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The Impact of Anchoring Bias on the Profitability of Time-Series Momentum

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Abstract

The motivation of this study bases on the role of anchoring bias on the profitability of the time-series momentum strategy. Market-wide nearness to the Dow 52-week high is computed, we use a market-timing approach that relies on the ability of nearness to the Dow 52-week high to predict future time-series momentum returns. Findings show that the market-timing strategy based on nearness to Dow 52-week high is more profitable than conventional momentum strategies. Our results support the contention that investors' reluctance to bid up the price of a stock in response to positive information is due to anchoring bias. This behavioral bias leads to stronger underreaction to good news.

Keywords: time-series momentum; anchoring bias; nearness to Dow 52-week high.

1. Introduction

Moskowitz et al. (2012) propose a strategy that buys futures contracts with positive prior-year returns and sells futures contracts with negative prior-year returns to earn significant profits, called time-series momentum (hereafter, TSMOM). A growing literature has documented evidence on TSMOM across assets (e.g., Moskowitz et al., 2012; Hurst et al., 2013; He and Li, 2015; Levine and Pedersen, 2016; Baltas and Kosowski, 2017). However, disagreement concerning the source and the interpretation of evidence for it remains unresolved, particularly for equities markets.[1]

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Recently, Lim et al. (2018) document that there is strong TSMOM in individual stocks and argue that continuously arriving information generates higher TSMOM profits. One of the explanations for the TSMOM effect in stock markets may be attributed to market underreactions in the short-run. In an influential recent study, George and Hwang (2004) argue that a stock's being at or near its 52-week high is good news that has recently arrived and this may be precisely the time when traders' underreaction to good news is due to anchoring bias. Specifically, a stock's proximity (distance) to its 52-week high price delays the incorporation of good (bad) news into its price as investors are averse to bid up the stock (short sell), causing it to be underpriced (overpriced). As a result, the gradual impounding of news shows is reflected by price continuation, leading to higher momentum profits.[2] Accordingly, nearness to the 52-week high is positively associated with stock

1 For example, Moskowitz et al. (2012) find strong momentum returns in the relatively liquid futures market and no correlation between their abnormal returns and measures of liquidity or sentiment. Hurst et al. (2013) demonstrate that TSMOM produces large correlations with Managed Futures indices and individual manager returns. More recently, Levine and Pedersen (2016) demonstrate the TSMOM returns dependence on past prices and returns by horizon. Baltas and Kosowski (2017) further show that the volatility estimation and price trend detection can significantly affect the performance of TSMOM. However, except for Lim et al. (2018), these studies have been less concerned with stock markets.

2 George and Hwang (2004) suggest that traders use the 52-week high as an anchor when assessing the increment in stock value implied by new information.

prices. In particular, TSMOM profits are stronger when there is interaction between anchoring bias and investor attention.

Academic literature indicates, on the other hand, that continuously arriving information leads to higher time-series of momentum profits because of investor attention (Hou et al., 2009; Lim et al., 2018). Hou et al. (2009) suggest that investors' attention can interact with their behavioral biases to process information, which generates positive serial correlation return patterns. Moreover, limited investor attention leads to category-learning behavior (Peng and Xiong, 2006). Investors tend to process more market-wide than firm-specific information when there is limited investor attention. Therefore, when the lagged market return reaches a peak near the median level of market performance and time-series momentum increases, there are significant strategy profits from price continuation when the lagged market return is highest (Cooper et al., 2004). Motivated by George and Hwang (2004) and Peng and Xiong (2006), the current study investigates the predictability of anchoring bias on TSMOM profits by using Dow nearness to the Dow 52-week high. Li and Yu (2012) indicate that the Dow index is arguably the most widely available information about the market, investors are likely using the Dow index as a benchmark to evaluate new market-wide information.[3] Therefore, nearness to the Dow 52-week high may capture the extent of underreaction, and facilitates our empirical analysis to understand the role of anchoring bias on TSMOM returns.

To show this, we use the Dow Jones Industrial Average index (DJIA) to compute nearness to the 52-week high to investigate the prediction ability of nearness to the Dow 52-week high on TSMOM profits. We construct the new strategy based on nearness to the Dow 52-week high as a trading signal. Our findings show that a strategy based on nearness to the Dow 52-week high can earn significantly higher TSMOM profits than a conventional TSMOM strategy. The strategy of nearness to the Dow 52-week high is more profitable in the short horizons. These findings are robust when we use market states by Cooper et al. (2004) as a predictive variable instead of nearness to the Dow 52-week high. Our results document that investors' reluctance to bid up the price of a stock in response to positive information would be strong when the stock has recently traded at an elevated price. This behavior generates stronger underreaction to good news for stocks close to their 52-week high price. Consequently, the gradual slow impounding of news shows up as a price continuation that appears as time-series momentum profits. Overall, our study addresses the gap of time-series momentum on equities markets, demonstrating the significant predictive power of nearness to the Dow 52-week high on TSMOM returns.

This study makes three contributions to the literature. First, it shows that a readily implementable strategy based on nearness to the Dow 52-week high price has remarkable prediction ability for TSMOM returns and that this finding presents a challenge to the efficient market hypothesis. Second, we show that the time-series momentum strategy conditioned on nearness to the Dow 52-week high outperforms a conventional time-series momentum strategy. This finding has important implications for investor decisions. Finally, we contribute to the behavioral finance literature by offering evidence on the potential role of anchor bias in investors' trading decisions.

2. Data and sample construction

2.1 Data

Stock return data are from the Center for Research in Security Prices (CRSP), including all common stocks (with Share Code 10 or 11) traded on the NYSE, AMEX, and NASDAQ from January 1964 to December 2018. We also obtain monthly value-weighted NYSE/Amex returns from CRSP. The Kenneth French online data library is the source for monthly risk-free rates (on one-month Treasury bills) and returns on risk factors, including the market excess returns (MKT), the small-minus-big firm returns (SMB), the high-minus-low book-to-market returns (HML), the spread between the returns on portfolios with robust and weak profitability (RMW) and the spread between the returns on portfolios of low-and high-investment firms (CMA).[4] Monthly S&P 500 stock index and Dow Jones Industrial Average are obtained from Compustat and Wall Street Journal,[5] respectively.

[3] Peng and Xiong (2006) point out that investors tend to process more market-wide information than firm-specific information.

[4] We thank Kenneth French for providing the time-series of three and five risk factors. These risk factors are from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[5] This data is from the website of the Wall Street Journal:

2.2 Time-series momentum trading strategies in stock returns

Following Moskowitz et al. (2012), we construct time-series momentum by assigned stocks into two groups. Specifically, we calculate the formation returns for each stock, and stock is sorted into the winner (loser) if the sign of pre-formation returns is positive (negative). Winner portfolio consists of stocks with positive pre-formation returns and the loser portfolio consists of stocks with negative returns. We then take long positions for the winner portfolio and short positions for the loser portfolio. The return of time-series momentum is calculated by returns of the winner portfolio minus returns of the loser portfolio over the holding months (the holding period) after formation months. To mitigate bid-ask bounce effects, we skip month t between the end of the formation period and the beginning of the holding period. We delete all stocks that are priced less than $1 at the beginning of the holding period. For trading strategies, we consider four pre-formation periods (*k*) including 3, 6, 9, and 12 months and holding periods (*h*) are 6-and 9-months.

For portfolio returns, we use three weighting schemes including value, equal and volatility. A stock in the value-weighted winner portfolio is weighted by its share of market value to the sum of market values of all winner stocks. For the volatility weighting scheme, we use daily returns over the formation period to estimate volatility for each stock. The volatility weighting for a stock in the winner portfolio is its inverse volatility, divided by the sum of the inverse volatilities of all winner stocks. Stocks are equally weighted in the winner portfolio when implementing the equal-weighted scheme. The weighting of loser portfolios is similar to that of winner portfolios.

We follow Li and Yu (2012) in using the Dow Jones 30-stock Industrial Average index for measurement nearness to the 52-week high (nearness to the Dow 52-week high). Similar to George and Hwang (2004), nearness to the 52-week high is calculated by the current Dow index over the highest Dow index during the 12-month period. More specifically, P_t denotes the level of the DJIA index at last trading day of month t and $P_{52,t}$ is its 52-week high at the last trading day of month t. Nearness to the 52-week high is computed as the ratio of the current Dow index and its 52-week high,

$$high_t = \frac{P_t}{P_{52,t}}. \tag{1}$$

Accordingly, the ratio of the 52-week high is higher when the Dow reaches a record high at the last trading day of month t during a year. The Dow Jones Industrial Average index is arguably the most widely used and visible index, so it may have stronger predictive power due to anchoring bias (Li and Yu, 2012). Furthermore, statistical concerns from overlapping observations are reduced by using monthly observations. For robustness, we also use the S&P 500 index as an alternative proxy to calculate nearness to the 52-week high.

Panel A of Table 1 reports summary statistics for variables. For the variables of nearness to 52-week high, either for Dow or S&P 500 indices, the average values are close to 1 and persistent. Li and Yu (2012) indicate that the Dow index is increasing over time, which would lead to a higher average value. There are highly negative skewness and kurtosis for ratios of nearness to the 52-week high, particularly for the Dow index, suggesting that investors are underreaction to good news when nearness to 52-week high reaches its peak. With a correlation matrix for variables, Panel B shows that the variables of nearness to the 52-week high are highly correlated, with a correlation coefficient of 0.741. As expected, the S&P 500 index should be correlated with the Dow index because stocks of the Dow index are included in the S&P 500 index. Therefore, nearness to 52-week high calculated by the S&P 500 is an alternative proxy for our robustness test. The TSMOM profit is positively correlated with nearness to the 52-week high and highly correlated with returns for the winner portfolio.[6] Overall, Table 1 provides a preliminary profile to demonstrate that investors' anchoring bias affects the profitability of the time-series strategy.

https://quotes.wsj.com/index/DJIA/historical-prices.

6 In this case, we implement the 6-month formation-holding-period strategy for generating portfolio returns.

Table 1. Summary statistic

	Loser	Winner	TSMOM	$high_{S\&P}$	$high_{Dow}$	MKT	HML	SMB	RMW	CMA
Panel A Summary statistic										
Mean	0.512	0.845	0.333	0.947	0.934	0.518	0.240	0.319	−0.612	0.943
Standard deviation	0.020	0.018	0.012	0.078	0.132	0.044	0.031	0.028	0.020	0.028
Skewness	−0.297	−0.366	−1.260	−2.093	−4.682	0.044	0.031	0.028	0.020	0.028
Kurtosis	4.260	5.049	11.377	8.002	29.007	4.961	8.301	5.059	6.360	14.411
Max.	6.421	7.168	5.606	1.000	1.000	0.161	0.217	0.129	0.053	0.121
Min.	−0.083	−0.064	−0.073	0.525	0.067	−0.232	−0.169	−0.111	−0.124	−0.210
AC(1)	0.844	0.861	0.696	0.898	0.918	0.074	0.037	0.172	0.196	0.119
Panel B Correlation matrix										
Loser	1.000									
Winner	0.814	1.000								
TSMOM	−0.503	0.923	1.000							
$high_{S\&P}$	−0.237	0.691	0.304	1.000						
$high_{Dow}$	−0.232	0.800	0.210	0.741	1.000					
MKT	0.002	0.055	0.077	−0.050	−0.059	1.000				
HML	−0.023	0.016	0.064	−0.014	−0.061	0.291	1.000			
SMB	−0.046	0.011	0.096	0.017	0.018	−0.261	−0.193	1.000		
RMW	0.017	0.030	0.016	−0.003	−0.029	0.278	−0.049	−0.481	1.000	
CMA	0.007	0.005	−0.005	−0.030	−0.028	−0.077	−0.466	0.126	0.388	1.000

Panel A shows the mean, standard deviation, autocorrelation (AC), skewness, kurtosis minimum, and maximum values. Nearness to the 52-week high (high) is calculated by the current Dow index over the highest Dow or S&P 500 index during the 12-month period. Use three weighting schemes, including value- equal- and inverse volatility, to calculate monthly portfolio returns. Use the 6-month formation-holding-period strategy (k,h=6) to form portfolio returns. Nearness to the 52-week high is computed as the ratio of the current Dow or S&P 500 index and its 52-week high. $high_{S\&P}$ and $high_{Dow}$ denote the calculated nearness to the 52-week high by using the S&P 500 and Dow indices, respectively. MKT is the market excess returns, SMB indicates the return spread between small and big firms, HML is return spread between the high and low book-to-market stocks. RMW is the return difference between returns on portfolios with robust and weak profitability and CMA is the return spread between returns on portfolios of low-and high-investment firms

3. Market timing strategies: nearness to the signal based on the Dow 52-week high

To investigate predictive ability of nearness to the Dow 52-week high on time-series momentum profits, we construct a trading strategy following Kim and Suh (2018) to predict TSMOM return during the holding periods. This trading strategy is based on market timing. We classify the current nearness to Dow 52-week high into three states in an ex-ante way. Specifically, if the nearness to the Dow 52-week high at month t exceeds the 70th percentile of the historical nearness to the Dow 52-week high up to t−1, then month t is classified as the "high" (H) market period. Likewise, the "low" (L) market period is the current nearness to the Dow 52-week high is less than the 30th percentile of historical nearness to the Dow 52-week high. The remaining case is referred to as the "medium" (M) market period. The market period is introduced by dummy variables, taking 1 for "high", 0 for "medium", and −1 for "low" market periods.

By distinguishing market states, we evaluate the ability of nearness to the Dow 52-week high to predict TSMOM return during the holding period. At each period t, we use the available historical information (up to t−1) to calculate an empirical Sharpe ratio (SR) for each of the three market states as follows:

$$SR_{t-1}(S) = \frac{R_{t-1}(S)}{[Var_{t-1}(S)]^{1/2}}, \qquad S = [\mathrm{H}, \mathrm{M}, \mathrm{L}], \tag{2}$$

where

$$\bar{R}_{t-1}(S) = \frac{1}{\#(N(S, t-1))} \sum_{\tau \in N(S,t-1)} R_\tau, \tag{3}$$

and

$$Var_{t-1}(S) = \frac{1}{\#\big(N(S, t-1)\big) - 1} \sum_{\tau \in N(S,t-1)} [R_\tau - \bar{R}_{t-1}(S)]^2, \tag{4}$$

$$\mathrm{N}(\mathrm{S}, \mathrm{t}-1) = \{\tau | S_t, \tau + K \leq t - 1\}, \tag{5}$$

$$R_\tau = \omega_\tau \sum_{k=1}^{K} \big(R_{w,\tau k} - R_{L,\tau k}\big), \tag{6}$$

$$\omega_\tau = \tau \cdot c_{t-1}, \tag{7}$$

where $\#(N)$ denotes the number of elements of set N, S_t is the market state at τ, and $\mathrm{N}(\mathrm{S}, \mathrm{t}-1)$ indicates the set of historical periods up to t−1 that belong to market state S. There is more weight on recent information by using time weight ω_τ, where c_{t-1} is a normalizing constant to make the sum of the time weight equal to one.

Then we measure the informativeness of nearness to the Dow 52-week high as the normalized Sharpe ratio difference between the market states H and L,

$$\Delta SR_{t-1} = SR_{t-1}(H) - SR_{t-1}(L) \in [-1, 1], \tag{8}$$

$$\delta_{t-1} = \frac{\Delta SR_{t-1}}{\sigma_{t-1}} \in [-1, 1], \tag{9}$$

$$\sigma_{t-1} = \left[\frac{1}{t-2} \sum_{\tau=1}^{t-1} [\Delta SR_\tau - \overline{\Delta SR}_{t-1}]^2\right]^{1/2}, \tag{10}$$

$$\overline{\Delta SR}_{t-1} = \frac{1}{t-1} \sum_{\tau=1}^{t-1} \Delta SR_\tau. \tag{11}$$

We follow Kim and Suh (2018) to restrict ΔSR and δ within $[-1, 1]$ to maintain stability and use the 24-month sample period to estimate the empirical Sharpe ratio and δ. Increased nearness to the Dow 52-week high is associated with higher TSMOM profits in the future, so δ and the normalized Sharpe ratio difference are positive. Accordingly, we invest more (less) with increase (decrease) in nearness to the Dow 52-week high signals. The TSMOM profits of market timing (overlapping) are calculated as,

$$R_{TSMOM,t} = \frac{1}{h} \sum_{i=1}^{h} (1 + \delta_{t-i-1} D_{t-i})(R_{w,t-i} - R_{L,t-i}). \tag{12}$$

Specifically, the portfolio weight increase (decrease) is according to δ with market signals (nearness to the Dow 52-week high). For robustness, we also apply this trading strategy on market states defined by Cooper et al. (2004) as a predictor variable instead of nearness to the Dow 52-week high. With their method, we identify “up” and “down” market states using the returns of the market for a 12-month period prior to the beginning of the strategy's holding period. If market return is positive (negative), we classify the market state as “up” (“down”). This comparison can help to determine whether the market-timing TSMOM strategy based on nearness to the Dow 52-week high is outperformance. Results for the performance of market timing strategies are presented in Table 2.

Table 2 shows the market-timing TSMOM strategies based on nearness to the Dow 52-week high outperform TSMOM alone for all of the weighted schemes. Measured by the Dow index (Panel A), the return differences between market-timing of nearness to the 52-week high (HTSMOM) and TSMOM are positive with statistical significance. The equal-weighted return spreads (Panel A1) are higher than the value-weighted spreads (Panel A2). Fig. 1 demonstrates the time trend for cumulative returns of the TSMOM and market-timing TSMOM (HTSMOM) strategies for momentum strategy cases (*k, h*=6, 9). In all cases, cumulative returns of the market-timing TSMOM strategy significantly exceed the conventional time-series momentum (TSMOM) strategy, particularly in the latter part of the sample period. By using the (HTSMOM) strategy based on nearness to the Dow 52-week high, we can earn an excess of 1000 dollars over 50 years when the initial investment is 10 dollars. The equal-weighted returns for the market-timing TSMOM strategy are more profitable than the value-weighted and volatility-weighted returns, showing that the market-timing TSMOM strategy based on nearness to the Dow 52-week high outperforms small stocks. The profits based on market-timing of nearness to Dow 52-week high are higher for the short horizons. The profiles for cumulative returns of trading strategies shown in Fig. 2 are consistent with Fig. 1, indicating the robustness of our findings.

Table 2. Raw returns for market-timing strategies

k	*h*	HTSMOM	MTSMOM	TSMOM	HTS−MTS	HTS−TS
Panel A Calculated by Dow index						
Panel A1. Equal-weighted						
	6	0.297***	0.258**	0.207**	0.040*	0.091**
3		(3.559)	(2.922)	(2.486)	(1.765)	(1.971)
	9	0.541***	0.476***	0.465***	0.065**	0.076**
		(5.559)	(4.174)	(4.599)	(1.989)	(1.933)
	6	0.394***	0.359***	0.326***	0.035*	0.069**
6		(3.889)	(3.741)	(3.266)	(1.729)	(2.034)
	9	0.407***	0.340***	0.344***	0.067**	0.063**
		(4.239)	(3.573)	(3.533)	(2.243)	(1.978)
	6	0.263***	0.180**	0.241**	0.083**	0.023
9		(3.399)	(2.343)	(3.011)	(2.503)	(1.316)
	9	0.285***	0.244**	0.239**	0.041*	0.046*
		(3.450)	(2.218)	(2.997)	(1.739)	(1.705)
	6	0.116**	0.115*	0.088*	0.002	0.029
12		(2.263)	(1.883)	(1.850)	(0.741)	(1.448)
	9	0.140**	0.109*	0.112**	0.031*	0.028
		(2.450)	(1.736)	(2.859)	(1.700)	(1.427)

Panel A2. Value-weighted						
	6	0.279**	0.235**	0.226**	0.043*	0.053*
3		(3.043)	(2.863)	(2.596)	(1.807)	(1.835)
	9	0.441***	0.399***	0.375***	0.042*	0.066*
		(4.344)	(3.890)	(3.742)	(1.787)	(1.942)
	6	0.349***	0.317***	0.254**	0.032*	0.095**
6		(3.420)	(3.574)	(2.845)	(1.691)	(2.194)
	9	0.322***	0.302***	0.260**	0.019	0.062*
		(3.571)	(3.784)	(2.926)	(1.315)	(1.880)
	6	0.174**	0.135**	0.140**	0.039	0.034
9		(2.648)	(2.135)	(2.253)	(1.638)	(1.566)
	9	0.129**	0.117*	0.102*	0.012	0.027
		(2.339)	(1.930)	(1.838)	(1.283)	(1.394)
	6	0.069*	0.022	0.058	0.048*	0.011*
12		(1.816)	(1.445)	(1.230)	(1.841)	(1.645)
	9	0.043	0.017	0.017	0.025*	0.025
		(1.105)	(1.387)	(0.445)	(1.726)	(1.377)
Panel A3. Volatility-weighted						
	6	0.285***	0.244**	0.217**	0.041*	0.069*
3		(3.142)	(2.920)	(2.503)	(1.785)	(1.896)
	9	0.518***	0.421***	0.416***	0.097**	0.103**
		(5.068)	(4.044)	(4.131)	(2.749)	(2.670)
	6	0.377***	0.344**	0.306**	0.034*	0.072**
6		(3.436)	(2.672)	(3.047)	(1.748)	(2.302)
	9	0.388***	0.320***	0.312***	0.069*	0.076**
		(3.775)	(3.287)	(3.337)	(1.905)	(2.398)
	6	0.219**	0.176**	0.175**	0.043*	0.044*
9		(3.032)	(2.286)	(2.912)	(1.815)	(1.874)
	9	0.195**	0.156**	0.132**	0.039*	0.063**
		(2.911)	(2.036)	(2.719)	(1.730)	(2.263)
	6	0.103**	0.072*	0.060	0.031*	0.044*
12		(2.155)	(1.746)	(1.412)	(1.662)	(1.863)
	9	0.084*	0.061	0.026	0.023	0.058**
		(1.665)	(1.512)	(1.373)	(1.349)	(2.208)
Panel B1. Equal-weighted						
	6	0.319***	0.269***	0.236***	0.050	0.083**
3		(3.958)	(3.325)	(3.309)	(1.504)	(2.577)
	9	0.531***	0.429***	0.342***	0.102**	0.189**
		(4.898)	(4.423)	(4.041)	(2.913)	(2.838)
	6	0.355***	0.314***	0.289***	0.041*	0.066**
6		(4.242)	(3.984)	(3.676)	(1.689)	(2.567)
	9	0.467***	0.412***	0.396***	0.055*	0.071**
		(4.593)	(4.232)	(4.340)	(1.753)	(2.466)

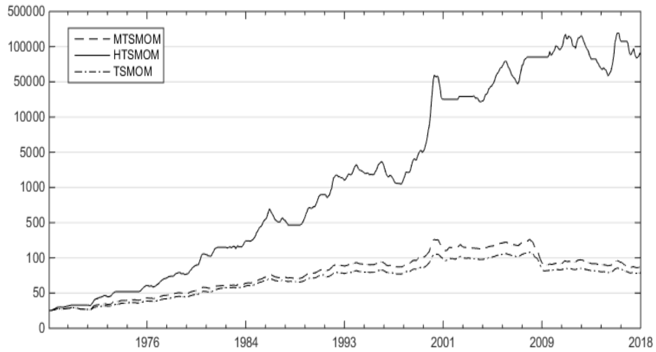
	6	0.256***	0.237***	0.218***	0.019	0.038
9		(3.350)	(3.284)	(3.104)	(1.381)	(1.604)
	9	0.239***	0.184**	0.135**	0.055	0.104**
		(3.300)	(2.752)	(2.964)	(1.570)	(3.074)
	6	0.116**	0.069*	0.042	0.047	0.075*
12		(2.726)	(1.765)	(1.620)	(1.486)	(1.909)
	9	0.063	0.039	0.011	0.024	0.052*
		(1.450)	(1.588)	(0.596)	(1.386)	(1.711)
Panel B2. Value-weighted						
	6	0.287***	0.235***	0.226**	0.051	0.061**
3		(3.473)	(3.284)	(3.060)	(1.534)	(2.221)
	9	0.455***	0.355***	0.317***	0.099**	0.137**
		(4.424)	(3.690)	(3.174)	(2.894)	(2.550)
	6	0.289***	0.242**	0.226**	0.047*	0.063*
6		(3.115)	(3.066)	(2.888)	(1.704)	(1.866)
	9	0.309***	0.265***	0.253***	0.044*	0.056*
		(3.472)	(3.284)	(3.209)	(1.680)	(1.737)
	6	0.175**	0.163**	0.140*	0.012	0.035
9		(2.715)	(2.670)	(1.943)	(1.315)	(1.599)
	9	0.124**	0.097	0.085	0.027	0.040*
		(2.381)	(1.542)	(1.373)	(1.478)	(1.756)
	6	0.069*	0.048	0.028	0.021	0.041*
12		(1.816)	(1.070)	(0.626)	(1.376)	(1.729)
	9	0.043	0.017	0.009	0.025	0.034
		(1.105)	(0.549)	(0.234)	(1.413)	(1.518)
Panel B3. Volatility-weighted						
	6	0.294***	0.241***	0.217***	0.053	0.077**
3		(3.454)	(3.307)	(3.251)	(1.543)	(2.321)
	9	0.510***	0.406***	0.339***	0.104***	0.171**
		(4.479)	(4.363)	(3.888)	(3.356)	(2.760)
	6	0.307***	0.262***	0.257***	0.046*	0.050*
6		(3.593)	(3.104)	(3.396)	(1.686)	(1.799)
	9	0.388***	0.342***	0.312***	0.046*	0.076**
		(4.143)	(3.647)	(3.871)	(1.699)	(2.527)
	6	0.215***	0.181**	0.175**	0.034	0.040*
9		(3.198)	(3.080)	(2.691)	(1.513)	(1.698)
	9	0.181**	0.134**	0.092*	0.048*	0.089**

		(2.690)	(2.545)	(1.725)	(1.718)	(2.624)
	6	0.094*	0.050*	0.031	0.044*	0.063*
12		(1.874)	(1.688)	(0.931)	(1.659)	(1.725)
	9	0.057	0.019	0.008	0.038	0.049*
		(1.212)	(0.761)	(0.173)	(1.560)	(1.660)

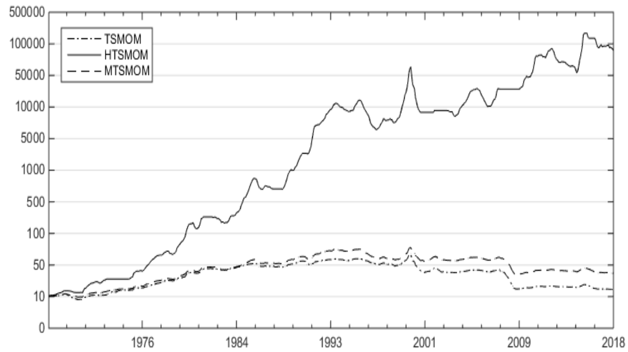
We use nearness to the 52-week high as a market signal to determine investment decisions. Market-timing strategies of TSMOM are constructed by classifying current nearness to the 52-week high into market states in an ex-ante way. We evaluate the ability of nearness to the 52-week high signal to predict TSMOM return during the holding period. At each period t, we use the available historical information (up to t−1) to calculate an empirical Sharpe ratio (SR) for each of the market states. In addition, we apply this trading strategy on market states defined by Cooper et al. (2004) as a predictor variable to compare the performance. We identify "up" and "down" market states using returns of the market for a 12-month period prior to the beginning of the strategy's holding period. If market return is positive (negative), we classify the market state as "up" ("down"). HTSMOM indicates the TSMOM profits based on market-timing of nearness to the 52-week high, MTSMOM denotes TSMOM profits based on market states defined by Cooper et al. (2004), and TSMOM is time-series momentum profits. HTS—MTS indicates the return difference between HTSMOM and MTSMOM, HTS—TS is the return difference between HTSMOM and TSMOM. Newey and West (1987) adjusted t-statistics are reported in parentheses. In addition, *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

(k=6, h=6)

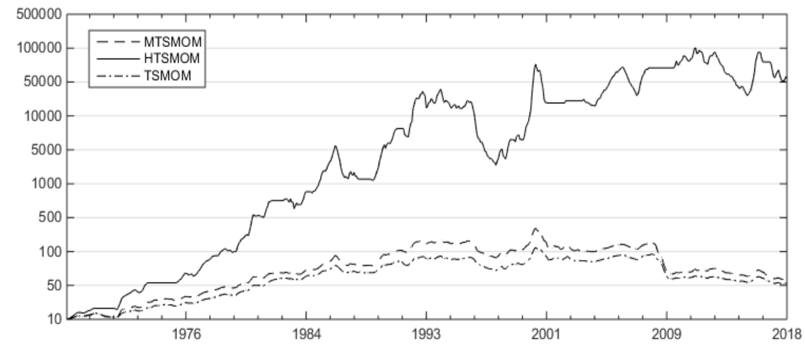
Equal-weighted



Value-weighted

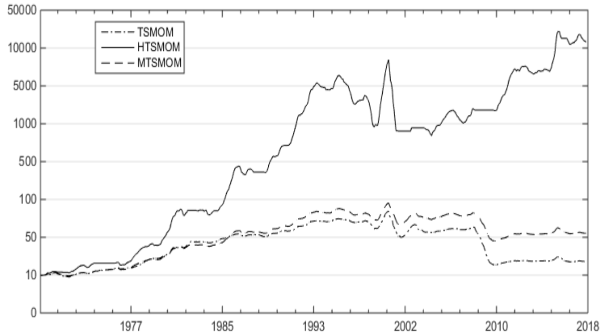


Volatility-weighted



(k=9, h=9)

Equal-weighted



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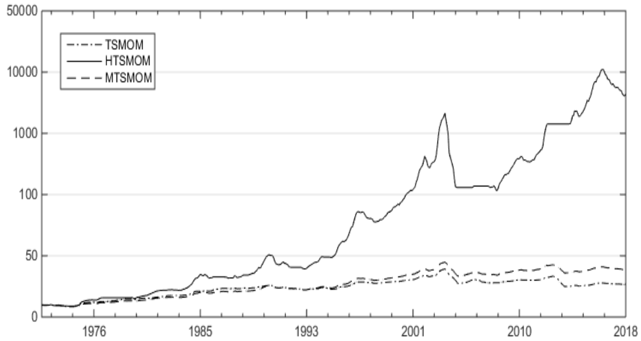

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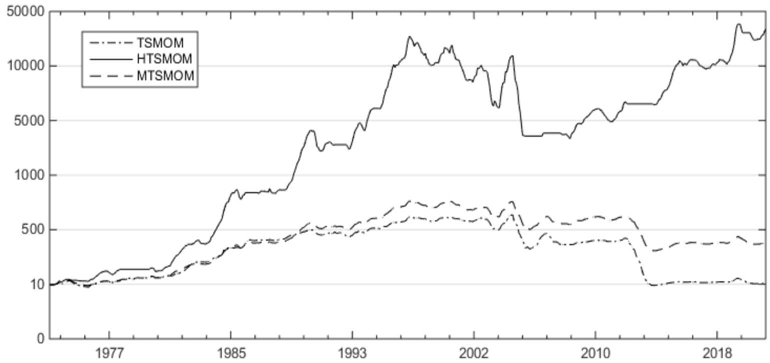
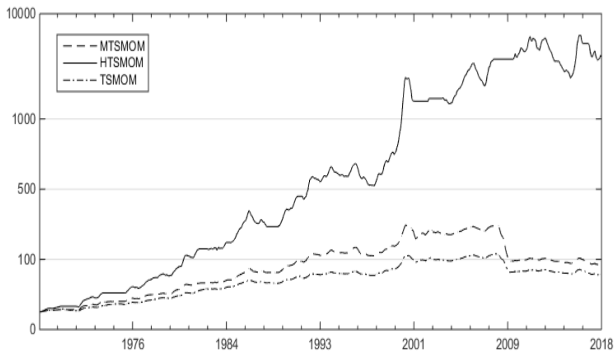


Fig 1. Cumulative time-series momentum profits for market-timing strategies based on Dow index.

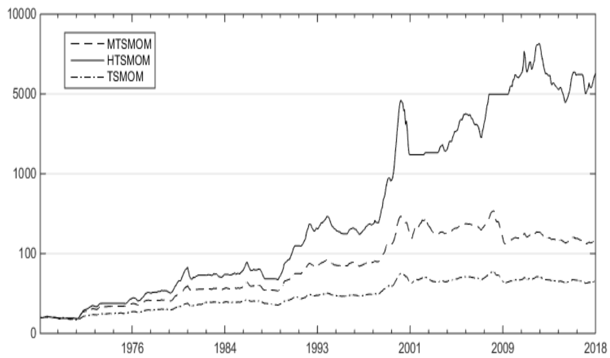
This figure shows the time trend of the cumulative return of the time-series momentum (TSMOM) and the market-timing TSMOM strategies based on past market returns (MTSMOM) and nearness to the 52-week high (HTSMOM). For the HTSMOM strategy, we calculate nearness to the 52-week high using the Dow index and then implementing this ratio as a signal for market-timing. The MTSMOM strategy identifies “up” and “down” market states using market returns for a 12-month period prior to the beginning of the strategy's holding period. If market return is positive (negative), we classify the market state as “up” (“down”) as a signal for market-timing. The cases of TSMOM strategies are considered with a k-month formation period and an h-month holding period (*k,h*=6,9).

(k=6, h=6)

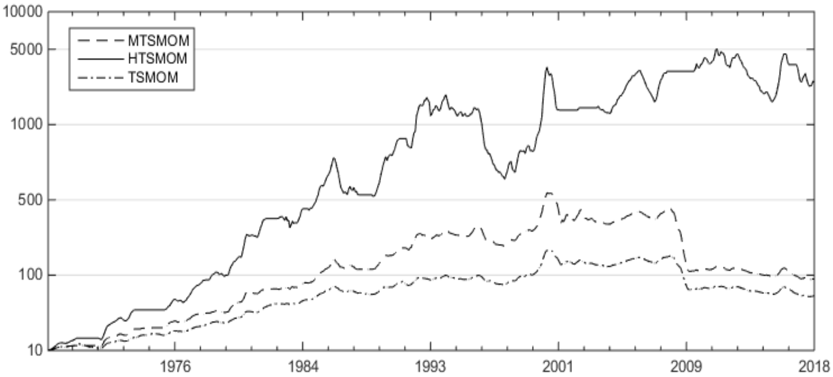
Equal-weighted



Value-weighted

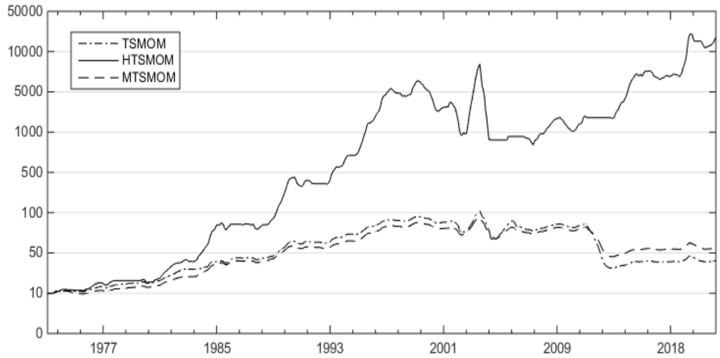


Volatility-weighted

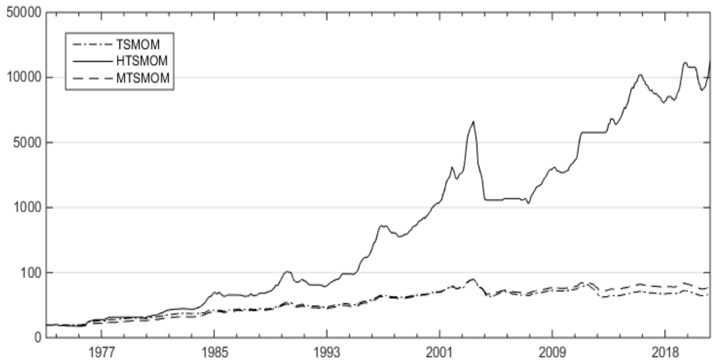


(k=9, h=9)

Equal-weighted



Value-weighted



Volatility-weighted

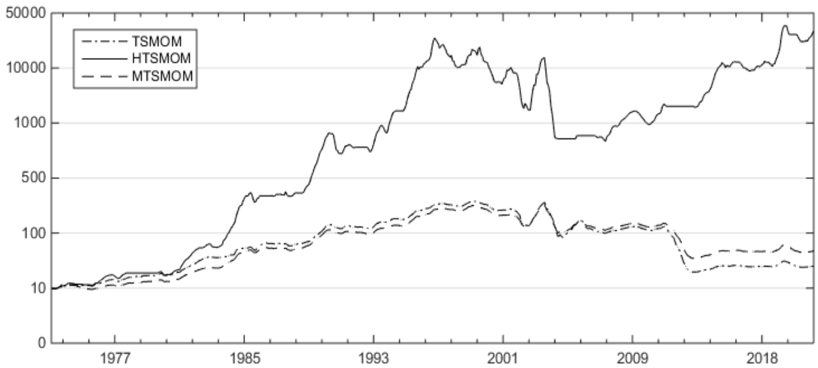


Fig 2. Cumulative time-series momentum profits for market-timing strategies based on the S&P 500 index. This figure shows the time trend of the cumulative return for the time-series momentum (TSMOM) and the market-timing TSMOM strategies based on past market returns (MTSMOM) and nearness to the 52-week high (HTSMOM). For the HTSMOM strategy, we calculate nearness to the 52-week high using the S&P 500 index and then implement this ratio as a signal for market-timing. MTSMOM strategy is identified for "up" and "down" market states using the market returns for a 12-month period prior to the beginning of the strategy's holding period. If the market return is positive (negative), we classify the market state as "up" ("down") as a

signal for market-timing. Eight cases of TSMOM strategies are considered with a k-month formation period and an h-month holding period.

Compared to the market timing of Cooper et al. (2004), the HTSMOM strategy is more profitable in the short-run (*k, h*<6). The return differences between these two market-timing strategies are significantly positive, showing that the HTSMOM returns outperform. The returns pattern of HTSMOM monotonically decreases over a longer period (*k, h*>9) but remains profitable. Using the S&P 500 index as a market timing signal (Panel B), the HTSMOM still outperforms the MTSMOM and TSMOM. Our results are robust, demonstrating that the market timing strategy of nearness to the 52-week high has higher earning than other strategies.

Considering the influence of risk factors, we perform risk adjustment by forming a time series of TSMOM returns based on market timing strategies corresponding to each event month of the holding period. In accordance with Cooper et al. (2004), we form FF3- (Fama and French, 1993) and FF5- (Fama and French, 2015) risk-adjusted profits, for each holding-period month. Specifically, the portfolio returns are regressed on the appropriate factors and a constant. Accordingly, we obtain estimated factor loadings for each portfolio and holding-period month, which we use to derive risk-adjusted profits as follows:

$$R_{h,t}^{adj} = R_{h,t} - \sum_{t} \beta_{i,h} f_{i,t}, \tag{13}$$

where $R_{h,t}$ indicates the raw returns of each TSMOM portfolio for the strategy in the holding-period month h, in calendar month t, $f_{i,t}$ is the risk factor i in calendar month t, and $\beta_{i,h}$ is the estimated factor loading in month h on $f_{i,t}$. Accordingly, the monthly Fama–French-adjusted profits are summed to form the holding-period profits (CAR),

$$\mathrm{CAR}_{t+h} = \sum_{i=1}^{h} R_{t+i}. \tag{14}$$

Tables 3 and 4 represent the returns of three-factor and five-factor risk adjustments, respectively. By risk adjustments, the results are consistent with Table 3, showing the returns differences are significantly positive, showing that market timing strategies of nearness to the Dow 52-week high are profitable. The HTSMOM profits are higher for short periods, and decrease over longer periods. The results for risk adjustment demonstrate the influential role of nearness to the Dow 52-week on TSMOM. Overall, our findings show that slow information diffusion due to investors' anchoring bias leads to stronger TSMOM profits.

Table 3. Returns for market timing strategies with three-factor adjustments

k	*h*	HTSMOM	MTSMOM	TSMOM	HTS−MTS	HTS−TS
Panel A Calculated by Dow index						
Panel A1. Equal-weighted						
	6	0.361***	0.311***	0.264***	0.051*	0.097**
3		(3.666)	(3.433)	(3.111)	(1.896)	(2.422)
	9	0.552***	0.512***	0.488***	0.040*	0.064**
		(4.975)	(4.372)	(4.818)	(1.776)	(2.378)
	6	0.382***	0.333***	0.317***	0.050*	0.065**
6		(3.860)	(3.599)	(3.371)	(1.836)	(2.460)
	9	0.415***	0.370***	0.342***	0.045*	0.073**
		(4.306)	(3.516)	(3.442)	(1.736)	(2.158)
	6	0.254***	0.219**	0.208**	0.036*	0.047
9		(3.255)	(2.904)	(2.763)	(1.741)	(1.598)
	9	0.283***	0.257***	0.238***	0.026	0.045*
		(3.399)	(3.183)	(3.156)	(1.519)	(1.723)
	6	0.179**	0.152**	0.126**	0.027	0.053*
12		(2.870)	(2.706)	(2.642)	(1.576)	(1.943)

	9	0.196**	0.176**	0.170**	0.020	0.026
		(2.983)	(2.795)	(2.721)	(1.468)	(1.462)
Panel A2. Value-weighted						
	6	0.317***	0.257**	0.225**	0.061*	0.092**
3		(3.378)	(3.053)	(2.850)	(1.957)	(2.316)
	9	0.449***	0.398***	0.377***	0.051*	0.072**
		(4.624)	(4.479)	(4.307)	(1.821)	(2.184)
	6	0.323***	0.282***	0.267***	0.042*	0.056**
6		(3.425)	(3.311)	(3.151)	(1.698)	(2.396)
	9	0.373***	0.333***	0.302**	0.039	0.071**
		(3.589)	(4.190)	(3.003)	(1.356)	(2.096)
	6	0.174**	0.155**	0.129**	0.019	0.045
9		(2.568)	(2.664)	(2.510)	(1.109)	(1.170)
	9	0.247***	0.204**	0.163**	0.043*	0.084***
		(3.214)	(2.811)	(2.785)	(1.719)	(3.331)
	6	0.093	0.070	0.058	0.023	0.036
12		(1.593)	(1.440)	(1.323)	(1.276)	(1.251)
	9	0.089	0.056	0.035	0.033	0.054
		(1.360)	(1.259)	(1.177)	(1.439)	(1.562)
Panel A3. Volatility-weighted						
	6	0.346***	0.292***	0.241**	0.053*	0.104**
3		(3.520)	(3.300)	(3.033)	(1.916)	(2.694)
	9	0.503***	0.425***	0.433***	0.078**	0.071**
		(4.678)	(4.345)	(4.777)	(2.470)	(2.427)
	6	0.341***	0.303***	0.286***	0.038*	0.055**
6		(3.655)	(3.461)	(3.196)	(1.673)	(2.360)
	9	0.384***	0.352***	0.324***	0.032	0.060*
		(3.720)	(3.409)	(3.390)	(1.298)	(1.920)
	6	0.229**	0.177**	0.185**	0.053*	0.044
9		(3.006)	(2.838)	(2.755)	(1.864)	(1.373)
	9	0.261***	0.237**	0.203**	0.025	0.058*
		(3.322)	(2.987)	(3.010)	(1.476)	(1.842)
	6	0.134**	0.103*	0.107**	0.031	0.027
12		(2.553)	(1.761)	(2.385)	(1.629)	(1.167)
	9	0.142**	0.119**	0.085	0.023	0.057
		(2.418)	(2.305)	(1.465)	(1.478)	(1.482)
Panel B. Calculated by S&P 500 index						
Panel B1. Equal-weighted						
	6	0.288**	0.263**	0.246**	0.024	0.041
3		(3.040)	(2.782)	(2.781)	(1.151)	(1.584)
	9	0.517***	0.437***	0.428***	0.081*	0.089*
		(4.940)	(4.394)	(4.318)	(1.723)	(1.945)
	6	0.337***	0.307***	0.271**	0.031	0.067*
6		(3.832)	(3.528)	(2.849)	(1.269)	(1.755)
	9	0.488***	0.441***	0.415***	0.047*	0.073*
		(4.614)	(4.532)	(4.365)	(1.655)	(1.857)
	6	0.269**	0.232**	0.229**	0.037	0.040
9		(2.736)	(2.592)	(2.476)	(1.305)	(1.636)
	9	0.283**	0.233**	0.203**	0.050*	0.080*
		(2.991)	(2.684)	(2.546)	(1.675)	(1.874)
	6	0.148**	0.124*	0.106*	0.023	0.042
12		(2.170)	(1.860)	(1.703)	(1.109)	(1.547)
	9	0.196**	0.123*	0.108*	0.073*	0.088*

		(2.251)	(1.819)	(1.767)	(1.771)	(1.904)
Panel B2. Value-weighted						
	6	0.262**	0.237**	0.215**	0.026	0.047*
3		(2.981)	(2.749)	(2.501)	(1.187)	(1.652)
	9	0.439***	0.380***	0.377***	0.059	0.062*
		(4.480)	(3.761)	(3.737)	(1.579)	(1.690)
	6	0.280***	0.255**	0.231**	0.025	0.049
6		(3.166)	(2.820)	(2.751)	(1.160)	(1.554)
	9	0.325***	0.284***	0.263**	0.041	0.062*
		(4.519)	(3.190)	(2.930)	(1.332)	(1.741)
	6	0.180**	0.168**	0.141*	0.012	0.038
9		(2.918)	(2.066)	(1.746)	(0.912)	(1.518)
	9	0.169***	0.152*	0.140*	0.017	0.030
		(3.414)	(1.811)	(1.712)	(1.036)	(1.438)
	6	0.093	0.067	0.061	0.026	0.032
12		(1.593)	(1.440)	(1.373)	(1.290)	(1.470)
	9	0.089	0.051	0.040	0.038	0.049
		(1.558)	(1.373)	(1.274)	(1.488)	(1.604)
Panel B3. Volatility-weighted						
	6	0.252**	0.242**	0.222**	0.010	0.030
3		(3.019)	(2.677)	(2.610)	(0.933)	(1.459)
	9	0.479***	0.405***	0.412***	0.074*	0.067*
		(4.514)	(3.812)	(4.129)	(1.705)	(1.794)
	6	0.317	0.271***	0.235**	0.046	0.082*
6		(3.583)	(3.159)	(2.793)	(1.547)	(1.904)
	9	0.455***	0.363***	0.353***	0.093**	0.102**
		(4.589)	(3.469)	(4.028)	(2.158)	(2.831)
	6	0.238**	0.214**	0.175**	0.024	0.064*
9		(2.676)	(2.428)	(1.866)	(1.196)	(1.715)
	9	0.251**	0.183**	0.195**	0.068*	0.056*
		(2.767)	(2.174)	(1.910)	(1.718)	(1.646)
	6	0.116**	0.071*	0.096*	0.045	0.020
12		(1.983)	(1.725)	(1.682)	(1.532)	(1.109)
	9	0.164**	0.068	0.077	0.095**	0.087*
		(2.183)	(1.580)	(1.595)	(2.225)	(1.937)

This table reports risk-adjusted returns for time-series momentum (TSMOM) profits and TSMOM profits based on market-timing strategies. HTSMOM indicates the TSMOM profits based on market-timing of nearness to the 52-week high, MTSMOM denotes TSMOM profits based on market states as defined by Cooper et al. (2004), TSMOM is time-series momentum profits. HTS−MTS indicates the return difference between HTSMOM and MTSMOM, HTS-TS is the return difference between HTSMOM and TSMOM. Newey and West (1987) adjusted t-statistics are reported in parentheses. In addition, *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively

Table 4. Returns for market timing strategies with five-factor adjustments

k	*h*	HTSMOM	MTSMOM	TSMOM	HTS−MTS	HTS−TS
Panel A Calculated by Dow index						
Panel A1. Equal-weighted						
	6	0.285***	0.221***	0.188**	0.063**	0.096**
3		(3.490)	(3.269)	(2.950)	(2.784)	(2.783)
	9	0.516***	0.468***	0.448***	0.047**	0.067**
		(4.617)	(4.372)	(4.386)	(2.359)	(2.886)
	6	0.377***	0.313***	0.176**	0.065**	0.202**
6		(3.698)	(3.543)	(2.461)	(2.809)	(2.929)

	9	0.512***	0.460***	0.397***	0.052**	0.115**
		(4.581)	(4.269)	(3.761)	(2.525)	(2.018)
	6	0.224**	0.185**	0.180**	0.039**	0.044*
9		(2.693)	(2.560)	(2.513)	(2.004)	(1.941)
	9	0.271**	0.257***	0.225**	0.014*	0.046*
		(3.079)	(3.351)	(2.964)	(1.654)	(1.801)
	6	0.144***	0.125**	0.101**	0.018*	0.042*
12		(3.405)	(2.706)	(2.220)	(1.667)	(1.930)
	9	0.140***	0.116**	0.076**	0.024*	0.064*
		(3.175)	(2.509)	(2.304)	(1.710)	(1.863)
Panel A2. Value-weighted						
	6	0.233***	0.187**	0.156**	0.047**	0.078**
3		(3.208)	(2.955)	(2.828)	(2.335)	(2.580)
	9	0.414***	0.363***	0.334***	0.051**	0.080**
		(4.086)	(3.765)	(3.719)	(2.444)	(3.192)
	6	0.329***	0.274***	0.154**	0.054**	0.174**
6		(3.502)	(3.171)	(2.471)	(2.495)	(2.845)
	9	0.401***	0.357***	0.238***	0.044**	0.163**
		(3.856)	(3.571)	(3.178)	(2.291)	(2.712)
	6	0.153**	0.135**	0.134**	0.018*	0.019
9		(2.408)	(2.299)	(2.217)	(1.682)	(1.551)
	9	0.140**	0.128**	0.130**	0.012	0.010
		(2.257)	(2.171)	(2.194)	(1.547)	(1.243)
	6	0.093**	0.079	0.071*	0.014	0.022*
12		(2.473)	(1.452)	(1.873)	(1.590)	(1.761)
	9	0.099**	0.061	0.039*	0.038*	0.060*
		(2.639)	(1.361)	(1.907)	(1.777)	(1.820)
Panel A3. Volatility-weighted						
	6	0.274***	0.177**	0.174**	0.097***	0.100**
3		(3.330)	(3.038)	(2.892)	(3.156)	(2.878)
	9	0.463***	0.404***	0.385***	0.059**	0.079**
		(4.368)	(3.981)	(4.235)	(2.546)	(3.056)
	6	0.341***	0.291**	0.163**	0.049**	0.177**
6		(3.553)	(3.209)	(2.380)	(2.432)	(2.740)
	9	0.468***	0.403***	0.323***	0.065**	0.145**
		(3.720)	(3.874)	(3.581)	(2.685)	(2.596)
	6	0.184**	0.153**	0.150**	0.030*	0.034*
9		(2.562)	(2.415)	(2.425)	(1.962)	(1.829)
	9	0.214**	0.163**	0.199**	0.051**	0.016
		(2.802)	(2.609)	(2.756)	(2.493)	(1.414)
	6	0.102**	0.082	0.085*	0.020*	0.017
12		(2.553)	(1.584)	(1.897)	(1.685)	(1.644)
	9	0.118**	0.073	0.053**	0.046*	0.065*
		(2.940)	(1.374)	(2.191)	(1.951)	(1.873)
Panel B. Calculated by S&P 500 index						
Panel B1. Equal-weighted						
	6	0.281***	0.211**	0.173**	0.071**	0.109**
3		(3.498)	(2.786)	(2.346)	(2.384)	(2.821)
	9	0.462***	0.412***	0.395***	0.049*	0.067**
		(4.472)	(4.137)	(3.857)	(1.708)	(2.210)
	6	0.272***	0.223**	0.209**	0.048*	0.062*
6		(3.393)	(2.832)	(2.614)	(1.719)	(1.923)
	9	0.436***	0.362***	0.337***	0.074**	0.099**

		(4.245)	(3.752)	(3.761)	(2.428)	(2.678)
	6	0.226**	0.185**	0.178**	0.041*	0.048*
9		(2.889)	(2.674)	(2.393)	(1.662)	(1.751)
	9	0.271***	0.237***	0.202**	0.034	0.069**
		(3.279)	(3.111)	(2.734)	(1.511)	(2.285)
	6	0.146**	0.105*	0.099**	0.040*	0.047*
12		(2.471)	(1.706)	(2.157)	(1.655)	(1.688)
	9	0.240**	0.198**	0.172**	0.042*	0.068**
		(2.975)	(2.395)	(2.319)	(1.679)	(2.123)
Panel B2. Value-weighted						
	6	0.251***	0.187***	0.157**	0.064*	0.095**
3		(3.385)	(3.116)	(2.776)	(1.891)	(2.491)
	9	0.376***	0.330***	0.324***	0.046*	0.052*
		(3.807)	(3.649)	(3.541)	(1.665)	(1.818)
	6	0.226**	0.178***	0.154**	0.048*	0.072**
6		(3.000)	(3.129)	(2.736)	(1.694)	(1.974)
	9	0.370***	0.327***	0.314***	0.043*	0.056*
		(3.686)	(3.571)	(3.508)	(1.657)	(1.713)
	6	0.173**	0.152**	0.129**	0.022	0.044*
9		(3.041)	(2.899)	(2.116)	(1.351)	(1.659)
	9	0.183**	0.148**	0.126*	0.035	0.057*
		(3.065)	(2.772)	(1.840)	(1.583)	(1.708)
	6	0.093*	0.079*	0.057	0.014	0.036
12		(1.773)	(1.645)	(1.549)	(1.149)	(1.619)
	9	0.199***	0.149**	0.138**	0.050*	0.060*
		(3.164)	(2.655)	(2.584)	(1.744)	(1.798)
Panel B3. Volatility-weighted						
	6	0.271***	0.192**	0.169**	0.079**	0.102**
3		(3.417)	(2.605)	(2.319)	(2.491)	(2.513)
	9	0.407***	0.379***	0.373***	0.028*	0.034
		(4.197)	(3.889)	(3.740)	(1.691)	(1.522)
	6	0.246***	0.208**	0.184**	0.038*	0.062**
6		(3.174)	(2.974)	(2.677)	(1.659)	(2.098)
	9	0.398***	0.340***	0.326***	0.058**	0.072**
		(4.099)	(3.593)	(3.696)	(2.127)	(2.338)
	6	0.188**	0.170**	0.143**	0.018	0.045*
9		(2.960)	(2.730)	(2.245)	(1.247)	(1.713)
	9	0.248***	0.213**	0.151**	0.036	0.097**
		(3.160)	(3.003)	(1.983)	(1.534)	(2.497)
	6	0.130**	0.095*	0.072	0.034	0.058*
12		(2.147)	(1.669)	(1.620)	(1.653)	(1.744)
	9	0.205**	0.184**	0.160**	0.021	0.045*
		(3.060)	(2.288)	(2.238)	(1.508)	(1.660)

This table reports risk-adjusted returns for time-series momentum (TSMOM) profits and TSMOM profits based on market-timing strategies. HTSMOM indicates the TSMOM profits based on market-timing of nearness to the 52-week high, MTSMOM denotes TSMOM profits based on market states as defined by Cooper et al. (2004), TSMOM is time-series momentum profits. HTS − MTS indicates the return difference between HTSMOM and MTSMOM, HTS−TS is the return difference between HTSMOM and TSMOM. Newey and West (1987) adjusted t-statistics are reported in parentheses. In addition, *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

4. Conclusions

In this study, we examine the role of investors' anchor bias on the performance of time-series momentum. For this purpose, we calculate nearness to the 52-week high by using the Dow index to investigate the predictive ability of nearness to the Dow 52-week high on time-series momentum profits. Using nearness to the Dow 52-week high as a trading signal, our results show that market-timing TSMOM strategies based on nearness to the Dow 52-week high are more profitable than TSMOM strategies. There are significant return spreads between TSMOM strategies based on nearness to the Dow 52-week high and conventional TSMOM strategies. The profits of TSMOM strategies based on nearness to the Dow 52-week high are higher for short horizons, and decrease over the longer horizons. Our findings support the "adjustment and anchoring'' bias proposed by Tversky and Kahneman (1974), in which investors' reluctance to bid up the price of a stock in response to positive information leads to stronger underreaction to good news for stocks close to the Dow 52-week high. Consequently, implementing a time-series momentum strategy earns higher profits.

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