Evolution of historical prices in momentum investing

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Abstract

We find that the acceleration and deceleration patterns of historical prices can predict future expected returns. Winners with accelerated historical price increases deliver higher future expected returns and losers with accelerated historical price decreases perform more poorly in the future. Hence, the profit from buying past accelerated winners and shorting past accelerated losers is significantly higher than the momentum profit by 51.47%. Such profit cannot be subsumed by certain characteristics that have been considered to explain momentum. Possible explanations for our results include extrapolative bias and overreaction.

Keywords: momentum; historical price evolution; expected return; extrapolative bias; overreaction (*JEL* G12, G14)

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Abstract

We find that the acceleration and deceleration patterns of historical prices are predictive of future expected returns in momentum investing in the U.S. equity market from 1962 to 2014. Winners with accelerated historical price increases deliver higher future expected returns and losers with accelerated historical price decreases perform more poorly in the future. Hence, the profit from buying past accelerated winners and shorting past accelerated losers is significantly higher than the momentum profit by 51.47%. Such profit cannot be subsumed by certain characteristics that have been considered to explain momentum. Possible explanations for our results include extrapolative bias and overreaction.

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1. Introduction

Most empirical momentum studies involve using past realized returns in a formation period to determine future expected returns. Whether the acceleration and deceleration patterns of historical prices in a formation period have pricing information content in momentum investing is seldom discussed. By focusing on the evolution of historical prices, we confirm that in addition to past realized returns, the acceleration and deceleration patterns of historical prices are predictive of future expected returns in the U.S. Moreover, our results imply that extrapolative bias and overreaction strongly influence momentum.

Recent studies discuss the formation process of winners and losers for enhancing the profit and Sharpe ratio of the momentum strategy[1] (e.g., Grinblatt and Moskowitz, 2004; Novy-Marx, 2012; Bandarchuk and Hilscher, 2013; Da, Gurun, and Warachka, 2014; Barroso and Santa-Clara, 2015). Results have been established by distilling supplemental pricing information from past realized returns in a formation period. For example, Grinblatt and Moskowitz (2004) show that return consistency, as measured by the sign of the return in each month over a formation period, is a crucial driver of expected returns.[2] Novy-Marx (2012) shows that a past return with an intermediate horizon (measured over *t*-12 to *t*-7) more accurately predicts future returns than does a recent past return (measured

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[1] Momentum is prevalent in different markets (Rouwenhorst, 1998; Doukas and McKnight, 2005) and asset classes (Asness, Moskowitz, and Pedersen, 2013). It also exists between and within industries (Moskowitz and Grinblatt, 1999; Hameed and Mian, 2015).

[2] Grinblatt and Moskowitz (2004) create return consistency dummies to further categorize winners and losers. For example, consistent winners are stocks with positive returns in 15 of the 23 months from *t*-36 to *t*-13, whereas consistent losers are stocks with negative returns in at least 15 of these 23 months from *t*-36 to *t*-13.

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over $t-6$ to $t-2$). Da, Gurun, and Warachka (2014) find that there is stronger momentum when the past return consists of a series of frequent gradual changes rather than infrequent dramatic changes.[3] Blitz, Huij, and Martens (2011) demonstrate that sorting stocks according to their past residuals instead of gross returns produces a more stable version of momentum. Moreover, Barroso and Santa-Clara (2015) use an estimate of momentum risk to scale the exposure to the momentum strategy so that risk is constant over time. Such a risk-managed momentum strategy eliminates crashes and almost doubles the Sharpe ratio of the momentum strategy.

However, previous momentum studies rarely discuss the relation between the acceleration and deceleration patterns of historical prices in a formation period and future expected returns. We examine this relation in the U.S. market in this paper. We focus on how to distinguish the better (worse) stocks from a group of winner (loser) stocks whose past realized returns are sorted to the same level. To approximate the evolution of historical prices, we treat the historical prices as a continuous quadratic function for simplicity. We regress previous daily prices in a formation period on an ordinal time variable and the square of the ordinal time variable for each stock. The coefficient of the square of the ordinal time variable is denoted as γ. We use γ to measure the convexity or concavity of historical prices (i.e., the evolution of historical prices).

Our results demonstrate that the γ can provide predictive power for future expected returns in extreme portfolios. The values of γ and future expected returns are

[3] Da, Gurun, and Warachka (2014) design a variable denoted as ID, which is defined as the sign of the cumulative return during a formation period after skipping the most recent month multiplied by the difference of the percentage of days during the formation period with negative and positive returns. The sign of the cumulative return during the formation period is equal to 1 when the cumulative return is positive and -1 otherwise.

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positively related. To control for past realized returns, we use sequential double-sorted portfolios conditioned on formation period realized returns, and then on γ. The results show that winners (losers) with convex-shaped historical prices possess higher future expected returns than do winners (losers) with concave-shaped historical prices. Specifically, winners whose historical prices increase at an accelerated rate (accelerative winners) deliver higher expected returns and losers whose historical prices decrease at an accelerated rate (accelerative losers) perform more poorly in the future.

Next, we design two new trading strategies to highlight the predictive power of γ on future expected returns. For the situation of a 12-month formation period and a 6-month holding period, the plain momentum strategy (buy winners and sell losers) produces a profit of 62.77 bps per month and a monthly Sharpe ratio of 0.12. Meanwhile, a strategy that buys the winners whose historical prices are convex shaped and shorts the losers whose historical prices are concave shaped (i.e., buy accelerative winners and short accelerative losers, denoted as the "acceleration strategy") generates 95.08 bps per month and a monthly Sharpe ratio of 0.17, improving the momentum profit by 51.47%. However, the strategy that buys and sells stocks in a manner opposite that of the acceleration strategy produces the lowest return: 49.71 bps per month and a Sharpe ratio of 0.09. The Fama–Macbeth regressions show that the predictive power of γ cannot be subsumed by other firm characteristics that have been found to provide explanatory power for momentum, e.g., the 52-week high price in George and Hwang (2004); the earnings surprises in Novy-Marx (2015) and Chordia and Shivakumar (2005); the turnover in Lee and Swaminathan (2000); the idiosyncratic volatility in Bandarchuk and Hilscher (2013); and the intermediate-horizon past realized return in Novy-Marx (2012). Our results are not materially changed after we control for past realized returns, which means that the higher future return of the acceleration strategy is not simply a manifestation of finer partition

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based on the past realized returns.

Our results warrant further exploration, but extrapolative bias and overreaction are the two most likely explanations. In Barberis et al. (2015), the extrapolators believe that the expected price change of the stock market is a weighted average of past price changes, where more recent price changes are weighted more heavily. Assuming the price of each stock i follows a geometric Brownian motion, we derive that when two stocks have identical past realized returns in a formation period, the sorting of γ is related to the sorting of their drifts (i.e., expected returns). Moreover, how an investor evaluates the past information in each short period within a formation period determines whether the two sortings are identical or reversed. When investors assign more weight to recent past information (i.e., there is the extrapolative bias), the sorting of γ and the sorting of the drift (i.e., expected returns) are identical. Thus, the stock with convex-shaped historical prices possesses a higher drift than does the stock with concave-shaped historical prices. Conversely, when investors assign more weight to distant past information, the sorting of γ and the sorting of expected returns are reversed. The opposite situation is expected. Our results provide supportive evidence that momentum traders are probably extrapolators.

Furthermore, the primary cause of the initial momentum and ultimate reversals in Daniel, Hirshleifer, and Subrahmanyam (1998) is that stock prices overreact to private information signals and underreact to public signals: An overconfident investor would overestimate the precision of his private information signal. Such overconfidence causes the stock price to overreact, which ultimately reverses as fundamental news arrives. The rapid reversals in the acceleration strategy highlight the role of overreaction in momentum.

This paper contributes to momentum research theoretically and practically. Theoretically, we show that the acceleration and deceleration of historical prices in addition to the past realized returns in a formation period provide predictive power on

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future expected returns after other return determinants are controlled for. Our findings emphasize the roles of overreaction and extrapolative bias in momentum. Practically, we find a method to distinguish the better (worse) stocks from a group of winner (loser) stocks by observing the evolution of historical prices. We design a new strategy for buying and shorting a subset of winner and loser stocks based on the evolution of their historical prices. Given the higher profit and the low number of stocks required, transaction costs are less of greater concern than the plain momentum strategy (Lesmond, Schill, and Zhou, 2004). The acceleration strategy calls for transactions in only approximately 200 stocks, in contrast to the 1,000 to 2,000 required by the plain momentum strategy. Our findings also practically supplement Novy-Marx (2012), who finds that intermediate-horizon past performance distinguishes winners or losers from the whole sample more precisely.

The remainder of this paper is organized as follows: In Section 2, we detail our procedures for measuring the evolution of historical prices and propose new trading strategies. We report the findings in Section 3. In Section 4, we present the auxiliary tests. We discuss some possible explanations for our results in Section 5. We conclude in Section 6.

2. Data and trading strategies

We now provide evidence for our mathematical derivation introduced above. The sample includes all common stocks (share codes 10 and 11) listed in the NYSE, AMEX, and NASDAQ. The data are collected from the Center for Research in Security Prices (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 2014. We filter

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out the stocks whose prices are below $5 on the portfolio formation date.[4] We also retrieve accounting data from Compustat to calculate book-to-market ratios and other variables for our regression analyses. The factor data are collected from Kenneth French's website. 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.

On the basis of our mathematical derivation that two stocks share the same past realized return over a formation period, we first sort stocks into quintiles according to past *J*-month realized returns at the beginning of each month *t*, as in Jegadeesh and Titman (1993). The top 20% is categorized as the winner group and the bottom 20% as the loser group. We skip one full month between the formation period and the holding period to avoid microstructure issues, such as bid-ask bounce (Jegadeesh and Titman, 1993; Chan, Jegadeesh, and Lakonishok, 1996).

We further sort stocks in each return group into quintiles based on γ in equation (1).

$$Q_i(t) = \alpha_i + \beta_i t + \gamma_i t^2. \tag{1}$$

Equation (1) is run for each stock using daily data over the past *J* months skipping the most recent month, where $Q_i(t)$ denotes the daily price of stock *i* at day *t*, and *t* is an ordinal variable, which is equal to 1, 2, 3… or *n* for the indication of the past *n*, …, 3, 2, or 1 day respectively.[5] Finally, we have 5×5 portfolios.

When γ is positive (negative), the evolution of historical price is a convex (concave) function of time in the past *J* months. The stocks whose γ are in the top 20% of the winner group have convex-shaped historical prices, which means that their historical

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

[5] Running equation (1) with weekly data does not change the results significantly.

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prices increase at an accelerated rate.[6] We label these stocks *AcWinners*. *Ac* refers to an acceleration of price increase. The stocks whose γ are in the bottom 20% of the winner group have concave-shaped historical prices, thereby illustrating that the increasing speed of price rises gradually slows down. These stocks are labeled *DeWinners*. *De* refers to a deceleration of the price increase. Conversely, the losers whose γ are in the top 20%—that is, those that have convex-shaped historical prices—illustrate that the decreasing speed of historical prices gradually slows down. These losers are denoted *DeLosers*. Meanwhile, the losers whose γ are in the bottom 20% have concave-shaped historical prices, which means that their historical prices decrease at an accelerated rate. These losers are denoted *AcLosers*.

We next design three trading strategies to highlight the predictability of the γ on future expected returns. The first strategy is the plain momentum strategy documented in Jegadeesh and Titman (1993).

1. The plain momentum strategy: Buy winners and sell losers.
2. The acceleration strategy: Buy AcWinners and sell AcLosers.
3. The deceleration strategy: The opposite of the acceleration strategy. Buy DeWinners and sell DeLosers.

In accordance with Jegadeesh and Titman (1993), we hold overlapping portfolios for all strategies. Specifically, the sorting and portfolio formation procedure is repeated for each month, and the returns of the long-short portfolio are equally-weighted averages of

[6] Indeed, there is no guarantee that the stocks with the highest γ amongst the winners will be positive. In fact, it is possible that most of winners have negative γ during a certain period. However, there are no such circumstances in our tests.

the monthly returns on the overlapping portfolios. Each zero-investment portfolio is held for K months. The t-values for the portfolio returns are corrected for serial correlations using the Newey-West adjustment. For brevity, we focus on the case $(J, K) = (12, 6)$ for the remainder of this paper. We employ the prior year as a formation period because Moskowitz and Grinblatt (1999) show that the 1-year momentum of an individual stock is the strongest among numerous past return variables and remains significant even after accounting for industry effects.

3. Results

We report the returns for the above trading strategies in this section. We also run Fama–Macbeth regressions to assess whether our results still hold after certain firm characteristics are controlled for.

3.1 Descriptive statistics

The descriptive statistics of γ are presented in Table 1. For ease of interpretation, the value of γ is scaled up by 10^3. The mean of γ is 0.0015, which suggests that empirically the charts of historical prices for most stocks do not exhibit obvious patterns. However, the large variances of γ in the top and bottom groups suggest that some stocks have extreme values of γ.[7] The maximum value of γ is 62.0490.

[TABLE 1 HERE]

[7] The deletion of outliers does not materially change our conclusion.

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We observe several firm characteristics under different γ quintiles in the winner and loser groups. Table 2 shows the values and percentile rank ratios of firm characteristics. Panels A and B present the statistics for the winner and loser groups, respectively. Unlike the values, the percentile rank ratios mitigate noise from outliers. For each month, we rank stocks by the value of a particular characteristic, say illiquidity, and assign the rank value to the stock. We then calculate the percentile rank ratio by dividing each rank value by the cross-sectional sample size. For each category of stocks, we compute the cross-sectional means of the value and the percentile rank ratio of a particular firm characteristic for each month. We then average these monthly means across time to obtain the final average.

In the winner group, the AcWinners (winners with accelerating historical prices) have higher book-to-market ratios (*BM*), lower Amihud's illiquidity (*Illiq*) (Amihud, 2002), higher turnover rate (*Turnover*), smaller volume (*Volume*), and larger standardized unexpected earnings (*SUE*) than DeWinners (winners whose increasing speed of historical prices gradually slows). Both AcWinners and DeWinners enjoy more liquidity than the whole sample does. For example, the illiquidity of AcWinners is 0.2513 and of DeWinners is 0.3675. The *t*-value for the mean difference test between the two groups is -10.35, which means that the AcWinners are more liquid than the DeWinners. The Amihud's illiquidity for the whole sample is 0.5466. The results obtained using the values of firm characteristics prevail when we observe the percentile rank ratios. For example, AcWinners and DeWinners still enjoy more liquidity than the whole sample does. The illiquidity of AcWinners is 0.3568 and of DeWinners is 0.4041. The Amihud's illiquidity for the whole sample is 0.4676.

In the loser group, the AcLosers (the losers with accelerating downward historical prices) have smaller size (*Size*), lower book-to-market ratios (*BM*), higher idiosyncratic volatility (*IVol*), higher turnover rate (*Turnover*), and smaller standardized unexpected earnings (*SUE*) than DeLosers (the losers whose decreasing speed of historical prices gradually slows). Moreover, both AcLosers and DeLosers enjoy more liquidity than the whole sample does in terms of Amihud's illiquidity. Using the values of firm characteristics, the *t*-value for the mean difference test is -11.52 between the AcLosers and the whole sample and -9.26 between the DeLosers and the whole sample. In most cases, the results derived using the percentile rank ratios are more significant than those derived using the values of firm characteristics. We also conduct tests of the median difference for Table 2. The results do not materially change.

[TABLE 2 HERE]

3.2 The profits of the new strategies

We next examine whether the evolution of historical prices can further distinguish the better (worse) stocks from a group of winners and losers. Panel A of Table 3 reports the value-weighted average monthly raw return of buying AcWinners and selling DeWinners under the alternative ranking (*J*) and holding (*K*) periods. Panel B shows the value-weighted average monthly raw returns of buying DeLosers and selling AcLosers. In Panel A, the returns of AcWinners are significantly higher than those of DeWinners under most of (*J*, *K*) combinations. The significant outperformance of DeLosers can also be found in many (*J*, *K*) combinations in Panel B, which means that selling AcLosers is better than selling all losers in a zero-investment portfolio. Moreover, the return difference between AcWinners and DeWinners is more significant than that between AcLosers and DeLosers. However, such significant outperformance of AcWinners and DeLosers does not prevail when *J*=3. Overall, the outperformance of AcWinners (DeLosers) over

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DeWinners (AcLosers) provides supportive evidence that the evolution of historical prices possess new information in the cross-sectional pricing of stocks. We also repeat the tests using equal-weighted portfolios. The return differences are even more significant under equal-weighted portfolios.[8]

[TABLE 3 HERE]

Next, we discuss the returns of the three value-weighted trading strategies. For brevity, we focus on the case (J, K) = (12, 6). Based on the results in Table 3, the acceleration strategy should achieve the highest returns among the three strategies. The deceleration strategy will yield the lowest returns.

The results in Table 4 are consistent with our conjectures. Panel A of Table 4 presents the average monthly raw and risk-adjusted returns of the three value-weighted trading strategies. We also conduct mean difference tests to examine whether the returns of the newly-developed strategies significantly outperform or underperform the plain momentum strategy. The results are reported in Panel B. Three features stand out. First, the acceleration strategy achieves the highest returns. Its raw return is 95.08 bps, approximately 12.03% annually. Moreover, its Sharpe ratio, 0.17, is higher than that of the plain momentum strategy, 0.12. Second, contrary to the acceleration strategy, the performance of the deceleration strategy is 49.71 bps per month, thereby achieving the least profit among the three strategies. We buy and short stocks whose prices change at a slowing speed in the winner and loser groups (i.e., buys DeWinners and shorts DeLosers) in the deceleration strategy. Both the outperformance of the acceleration strategy and the underperformance of the deceleration strategy are significant in Panel B. Third, the profit

[8] The e results are available from the authors upon request.

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of the acceleration strategy totally comes from non-January months and becomes negative in January. This characteristic is also identified in the momentum investing in Jegadeesh and Titman (1993). When we repeat the tests for Table 4 but use equal-weighted portfolios, the results are more significant. Moreover, all results remain unchanged in the immediate succeeding month (i.e., (J, K) = (12, 1))[9]. Overall, the results in Table 4 not only confirm the predictive power of γ but also provide a method to improve the momentum investing.

[TABLE 4 HERE]

3.3 Fama–Macbeth regression

The predictive power of γ may incidentally capture the predictability of other return determinants. Hence, we run Fama–Macbeth regressions to assess whether our results still hold after certain firm characteristics are controlled for.

The dependent variable in these regressions is the month t return to stock i, $R_{i,t}$. Several control variables are included. *Ln(Size)* is the natural log of firm capitalization. *Ln(BM)* is the natural log of book-to-market ratio. Turnover rate (*Turnover*) is the shares traded within one month divided by the outstanding shares. Monthly idiosyncratic volatility (*IVol*) is the standard deviation of regression residuals of the Fama and French (1993) three-factor model. We follow Amihud (2002) to compute the monthly illiquidity measure (*Illiq*). The control variables also include the intermediate-horizon past realized return from month t – 7 to t – 12 ($R_{(7,12)}$) and standardized unexpected earnings (*SUE*), which provide explanatory power for momentum in Novy-Marx (2012, 2015), respectively. Standardized unexpected earnings (*SUE*) for stock i in each month is computed as the most

[9] All untabulated results are available from the authors upon request.

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recently announced earnings less the earnings four quarters ago and then standardized by its standard deviation estimated over the prior eight quarters. The lagged one-month realized return from $t-1$ to $t-2$ ($R_{(1,2)}$) is included to determine whether our results are not simply a manifestation of the monthly reversals presented by Jegadeesh (1990) and to mitigate the impact of any potential bid-ask bounce. The past realized return from month $t-2$ to $t-13$ ($R_{(2,13)}$) and the nearness to the 52-week high price (*52WH*) are included. The nearness to the 52-week high price (*52WH*) is computed as the stock price at the end of month $t-1$ dividing by the highest price during the 12-month period that ends on the last day of month $t-1$.

To measure the evolution of historical prices, γ in equation (1) is employed. Because the accelerative patterns are measured using γ with opposite signs in the winner and loser groups, we run the following regression for the winner and loser groups separately:

$$R_{i,t} = \beta_{0jt} + \beta_{1jt} ln(Size)_{i,t-1} + \beta_{2jt} ln(BM)_{i,t-1} + \beta_{3jt} Turnover_{i,t-1} + \beta_{4jt} IVol_{i,t-1} + \beta_{5jt} Illiq_{i,t-1} + \beta_{6jt} SUE_{i,t-1} + \beta_{7jt} R_{(1,2)\ i,t-1} + \beta_{9jt} R_{(7,12)\ i,t-j} + \beta_{8jt} R_{(2,13)\ i,t-j} + \beta_{10jt} 52WH_{i,t-j} + \beta_{11jt} \gamma_{i,t-j} + \epsilon_{i,t}. \quad (2)$$

The returns to (12, 6) strategies involve portfolios formed over six of the prior seven months. Therefore, like the method employed in George and Hwang (2004), we first compute the individual coefficients from separate cross-sectional regressions for each month $t-j$, where $j = 2, \ldots, 7$. Next we average these coefficients to be the monthly coefficient for a given month. For example, the monthly coefficient of $\gamma_{i,t-j}$ for a given month can be expressed as $\frac{1}{6}(\sum_{j=2}^{7} \beta_{11jt})$. In other words, the subscript $t-j$ indicates that the coefficient estimates of a given independent variable for a given month are averaged

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over j = 2, …. , 7 under (J, K) = (12, 6). Finally, the coefficients reported in Table 5 are the time-series averages of these averages.[10] The t-values are corrected using the Newey-West procedure. For ease of exposition, we scale up the illiquidity measure by 10^6.

Panel A of Table 5 provides the results for the (12, 6) strategy. In the winner group, the variable $\gamma_{i,t-j}$ is significantly positive after including other control variables, which means that the future expected return of a stock with convex-shaped historical prices is higher than the one with concave-shaped historical prices. For example, in column (4), the coefficient of $\gamma_{i,t-j}$ is 1.7457 (t=2.94). The variables *52WH* and $R_{(7,12)}$ are insignificant in column (4). The insignificance of $R_{(7,12)}$ indicates that further past performance does not influence the future expected returns of winner and loser stocks. This result does not contradict that of Novy-Marx (2012) because he focuses on whether the intermediate-horizon past realized return can more precisely distinguish winners and losers from the whole sample, not on distinguishing the better (worse) stocks from a group of winner (loser) stocks. Moreover, the variable $R_{(2,13)}$ is marginally significant. Because we include $R_{(2,13)}$ as a control variable, the significance of the variable γ does not simply reflect the influence of extreme past returns (Bandarchuk and Hilscher, 2013). Overall, the γ (i.e., the evolution of historical prices) can further identify the better stocks from a group of winners.

In the loser group, the positive coefficient of $\gamma_{i,t-j}$ indicates that the returns of stocks, whose historical prices decrease at an accelerating pace, will decrease more significantly in the future. In other words, shorting AcLosers is more profitable. However, after including other control variables in the regression for column (4), the coefficient of

[10] In Novy-Marx (2012), the coefficient of $R_{(7,12)}$ in a given month is not the average of separate cross-sectional regressions in the past months because he focuses on the case of (J, K) = (12, 1).

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$\gamma_{i,t-j}$ in the loser group becomes marginally significant (t=1.97). This result is consistent with Table 3, where the return difference between AcLosers and DeLosers is less significant. In other words, the outperformance of the acceleration strategy asymmetrically comes from the long side. Given the short-selling constraints, such asymmetry is practically beneficial for investors. Based on the Fama–Macbeth regressions, the predictive power of γ on future expected returns, especially in the long side, is not simply a manifestation of other return determinants or of the plain momentum strategy with finer partition.

However, the coefficient of $\gamma_{i,t-j}$ becomes marginally significant when K is 12. Panel B of Table 5 provides the results for the (12, 12) strategy. The coefficients of $\gamma_{i,t-1}$ are marginally significant at the 10% level in the winner side but become insignificant in the loser side. The insignificance of $\gamma_{i,t-j}$ under a longer holding period is consistent with the overreaction argument.

[TABLE 5 HERE]

3.4 Time series regression

In this subsection, we show that the outperformance of the acceleration strategy is not fully captured by other trading strategies in time series regressions. The time-series regression does not require parametric assumptions regarding the functional form of the relation between expected returns and the predictive variables and avoids measurement error in cross-sectional regressions. These time series regressions are used to determine which strategy generates significant abnormal returns relative to the others. Two strategies are included for comparison: the plain momentum strategy (MOM) and the acceleration

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strategy (ACE). We regress the average returns of a test strategy on the returns of explanatory strategies as follows:

$$y_t = \alpha + \boldsymbol{\beta}'\boldsymbol{X_t} + \varepsilon_t, \tag{3}$$

where y_t represents the excess returns to the MOM or ACE strategy and the explanatory factors are the returns of the Fama and French five factors (MKT, SMB, HML, RMW, and CMA) downloaded from Kenneth French's website. The returns of the earning momentum strategy (SUE), the 52-week high strategy (52WH), and the intermediate return strategy (INR) are also included as supplementary explanatory factors because these strategies are found to provide explanatory power for momentum (George and Hwang, 2004; Novy-Marx, 2012, 2015). A significant alpha suggests that an investor already trading the explanatory strategies could realize significant gains by trading the test strategy.

The 52-week high strategy (52WH) is constructed following George and Hwang (2004): the winner (loser) portfolio is a portfolio of the 20% of stocks with the highest (lowest) ratio of current price to the 52-week high. The intermediate return strategy (INR) is constructed following Novy-Marx (2012). We sort stocks into quintiles based on the past returns from month $t-7$ to $t-12$, buying the upper quintile and selling the bottom quintile. The standardized unexpected earnings strategy (SUE) is formed as a zero-investment portfolio. We buy the upper quintile and sell the bottom quintile of the earnings surprise portfolios based on the standardized unexpected earnings in Chordia and Shivakumar (2005). All zero-investment portfolios are value-weighted and held for six months. Because micro-cap and small-cap stocks are so numerous, the performance of all strategies is possibly driven disproportionately by small-cap stocks. To alleviate the concern that the results are absent from the large-cap sample, which accounts for a large majority of market capitalization, we also examine whether the results hold among large-cap stocks.

Table 6 presents the results for the whole sample and for the subsamples under size

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dichotomy partitioned by the median.[11] In Panel A, the results for the profit of the ACE strategy cannot be explained by the other strategies, regardless of firm size. This finding shows that the supplemental predictive power provided by γ can generate significant abnormal returns relative to other trading strategies. For example, the profit of the ACE strategy under the five-factor model is 107.05 bps (t = 4.63) and 140.84 bps (t = 6.17) in the large-size and small-size group, respectively.

Turning to the results for the MOM strategy in Panel B of Table 6, it only generates positive alphas under the five-factor model. Adding the SUE, ACE, and INR strategies as explanatory variables in the time series regression, the alphas of the MOM strategy lose their significance and become negative regardless of size. Based on the scale of the coefficients, the MOM strategy loads heavily on both the ACE and INR strategies, which means that they drive the success of the MOM strategy. This finding uncovers another hidden part of the MOM strategy in addition to the intermediate return found by Novy-Marx (2012). An investor who wants to benefit from momentum only needs to implement the ACE and INR strategies and would lose nothing by completely ignoring the MOM strategy.[12] The untabulated results show that the major findings remain unchanged under the case (J, K) = (12, 1).[13]

[11] Using the mean to divide the whole sample in to two subsamples does not change the conclusion materially.

[12] An interesting practical question is whether the ACE and INR strategies can be integrated. To answer this question, we first identify the winners and losers based on the intermediate past returns measured from *t-12* to *t-7*, as Novy-Marx (2012) does. The stocks in the winner and losers groups are further sorted based on the convexity of their historical prices measured from *t-12* to *t-2*; that is, γ in equation (1). We find that such integration can further enhance the profit of the acceleration strategy and reduce the profit of the deceleration strategy. The results are available upon request.

[13] While not the focus of this paper, an obvious and relevant question is whether the INR and 52WH can be explained by the ACE strategy. The untabulated results show that the INR strategy cannot be subsumed by the ACE strategy. This finding suggests that the INR strategy competes with the ACE strategy on equal terms because the two strategies cannot subsume each other. This means that an investor already employing one strategy could still realize significant profit by employing the other strategy. Furthermore, the 52WH strategy only generates positive alphas under the five-factor model in the small-size group, meaning that the profits of the 52WH strategy are mainly driven by small firms. As long as other strategies are included in the time series regressions, the alphas of the 52WH strategy become significantly negative regardless of size. The results are available upon request.

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[TABLE 6 HERE]

4. Auxiliary tests

4.1 Nonparametric test

The γ used in the previous tests is based on a parametric estimation of the quadratic model. Here, we use a nonparametric test to alleviate model misspecification. We first sort the stocks into quintiles based on the past 12-month returns lagged one month to identify the 12-month winners and 12-month losers. In the 12-month winner group, we further sort these stocks into quintiles based on their past 3-month returns lagged one month and denote the stocks in the top (bottom) quintile as AcWinners (DeWinners). Similarly, in the 12-month loser group, the stocks in the bottom (top) quintile based on their past 3-month returns lagged one month are denoted as AcLosers (DeLosers). All portfolios are value-weighted and held for six months.

The results in Table 7 for the nonparametric test are similar to those in Table 4. Compared with the plain momentum strategy, the acceleration strategy continues to outperform, whereas the deceleration strategy underperforms. Compared with the results in Table 4, the monthly raw returns and the risk-adjusted returns of the acceleration strategy become higher in terms of magnitude and significance. However, the underperformance of the deceleration strategy is less significant. Overall, we could still distinguish the better stocks from a group of winner stocks through double partition based on past returns at different horizons.

[TABLE 7 HERE]

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4.2 Longer holding periods

We next investigate whether the reversals can be observed in the acceleration strategy and the deceleration strategy. In accordance with Jegadeesh and Titman (1993), we calculate the average monthly returns when the holding period is extended to *K* months and the returns of the zero-cost strategies in the 60 months after portfolio formation. The formation period (*J*) is set at 12.

Figure 1 illustrates the results. Panel A is a plot of the returns of the zero-cost strategies in the 60 months after portfolio formation. Panel B is a plot of the average monthly returns when the holding period is extended to *K* months. In Panel A, the results confirm the existence of reversals for a holding period of eleven months or longer in both panels for all three strategies. For example, the profits of the momentum and acceleration strategies become significantly negative at the end of eleven months after portfolio formation. This finding is consistent with Jegadeesh and Titman (1993). Moreover, compared with the plain momentum strategy, the profit of the acceleration strategy declines on a larger scale than does the plain momentum strategy. The same trend can be found in Panel B. The average monthly returns of the three strategies become trivial and insignificant after the portfolios are held for more than two years.[14]

The rapid profit decline of the acceleration strategy is consistent with the overreaction argument. Further discussion of possible explanations for our results is presented in Section 5.

[FIGURE 1 HERE]

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[14] The raw numbers for Figure 1 are available upon request.

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4.3 Lagged one month, data filter, outliers, time partition, and exchanges

We also calculate the profits for the three strategies: (1) without skipping a month between the ranking and holding periods; (2) without removing stocks whose prices are below \$5; (3) after deleting stocks whose market capitalizations are in the smallest NYSE/AMEX/NASDAQ decile; (4) by using midpoints of bid-ask quotes; (5) in different subperiods; and (6) in different exchanges.

Overall, the major findings remain unchanged under these filters. We find that the difference in profit between the acceleration strategy and the plain momentum strategy is larger without skipping one month, especially when the formation period is long (i.e., $J > 12$) and the holding period is short (i.e., $K < 6$). Furthermore, the difference in profit between the acceleration strategy and the momentum strategy is made more significant by deleting stocks priced below \$5 or whose market capitalizations are small at the beginning of the holding period.

Furthermore, 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 ensure that our results above are not driven by bid-ask bounce, we repeat the analysis by replacing closing prices with the midpoints of the closing bid and ask quotes obtained from CRSP. Because CRSP only began reporting the closing quotes in the early 90s, this analysis relates specifically to the 1994–2014 period. We find that that our results are not attributed to the bid-ask bounce. The untabulated results show that the acceleration strategy continues to outperform and the deceleration strategy continues to underperform the plain momentum strategy by 38.76 (t = 2.66) and -6.09 (t = -2.41) bps per month respectively under (J, K) = (12, 6).

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To investigate whether our findings are conditional on time, we examine the performance of the three strategies in two equal and non-overlapping subperiods (1962–1987 and 1988–2014). The evidence indicates that the acceleration strategy always outperforms the plain momentum strategy. In the last two decades (1988–2014), the profit of the acceleration strategy achieves 81.86 bps per month; approximately 10.28% annually. We also follow Chordia and Shivakumar (2002) to analyze whether the profitability of these strategies is related to business cycles. We divide our whole sample into two economic environments: expansionary and recessionary periods, based on the definition provided by the National Bureau of Economic Research.[15] The untabulated results corroborate the findings of Chordia and Shivakumar (2002), Cooper, Gutierrez, and Hameed (2004), and Daniel and Moskowitz (2014). The profitability of all strategies is significantly positive during the expansionary period, but insignificant during the recessionary period. During the expansionary period, the acceleration strategy earns a significant profit of 137.37 bps, but yields only an insignificant profit of 34.46 bps during the recessionary period.[16]

Finally, the profit of three strategies under different exchanges is illustrated in Table 8. 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 89.38 (121.77) bps per month. To conclude, our findings remain robust in relation to all of the data truncation, alternative specifications, and various ranking/holding periods.

[TABLE 8 HERE]

[15] See http://www.nber.org/cycles.html.
[16] All the results outlined above are available upon request.

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5. Possible explanations

In this section, we discuss some possible explanations for our findings. Barberis et al. (2015) focus on the extrapolative bias and assume that the extrapolators believe that the expected price change of the stock market is a weighted average of past price changes, where more recent price changes are weighted more heavily.[17] Rational investors are fully rational. If extrapolators react to past price changes with some delay when forming their expectations, both negative long-term and positive short-term autocorrelations in price changes are generated.

If investors possess extrapolative bias suggested by Barberis et al. (2015), we derive that when two stocks have identical past realized returns in a formation period, the sorting of γ reveals the sorting of the drifts (i.e., expected returns). Namely, the evolution of historical prices are predictive of expected returns. Hence, the extrapolative bias provides a possible explanation for our findings. For brevity, the detailed mathematical derivation is available upon request but we summarize it as follows.

We first assume that the price of each stock i follows a geometric Brownian motion (GBM). The formation period $[0, T]$ is divided into n short periods of the same length, Δt. Thus, we can derive that the drift μ_i (i.e., the expected return) of a stock is a weighted average of the past return in each short period. The weight assigned to a short period depends on how an investor evaluates the information within that period. When investors possess extrapolative bias, more recent past returns are weighted more heavily. For mathematical tractability, we treat the prices as a continuous quadratic function over

[17] The representativeness bias in Kahneman and Tversky (1982) also portrays a cognitive bias that people give too much weight to recent patterns in the data and too little to the properties of the population that generates the data.

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time, as in equation (1). When two stocks have identical past realized returns in a formation period and the investors employ all information within the formation period $[0, T]$ to estimate the drift μ_i (i.e., expected returns), one can derive three scenarios. First, when the importance of past information monotonically increases within a formation period (i.e., investors possess extrapolative bias), the sorting of γ and the sorting of expected returns are identical. Thus, the stock with convex-shaped historical prices possesses a higher expected return than does the stock with concave-shaped historical prices. Conversely, when the importance of past information monotonically decreases within a formation period, the sorting of γ and the sorting of expected returns are reversed. Thus, the stock with convex-shaped historical prices possesses a lower expected return than does the stock with concave-shaped historical prices. Third, when past information in each short period is equally important, the sorting of γ and the sorting of expected returns are irrelevant. Then the expected return of the stock with convex-shaped historical prices should be identical to that of the stock with concave-shaped historical prices.

Based on the finding that γ is predictive of future expected returns, the third scenario introduced above can be ruled out. That is, past information at different horizons is not equally important. Moreover, when more recent past returns are weighted more heavily (i.e., investors possess extrapolative bias), the outperformance of the acceleration strategy can be expected. Hence, the extrapolative bias provides a possible explanation for our results. Our results also suggest a role for extrapolative bias in momentum investing.

Furthermore, the extrapolative bias can impact our results through limited investor attention. Historical prices are always reported in financial websites, the media, and trading

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tools. Moreover, these prices are usually and easily reported via the use of charts.[18] According to dual-coding theory, picture stimuli have an advantage over word stimuli as they are dually encoded (Paivio, 1971, 1986). Pictures generate a verbal and image code, whereas word stimuli generate only a verbal code. Concepts that are learned by viewing pictures are recalled more easily and frequently than those learned by viewing written words from counterparts (Paivio, 1986). With the extrapolative bias, recent price acceleration strengthens the incorrect belief that trends will continue indefinitely. Therefore, investors are more easily attracted by the stocks whose historical increase or decrease at an accelerative speed even these stocks share similar past realized returns in numbers, thereby resulting in an overreaction to trends.

In addition to extrapolative bias, overreaction is an influential factor in our findings. Daniel, Hirshleifer, and Subrahmanyam (1998) suggest that overconfident investors are likely to overestimate the precision of their private information, but not that of public information signals. This suggests that public information can trigger further overreaction to a private signal. Such overreaction can induce momentum in security prices, but such momentum is eventually reversed as further public information gradually draws the price back toward fundamentals.

Our results provide evidence of the role of investor overreaction in momentum along three horizons. First, investor overconfidence induces higher stock turnover (Barber and Odean, 2000). Table 2 shows that AcWinners and AcLosers possess the highest turnover rate in the winner and loser groups, respectively, which suggests that their extreme returns are possibly caused by investor overreaction. Second, the reversals of the acceleration strategy presented in Figure 1 are consistent with the overreaction argument.

[18] In the Internet era, these charts come in a variety of formats. However, most of our data are collected from the pre-Internet era. During this period, the main sources of information about a stock for retail investors were investment handbooks, such as the Value Line Investment Survey. These handbooks feature charts and present them using a fairly standard format.

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Compared with the reversals in the plain momentum strategy, the reversals in the acceleration strategy are more significant and rapid. Finally, in Table A4 in Appendix A the significance of the coefficient of $\gamma_{i,t-j}$ in the Fama-Macbeth regressions declines when the holding period is extended to 12 months, meaning that the predictability of γ gradually decreases in the long run.

In sum, extrapolative bias and investor overreaction may have influenced our results. Future research could explore this possibility in greater detail.

6. Conclusion

The relation between the acceleration and deceleration patterns of historical prices in a formation period and future expected returns are rarely discussed in the literature. We provide novel insight into momentum investing that the evolution of historical prices in a formation period can provide supplemental predictive power in determining future expected returns after past realized returns are controlled for.

Our results using the U.S. sample demonstrate that winner stocks with accelerated historical price increases (accelerative winners) deliver higher expected returns and loser stocks with accelerated historical price decreases (accelerative losers) perform more poorly in the future. We design an acceleration strategy and a deceleration strategy that transact in only a subset of winner and loser stocks with specific evolution of historical prices. The acceleration strategy—buying accelerative winners and shorting accelerative losers—generates a monthly raw return of 95.08 bps (12.03% annually). The average monthly profit of the acceleration strategy is significantly higher than the momentum profit by 51.47%. Such outperformance of the acceleration strategy does not simply come from a finer return partition or other return determinants.

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Extrapolative bias and investor overreaction are two potential explanations for our results. The extrapolators believe that the expected price change of the stock market is a weighted average of past price changes and assign more weight to recent past information. Given such behavioral bias, the outperformance of the acceleration strategy can be expected. Furthermore, the profit pattern in the acceleration strategy is also consistent with the overreaction explanation.

We propose a novel method to distill supplemental pricing information from past realized returns for the momentum phenomenon. Future momentum studies should continue to explore the importance of past information at different horizons and discuss other possible explanations in greater detail. Investigating such inequality of past information not only may lead to possible explanations for momentum but also facilitate the design of more profitable momentum strategies.

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Table 1
Descriptive statistics of γ

This table reports the descriptive statistics of the convexity of stock historical prices from January 1962 to December 2014. The sample covers all common stocks listed in NYSE, AMEX, and NASDAQ from January 1962 to December 2014. At the time of sorting and portfolio formation, stocks with a share price of \$5 or lower are deleted. The convexity of a stock's historical prices is computed by regressing the daily prices in the past 12 months skipping the most recent month on the variable t and the square of t, where t is an ordinal variable, 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. The stocks are sorted to quintiles based on the value of γ in the beginning of each month.

Rank by convexity (γ)	Mean	Median	Std. Dev.	Min	Max	Observations
1 (Low)	-0.4807	-0.3215	0.7476	-59.4524	0.2375	318,170
2	-0.0903	-0.0771	0.1316	-0.8880	0.3827	318,421
3	0.0132	0.0119	0.1093	-0.4574	0.5747	318,409
4	0.1130	0.0961	0.1272	-0.2244	0.9426	318,421
5 (High)	0.4514	0.3159	0.6432	-0.1006	62.0490	318,670
All	0.0015	0.0141	0.5429	-59.4524	62.0490	1,592,091

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Table 2

Firm characteristics of stocks in different convexity quintiles

This table presents the values and the percentile rank ratios of firm characteristics for various stock categories. The sample covers all common stocks listed in NYSE, AMEX, and NASDAQ from January 1962 to December 2014. 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 skipping one month. In each return quintile, stocks are sorted into quintiles based on the convexity of historical prices (γ) computed using equation (1). Panel A (Panel B) presents the average values and percentile rank ratios of firm characteristics for the winner (loser) group. For each category of stocks, we first compute the cross-sectional means of the values and the percentile rank ratios for each month; we then average these monthly means 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. *BM* is the book-to-market ratio. We follow Amihud (2002) to compute the monthly illiquidity measure (*Illiq*) for each stock. The *Illiq* variable is scaled up by 10^6. Monthly idiosyncratic volatility (*IVol*) is the standard deviation of regression residuals of the Fama and French (1993) three-factor model. Turnover rate (*Turnover*) is the shares traded divided by the outstanding shares. Volume (*Volume*) is the number of traded shares in thousands. Standardized unexpected earnings (*SUE*) is the most recently announced earnings less the earnings four quarters ago and then standardized by its standard deviation estimated over the prior eight quarters. The *t*-values for the mean-difference test between different categories of stocks are reported in parentheses. * or ** indicates significance at the 5% and 1% levels, respectively.

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Panel A. Winner							
Value							
	Size	*BM*	*Illiq*	*IVol*	*Turnover*	*Volume*	*SUE*
AcWinner	2,495,617	0.7053	0.2513	0.0237	2.0548	10,411.3106	1.2250
DeWinner	2,428,598	0.6085	0.3675	0.0239	1.6945	11,020.6025	1.1812
Whole sample	1,614,655	0.7655	0.5466	0.0246	1.6099	8,677.0488	1.0320
The *t* -value of the mean difference test (AcWinner-DeWinner)	(0.88)	(18.02)**	(-10.35)**	(-1.71)	(17.32)**	(-2.33)*	(4.19)**
The *t* -value of the mean difference test (AcWinner-Whole sample)	(15.92)**	(-13.02)**	(-32.74)**	(-13.32)**	(24.03)**	(9.76)**	(24.39)**
The *t* -value of the mean difference test (DeWinner-Whole sample)	(13.90)**	(-37.35)**	(-14.67)**	(-11.62)**	(6.80)**	(10.43)**	(18.42)**
Percentile rank ratio							
	Size	*BM*	*Illiq*	*IVol*	*Turnover*	*Volume*	*SUE*
AcWinner	0.5982	0.4554	0.3568	0.5445	0.6691	0.6029	0.6638
DeWinner	0.5627	0.3987	0.4041	0.5552	0.6245	0.5842	0.6523
Whole sample	0.4953	0.4838	0.4676	0.5653	0.6092	0.5378	0.6340
The *t* -value of the mean difference test (AcWinner-DeWinner)	(23.79)**	(33.22)**	(-30.95)**	(-6.99)**	(27.36)**	(11.64)**	(6.42)**
The *t* -value of the mean difference test (AcWinner-Whole sample)	(89.56)**	(-21.21)**	(-95.20)**	(-17.31)**	(47.76)**	(53.00)**	(21.90)**
The *t* -value of the mean difference test (DeWinner-Whole sample)	(56.86)**	(-64.52)**	(-51.68)**	(-8.72)**	(11.89)**	(36.86)**	(13.00)**

Panel B. Loser							
Value							
	Size	*BM*	*Illiq*	*IVol*	*Turnover*	*Volume*	*SUE*
AcLoser	1,371,896	0.5789	0.7812	0.0273	1.5265	12,937.2638	-0.3481
DeLoser	1,531,852	0.6055	0.6888	0.0252	1.4560	12,463.8970	-0.2555
Whole sample	1,084,668	0.6929	1.1800	0.0267	1.2118	10,716.2157	-0.3308
The *t* -value of the mean difference test (AcLoser-DeLoser)	(-3.12)**	(-4.15)**	(1.82)	(22.41)**	(3.84)**	(0.98)	(-10.07)**
The *t* -value of the mean difference test (AcLoser-Whole sample)	(7.65)**	(-31.16)**	(-11.52)**	(7.99)**	(28.12)**	(5.07)**	(-2.38)*
The *t* -value of the mean difference test (DeLoser-Whole sample)	(11.13)**	(-14.87)**	(-9.26)**	(-20.99)**	(15.06)**	(5.65)**	(10.94)**
Percentile rank ratio							
	Size	*BM*	*Illiq*	*IVol*	*Turnover*	*Volume*	*SUE*
AcLoser	0.4881	0.3938	0.4915	0.6134	0.6052	0.5713	0.3323
DeLoser	0.5151	0.4153	0.4737	0.5741	0.5831	0.5709	0.3475
Whole sample	0.4311	0.4651	0.5644	0.6015	0.5329	0.5051	0.3353
The *t* -value of the mean difference test (AcLoser-DeLoser)	(-17.61)**	(-13.12)**	(11.07)**	(25.94)**	(13.50)**	(0.29)	(-8.44)**
The *t* -value of the mean difference test (AcLoser-Whole sample)	(47.59)**	(-56.40)**	(-58.09)**	(10.12)**	(56.74)**	(52.30)**	(-2.11)*
The *t* -value of the mean difference test (DeLoser-Whole sample)	(71.13)**	(-38.57)**	(-73.19)**	(-23.33)**	(39.56)**	(52.04)**	(8.98)**

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Table 3

Performance of portfolios of stocks sorted by convexity in the winner and loser groups

This table reports the average raw returns in basis points of portfolios from January 1962 to December 2014. 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. We first sort stocks into quintiles based on the past J-month returns lagged one month. 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., γ computed using equation (1). We hold all value-weighted portfolios for K months. Each cell in this table reports the average monthly raw return of buying the stocks whose γ are in the top 20% and selling the stocks whose γ are in the bottom 20% under alternative ranking (J) and holding (K) periods in the winner (Panel A) and loser groups (Panel B). The t-statistics in parentheses are corrected for autocorrelation by the Newey-West procedure. * or ** indicate significance at the 5% and 1% levels, respectively.

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	Panel A. Winner								Panel B. Loser							
J K =	1	3	6	9	12	24	36	60	1	3	6	9	12	24	36	60
3	14.20	6.02	2.03	0.73	4.83	-2.40	-2.86	-0.39	1.08	0.12	5.76	0.25	3.96	0.71	-0.13	-0.51
	(0.94)	(0.86)	(0.43)	(0.19)	(1.43)	(-0.93)	(-1.25)	(-0.19)	(0.06)	(0.02)	(1.08)	(0.05)	(1.07)	(0.25)	(-0.06)	(-0.26)
6	8.03	14.73	8.90	10.36	13.55	6.93	4.29	1.94	2.57	10.09	4.62	2.43	7.45	6.93	5.19	4.99
	(1.97)*	(1.42)	(1.99)*	(2.29)*	(3.50)**	(2.56)*	(1.93)	(1.12)	(0.68)	(2.12)*	(2.35)*	(1.72)	(1.87)	(2.33)*	(2.16)*	(2.64)**
12	17.98	25.93	32.66	31.94	26.53	14.33	8.21	5.34	3.08	12.22	12.71	26.99	21.70	14.29	9.99	7.16
	(2.29)*	(2.21)*	(3.57)**	(4.39)**	(4.49)**	(3.85)**	(2.81)**	(2.49)*	(0.74)	(0.83)	(2.13)*	(3.26)**	(3.15)**	(3.14)**	(2.69)**	(2.41)*
24	38.09	39.63	28.55	25.66	26.93	14.27	8.65	2.02	22.51	41.01	46.22	39.55	34.13	8.94	2.32	3.22
	(2.43)*	(2.80)**	(2.29)*	(2.26)*	(2.69)**	(2.32)*	(1.95)	(0.59)	(1.30)	(2.66)**	(3.32)**	(3.25)**	(3.20)**	(1.40)	(0.48)	(0.88)
36	46.78	40.69	39.80	36.35	34.20	19.70	14.34	5.42	49.42	55.41	45.52	39.61	29.30	9.92	11.67	8.42
	(2.86)**	(2.68)**	(2.84)**	(2.83)**	(2.92)**	(2.41)*	(2.48)*	(1.26)	(2.64)**	(3.31)**	(2.96)**	(2.79)**	(2.26)*	(1.09)	(1.66)	(1.64)
60	37.40	39.14	31.80	27.80	27.36	22.35	14.58	5.36	33.20	23.97	11.83	10.97	10.22	8.76	5.80	10.05
	(2.29)*	(2.53)*	(2.20)*	(2.05)*	(2.10)*	(2.14)*	(1.69)	(0.79)	(1.92)	(1.40)	(0.74)	(0.72)	(0.69)	(0.73)	(0.62)	(1.55)

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Table 4

Performance of trading strategies estimated by simple raw returns and risk-adjusted returns

This table reports the average monthly returns in basis points, the *t*-values, and the monthly Sharpe ratios for three trading strategies from January 1962 to December 2014. 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 stocks are first sorted into quintiles based on the past 12-month returns lagged one month. In each return quintile, the stocks are further sorted to quintiles based on convexity, i.e., γ computed using equation (1). The three trading strategies are constructed by buying and selling stocks with different categories of stocks. We hold all value-weighted portfolios for six months. Panel A presents the returns in basis points, the *t*-values, and the Sharpe ratios of the three trading strategies. The Sharpe ratio in brackets is dividing the excess return of a portfolio by the standard deviation of this excess return (in raw return) or as the alpha divided by the idiosyncratic volatility of the portfolio returns (under the Fama-French three-factor model). 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 strategies is significantly different from zero. * or ** indicate significance at the 5% and 1% levels, respectively.

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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. Plain momentum strategy	Return (bps)	62.77	-152.77	81.99	92.06	-33.40	106.01
Long Winners	*t*-value	(3.06)**	(-1.92)	(3.90)**	(4.63)**	(-0.37)	(5.26)**
Short Losers	Sharpe ratio	[0.12]	[-0.27]	[0.16]	[0.19]	[-0.05]	[0.22]
2. The acceleration strategy	Return (bps)	95.08	-102.26	112.68	121.91	37.25	135.47
Long AcWinners (Accelerative winner)	*t*-value	(4.13)**	(-0.99)	(4.85)**	(5.37)**	(0.32)	(6.01)**
Short AcLosers (Accelerative loser)	Sharpe ratio	[0.17]	[-0.14]	[0.20]	[0.22]	[0.04]	[0.25]
3. The deceleration strategy	Return (bps)	49.71	-159.71	68.38	81.92	-39.86	93.12
Long DeWinners (Slowing-down winner)	*t*-value	(2.32)*	(-2.03)*	(3.10)**	(3.94)**	(-0.45)	(4.36)**
Short DeLosers (Slowing-down loser)	Sharpe ratio	[0.09]	[-0.28]	[0.13]	[0.16]	[-0.06]	[0.18]

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 (bps)	32.31	50.51	30.69	29.86	70.65	29.46
	t-value	(3.52)**	(1.14)	(3.34)**	(3.18)**	(1.38)	(3.16)**
3-1	Return (bps)	-13.06	-6.94	-13.61	-10.13	-6.46	-12.89
	t-value	(-2.53)*	(-0.18)	(-2.57)*	(-2.17)*	(-0.14)	(-2.48)*

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Table 5
Fama–Macbeth regressions to control for other return determinants

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 2014. Stocks with a share price of \$5 or lower at the time of portfolio construction are deleted. Each month, we regress cross-sectionally returns on the various control variables. In Panel A, the coefficient estimates of a given independent variable with subscript $t-j$ are averaged over $j = 2,\ldots, 7$ for the (12, 6) strategy. In Panel B, the coefficient estimates of a given independent variable with subscript $t-j$ are averaged over $j = 2,\ldots, 13$ for the (12, 12) strategy. The *Illiq* variable is scaled up by 10^6. The *t*-statistics (in parentheses) are calculated from the times series and adjusted for autocorrelation using the Newey-West covariance matrix. * or ** indicate significance at the 5% and 1% levels, respectively.

Panel A. $(J, K) = (12, 6)$

	Winner				Loser			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Intercept	0.0353	0.0238	0.0377	0.0503	0.0351	0.0286	0.0355	0.0434
	(5.95)**	(3.70)**	(5.46)**	(6.59)**	(5.55)**	(4.37)**	(5.42)**	(5.98)**
ln(Size)	-0.0006	-0.0008	-0.0015	-0.0019	-0.0003	-0.0007	-0.0015	-0.0017
	(-1.44)	(-2.16)*	(-3.96)**	(-4.67)**	(-0.90)	(-2.01)*	(-4.22)**	(-4.25)**
ln(BM)	0.0019	0.0013	0.0008	0.0020	0.0032	0.0025	0.0020	0.0023
	(3.01)**	(2.22)*	(1.44)	(3.16)**	(4.55)**	(3.91)**	(3.25)**	(3.33)**
Turnover			0.0022	0.0017			0.0057	0.0081
			(1.97)*	(1.38)			(4.51)**	(4.21)**
IVol			-0.3586	-0.2332			-0.3600	-0.2902
			(-8.06)**	(-4.61)**			(-10.05)**	(-7.17)**
Illiq			0.0002	0.0015			0.0002	-0.0011
			(0.63)	(0.70)			(0.60)	(-1.31)
SUE				0.0041				0.0035
				(14.38)**				(13.17)**
$R_{(1,2)}$			-0.0286	-0.0388			-0.0577	-0.0644
			(-6.87)**	(-8.09)**			(-13.22)**	(-14.26)**
$R_{(7,12)}$		-0.0025	-0.0038	-0.0022		0.0003	-0.0006	0.0012
		(-2.63)**	(-3.74)**	(-1.95)		(0.22)	(-0.40)	(0.67)
$R_{(2,13)}$		0.0034	0.0044	0.0021		0.0092	0.0014	-0.0014
		(3.17)**	(4.56)**	(2.03)*		(3.08)**	(0.50)	(-0.45)
52WH		0.0097	0.0064	0.0019		0.0085	0.0142	0.0059
		(4.23)**	(2.96)**	(0.82)		(2.52)*	(4.93)**	(1.82)
γ	3.5436	1.6192	1.6353	1.7457	2.8193	2.3283	1.0891	0.3911
	(5.53)**	(2.90)**	(3.00)**	(2.94)**	(2.93)**	(2.58)**	(2.19)*	(1.97)*
Average R^2	0.02	0.03	0.06	0.06	0.02	0.03	0.06	0.06

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(continued)

Panel B. (J, K) = (12, 12)								
	Winner				Loser			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Intercept	0.0163	0.0119	0.0305	0.0346	0.0176	0.0134	0.0251	0.0308
	(2.76)**	(1.98)*	(5.21)**	(5.55)**	(2.96)**	(2.33)*	(5.02)**	(5.70)**
ln(Size)	-0.0002	-0.0005	-0.0012	-0.0017	-0.0006	-0.0009	-0.0016	-0.0018
	(-0.46)	(-1.18)	(-3.32)**	(-4.44)**	(-1.47)	(-2.33)**	(-4.68)**	(-4.75)**
ln(BM)	0.0021	0.0014	0.0011	0.0022	0.0029	0.0024	0.0020	0.0022
	(3.31)**	(2.45)**	(1.93)	(3.62)**	(4.29)**	(3.82)**	(3.39)**	(3.43)**
Turnover			0.0306	0.0214			0.0607	0.0674
			(2.66)**	(1.73)			(5.20)**	(4.44)**
IVol			-0.3916	-0.2498			-0.3384	-0.2524
			(-9.81)**	(-5.52)**			(-9.71)**	(-6.58)**
Illiq			0.0001	0.0004			0.0003	-0.0003
			(0.46)	(0.22)			(1.52)	(-0.29)
SUE				0.0039				0.0037
				(15.01)**				(13.71)**
$R_{(1,2)}$			-0.0356	-0.0429			-0.0555	-0.0623
			(-8.78)**	(-9.60)**			(-12.65)**	(-13.83)**
$R_{(7,12)}$		-0.0022	-0.0031	-0.0018		-0.0042	-0.0050	-0.0039
		(-3.66)**	(-5.24)**	(-2.85)**		(-4.25)**	(-5.02)**	(-3.30)**
$R_{(2,13)}$		0.0020	0.0025	0.0011		0.0047	-0.0001	-0.0023
		(2.33)*	(3.47)**	(1.34)		(1.90)	(-0.05)	(-0.83)
52WH		0.0081	0.0048	0.0016		0.0088	0.0107	0.0024
		(4.52)**	(2.86)**	(0.89)		(3.13)**	(4.65)**	(0.99)
γ	2.4029	0.7879	0.8137	0.6888	3.7305	1.0874	0.6254	0.1734
	(6.13)**	(2.16)*	(2.30)*	(1.80)	(6.33)**	(1.82)	(1.05)	(0.27)
Average R^2	0.02	0.03	0.06	0.06	0.02	0.03	0.06	0.06

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Table 6

Time-series regressions of trading strategies

This table presents the monthly risk-adjusted returns in basis points and its *t*-value under the time-series regressions for the acceleration strategy (ACE) and the plain momentum strategy (MOM). All common stocks listed in NYSE, AMEX, and NASDAQ from January 1962 to December 2014 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 formation period of twelve months lagged one month and a holding period of six months. Size dichotomy is partitioned by the size median. We regress the returns of a test strategy on the returns of explanatory strategies as follows: $y_t = \alpha + \boldsymbol{\beta}'\boldsymbol{X_t} + \varepsilon_t$, where the y_t are the monthly excess returns to the ACE or the MOM strategies and the supplementary explanatory factors are the returns to the Fama and French five factors (MKT, SMB, HML, RMW, and CMA). The returns of the earning momentum strategy (SUE), the 52-week high strategy (52WH), and the intermediate return strategy (INR) are also included as supplementary explanatory factors. The constructions of the 52-week high strategy (52WH) and the intermediate return strategy (INR) follow the methods in George and Hwang (2004) and Novy-Marx (2012), respectively. The Sharpe ratio is defined as dividing the alpha under the three-factor model by the idiosyncratic volatility of the portfolio returns. * or ** indicate significance at the 5% and 1% levels, respectively.

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Panel A. y = Acceleration strategy (ACE)												
	All firms				Large firms				Small firms			
	(1)		(2)		(3)		(4)		(5)		(6)	
$\propto$	120.82	(5.10)**	33.18	(3.29)**	107.05	(4.63)**	27.47	(2.63)**	140.84	(6.17)**	21.89	(2.03)*
β_{MKT}	-0.16	(-2.79)**	0.05	(1.85)	-0.14	(-2.48)*	0.05	(2.05)*	-0.15	(-2.71)**	0.06	(2.47)*
β_{SMB}	0.08	(1.03)	0.06	(1.78)	0.17	(2.13)*	0.06	(1.59)	0.17	(2.10)*	0.19	(5.28)**
β_{HML}	-0.61	(-5.37)**	0.07	(1.35)	-0.60	(-5.43)**	0.07	(1.29)	-0.64	(-5.89)**	0.03	(0.50)
β_{RMW}	-0.05	(-0.44)	-0.17	(-3.20)**	-0.25	(-2.12)*	-0.15	(-2.85)**	0.11	(0.95)	-0.25	(-4.35)**
β_{CMA}	0.11	(0.62)	-0.14	(-2.04)*	-0.12	(-0.71)	-0.17	(-2.29)*	0.38	(2.31)*	-0.17	(-2.29)*
β_{MOM}			0.99	(28.27)**			0.89	(21.53)**			0.83	(19.36)**
β_{SUE}			0.05	(1.23)			0.05	(1.08)			0.08	(1.88)
β_{52WH}			0.19	(6.62)**			0.24	(6.23)**			0.37	(12.21)**
β_{INR}			-0.03	(-0.85)			0.09	(2.34)*			0.00	(-0.04)
Average R-square	0.07		0.86		0.12		0.84		0.07		0.84	
Sharpe ratio	0.21		0.13		0.19		0.11		0.25		0.08	
Panel B. y = Plain momentum strategy (MOM)												
	All firms				Large firms				Small firms			
	(1)		(2)		(3)		(4)		(5)		(6)	
$\propto$	89.06	(4.29)**	-27.93	(-3.62)**	77.81	(3.92)**	-20.33	(-2.60)**	93.85	(5.43)**	-9.62	(-1.19)
β_{MKT}	-0.14	(-2.80)**	-0.03	(-1.51)	-0.13	(-2.69)**	-0.04	(-2.13)*	-0.10	(-2.35)*	-0.02	(-1.27)
β_{SMB}	0.04	(0.54)	0.00	(-0.10)	0.11	(1.53)	-0.04	(-1.62)	0.09	(1.55)	0.01	(0.55)
β_{HML}	-0.66	(-6.67)**	-0.14	(-3.70)**	-0.66	(-6.98)**	-0.10	(-2.73)**	-0.68	(-8.21)**	-0.27	(-7.42)**
β_{RMW}	-0.01	(-0.11)	-0.05	(-1.23)	-0.21	(-2.09)*	-0.06	(-1.52)	0.03	(0.38)	-0.20	(-4.62)**
β_{CMA}	0.12	(0.77)	0.04	(0.71)	-0.08	(-0.59)	-0.03	(-0.48)	0.30	(2.39)*	0.02	(0.43)
β_{SUE}			0.11	(3.40)**			0.12	(3.85)**			0.04	(1.27)
β_{52WH}			-0.05	(-2.07)*			0.00	(0.06)			-0.02	(-0.89)
β_{ACE}			0.58	(28.27)**			0.50	(21.53)**			0.47	(19.36)**
β_{INR}			0.31	(15.22)**			0.39	(15.42)**			0.34	(13.65)**
Average R-square	0.10		0.89		0.16		0.89		0.13		0.85	
Sharpe ratio	0.17		-0.15		0.16		-0.11		0.22		-0.05	

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Table 7 Performance of trading strategies constructed using the nonparametric method

This table reports the average monthly returns, the *t*-values, and the monthly Sharpe ratios for three trading strategies from January 1962 to December 2014. 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 stocks are first sorted into quintiles based on the past 12-month returns lagged one month. In each return quintile, the stocks are further sorted into quintiles based on the past 3-month returns. The winner stocks in the top (bottom) quintile are denoted as AcWinners (DeWinners). Similarly, AcLosers (DeLosers) denote the loser stocks whose past 3-month returns are sorted into the bottom (top) quintile. All value-weighted portfolios are held for six months. Panel A presents the returns in basis points, the *t*-values, and the Sharpe ratios of the three trading strategies. 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 strategies is significantly different from zero. * or ** indicate significance at the 5% and 1% levels, respectively.

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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. Plain momentum strategy	Return (bps)	62.77	-152.77	81.99	92.06	-33.40	106.01
Long Winners	*t* -value	(3.06)**	(-1.92)	(3.90)**	(4.63)**	(-0.37)	(5.26)**
Short Losers	Sharpe ratio	[0.12]	[-0.27]	[0.16]	[0.19]	[-0.05]	[0.22]
2. The acceleration strategy	Return (bps)	121.67	-120.94	143.31	150.73	54.87	168.23
Long AcWinners (Accelerative winner)	*t* -value	(4.57)**	(-1.09)	(5.28)**	(5.77)**	(0.44)	(6.45)**
Short AcLosers (Accelerative loser)	Sharpe ratio	[0.18]	[-0.15]	[0.22]	[0.23]	[0.06]	[0.27]
3. The deceleration strategy	Return (bps)	48.52	-116.47	63.23	73.42	-72.55	83.77
Long DeWinners (Slowing-down winner)	*t* -value	(2.52)*	(-1.55)	(3.20)**	(3.98)**	(-0.82)	(4.47)**
Short DeLosers (Slowing-down loser)	Sharpe ratio	[0.10]	[-0.22]	[0.13]	[0.16]	[-0.11]	[0.19]

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 (bps)	58.90	31.83	61.32	58.69	88.27	62.24
	t -value	(4.11)**	(0.54)	(4.18)**	(4.06)**	(1.31)	(4.28)**
3-1	Return (bps)	-14.25	36.30	-18.76	-18.62	-39.14	-22.23
	t -value	(-1.17)	(0.60)	(-1.55)	(-1.51)	(-0.58)	(-1.84)

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Table 8 Performance of trading strategies in different exchanges

This table presents the value-weighted raw returns of repeating the analysis reported in Table 4 by partitioning the sample by stock exchanges. All the panels are for a formation period of twelve months lagged one month and holding periods of six months. Panel A provides 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 2014. 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. All the *t*-values are corrected for autocorrelation with the Newey-West adjustment. * or ** indicate significance at the 5% and 1% levels, respectively.

Panel A. NYSE and AMEX					Panel B. NASDAQ		
		Raw return			Raw return		
		All months	January only	January excluded	All months	January only	January excluded
1. Plain momentum strategy	Return (bps)	62.58	-131.27	79.86	78.44	-200.96	103.22
Long Winners	*t*-value	(3.31)**	(-1.64)	(4.17)**	(3.25)**	(-1.69)	(4.35)**
Short Losers	Sharpe ratio	[0.13]	[-0.23]	[0.17]	[0.15]	[-0.27]	[0.20]
2. The acceleration strategy	Return (bps)	89.38	-106.97	106.89	121.77	-105.76	141.95
Long AcWinners (Accelerative winner)	*t*-value	(4.27)**	(-1.06)	(5.13)**	(4.10)**	(-0.70)	(4.85)**
Short AcLosers (Accelerative loser)	Sharpe ratio	[0.17]	[-0.15]	[0.21]	[0.19]	[-0.11]	[0.23]
3. The deceleration strategy	Return (bps)	55.47	-100.53	69.38	50.56	-228.00	75.27
Long DeWinners (Slowing-down winner)	*t*-value	(2.76)**	(-1.24)	(3.37)**	(2.03)*	(-1.84)	(3.08)**
Short DeLosers (Slowing-down loser)	Sharpe ratio	[0.11]	[-0.17]	[0.14]	[0.09]	[-0.29]	[0.14]
		Mean Comparison			Mean Comparison		
Trading strategy comparison		All months	January only	January excluded	All months	January only	January excluded
2-1	Return (bps)	26.81	24.31	27.03	43.33	95.20	38.73
	t-value	(3.00)**	(0.58)	(3.01)**	(3.04)**	(1.24)	(2.77)**
3-1	Return (bps)	-7.10	30.74	-10.48	-27.88	-27.05	-27.96
	t-value	(-0.80)	(0.72)	(-1.17)	(-2.19)*	(-0.52)	(-2.13)*

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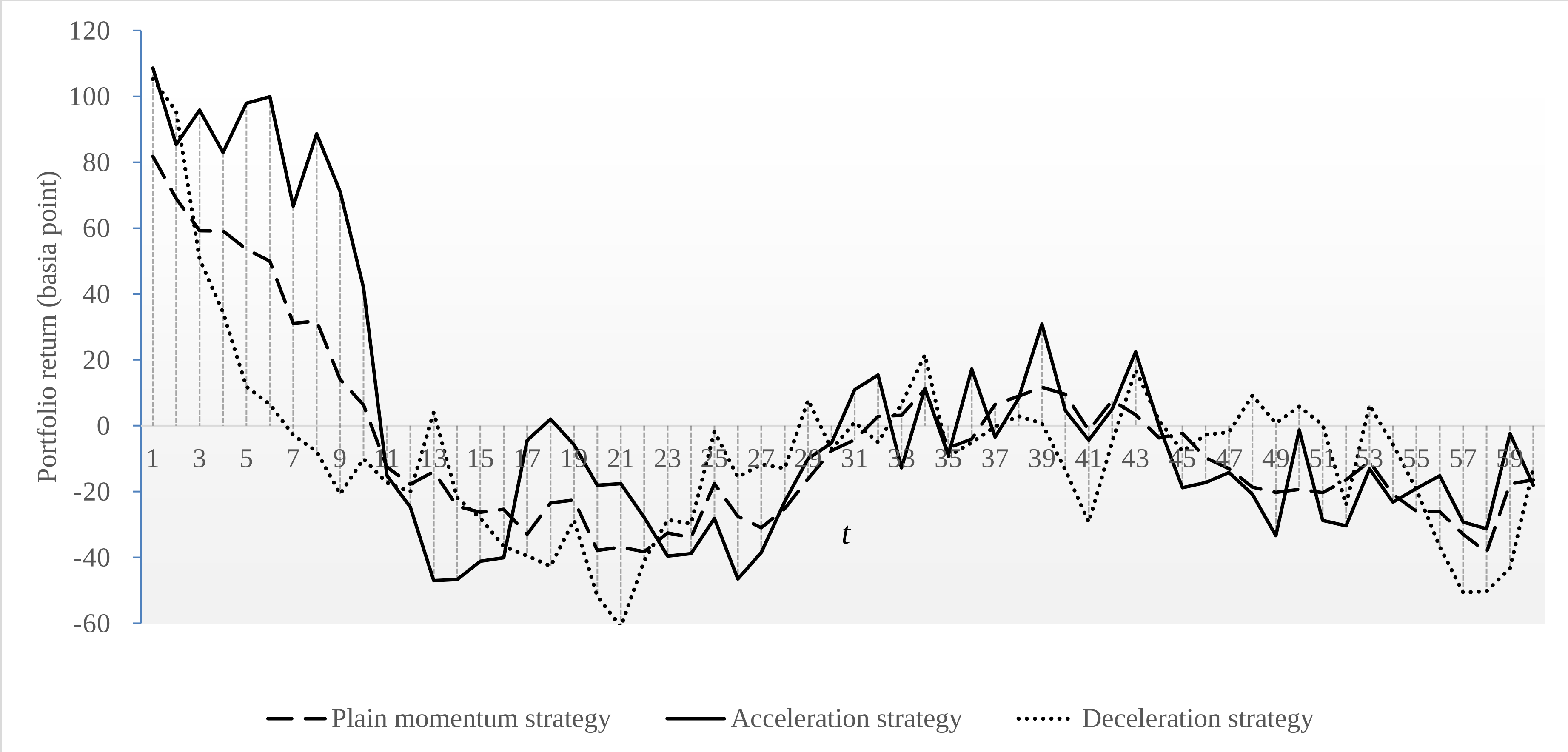

A. Portfolio return in each month *t* following the formation period

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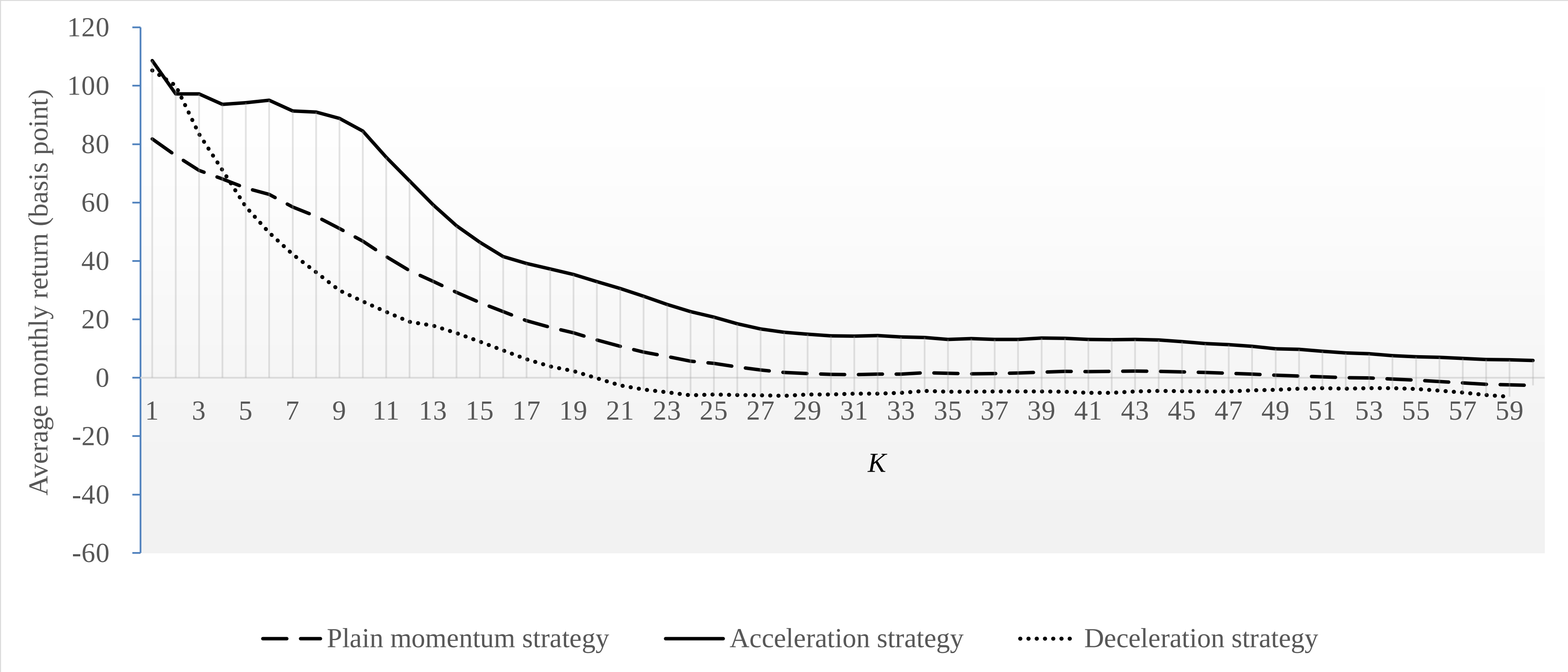

B. Average monthly raw return under a *K*-month holding period

Figure 1
Monthly raw returns under longer holding periods

This graph is a plot of the raw returns of the three strategies. Panel A depicts the raw returns of the three trading strategies in each month following the formation period; *t* is the month following portfolio formation. Panel B shows the average monthly raw returns of three strategies when the holding period is extended to *K* months.

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