each category of stocks, a cross-sectional monthly mean is revealed for each month; then, the mean size is averaged across time to obtain the final average. Firm size (in thousand dollars) is the product of the number of shares outstanding and the stock price. Monthly volatility is calculated using daily prices within each portfolio formation month. Bid-ask spread is measured as dividing the difference between ask and bid by the midpoint of bid and ask. The monthly illiquidity measure 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 t-values for the mean-difference test between different categories of stocks and between the universe and a category of stocks are also reported. Bold t-values correspond to a significance level of 5% or higher.

Panel A. Winner					
	Size	BM	Volatility	Bid-ask spread	Illiquidity
1 (accerlerative winners whose convexity are in the top 20%)	2,264,826	1.8624	0.0282	1.4390	7.0942
2	974,338	1.3414	0.0291	2.0140	10.7693
3	787,400	2.0496	0.0293	2.2290	11.3431
4	958,870	2.2019	0.0289	2.1626	11.1952
5 (slowing-down winners whose convexity are in the bottom 20%)	2,224,354	3.1903	0.0285	1.6887	8.1484
All	1,442,020	2.1300	0.0288	1.9086	9.6978
The t-value of the mean difference test (1-5)	0.64	-0.85	**-3.50**	**-16.65**	**-3.41**
The t-value of the mean difference test (1-All)	**17.82**	-0.24	**-7.95**	**-41.20**	**-13.63**
The t-value of the mean difference test (5-All)	**16.21**	0.84	**-3.63**	**-17.93**	**-5.09**
Panel B. Loser					
	Size	BM	Volatility	Bid-ask spread	Illiquidity
1 (accerlerative losers whose convexity are in the bottom 20%)	1,311,357	1.0935	0.0322	2.3765	10.7318
2	754,987	0.7042	0.0315	3.0839	16.5309
3	655,546	4.3236	0.0311	3.2187	17.6608
4	846,833	0.8501	0.0307	2.9260	15.1065
5 (slowing-down losers whose convexity are in the top 20%)	1,396,791	0.4403	0.0300	2.1552	9.6635
All	993,169	1.4788	0.0311	2.7537	13.9230
The t-value of the mean difference test (1-5)	**-2.01**	**2.04**	**21.73**	**11.29**	**2.32**
The t-value of the mean difference test (1-All)	**9.72**	-0.51	**13.64**	**-23.46**	**-8.65**
The t-value of the mean difference test (5-All)	**12.64**	-1.51	**-14.23**	**-39.79**	**-11.16**

Table 8 Performance of Trading Strategies Conditional on Time

This table presents the monthly raw returns, the *t*-values, and the Sharpe ratios for nine trading strategies in three non-overlapping sub-periods. The holding periods are also classified into two business cycles determined by the NBER (www.nber.org/cycles.html). The sample includes all common stocks listed in NYSE, AMEX, and Nasdaq from January 1962 to December 2011. Stocks whose share prices are lower than \$5 at the time of sorting and portfolio formation are deleted. The ranking period is 12 months lagged 1 month and the holding period is 6 months. Panel A reports the average monthly returns in basis points, the t-values, and Sharpe ratios. Sharpe ratios are calculated using monthly portfolio excess returns and standard deviations. Panel B reports the *t*-statistics (in parentheses) for the mean-difference test of returns between different trading strategies. The *t*-statistics are corrected for autocorrelation using the Newey-West procedure. Bold *t*-values correspond to a significance level of 5% or higher.

Panel A. Raw returns						
Trading strategy		196201-197808	1978/09-1995/04	1995/05-2011/12	Expansion	Recession
1. Long (Winner)	Return (bp)	98.27	106.19	46.19	98.07	30.31
Short (Loser)	T-value	**(4.45)**	**(4.76)**	(1.17)	**(5.53)**	(0.56)
	Sharpe ratio	[0.266]	[0.348]	[0.090]	[0.259]	[0.054]
2. Long (Winner)	Return (bp)	103.83	98.11	42.84	94.08	33.50
Short (Highly convex in loser)	T-value	**(4.39)**	**(4.46)**	(1.03)	**(4.92)**	(0.61)
	Sharpe ratio	[0.280]	[0.316]	[0.082]	[0.247]	[0.058]
3. Long (Winner)	Return (bp)	133.29	134.90	70.21	130.39	49.52
Short (Highly concave in loser)	T-value	**(5.01)**	**(5.73)**	(1.80)	**(7.69)**	(0.74)
	Sharpe ratio	[0.342]	[0.420]	[0.121]	[0.318]	[0.078]
4. Long (Highly concave in winner)	Return (bp)	65.75	82.59	-0.50	59.57	15.66
Short (Loser)	T-value	**(3.11)**	**(3.57)**	(-0.01)	**(3.07)**	(0.32)
	Sharpe ratio	[0.173]	[0.258]	[-0.001]	[0.159]	[0.029]
5. Long (Highly convex in winner)	Return (bp)	115.28	121.07	74.52	122.51	29.79
Short (Loser)	T-value	**(4.60)**	**(4.90)**	(1.70)	**(6.21)**	(0.48)
	Sharpe ratio	[0.268]	[0.365]	[0.124]	[0.278]	[0.048]
6. Long (Highly convex in winner)	Return (bp)	150.30	149.78	98.53	154.83	49.00
Short (Highly Concave in Loser)	T-value	**(5.04)**	**(5.74)**	**(2.22)**	**(7.99)**	(0.65)
	Sharpe ratio	[0.340]	[0.430]	[0.145]	[0.324]	[0.071]
7. Long (Highly Concave in Winner)	Return (bp)	71.32	74.50	-3.85	55.58	18.85
Short (Highly Convex in Loser)	T-value	**(3.21)**	**(3.30)**	(-0.09)	**(2.77)**	(0.40)
	Sharpe ratio	[0.189]	[0.230]	[-0.008]	[0.146]	[0.034]
8. Long (Highly Convex in Winner)	Return (bp)	120.84	112.99	71.16	118.52	32.97
Short (Highly Convex in Loser)	T-value	**(4.82)**	**(4.70)**	(1.60)	**(5.92)**	(0.53)
	Sharpe ratio	[0.287]	[0.341]	[0.122]	[0.277]	[0.053]
9. Long (Highly Concave in Winner)	Return (bp)	100.78	111.29	23.52	91.89	34.87
Short (Highly Concave in Loser)	T-value	**(4.23)**	**(4.74)**	(0.63)	**(5.24)**	(0.60)
	Sharpe ratio	[0.270]	[0.344]	[0.047]	[0.245]	[0.059]

Panel B. Mean comparison						
Trading strategy comparison		196201-197808	1978/09-1995/04	1995/05-2011/12	Expansion	Recession
2-1	Return (bp)	5.57	-8.08	-3.36	-3.99	3.19
	T-value	(0.73)	(-1.05)	(-0.25)	(-0.53)	(0.19)
3-1	Return (bp)	35.02	28.70	24.01	32.32	19.21
	T-value	**(3.35)**	**(3.84)**	(1.67)	**(5.09)**	**(0.86)**
4-1	Return (bp)	-32.51	-23.61	-46.69	-38.50	-14.65
	T-value	**(-3.26)**	**(-3.90)**	**(-3.63)**	**(-5.80)**	(-0.79)
5-1	Return (bp)	17.01	14.88	28.32	24.44	-0.53
	T-value	(1.81)	**(2.71)**	**(2.24)**	**(3.73)**	(-0.03)
6-1	Return (bp)	52.04	43.58	52.34	56.76	18.68
	T-value	**(3.38)**	**(4.31)**	**(2.44)**	**(5.78)**	(0.57)
7-1	Return (bp)	-26.95	-31.69	-50.05	-42.49	-11.47
	T-value	**(-2.33)**	**(-3.43)**	**(-2.69)**	**(-4.85)**	(-0.55)
8-1	Return (bp)	22.58	6.79	24.97	20.45	2.66
	T-value	**(2.59)**	(0.80)	(1.65)	**(2.65)**	(0.12)
9-1	Return (bp)	2.51	5.10	-22.68	-6.18	4.56
	T-value	(0.24)	(0.71)	**(-2.02)**	(-0.95)	(0.25)
3-2	Return (bp)	29.46	36.79	27.37	36.31	16.02
	T-value	**(2.03)**	**(2.95)**	(1.21)	**(3.36)**	(0.54)
5-4	Return (bp)	49.53	38.49	75.01	62.94	14.13
	T-value	**(3.27)**	**(4.46)**	**(3.54)**	**(5.96)**	(0.50)

Table 9 Performance of Trading Strategies Measured by Midpoints of Bid and Ask Quotes

This table presents the monthly profit in basis points, its *t*-value, and the Sharpe ratio for nine trading strategies in Panel A. Panel B reports the *t*-values for the mean difference tests. All aspects of the strategy and calculations are identical to those in Table 3, with the exception that we replace the daily closing prices by the midpoints of bid and ask quotes in the return calculation. All common stocks listed in NYSE, AMEX, and Nasdaq from January 1962 to December 2011 are included. However, stocks whose share prices are lower than a mid-quote of $5 at the time of sorting and portfolio formation are deleted. All the panels are for a ranking period of 12 months lagged 1 month and holding periods of 6 months. The Sharpe ratio in brackets is defined as dividing the monthly portfolio excess return by the standard deviation of excess returns; that is, we divide alpha by the idiosyncratic volatility of the portfolio returns to give the Sharpe ratio. All the *t*-values in parentheses are adjusted for potential autocorrelation with the Newey-West procedure. Bold *t*-values correspond to a significance level of 5% or higher.

Panel A. Portfolio return							
		Raw return			Alphas from the Fama-French three-factor model		
Trading strategy		All months	January only	January excluded	All months	January only	January excluded
1. Long (Winner)	Return (bp)	92.96	-67.73	107.66	114.03	-66.10	134.06
Short (Loser)	T-value	**(3.43)**	(-1.06)	**(3.73)**	**(5.05)**	(-1.00)	**(5.69)**
	Sharpe ratio	[0.204]	[-0.172]	[0.235]	[0.204]	[-0.172]	[0.235]
2. Long (Winner)	Return (bp)	82.42	-56.76	94.79	101.56	-68.24	118.88
Short (Highly convex in loser)	T-value	**(3.05)**	(-0.73)	**(3.37)**	**(4.20)**	(-0.93)	**(4.92)**
	Sharpe ratio	[0.180]	[-0.134]	[0.207]	[0.180]	[-0.134]	[0.207]
3. Long (Winner)	Return (bp)	118.39	-39.31	132.41	138.38	-6.95	157.22
Short (Highly concave in loser)	T-value	**(4.50)**	(-0.45)	**(4.63)**	**(6.01)**	(-0.09)	**(6.22)**
	Sharpe ratio	[0.239]	[-0.061]	[0.277]	[0.239]	[-0.061]	[0.277]
4. Long (Highly concave in winner)	Return (bp)	60.81	-76.10	73.33	81.97	-72.56	98.35
Short (Loser)	T-value	**(2.01)**	(-1.22)	**(2.32)**	**(3.41)**	(-1.00)	**(4.12)**
	Sharpe ratio	[0.132]	[-0.164]	[0.160]	[0.132]	[-0.164]	[0.160]
5. Long (Highly convex in winner)	Return (bp)	126.06	-64.85	143.52	146.84	-68.90	171.13
Short (Loser)	T-value	**(3.90)**	(-0.99)	**(4.28)**	**(5.11)**	(-1.04)	**(5.75)**
	Sharpe ratio	[0.233]	[-0.133]	[0.265]	[0.233]	[-0.133]	[0.265]
6. Long (Highly convex in winner)	Return (bp)	144.43	-69.34	163.43	165.03	-33.75	190.06
Short (Highly Concave in Loser)	T-value	**(4.83)**	(-0.68)	**(4.94)**	**(5.85)**	(-0.40)	**(6.01)**
	Sharpe ratio	[0.253]	[-0.091]	[0.298]	[0.253]	[-0.091]	[0.298]
7. Long (Highly Concave in Winner)	Return (bp)	46.13	-111.14	60.11	65.66	-107.80	82.88
Short (Highly Convex in Loser)	T-value	(1.60)	(-1.46)	**(1.99)**	**(2.63)**	(-1.31)	**(3.30)**
	Sharpe ratio	[0.100]	[-0.254]	[0.130]	[0.100]	[-0.254]	[0.130]
8. Long (Highly Convex in Winner)	Return (bp)	108.46	-86.79	125.82	128.22	-95.04	151.71
Short (Highly Convex in Loser)	T-value	**(3.73)**	(-1.17)	**(4.15)**	**(4.64)**	(-1.37)	**(5.37)**
	Sharpe ratio	[0.214]	[-0.187]	[0.247]	[0.214]	[-0.187]	[0.247]
9. Long (Highly Concave in Winner)	Return (bp)	82.10	-93.69	97.72	102.47	-46.50	121.23
Short (Highly Concave in Loser)	T-value	**(3.11)**	(-1.15)	**(3.52)**	**(4.64)**	(-0.64)	**(5.21)**
	Sharpe ratio	[0.180]	[-0.150]	[0.224]	[0.180]	[-0.150]	[0.224]

Panel B. Mean Comparison							
		Raw return			Alphas from the Fama-French three-factor model		
Trading strategy comparison		All months	January only	January excluded	All months	January only	January excluded
2-1	Return (bp)	-5.56	5.09	-6.50	-8.26	-6.14	-9.37
	T-value	(-0.60)	(0.20)	(-0.72)	(-1.05)	(-0.26)	(-1.19)
3-1	Return (bp)	30.41	22.53	31.11	28.55	55.16	28.98
	T-value	**(3.15)**	(0.42)	**(2.19)**	**(3.37)**	(1.46)	**(2.69)**
4-1	Return (bp)	-32.15	-8.37	-34.33	-32.06	-6.46	-35.71
	T-value	**(-3.22)**	(-0.16)	**(-3.40)**	**(-3.69)**	(-0.14)	**(-4.11)**
5-1	Return (bp)	33.09	2.88	35.86	32.81	-2.80	37.07
	T-value	**(2.93)**	(0.06)	**(3.29)**	**(3.02)**	(-0.09)	**(3.46)**
6-1	Return (bp)	56.45	-7.50	62.13	55.21	28.36	61.81
	T-value	**(3.94)**	(-0.10)	**(3.15)**	**(3.93)**	(0.50)	**(3.49)**
7-1	Return (bp)	-41.85	-49.29	-41.19	-44.17	-45.70	-45.36
	T-value	**(-3.30)**	(-1.32)	**(-3.03)**	**(-3.61)**	(-1.04)	**(-3.43)**
8-1	Return (bp)	20.48	-24.95	24.52	18.39	-32.94	23.47
	T-value	**(1.98)**	(-1.01)	**(2.22)**	(1.83)	**(-2.08)**	**(2.24)**
9-1	Return (bp)	-5.88	-31.85	-3.57	-7.35	15.60	-7.01
	T-value	(-0.69)	(-0.59)	(-0.37)	(-0.83)	(0.50)	(-0.75)
3-2	Return (bp)	35.97	17.45	37.61	36.81	61.30	38.35
	T-value	**(2.42)**	(0.25)	**(2.07)**	**(2.57)**	(1.03)	**(2.32)**
5-4	Return (bp)	65.25	11.25	70.19	64.87	3.66	72.78
	T-value	**(4.26)**	(0.26)	**(3.96)**	**(4.30)**	(0.08)	**(4.23)**

Appendix 1 Performance of Trading Strategies Estimated by Simple Raw Returns and Risk-Adjusted Returns: Alternative Ranking and Holding Periods

This table reports the average monthly returns, the *t*-values, and the Sharpe ratios for nine trading strategies from January 1962 to December 2011. The sample includes all common stocks listed in NYSE, AMEX, and Nasdaq. At the time of sorting and portfolio formation, stocks with a share price of $5 or lower are deleted. For brevity, stocks are sorted into quintiles based on the past 12-month returns lagged 1 month. All equally-weighted portfolios are held for 6 months. The convexity for each stock is defined by regressing the daily prices in the past 24 months on the variable t and the square of t for each stock, where t is an arithmetic sequence, which is equal to 1, 2, 3… or n for the indication of the past n, …, 3, 2, or 1 day respectively. Stocks whose coefficients of the square of t are in the top 20% are those with an accelerative speed of price increase; conversely, stocks whose coefficients of the square of t are in the bottom 20% are those whose decreasing speed of historical prices slows. The nine trading strategies are constructed by buying and selling the stocks with different visual patterns of historical prices. Panel A presents the returns in basis points, the *t*-values, and the Sharpe ratios of the nine trading strategies. The Sharpe ratio in brackets is defined as dividing the excess return of a portfolio by the standard deviation of this excess return. The Sharpe ratio is actually the appraisal ratio: alpha divided by the idiosyncratic volatility of the portfolio returns. The *t*-statistics in parentheses are adjusted for autocorrelation using the Newey-West covariance matrix. For Panel B, the *t*-statistics in parentheses examine whether the performance difference between two different portfolios is significantly different from zero, and bold *t*-values correspond to a significance level of 5% or higher.

Panel A. Portfolio return							
		Raw return			Alphas from the Fama-French three-factor model		
Trading strategy		All months	January only	January excluded	All months	January only	January excluded
1. Long (Winner)	Return (bp)	35.86	-290.28	64.89	73.40	-113.77	91.24
Short (Loser)	T-value	**(2.22)**	**(-3.32)**	**(3.69)**	**(5.24)**	(-1.44)	**(6.57)**
	Sharpe ratio	[0.095]	[-0.600]	[0.185]	[0.095]	[-0.600]	[0.185]
2. Long (Winner)	Return (bp)	14.23	-279.48	40.38	45.98	-105.15	61.84
Short (Highly convex in loser)	T-value	(0.84)	**(-3.64)**	**(2.24)**	**(2.67)**	(-1.43)	**(3.54)**
	Sharpe ratio	[0.037]	[-0.599]	[0.109]	[0.037]	[-0.599]	[0.109]
3. Long (Winner)	Return (bp)	83.05	-188.02	107.18	121.95	-24.55	136.25
Short (Highly concave in loser)	T-value	**(4.17)**	**(-2.28)**	**(5.01)**	**(7.03)**	(-0.26)	**(7.83)**
	Sharpe ratio	[0.190]	[-0.374]	[0.254]	[0.190]	[-0.374]	[0.254]
4. Long (Highly concave in winner)	Return (bp)	1.43	-369.82	34.48	37.02	-149.31	54.45
Short (Loser)	T-value	(0.08)	**(-3.71)**	(1.88)	**(2.39)**	(-1.83)	**(3.50)**
	Sharpe ratio	[0.004]	[-0.678]	[0.097]	[0.004]	[-0.678]	[0.097]
5. Long (Highly convex in winner)	Return (bp)	64.44	-337.52	100.22	119.56	-122.27	141.61
Short (Loser)	T-value	**(3.26)**	**(-3.63)**	**(4.64)**	**(7.44)**	(-1.61)	**(8.70)**
	Sharpe ratio	[0.138]	[-0.599]	[0.228]	[0.138]	[-0.599]	[0.228]
6. Long (Highly convex in winner)	Return (bp)	111.63	-235.25	142.51	168.12	-33.04	186.62
Short (Highly Concave in Loser)	T-value	**(4.65)**	**(-2.76)**	**(5.50)**	**(8.16)**	(-0.36)	**(8.86)**
	Sharpe ratio	[0.210]	[-0.394]	[0.276]	[0.210]	[-0.394]	[0.276]
7. Long (Highly Concave in Winner)	Return (bp)	-20.20	-359.02	9.96	9.61	-140.69	25.05
Short (Highly Convex in Loser)	T-value	(-1.08)	**(-3.98)**	(0.51)	(0.49)	(-1.80)	(1.24)
	Sharpe ratio	[-0.049]	[-0.657]	[0.026]	[-0.049]	[-0.657]	[0.026]
8. Long (Highly Convex in Winner)	Return (bp)	42.81	-326.71	75.71	92.14	-113.65	112.21
Short (Highly Convex in Loser)	T-value	**(2.34)**	**(-3.97)**	**(3.87)**	**(5.62)**	(-1.56)	**(6.77)**
	Sharpe ratio	[0.094]	[-0.605]	[0.175]	[0.094]	[-0.605]	[0.175]
9. Long (Highly Concave in Winner)	Return (bp)	48.62	-267.56	76.76	85.58	-60.09	99.47
Short (Highly Concave in Loser)	T-value	**(2.64)**	**(-3.01)**	**(3.85)**	**(5.17)**	(-0.60)	**(5.99)**
	Sharpe ratio	[0.120]	[-0.523]	[0.200]	[0.120]	[-0.523]	[0.200]

Panel B. Mean Comparison							
		Raw return			Alphas from the Fama-French three-factor model		
Trading strategy comparison		All months	January only	January excluded	All months	January only	January excluded
2-1	Return (bp)	-21.62	10.81	-24.51	-25.13	-2.37	-26.49
	T-value	**(-2.69)**	(0.37)	**(-2.96)**	**(-3.20)**	(-0.08)	**(-3.25)**
3-1	Return (bp)	47.21	102.26	42.31	47.78	53.77	45.86
	T-value	**(5.67)**	**(2.66)**	**(4.97)**	**(6.36)**	(1.56)	**(5.89)**
4-1	Return (bp)	-34.45	-79.54	-30.44	-29.72	-28.54	-30.13
	T-value	**(-4.05)**	**(-2.75)**	**(-3.42)**	**(-3.73)**	(-1.40)	**(-3.52)**
5-1	Return (bp)	28.60	-47.23	35.35	34.29	-15.87	38.93
	T-value	**(3.16)**	(-1.84)	**(3.84)**	**(3.49)**	(-0.53)	**(4.02)**
6-1	Return (bp)	75.82	55.03	77.67	82.07	37.90	84.79
	T-value	**(5.33)**	(1.39)	**(5.31)**	**(5.64)**	(0.76)	**(5.78)**
7-1	Return (bp)	-56.07	-68.73	-54.94	-54.84	-30.91	-56.63
	T-value	**(-4.28)**	(-1.70)	**(-4.06)**	**(-4.29)**	(-0.87)	**(-4.19)**
8-1	Return (bp)	6.98	-36.42	10.85	9.16	-18.24	12.44
	T-value	(0.89)	(-0.98)	(1.47)	(1.04)	(-0.42)	(1.53)
9-1	Return (bp)	12.76	22.72	11.88	18.07	25.23	15.72
	T-value	(1.67)	(0.69)	(1.46)	**(2.28)**	(0.65)	(1.90)
3-2	Return (bp)	68.83	91.46	66.82	72.91	56.14	72.35
	T-value	**(5.10)**	**(2.09)**	**(4.73)**	**(5.59)**	(1.13)	**(5.32)**
5-4	Return (bp)	63.05	32.31	65.79	64.01	12.67	69.06
	T-value	**(4.17)**	(0.83)	**(4.15)**	**(3.97)**	(0.30)	**(4.14)**

Appendix 2 Fama-MacBeth Regressions to Control for Other Return Determinants: (12, 12) Strategy

Panel A. The Dummies *Winner* and *Loser* are the top and bottom 20% respectively					
	(1)	(2)	(3)	(4)	(5)
Intercept	0.0112	0.0117	0.0137	0.0130	0.0146
	(3.89)	**(4.02)**	**(4.37)**	**(5.71)**	**(5.86)**
Size	-0.2690	-0.2804	-0.3216	-0.2611	-0.3066
	(-1.74)	(-1.89)	**(-2.80)**	**(-2.53)**	**(-3.45)**
B/M ratio	0.0022	0.0021	0.0017	0.0015	0.0013
	(3.72)	**(3.70)**	**(3.25)**	**(3.26)**	**(2.88)**
Turnover				0.0018	0.0017
				(0.23)	(0.21)
Vol				-0.0553	-0.0554
				(-1.13)	(-1.20)
Illiq				0.0261	0.0268
				(2.04)	**(2.05)**
R_{t-1}				-0.0001	-0.0007
				(-0.02)	(-0.21)
Winner			-0.0011		-0.0009
			(-0.79)		(-0.90)
Loser			-0.0035		-0.0037
			(-3.79)		**(-4.86)**
FHH			0.0004	-0.0001	0.0006
			(0.40)	(-0.05)	(0.81)
FHL			-0.0021	-0.0029	-0.0017
			(-2.75)	**(-4.34)**	**(-2.59)**
AcWinner		0.0008	0.0010	0.0012	0.0013
		(0.67)	(1.60)	**(2.21)**	**(2.30)**
DeWinner		-0.0024	-0.0015	-0.0020	-0.0013
		(-2.24)	**(-2.61)**	**(-3.63)**	**(-2.62)**
AcLoser		-0.0060	-0.0021	-0.0028	-0.0021
		(-6.94)	**(-4.05)**	**(-5.94)**	**(-4.36)**
DeLoser		-0.0031	0.0001	0.0003	0.0004
		(-3.34)	(0.23)	(0.51)	(0.66)
Average R-square	0.00	0.01	0.02	0.04	0.04

Panel B. The Dummies *Winner* and *Loser* are the top and bottom 4% respectively					
	(1)	(2)	(3)	(4)	(5)
Intercept	0.0112	0.0117	0.0135	0.0126	0.0143
	(3.89)	**(4.02)**	**(4.33)**	**(5.53)**	**(5.73)**
Size	-0.2690	-0.2804	-0.3339	-0.2634	-0.3126
	(-1.74)	(-1.89)	**(-2.87)**	**(-2.53)**	**(-3.49)**
B/M ratio	0.0022	0.0021	0.0017	0.0016	0.0013
	(3.72)	**(3.70)**	**(3.27)**	**(3.24)**	**(2.88)**
Turnover				0.0027	0.0023
				(0.34)	(0.28)
Vol				-0.0483	-0.0491
				(-0.98)	(-1.05)
Illiq				0.0260	0.0270
				(2.02)	**(2.05)**
R_{t-1}				-0.0001	-0.0007
				(-0.02)	(-0.21)
Winner			-0.0010		-0.0008
			(-0.72)		(-0.76)
Loser			-0.0036		-0.0037
			(-3.67)		**(-4.69)**
FHH			-0.0007	-0.0012	-0.0006
			(-0.56)	(-1.11)	(-0.59)
FHL			-0.0021	-0.0035	-0.0015
			(-1.80)	**(-3.54)**	**(-1.55)**
AcWinner		0.0008	0.0018	0.0017	0.0022
		(0.67)	**(2.08)**	(1.92)	**(2.81)**
DeWinner		-0.0024	-0.0009	-0.0016	-0.0005
		(-2.24)	(-1.12)	**(-2.07)**	(-0.72)
AcLoser		-0.0060	-0.0035	-0.0049	-0.0033
		(-6.94)	**(-4.80)**	**(-7.32)**	**(-5.10)**
DeLoser		-0.0031	-0.0012	-0.0015	-0.0007
		(-3.34)	(-1.57)	**(-2.42)**	(-1.18)
Average R-square	0.00	0.01	0.02	0.04	0.04

Appendix 3 Performance of Trading Strategies in Different Exchanges

This table presents the results of repeating the analysis reported in Table 3 by partitioning the sample according to exchanges. All the panels are for a ranking period of 12 months lagged 1 month and holding periods of 6 months. Panel A outlines the results for the common stocks listed in NYSE and AMEX, while and Panel B does likewise for Nasdaq stocks. The sample period spans January 1962 to December 2010. At the time of sorting and portfolio formation, stocks with a share price of \$5 or lower are deleted. The Sharpe ratio in brackets is defined as dividing the monthly portfolio excess return by the standard deviation of excess returns. For alphas, we divide alpha by the idiosyncratic volatility of the portfolio returns to give the Sharpe ratio. All the *t*-values are corrected for autocorrelation with the Newey-West adjustment. Bold *t*-values correspond to a significance level of 5% or higher.

Panel A. NYSE and AMEX				
		Raw return		
		All months	January only	January excluded
1. Long (Winner)	Return (bp)	69.77	-200.89	93.87
Short (Loser)	T-value	(4.22)	**(-2.83)**	**(5.19)**
	Sharpe ratio	[0.181]	[-0.419]	[0.256]
2. Long (Winner)	Return (bp)	67.72	-162.08	88.19
Short (Highly convex in loser)	T-value	**(4.12)**	**(-2.38)**	**(5.15)**
	Sharpe ratio	[0.173]	[-0.371]	[0.232]
3. Long (Winner)	Return (bp)	96.93	-83.19	112.97
Short (Highly concave in loser)	T-value	**(5.29)**	(-1.23)	**(5.60)**
	Sharpe ratio	[0.232]	[-0.149]	[0.283]
4. Long (Highly concave in winner)	Return (bp)	44.29	-228.58	68.59
Short (Loser)	T-value	**(2.71)**	**(-2.63)**	**(3.78)**
	Sharpe ratio	[0.115]	[-0.449]	[0.188]
5. Long (Highly convex in winner)	Return (bp)	87.27	-263.45	118.51
Short (Loser)	T-value	**(4.56)**	**(-3.53)**	**(5.72)**
	Sharpe ratio	[0.195]	[-0.458]	[0.281]
6. Long (Highly convex in winner)	Return (bp)	114.43	-145.75	137.60
Short (Highly Concave in Loser)	T-value	**(5.48)**	**(-2.04)**	**(5.99)**
	Sharpe ratio	[0.239]	[-0.222]	[0.303]
7. Long (Highly Concave in Winner)	Return (bp)	42.25	-189.77	62.91
Short (Highly Convex in Loser)	T-value	**(2.61)**	**(-2.31)**	**(3.62)**
	Sharpe ratio	[0.107]	[-0.409]	[0.165]
8. Long (Highly Convex in Winner)	Return (bp)	85.23	-224.64	112.82
Short (Highly Convex in Loser)	T-value	**(4.59)**	**(-3.23)**	**(5.83)**
	Sharpe ratio	[0.192]	[-0.424]	[0.265]
9. Long (Highly Concave in Winner)	Return (bp)	71.45	-110.88	87.69
Short (Highly Concave in Loser)	T-value	**(4.07)**	(-1.48)	**(4.52)**
	Sharpe ratio	[0.179]	[-0.203]	[0.231]

Mean Comparison				
Trading strategy comparison		All months	January only	January excluded
2-1	Return (bp)	-2.04	38.82	-5.68
	T-value	(-0.38)	(1.91)	(-0.99)
3-1	Return (bp)	27.16	117.71	19.10
	T-value	**(4.85)**	**(3.72)**	**(3.09)**
4-1	Return (bp)	-25.47	-27.69	-25.28
	T-value	**(-4.68)**	(-0.89)	**(-3.87)**
5-1	Return (bp)	17.51	-62.56	24.64
	T-value	**(3.21)**	**(-2.73)**	**(4.55)**
6-1	Return (bp)	44.67	55.15	43.73
	T-value	**(5.38)**	(1.43)	**(4.71)**
7-1	Return (bp)	-27.52	11.13	-30.96
	T-value	**(-3.60)**	(0.36)	**(-3.44)**
8-1	Return (bp)	15.46	-23.74	18.95
	T-value	**(2.42)**	(-0.98)	**(3.00)**
9-1	Return (bp)	1.69	90.02	-6.18
	T-value	(0.27)	**(4.17)**	(-0.88)
3-2	Return (bp)	29.20	78.89	24.78
	T-value	**(3.35)**	**(2.86)**	**(2.53)**
5-4	Return (bp)	42.98	-34.87	49.91
	T-value	**(5.15)**	(-0.84)	**(5.11)**

Panel B. Nasdaq				
		Raw return		
		All months	January only	January excluded
1. Long (Winner)	Return (bp)	94.62	-111.03	112.82
Short (Loser)	T-value	**(4.35)**	(-1.70)	**(4.92)**
	Sharpe ratio	[0.222]	[-0.242]	[0.269]
2. Long (Winner)	Return (bp)	84.49	-113.14	101.99
Short (Highly convex in loser)	T-value	**(3.57)**	(-1.33)	**(4.13)**
	Sharpe ratio	[0.192]	[-0.220]	[0.237]
3. Long (Winner)	Return (bp)	126.56	-60.39	143.11
Short (Highly concave in loser)	T-value	**(5.95)**	(-0.74)	**(6.26)**
	Sharpe ratio	[0.272]	[-0.094]	[0.323]
4. Long (Highly concave in winner)	Return (bp)	56.01	-197.97	78.50
Short (Loser)	T-value	**(2.41)**	**(-3.16)**	**(3.17)**
	Sharpe ratio	[0.130]	[-0.433]	[0.187]
5. Long (Highly convex in winner)	Return (bp)	120.26	-149.39	144.13
Short (Loser)	T-value	**(4.85)**	**(-2.23)**	**(5.46)**
	Sharpe ratio	[0.245]	[-0.290]	[0.299]
6. Long (Highly convex in winner)	Return (bp)	152.21	-98.75	174.42
Short (Highly Concave in Loser)	T-value	**(6.16)**	(-1.15)	**(6.47)**
	Sharpe ratio	[0.288]	[-0.136]	[0.348]
7. Long (Highly Concave in Winner)	Return (bp)	45.89	-200.08	67.66
Short (Highly Convex in Loser)	T-value	(1.85)	**(-2.38)**	**(2.58)**
	Sharpe ratio	[0.104]	[-0.396]	[0.157]
8. Long (Highly Convex in Winner)	Return (bp)	110.14	-151.50	133.30
Short (Highly Convex in Loser)	T-value	**(4.28)**	(-1.82)	**(4.90)**
	Sharpe ratio	[0.226]	[-0.274]	[0.280]
9. Long (Highly Concave in Winner)	Return (bp)	87.96	-147.33	108.79
Short (Highly Concave in Loser)	T-value	**(4.14)**	(-1.83)	**(4.96)**
	Sharpe ratio	[0.200]	[-0.227]	[0.265]
Mean Comparison				
Trading strategy comparison		All months	January only	January excluded
2-1	Return (bp)	-10.12	-2.11	-10.83
	T-value	(-1.22)	(-0.07)	(-1.29)
3-1	Return (bp)	31.95	50.64	30.29
	T-value	**(3.59)**	(0.91)	**(2.34)**
4-1	Return (bp)	-38.60	-86.95	-34.32
	T-value	**(-4.94)**	**(-3.78)**	**(-4.32)**
5-1	Return (bp)	25.65	-38.36	31.31
	T-value	**(3.07)**	(-1.60)	**(3.52)**
6-1	Return (bp)	57.59	12.28	61.61
	T-value	**(4.47)**	(0.19)	**(3.68)**
7-1	Return (bp)	-48.72	-89.05	-45.15
	T-value	**(-4.51)**	**(-2.12)**	**(-4.00)**
8-1	Return (bp)	15.52	-40.47	20.48
	T-value	(1.57)	(-1.20)	(1.94)
9-1	Return (bp)	-6.65	-36.30	-4.03
	T-value	(-0.79)	(-0.58)	(-0.40)
3-2	Return (bp)	42.07	52.75	41.12
	T-value	**(3.18)**	(0.67)	**(2.50)**
5-4	Return (bp)	64.25	48.58	65.64
	T-value	**(4.87)**	(1.29)	**(4.74)**