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The Effect of the Movement in 52-Week High on Momentum Profit: The Evidence from Taiwan

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ABSTRACT

Purpose:
This paper aims to examine the impact of price movements in 52-week highs on a 52-week high momentum strategy. This study refers to the upward or downward movement in 52-week highs as an updating effect and determines how this effect influences the profitability of the original 52-week high momentum strategy.

Design/methodology/approach:
This paper decomposes the ratio of stock price to 52-week high into denoted two components: price change and updating components. We construct two momentum strategies, each focusing on adjusting either the price change or the updating component. Additionally, we employ a portfolio approach and Fama-MacBeth regression analysis to investigate the profitability of each proposed momentum strategy.

Findings:
The empirical results reveal that removing the price change component (updating component) from the original 52-week high measure can increases (decreases) the momentum profit, implying that the updating component dominates the price change component. Moreover, our analysis shows that when a high ratio of stock price to 52-week high is driven by a downward updating event, the subsequent positive momentum for a winner portfolio is more substantial.

Research limitations/implications:
This paper investigates the influence of 52-week highs movement on momentum strategies, utilizing data from Taiwan stock market. The findings reveal that accounting for the updating effect of 52-week highs can enhance the profitability of the original momentum strategy. However, it is important to note that this conclusion is currently limited to relatively inefficient stock markets. The impact on relatively efficient markets remains an area that requires further research for a comprehensive understanding.

Originality/value:
The finance literature widely acknowledges the 52-week high price as a reference point that can impact investors' trading psychology. Numerous empirical studies have confirmed the profitability of the 52-week high momentum investing strategy. However, these studies have not thoroughly explored the implications and effects of price movements within the scope of a 52-week high momentum strategy. Taking behavioral perspectives into account, this paper considers that the updating of 52-week high prices can influence investors' attention and subsequently impact the profitability of the momentum strategy.

1. Introduction

Market anomalies in financial markets denote certain phenomena that contradict the efficient market hypothesis (Enow, 2023), and as a result the patterns of return or abnormal return seem to be predictable under some situations, such as the January effect, calendar effect, size effect, and so on. Since conventional financial theories find it difficult to answer these anomalies, behavioral finance looks to explain them via investors' cognitive biases from the 1980s. Among the broad array of anomalies, the momentum effect is one of the most popular topics in recent decades. As the

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most classical study on the momentum effect, Jegadeesh & Titman (1993) propose a strategy of buying winners and selling losers that can gain abnormal returns in the short and medium terms.

One strand of the momentum effect that has grabbed researchers' attention over the last decade is the 52-week high momentum strategy proposed by George & Hwang (2004). They find that being near to the 52-week high price can improve the forecasting power for future returns. Specifically, they suggest a strategy that buys (sell) stocks whose current price is close to (far from) its past 52-week high price and provide evidence that this strategy is superior to the conventional momentum strategy. The 52-week high momentum strategy, which combines the underreaction and anchoring effect theories, has also been applied to other issues recently. Li & Yu (2012) find that, except for Germany, the 52-week high can significantly predict future returns in G7 countries. Examining the 52-week high momentum strategy in 20 countries, Liu et al. (2011) present that this strategy is generally better than the traditional momentum strategy, and it can earn abnormal returns in most countries. Bianchi et al. (2016) show that 52-week high momentum exists among a large number of commodities futures and is superior to any conventional strategy. Both Chang (2011) and Hao et al. (2016) show that the profitability of the 52-week high strategy is remarkable in the Taiwan stock market. George et al. (2018) indicate that being near the 52-week high price not only can help predict future return, but also both future profitability (measured in ROE) and future investment growth.

Based on the 52-week high, several studies construct new investing strategies that can improve the 52-week high strategy. Park (2010) combines the moving average ratio with nearness to the 52-week high and presents significant abnormal returns. Hong et al. (2015) argue that investors likely underreact to industry information rather than firm-specific information and subsequently propose an industry 52-week high strategy that buys (sells) industries whose total market capitalizations are close to (far from) their 52-week highs. This industry 52-week high strategy outperforms the original 52-week high strategy. In spite of the 52-week high, Li & Yu (2012) suggest another anchor point, i.e. the historical high, indicating that abnormal returns in the 52-week high strategy would be stronger when the 52-week high equals the historical high. Hao et al. (2018) investigate that the interaction between investor's sentiment and the profitability of the 52-week high strategy. They find that the momentum profit from 52-week high strategy will be strengthened when the level of investor's sentiment is high.

In sum, the 52-week high strategy has been commonly accepted in financial research, but there is a gap in related literature, as few studies have investigated the dynamics of the 52-week high. More specifically, the 52-week high is computed from a rolling window with 52 weeks, meaning that the 52-week high is variable over the whole period. Does the evolution of the 52-week high matter? Bhootra & Hur (2013) first consider the formation timing of the 52-week high and define a recency ratio according to the number of days since the 52-week high formed. They show that the recency of the 52-week high can increase the profitability of the original 52-week high strategy by about twice as much. Hao et al. (2016) also find both the recency bias and anchoring effect in the Taiwan stock market. Nevertheless, there is no study in the literature that looks at the movement/updating of the 52-week high.

In order to fill the gap in the literature, this paper investigates why and how updating the 52-week high is noteworthy and useful. Undoubtedly, the ratio of a stock's current price to its 52-week high (PTH, hereafter, following George et al., 2018) changes every day, week, and month. Intuitively, any change of PTH either results from the change of the current price (numerator) or from the change of the 52-week high price (denominator) mathematically. However, none of related literature distinguishes the effects of these two determinants on momentum profits. Therefore, this paper attributes the change of PTH to two components: price change effect (the latest stock return) and updating effect (the movement of the 52-week high). With respect to the conventional PTH, this paper considers two PTH measures that straightforwardly adjust the price change effect and updating effect, respectively. The empirical results reveal that the updating effect dominates the price change effect in terms of the 52-week high momentum strategy.

To our best knowledge, this paper is the first to shed light on the movement of 52-week high prices. The present study contributes to the literature in two ways. First, the related literature usually seeks external factors (e.g., business cycle, macroeconomic states, or market volatility) for explaining 52-week high momentum profits (Liu et al., 2011; Yu, 2012). Aside from these factors, based on the formula of the PTH ratio, we explore a possible determinant for the 52-week high momentum profit, i.e. the movement of the 52-week high. Second, from behavioral perspectives, this paper explains the relevance of updating the 52-week high price with respect to both upward and downward updates. Without precedent in the literature, we further conclude that downward updating plays a crucial role in the 52-week high strategies' profitability.

The remainder of this paper is organized as follows. Section 2 demonstrates why and how the updating of the 52-week high is important to investors. Section 3 interprets the data sources. Section 4 provides the empirical results including a robustness test. Finally, Section 5 concludes this paper.

2. Why does the updating of the 52-week high matter?

PTH is a well-documented momentum investing issue over the recent decades. George & Hwang (2004) consider that investors tend to use the 52-week high price as a reference point and under-evaluate related new information, even though this reference point does not contain any information about the fundamental values. Consequently, investors present an anchor-and-adjust bias, in which they underreact to news, resulting in momentum profits over a certain period. The literature also finds that the 52-week high can influence trading behaviors, such as trading volume, turnover rate, short selling, and option-implied volatility (Huddart et al., 2009; Driessen et al., 2013; Lee & Piqueira,

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2017).[1] Using insider trading data, Lee & Piqueira (2019) show that insiders are inevitably influenced by this anchoring bias, though insiders own private information about the fundamentals.

Those studies echo the concept of George & Hwang (2004) in that the 52-week high serves as a salient reference point and can distort investors' psychology. However, as mentioned above, there is a lack of literature analyzing how updating the 52-week high can affect investors' trading perception. To deal with this issue, we first decompose the formula of PTH as follows:

$$PTH_{i,t} = \frac{P_{i,t}}{High_{i,t}} = \frac{P_{i,t}}{P_{i,t-1}} \times \frac{P_{i,t-1}}{High_{i,t-1}} \times \frac{High_{i,t-1}}{High_{i,t}} \quad (1)$$

Here, $PTH_{i,t}$ denotes the ratio of the price of stock i at period t ($P_{i,t}$) to its 52-week high price ($High_{i,t}$) in the same period. Equation (1) is very straightforward as $PTH_{i,t}$ consists of three components. Because $P_{i,t-1}/High_{i,t-1}$ is equal to $PTH_{i,t-1}$, equation (1) can be rewritten as:

$$\frac{PTH_{i,t}}{PTH_{i,t-1}} = \frac{P_{i,t}}{P_{i,t-1}} \times \frac{High_{i,t-1}}{High_{i,t}}$$

→ change of PTH = price change effect × updating effect (2)

From equation (2), it is obvious that the change of PTH is the product of the change of price (price change effect) and the change of the 52-week high (updating effect). Hence, an increase in PTH is driven by a positive return from period *t*-1 to *t*, a downward 52-week high from period *t*-1 to *t*, or both. We recall for the formation of the PTH portfolio that a stock is categorized into a winner portfolio at period *t* due to four reasons. First, a stock is originally categorized into a winner portfolio at period *t*-1 and suffers a slight price change and updating effects. Second, a stock shows a large upward movement in its price and then substantially improves its relative PTH into a winner portfolio. Third, the 52-week high price of a stock dramatically declines from period *t*-1 to *t*, which sequentially causes the relative PTH to go up in period *t*. The fourth reason is a compounding effect from the first three reasons.

This paper focuses on discussing the effects of price change and 52-week high update, because they are more easily observed and perceived by investors. As mentioned in Huddart et al. (2009), financial websites and news media usually provide a stock's price chart with a 52-week window, implying that the information coming into an investor's view will change as time passes.[2] Figure 1 presents an example about what information is related to a price change and 52-week high update in a chart over time. On a monthly basis, the upper panel shows a stock's price path from period *t*-12 to *t*-1 (52 weeks). The last price is the closing price at the end of period *t*-1, and the corresponding 52-week high denotes $High_{t-1}$ forming at period *t*-12. As shown in the lower panel, one month later, the stock's price path is updated, which covers from period *t*-11 to *t*. Additionally, the 52-week high price is replaced by $High_t$ forming at period *t*-9.

[1] Literatures also provide evidences that 52-week high prices can influence initial offer prices for initial public offerings and offer premiums for merger and acquisition. For example, Baker et al. (2012) and Lee (2022).

[2] Psychologists suggest that people's memory and recognition are more likely stimulated by pictures than words, it is reasonable that the proposed updating and price change effects can influence investors' decision making process. Please see McBride et al. (2002) and Whitehouse et al. (2006).

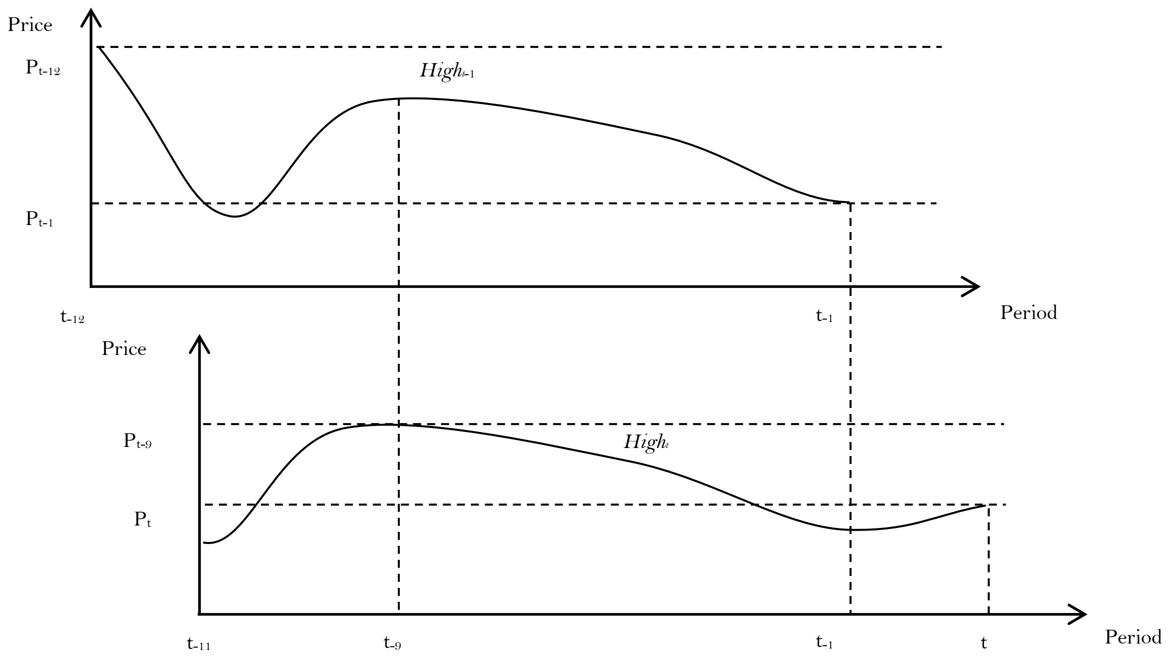
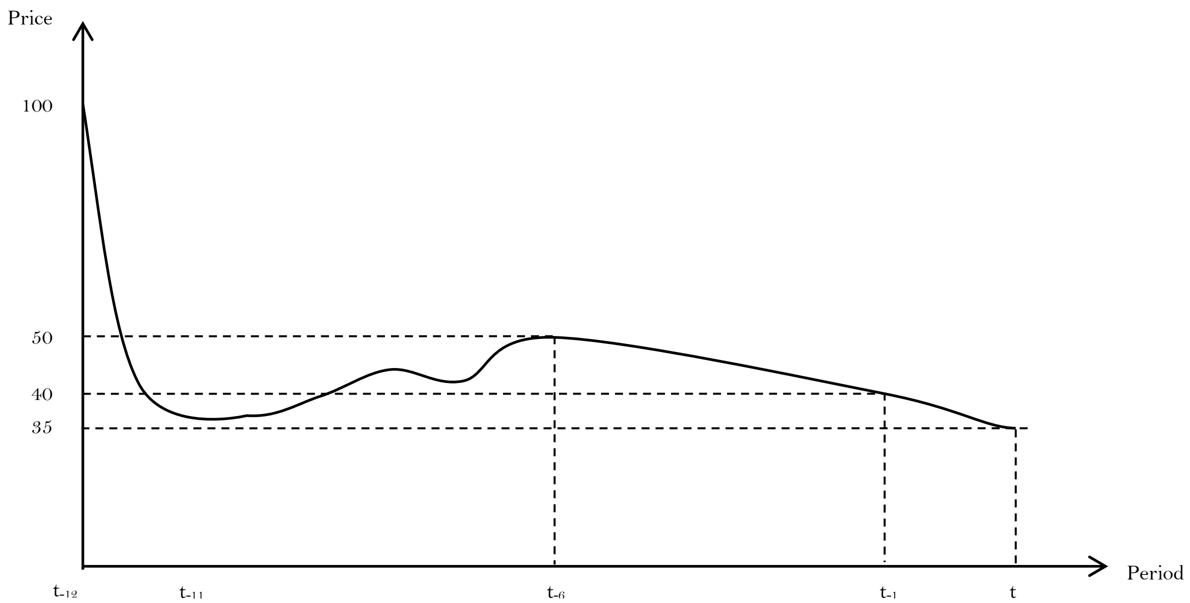


Figure 1: A graphic illustration of the evolution of 52-week price path

(a)



(b)

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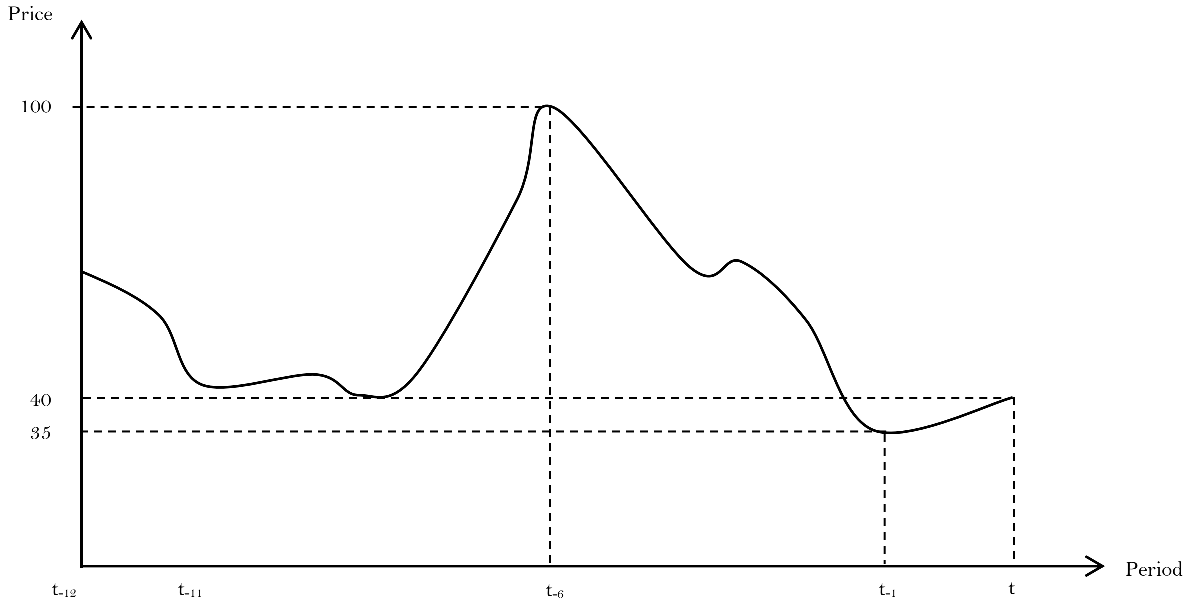

Figure 2: Two examples of rising the PTH ratios

There are two key visual differences between the two panels. First, the higher 52-week high ($High_{t-1}$) disappears and is replaced by a lower 52-week high ($High_t$). Second, the short-term trend for the end of period t-1 is downward, while that for the end of period t is upward. Intuitively, these two differences are equivalent to the mentioned updating effect ($High_{t-1}/High_t$) and price change effect (P_t/P_{t-1}), respectively. Figure 2 further provides two possible price patterns that show a raise of PTH ratios. In panel (a), bad news cause a decline in stock price from period t-1 to t, whereas the 52-week high price downward updates at the same time. In panel (b), good news push up the stock 14.3% to $40 from period t-1 to t and the 52-week high price remains the same value. As the result, the PTH ratio in panel (a) sharply goes up from 0.4 to 0.7 and the stock may become a winner in terms of the PTH momentum. However, the PTH ratio in panel (b) shows an increase of 0.1 because of good news, the stock possibly stays in loser group with respect to the PTH investing. Notice that, straightforwardly, price change effect contains all new information arrival, but updating effect does not reveal any news. It is valuable to explore why updating component matter indeed, if a stock experiences a high PTH ratio due to a movement of the 52-week high price.

This paper next individually interprets price and updating effects in theory regardless of the PTH ratio. The ratio of current price to one-month lagged price (P_t/P_{t-1}) is a kind of monthly return and widely analyzed in the literature. Specifically, the literature documents a strongly negative first-order serial correlation on a monthly or weekly basis and proposes a short-term reversal (Jegadeesh, 1990; Jegadeesh & Titman, 1995).[3] In terms of behavioral finance, the short-term reversal can be explained by fads and investors' overreaction to news (Da et al., 2013). Accordingly, a higher (P_t/P_{t-1}) thus implies a lower future return in the short run. However, the ratio of the last 52-week high to the current 52-week high ($High_{t-1}/High_t$) has received few researchers' attention.

This paper thus discusses the following two cases: upward and downward updating. If the ratio is less than unity, then it means that the price has broken through the previous 52-week high and the 52-week high is upwardly updated during the current period. Huddart et al. (2009) and Driessen et al. (2013) investigate the return pattern after the price crosses over its 52-week high, finding a positively sequential return and ascribing it to the anchoring effect and limited attention. On the one hand, the anchoring effect lets investors become more conservative when good news pushes the price to approach its 52-week high. If the information eventually prevails and the price crosses the anchor (its 52-week high), then it results in a continuative movement. On the other hand, a breakthrough is a remarkable event that can attract investor attentions, especially for individual investors. Hence, after the breakthrough event, buying pressure from a trade imbalance leads to a positive future return. However, the upward updating case usually (not always) accompanies a higher (P_t/P_{t-1}) at the same time, implying that the short-term reversal may weaken the effect of a breakthrough.

There is no direct evidence that discusses the intuition or implication of a downward updated 52-week high (i.e., $High_{t-1}/High_t$ is larger than unity). Our paper endeavors to illustrate this phenomenon through a mean-reverting behavior. Mean reversion denotes a tendency of the price to return to its long-run mean. Poterba and Summers (1988) find that stock returns present a negative serial correlation over a long horizon. Fama & French (1988) also indicate that negative autocorrelations are found for 2-year and 3-5 year returns. As the 52-week high is downward updated, it means that the price has not set a new high since at least one year ago (maybe longer than several years). Sequentially, the future price thus has a tendency toward mean-reverting behavior, and a higher return will be earned

[3] Jegadeesh (1990) also presents a positive serial correlation at longer lags, such as twelve-month lagged serial correlation.

under this mean reversion. To sum up, this paper suggests that both upward and downward updating cases will produce positively sequential returns based on a behavioral perspective.

The last issue is how price change and updating effects influence PTH momentum profitability. This paper presumes that the PTH momentum strategy is profitable. When a high PTH ratio is pushed by a large return from period t-1 to t, a short-term reversal may diminish the PTH momentum profit. Moreover, if a high PTH ratio is driven by a sharp decline in the 52-week high from period t-1 to t, then the PTH momentum profit will improve due to the aforementioned behavioral reasons. However, the future return of a stock that presents both a high PTH ratio and an upward updated 52-week high is unclear, even when positive effects including recency bias are discussed above. The opposite view is related to the frog-in-the-pan (FIP) hypothesis proposed by Da et al. (2014). The FIP hypothesis states that investors are less attentive to a price path of continuously gradual changes versus discretely dramatic changes. Accordingly, they find that the underreaction bias in momentum is more substantial for the case of information arriving continuously in small amounts. Chen & Lu (2017) echo the FIP hypothesis and show that momentum profits are superior for stocks whose information diffuses slowly. Intuitively, an upward updated 52-week high implies that the stock price crosses its previous 52-week high and usually coincides with a large return within the current period, meaning that an upward updating event attracts more attention than either a downward updating or non-updating condition. In accordance with the literature, we suggest that the future profit for a high PTH ratio with an upward updated 52-week high is less than that for a high PTH ratio with a downward updated 52-week high.

3. Data and Methods

This section describes the empirical data and introduces how to deal with price and updating effects on the PTH momentum strategy. We also provide a preliminary analysis of price change and 52-week high updating in the last subsection.

3.1 Data

This paper collects monthly data from the Taiwan Economic Journal (TEJ), which is a leading data vendor in Taiwan. One important feature of the Taiwan stock market is that individual investor trading accounts for a large proportion of its trading volume (e.g., 86.10% and 59.37% in 2000 and 2017, respectively). Barber et al. (2009) document that individual investors' trading behavior is highly subjected to behavioral biases. Moreover, the 52-week high momentum is induced by an anchor-and-adjust bias and an underreaction behavior. Hence, we consider that the proposed issue will be more pronounced in the Taiwan stock market, thus benefitting the related literature (Chang, 2021).

To avoid possible survivorship bias and delisting bias, the sample comprises all common stocks listed and delisted in the Taiwan Stock Exchange over the period from January 1987 to December 2017. The data before 1987 are excluded due to the following two reasons. First, the number of listed stocks before 1987 is relatively small, implying we may face a small-sample bias. Second, Taiwan's stock market experienced an extreme bull market from the 1970s, with the first bubble bursting in 1987. Specifically, the total market capitalization at year end rapidly grew from NT$17 million in 1970 to NT$1.386 billion in 1987. The Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) increased by around 400% from 1039.11 at the end of 1986 to 4,673.14 by October 1987. However, the TAIEX then sharply fell by 50% from October to December 1987. Accordingly, there are rare downward updating observations before 1987, and therefore it is preferable to investigate the role of price change and updating effects using the research period after 1987.

3.2 Empirical Approach

This subsection describes the measures of price change and updating components for empirical analysis. Each stock-month observation can be categorized into different groups according to price change or updating criterion. Specifically, based on price change criterion, we classify each observation into a positive, negative, or zero return group if $\ln(P_t/P_{t-1})$ is larger than, less than, or equal to zero, respectively. Moreover, based on the updating criterion, each observation is classed into an upward, downward, or non-change group if $High_{t-1}/High_t$ is less than, larger than, or equal to unity, respectively. Practically, no matter under what classification criterion, the number of observations among each group is quite imbalanced and not appropriate for the commonly-used portfolio approach. The aforementioned classification also does not clearly present the character that both price change and updating components are embedded in PTH. Consequently, we further construct two adjusted PTH ratios to capture price change and updating effects as follows:

$$PTH\_nonP_{i,t} = \frac{PTH_{i,t}}{P_{i,t}/P_{i,t-1}} \quad (3)$$

$$PTH\_nonU_{i,t} = \frac{PTH_{i,t}}{High_{i,t-1}/Hih_{i,t}} \quad (4)$$

The adjustments are straightforward and intuitive. *PTH_nonP* denotes that the original PTH ratio adjusts to the price change component, indicating that the original PTH ratio will decrease (increase) when the concurrent return is positive (negative). *PTH_nonU* denotes that the original PTH ratio adjusts to the updating component, showing that the PTH ratio will decrease (increase) when the 52-week high is upward (downward) updated. As described in section 2, if upward updating is less profitable than downward updating, then we expect that the profitability of the winner-

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loser portfolio derived from *PTH_nonP* is positive and more beneficial than that from the original PTH ratio. Moreover, if a large return may harm the PTH momentum profit, then we expect that the profitability of the winner-loser portfolio derived from *PTH_nonU* is still positive but less favorable than that from the original PTH ratio.

With respect to the momentum profits of different strategies, this paper calculates the equally-weighted portfolio returns by way of the well-accepted overlapping period approach. Taking the original PTH momentum as an example, in each month *t*, stocks ranked in the top (bottom) 30% of the *PTH* ratio are assigned to the winner (loser) portfolio. Accordingly, this momentum strategy buys the winner portfolio and sells the loser portfolio to establish a self-financing portfolio in each month *t*. All portfolios are held for six months from months *t*+2 to *t*+7, implying that there is one-month gap between the formation and holding periods in order to avoid a bid-ask bounce or lead-lag effect. In each month *t*, the monthly return for the winner (loser) portfolio is the equally weighted average of six separate winner portfolios formed in six previous months *t*-7 to *t*-2.[4] As a result, the monthly strategy return is the difference between the winner and loser portfolios.

The methods of portfolio formation and return computation for *PTH_nonP* and *PTH_nonU* momentum strategies are done in the same way. For the sake of convenience, these two strategies are called non-price PTH (excludes the price change effect) and non-updating PTH (excludes the updating effect), respectively. Aside from the three PTH-based strategies mentioned above, this paper also employs the conventional momentum strategy denoted as the JT strategy proposed by Jegadeesh & Titman (1993). With respect to this strategy, stocks are ranked by their individual past performance. In accordance with George & Hwang (2004), for the JT strategy, both the formation and holding periods are six months with a one-month skipped gap. Therefore, this paper compares the performances of two famous strategies (PTH and JT) with two proposed strategies (non-price and non-updating PTH) using the portfolio analysis approach.

3.3 First Look at Monthly Price Change and 52-week High Updating

Table 1 provides the basic information about monthly price change and 52-week high updating, which are the foundations of this study. The total number of stock-month observations is 206,024, while the distributions of price change and updating observations are extremely imbalanced. For instance, the proportions of both positive and negative observations are close to half, respectively. However, in regards to the updating case, only 15% of observations present upward updating and 18% of observations are downward updating. Figure 3 shows the numbers of stocks whose 52-week highs are upward or downward updated in each month, respectively. It is obvious that the numbers of upward and downward updated stocks are negatively related. Additionally, the occurrences of upward and downward updating highly depend on the market condition (bull or bear market), implying that it is difficult to form a self-financing portfolio via simple price change and updating classification criteria. For example, during the periods of the dot-com bubble and global financial crisis, the number of downward updated stocks is excessively larger than that of upward updated stocks.

Table 1: Average monthly returns for price change and updating observations

	Price change			Updating		
	Positive	Zero	Negative	Upward	No	Downward
N	101,357	3,422	101,245	29,156	131,150	35,093
Proportion	0.49	0.02	0.49	0.15	0.67	0.18
Raw return (%)						
1	1.02	0.51	-0.72	0.53	0.21	-0.25
	(23.52)	(2.39)	(-16.60)	(6.46)	(5.82)	(-3.22)
3	0.50	0.48	-0.17	0.54	0.23	-0.25
	(19.64)	(3.70)	(-6.53)	(11.82)	(10.08)	(-5.36)
6	0.32	0.23	0.03	0.45	0.09	0.34
	(17.56)	(2.40)	(1.46)	(13.14)	(5.94)	(10.42)
12	0.29	0.26	0.05	0.17	0.04	0.76
	(22.75)	(3.91)	(3.59)	(6.85)	(3.32)	(35.97)
Market-adjusted return (%)						
1	0.57	-0.04	-0.58	0.46	-0.03	-0.35
	(15.58)	(-0.19)	(-16.23)	(6.63)	(-1.04)	(-5.29)
3	0.17	0.11	-0.17	0.41	-0.01	-0.30
	(8.07)	(1.02)	(-8.03)	(10.39)	(-0.54)	(-7.90)
6	0.11	0.08	-0.08	0.27	-0.03	-0.03
	(7.58)	(1.03)	(-5.27)	(9.77)	(-2.34)	(-1.15)
12	0.12	0.08	-0.04	0.11	-0.04	0.28
	(11.42)	(1.52)	(-3.71)	(5.74)	(-4.27)	(15.72)

Notes: N is the number of observations for each category during 1987/1 to 2017/12. Positive, Zero and Negative denote the sign of return over t-1 to t, respectively. Upward, No, and Downward denote the direction of the 52-week high updating over t-1 to t,

[4] George & Hwang (2004) construct each portfolio in month *t* based on the PTH rank on the last day of month *t*-1. Thus, the monthly portfolio returns are the average of six portfolios formed in six consecutive prior months *t*-6 to *t*-1. Thus, the methodology is totally the same, although the time indicators of the present paper differ from George & Hwang (2004). Moreover, the present setting is identical to the setting of the Fama-MacBeth regression used in George & Hwang (2004).

respectively. Market-adjusted return defines the excess return adjusted to the market return; t-statistics are shown in parentheses. Here, 1, 3, 6, and 12 mean the average monthly return for forward one-, three-, six- and twelve-month periods.

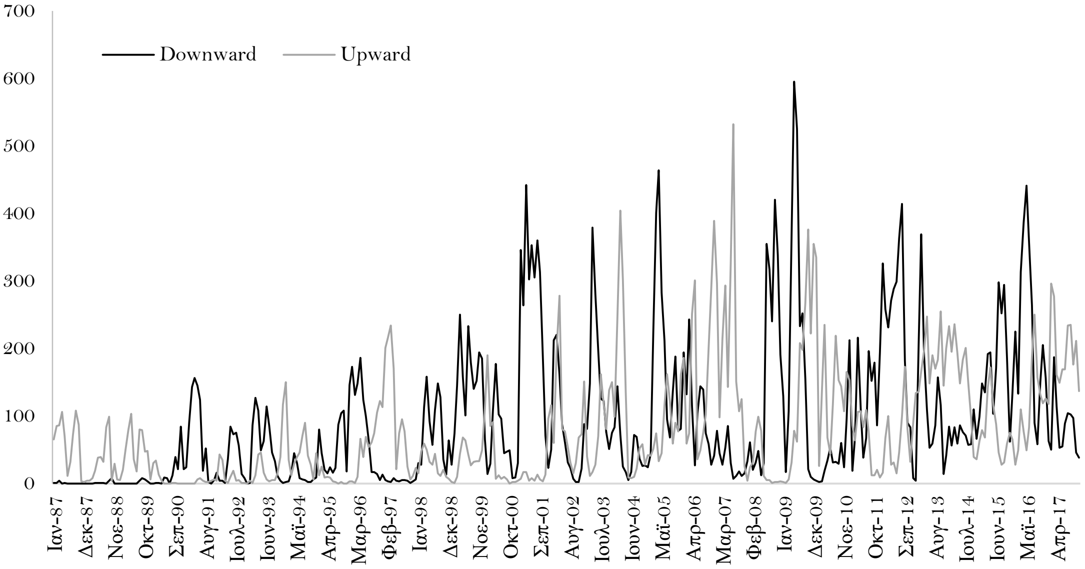

Figure 3: The numbers of 52-week high downward- and upward-updated

Table 1 also shows the follow-up average monthly return of each category. For the price change case, no matter whether the return measured is raw or market-adjusted, the return seems to present a positive first-order autocorrelation if the current return is either positive or negative. For the updating case, it is not surprising that the future returns are positive when the 52-week high is upward updated, because of the breakthrough effect mentioned by Huddart et al. (2009) and Driessen et al. (2013). The future return pattern of downward updating observations is more interesting. The average monthly return over the short term (one month and three months) is negative, whereas the long-term (twelve months) average turns into a positive value. It appears to support my explanation (long-term mean reversion) for downward updating. Nevertheless, the effects of price change and updating on momentum profits are unknown herein.

4. Results

4.1 Profits from PTH-based Strategies

To understand and to deal with how PTH momentum profits are driven by price change or updating effect, this paper implements the portfolio approach. Table 2 reports the average monthly returns of PTH, non-price PTH, and non-updating PTH strategies, respectively.[5] For raw returns, the PTH strategy generates a significant return of 0.63% (0.93%) per month (outside of January). The non-price PTH strategy presents a like result, which earns 0.64% (0.92) per month (outside of January). The non-updating PTH strategy also produces a slightly lower return of 0.59% (0.90%) per month (outside of January). Moreover, in terms of risk-adjusted returns using the Fama & French (2015) five-factor model, the non-price PTH strategy earns a statistically significant return of 0.49% (0.69%) per month (outside of January), which is the highest among the three PTH-based strategies, followed by the PTH strategy and non-updating PTH strategy. If we exclude January data, then the monthly profits from all strategies identically increase by 0.3% and 0.2% in raw and adjusted returns, respectively. This finding is in accordance with the literature, arguing that loser stocks tend to rebound in January (e.g., George & Hwang, 2004).

Table 2: Average monthly returns of the three strategies

	Raw returns		Adjusted returns by FF5	
	Jan. incl.	Jan. excl.	Jan. incl.	Jan. excl.
PTH strategy				
Winner	0.62%	0.48%	0.29%	0.36%
Loser	-0.01%	-0.45%	-0.15%	-0.29%
Winner – Loser	0.63%***	0.93%***	0.44%*	0.65%***
	(2.68)	(3.51)	(1.90)	(2.71)

[5] George & Hwang (2004) and Hao et al. (2016) point out a strong January effect in momentum-related strategies. Thus, we report both average monthly returns with and without January data.

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Non-price PTH strategy (PTH_nonP)				
Winner	0.62%	0.47%	0.32%	0.38%
Loser	-0.02%	-0.45%	-0.17%	-0.31%
Winner – Loser	0.64%***	0.92%***	0.49%**	0.69%***
	(2.93)	(3.75)	(2.43)	(3.40)
Non-updating PTH strategy (PTH_nonU)				
Winner	0.58%	0.45%	0.26%	0.33%
Loser	-0.01%	-0.45%	-0.13%	-0.28%
Winner – Loser	0.59%**	0.90%***	0.39%*	0.61%**
	(2.51)	(3.39)	(1.66)	(2.47)

Notes: The three strategies sort stocks into 3 portfolios (with top and bottom classes using 30% cutoffs) based on the PTH, PTH_nonP, and PTH_nonU ratios, respectively. The raw returns and adjusted returns by Fama & French's (2015) five-factor model are reported; t-statistics in parentheses are adjusted for autocorrelation using the Newey & West (1987) method. *, **, and *** denote the significant levels at 0.1, 0.05, and 0.01, respectively.

According to Table 2, all three PTH-based strategies are profitable in raw and adjusted returns, no matter whether January data are included or excluded, indicating that the original PTH and two adjustment PTH measures have forecasting abilities about future returns. In general, Table 2 reveals that the non-price PTH strategy is more profitable than the other two strategies, implying that the price change component (P_t/P_{t-1}) seems to be redundant in constructing PTH portfolios. Oppositely, the non-updating PTH strategy is less profitable than the other two strategies, meaning that the information of the updating component ($High_{t-1}/High_t$) is valuable. Hence, this finding basically supports our consideration that the updating component is more dominant than the price change component.

This paper further divides the whole data into sub-samples to examine the robustness of PTH-based strategies. The first test is the state of the business cycle, in which Yu (2012) and Hao et al. (2016) show that the profits from PTH momentum depend on the stages of the business cycle. Therefore, this present paper examines the performances of the three PTH-based strategies in expansion and contraction periods, respectively. The dating of each business cycle over the research period is obtained from Taiwan's National Development Council. The corresponding results are shown in Table 3.

During expansion periods, three PTH-based strategies generate positive returns, ranging from 0.35% (0.69%) to 0.41% (0.77%) per month (outside of January) in raw returns. All strategies gain statistically significant adjusted returns, ranging from 0.35% (0.53%) to 0.43% (0.61%) per month (outside of January). We note that although the profits from the original PTH strategy are the best, the differences in the profitability among the three strategies are indeed small in terms of raw and adjusted returns, but the results during contraction periods do show a distinct pattern. For raw returns, the performances of the three strategies are more pronounced, ranging from 1.16% (1.35%) to 1.39% (1.52%) per month (outside of January). Specifically, the raw return of the non-price PTH strategy increases by four times from 0.35% during expansions to 1.39% during contractions, while profits from the other two strategies increase about three times.

Table 3: Average monthly returns in different stages of the business cycle

	Expansion periods				Contraction periods			
	Raw returns		Adjusted by FF5		Raw returns		Adjusted by FF5	
	Jan. incl.	Jan. excl.	Jan. incl.	Jan. excl.	Jan. incl.	Jan. excl.	Jan. incl.	Jan. excl.
PTH strategy								
Winner	1.89	1.87	0.38	0.46	-2.81	-3.29	0.27	0.26
Loser	1.48	1.10	-0.05	-0.15	-4.02	-4.66	-0.07	-0.29
W – L	0.41	0.77**	0.43**	0.61***	1.21**	1.36***	0.34	0.55
	(1.46)	(2.41)	(2.08)	(2.99)	(2.59)	(2.82)	(0.61)	(1.04)
Non-price PTH strategy								
Winner	1.84	1.80	0.36	0.45	-2.67	-3.16	0.48	0.45
Loser	1.48	1.11	-0.0%	-0.16	-4.06	-4.68	-0.18	-0.41
W – L	0.35	0.69**	0.42**	0.61***	1.39***	1.52***	0.65	0.85*
	(1.39)	(2.36)	(2.58)	(3.57)	(2.93)	(3.08)	(1.23)	(1.67)
Non-updating PTH strategy								
Winner	1.86	1.84	0.33	0.41	-2.85	-3.31	0.24	0.25
Loser	1.49	1.10	-0.02	-0.13	-4.01	-4.65	-0.05	-0.27
W – L	0.38	0.74**	0.35*	0.53**	1.16**	1.35***	0.28	0.52
	(1.34)	(2.32)	(1.67)	(2.53)	(2.48)	(2.75)	(0.50)	(0.95)

Notes: The three strategies sort stocks into 3 portfolios (with top and bottom classes using 30% cutoffs) based on the PTH, PTH_nonP, and PTH_nonU ratios, respectively. The dating of economic expansions and contractions is from Taiwan's National Development Council. The raw returns and adjusted returns by Fama and French's (2015) five-factor model are reported; t-statistics in parentheses are adjusted for autocorrelation using the Newey & West (1987) method. *, **, and *** denote the significant levels at 0.1, 0.05, and 0.01, respectively.

After taking the five risk factors proposed by Fama & French (2015) into account, the three strategies still earn positive returns, ranging from 0.28% to 0.65% per month. The gap between the three strategies' performances is more substantial in that profit from the non-price PTH strategy is double that of the other two strategies. Outside of January, the non-price PTH strategy generates a statistically positive return of 0.85% per month during contraction periods. However, the profits from other two strategies are still insignificant.

Table 4 presents the profits from the three strategies in the pre- and post-2000 periods, respectively. During the pre-2000 period, all strategies produce significantly positive raw returns using non-January data. However, in other model specifications, only the non-price PTH strategy can earn statistically significant returns in the pre-2000 period. The return patterns in the post-2000 period are consistent with those in the pre-2000 period, and the reported numbers are more pronounced in the post-2000 period. Moreover, the result is robust, whereby the non-price PTH strategy is the best performer, while the non-updating PTH strategy is the worst in both the pre- and post-2000 periods.

Table 4: Average monthly returns in pre- and post-2000 periods

	Pre-2000 period (1987-2000)				Post-2000 period (2001-2017)			
	Raw returns		Adjusted by FF5		Raw returns		Adjusted by FF5	
	Jan. incl.	Jan. excl.	Jan. incl.	Jan. excl.	Jan. incl.	Jan. excl.	Jan. incl.	Jan. excl.
PTH strategy								
Winner	0.47	0.23	0.25	0.33	0.73	0.68	0.40	0.46
Loser	-0.08	-0.75	-0.09	-0.32	0.05	-0.21	-0.09	-0.22
W – L	0.55	0.98**	0.34	0.65	0.69**	0.89***	0.49**	0.68***
	(1.51)	(2.22)	(0.87)	(1.51)	(2.17)	(2.74)	(2.27)	(3.09)
Non-price PTH strategy								
Winner	0.48	0.22	0.30	0.39	0.73	0.67	0.43	0.47
Loser	-0.07	-0.74	-0.11	-0.35	0.02	-0.21	-0.14	-0.25
W – L	0.55*	0.97**	0.41	0.74**	0.71**	0.88***	0.56***	0.72***
	(1.72)	(2.57)	(1.27)	(2.16)	(2.31)	(2.69)	(2.92)	(3.55)
Non-updating PTH strategy								
Winner	0.44	0.20	0.22	0.30	0.70	0.66	0.35	0.42
Loser	-0.08	-0.75	-0.09	-0.31	0.05	-0.20	-0.08	-0.21
W – L	0.52	0.95**	0.31	0.62	0.62**	0.86***	0.43*	0.63***
	(1.42)	(2.15)	(0.78)	(1.40)	(2.05)	(2.66)	(1.95)	(2.87)

Notes: The three strategies sort stocks into 3 portfolios (with top and bottom classes using 30% cutoffs) based on the PTH, PTH_nonP, and PTH_nonU ratios, respectively. The raw returns and adjusted returns by Fama & French's (2015) five-factor model are reported; t-statistics in parentheses are adjusted for autocorrelation using the Newey & West (1987) method. *, **, and *** denote the significant levels at 0.1, 0.05, and 0.01, respectively.

This paper next examines whether the PTH-based strategies are robust across firm size groups. In each month *t*, the stocks ranked in the top (bottom) 30% of the market-capitalization are assigned to the large (small) group. The remaining 40% denotes the medium group. Within each size group, stocks are then classified into winner and loser portfolios according to the corresponding PTH ratios. The results are reported in Table 5.

Table 5: Momentum profits across different firm size groups

Panel A					
Size Group	Portfolios classified by PTH	All months		Exclude January	
		Raw	FF5	Raw	FF5
Large	Winner	0.40%	-0.01%	0.28%	0.06%
	Loser	0.20%	-0.12%	-0.15%	-0.24%
	Winner - Loser	0.21% (0.88)	0.12% (0.45)	0.43% (1.65)	0.28% (0.97)
Medium	Winner	0.51%	0.23%	0.38%	0.30%
	Loser	-0.05%	-0.15%	-0.35%	-0.28%
	Winner - Loser	0.46% (2.07)	0.38% (1.66)	0.73% (2.84)	0.58% (2.37)
Small	Winner	1.10%	0.92%	0.90%	0.95%
	Loser	-0.28%	-0.25%	-0.84%	-0.46%
	Winner - Loser	1.39% (4.94)	1.18% (5.41)	1.74% (5.14)	1.41% (5.84)
Panel B					
Size Group	Portfolios classified by PTH_nonP	All months		Exclude January	
		Raw	FF5	Raw	FF5
Large	Winner	0.40%	0.04%	0.27%	0.11%
	Loser	0.14%	-0.21%	-0.19%	-0.32%
	Winner - Loser	0.26% (1.15)	0.25% (1.22)	0.46% (2.00)	0.43% (2.02)
Medium	Winner	0.52%	0.25%	0.37%	0.31%
	Loser	0.03%	-0.17%	-0.35%	-0.28%
	Winner - Loser	0.49% (2.41)	0.42% (2.12)	0.72% (3.16)	0.60% (2.87)
Small	Winner	1.14%	0.96%	0.93%	0.99%
	Loser	-0.29%	-0.27%	-0.86%	-0.49%
	Winner - Loser	1.44% (5.00)	1.23% (5.56)	1.80% (5.82)	1.49% (6.24)

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Panel C Size Group	Portfolios classified by PTH_nonU	All months		Exclude January	
		Raw	FF5	Raw	FF5
Large	Winner	0.38%	-0.04%	0.25%	0.02%
	Loser	0.20%	-0.11%	-0.15%	-0.22%
	Winner - Loser	0.18% (0.76)	0.07% (0.27)	0.39% (1.49)	0.23% (0.84)
Medium	Winner	0.51%	0.22%	0.38%	0.30%
	Loser	0.05%	-0.14%	-0.36%	-0.27%
	Winner - Loser	0.46% (2.05)	0.36% (1.56)	0.74% (2.93)	0.58% (2.32)
Small	Winner	1.04%	0.86%	0.83%	0.88%
	Loser	-0.26%	-0.22%	-0.82%	-0.43%
	Winner - Loser	1.30% (4.18)	1.08% (4.44)	1.64% (5.29)	1.32% (5.29)

Notes: In each month from January 1987 to December 2017, stocks are first assigned to one of three size groups according to their market capitalizations (with top and bottom classes using 30% cutoffs). In each size group, the three strategies sort stocks into 3 portfolios (with top and bottom classes using 30% cutoffs) based on the PTH, PTH_nonP, and PTH_nonU ratios, respectively. The raw returns and adjusted returns by Fama & French's (2015) five-factor model are reported; t-statistics in parentheses are adjusted for autocorrelation using the Newey & West (1987) method. *, **, and *** denote the significant levels at 0.1, 0.05, and 0.01, respectively.

Panel A of Table 5 shows the profits from the conventional PTH strategy across the three size groups. Within the large size group, the PTH strategy presents positive returns ranging from 0.12% to 0.43%, but these numbers are statistically insignificant in terms of raw and adjusted return measures. The PTH momentum is obviously stronger in the small size group, and the PTH strategy produces a monthly return of 1.39% (1.18%) and 1.74% (1.41%) for raw (adjusted) returns using all months and non-January data, respectively. This finding is reasonable as information about small firms is relatively opaque compared to large firms. Thus, investors typically severely underreact to information on small firms, resulting in a more serious anchor-and-adjust bias as well as higher momentum in future.

Panels B and C illustrate the momentum profits from non-price and non-updating PTH strategies among the three size groups, respectively. In general, the patterns of Panels B and C are quite similar to that of Panel A, in which momentum is more pronounced in the small size group than in the other two size groups. Moreover, it is noteworthy that only the non-price PTH strategy can generate a statistically significant return of 0.46% (0.43%) per month in raw (adjusted) measures in the large size group using non-January data.

With respect to Tables 3-5, in summary, these robust examinations are consistent with the main result from Table 2. They suggest that the profitability of the non-price PTH strategy based on the *PTH_nonP* ratio is more substantial and pronounced than for the other two strategies. Specifically, when the price change component (P_t/P_{t-1}) is removed from the original PTH ratio, the corresponding strategy (non-price PTH) outperforms the conventional PTH strategy. Therefore, this paper considers that the price change component is unnecessary and dominated by the updating component. However, the results listed in this subsection are based on univariate analysis, meaning that a more careful test is needed to prove the dominance of the updating component in PTH momentum. This paper deals with this issue in the next subsection.

4.2 Comparison Between the Three PTH-based Momentum Strategies

George & Hwang (2004) implement two approaches to test the dominance of PTH momentum. One is an independent double-sorts method on pairwise momentum comparisons; the other one is the Fama-MacBeth (1973) cross-sectional regression. Since the latter approach is more careful and powerful, this paper uses the Fama-MacBeth cross-sectional regression to confirm the dominance of the updating component in PTH momentum.

As mentioned above, the holding period for each winner and loser portfolio is six months, and a one-month gap between formation and holding periods is set. Therefore, we estimate six cross-sectional regressions (for j=2 to 7) of the following form:[6]

$$R_{i,t} = b_{0jt} + b_{1jt}R_{i,t-1} + b_{2jt}Size_{i,t-1} + b_{3jt}JTH_{i,t-j} + b_{4jt}JTL_{i,t-j} + b_{5jt}MGH_{i,t-j} + b_{6jt}MGL_{i,t-j}$$
$$+b_{7jt}PTHH_{i,t-j} + b_{8jt}PTHL_{i,t-j} + b_{9jt}PTH_{adjP}H_{i,t-j} + b_{10jt}PTH_{adjP}L_{i,t-j}$$
$$+b_{11jt}PTH_{adjU}H_{i,t-j} + b_{12jt}PTH_{adjU}L_{i,t-j} + e_{i,t} \quad (5)$$

Here, $R_{i,t-1}$ and $Size_{i,t-1}$ are the return and the logged market capitalization of stock i in month t-1 in order to control the effects of bid-ask bounce and firm size. *JTH* (*JTL*) is a dummy variable that equals one if stock i is ranked in the top (bottom) 30% based on its past six cumulative returns at the end of months t–j and is zero otherwise. *MGH* (*MGL*) is a dummy variable that equals one if stock i is ranked in the top (bottom) 30% based on the past six cumulative returns of the industry in which stock i belongs at the end of months t–j and is zero otherwise. *PTHH* (*PTHL*) is a dummy variable that equals one if stock i's PTH ratio is ranked in the top (bottom) 30% at the end of

[6] Consistent with George & Hwang (2004), this paper also examines the well-known JT momentum (Jegadeesh & Titman, 1993) and MG momentum (Moskowitz & Grinblatt, 1999) in the Fama-MacBeth cross-sectional regression.

months $t{-}j$ and is zero otherwise. $PTH_{nonP}H$ ($PTH_{nonP}L$) and $PTH_{nonU}H$ ($PTH_{nonU}L$) are defined by the same way, but are ranked by the *PTH_nonP* and *PTH_nonU* ratios, respectively.[7]

Coefficients b_{3jt} - b_{12jt} represent the monthly returns of the corresponding winner and loser portfolios. Since individual coefficients are computed from six separate cross-sectional regressions, each reported coefficient in Table 6 is the time-series average of the estimated coefficients in each month t. Moreover, the difference in b_{3jt} and b_{4jt} is the monthly return of JT momentum. MG momentum and three PTH-based momentum profits are obtained by the same way.

For raw returns, the coefficients of both winner and loser portfolios based on JT momentum are significantly negative, and the coefficient of JT momentum is -0.08 (-0.03) using all months (non-January) data. The coefficients of the winner and loser portfolios based on MG momentum are near zero, and the difference between the two portfolios is positive, but insignificant. In addition, the winner portfolio based on the PTH ratio earns a positive return of 0.17% (0.19%) and the loser portfolio produces a significantly negative return of -0.28% (-0.31), using all months (non-January) data. As a result, the profitability from the PTH strategy is statistically positive with a return of 0.44% (0.50%) per month (outside of January). The aforementioned results are in accordance with Hao et al. (2016).

The coefficient of the winner (loser) portfolio based on the *PTH_nonP* ratio is statistically positive (negative) no matter with or without January returns. Thus, the non-price PTH momentum strategy generates returns of 0.51% and 0.61% using all months and non-January data, respectively. However, the non-updating PTH momentum strategy is unprofitable with near-zero returns of -0.04% and 0.03% using all months and non-January data, respectively. The results represent that the profit from the non-updating PTH strategy is totally diluted by other momentum strategies, while the profitability of the non-price PTH strategy is robust, even after controlling other momentum strategies.

In the case of adjusted returns (the last two columns of Table 6), the conclusion is generally the same as that in the raw returns case, but the reported numbers become more significant. The coefficients of $R_{i,t-1}$ and $Size_{i,t-1}$ are statistically negative, indicating that short-term reversal and small size effects do exist in Taiwan. It is notable that all winner portfolios of the five momentum strategies experience negative returns after adjusting Fama-French's five risk factors. Moreover, among the five momentum strategies, non-price PTH momentum is the strongest followed by PTH momentum, whereas the other three momentum strategies are unprofitable.

To sum up, the Fama-MacBeth cross-sectional regression confirms that the non-price PTH strategy dominates not only the conventional PTH and non-updating PTH strategies, but also the well-known JT and MG momentum strategies. Once again, the empirical results reveal that removing the price change component (updating component) from the original PTH measure increases (decreases) the momentum profit, implying that the updating component dominates the price change component in PTH momentum.

5. Robust Checks

5.1 Other Reward-risk Measures of Self-financing Portfolios

Sections 4.1 and 4.2 focus on the returns of PTH-based strategies, as some investors tend to place emphasis on the risks behind a trading strategy. Therefore, this subsection follows Bianchi et al. (2016) and provides more evidence about the reward-risk structure behind the three PTH-based strategies in Table 7.

On a basic reward/risk indicator (i.e. Sharpe ratio), the non-price PTH strategy (0.48) presents the highest Sharpe ratio, followed by the PTH strategy (0.45) and non-updating PTH strategy (0.42). Considering downside risk, the non-price PTH strategy has the highest Sortino ratio of 0.81, while the non-updating PTH strategy is still the worst (0.67). These sortings based on Sharpe and Sortino ratios remain unchanged even if January returns are excluded. These measures show that the non-price PTH strategy is the best in terms of risk-adjusted returns.

Table 6: Fama-MacBeth regression for comparing PTH-based strategies

	Raw returns		Adjusted returns by FF5	
	January incl.	January excl.	January incl.	January excl.
(1) Intercept	1.58	1.14	1.81***	1.70***
	(1.46)	(1.00)	(3.37)	(2.92)
(2) $R_{i,t-1}$	-0.00	0.01	-0.34***	-0.33***
	(-0.51)	(0.69)	(-9.00)	(-8.39)
(3) $Size_{i,t-1}$	-0.12	-0.09	-0.51***	-0.49***
	(-1.34)	(-0.93)	(-9.58)	(-8.61)
(4) JTH	-0.25**	-0.25**	-0.60***	-0.59***
	(-2.38)	(-2.34)	(-6.28)	(-5.94)
(5) JTL	-0.17**	-0.23***	-0.48***	-0.52***
	(-2.25)	(-3.05)	(-5.97)	(-6.54)
(6) MGH	0.04	0.03	-0.34***	-0.35***
	(0.45)	(0.35)	(-4.27)	(-4.32)
(7) MGL	-0.08	-0.10	-0.42***	-0.43***
	(-1.18)	(-1.35)	(-5.01)	(-4.96)

[7] *PTHH (PTHL)*, $PTH_{nonP}H$ ($PTH_{nonP}L$) and $PTH_{nonU}H$ ($PTH_{nonU}L$) may be correlated to each other. However, we do not find any serious multicollinearity problem in this analysis.

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(8) PTHH	0.17	0.19*	-0.19*	-0.19*
	(1.59)	(1.72)	(-1.86)	(-1.69)
(9) PTHL	-0.28**	-0.31***	-0.61***	-0.64***
	(-3.42)	(-3.37)	(7.26)	(-6.74)
(10) PTH$_{nonP}$H	0.12*	0.15**	-0.20***	-0.18***
	(1.94)	(2.16)	(-3.21)	(-2.79)
(11) PTH$_{nonP}$L	-0.38***	-0.47***	-0.67***	-0.73***
	(-5.11)	(-6.15)	(-9.75)	(-10.04)
(12) PTH$_{nonU}$H	-0.01	0.01	-0.32***	-0.30***
	(-0.10)	(0.12)	(-3.52)	(-3.18)
(13) PTH$_{nonU}$L	0.03	-0.02	-0.24***	-0.26***
	(0.40)	(-0.23)	(-2.81)	(-2.90)
JT momentum: (4) – (5)	-0.08	-0.03	-0.12	-0.07
	(-0.56)	(-0.19)	(-0.97)	(-0.57)
MG momentum: (6) – (7)	0.12	0.13	0.08	0.08
	(1.42)	(1.46)	(0.95)	(0.90)
PTH momentum: (8) – (9)	0.44***	0.50***	0.42***	0.45***
	(3.00)	(3.22)	(3.11)	(3.18)
Non-price PTH momentum: (10) – (11)	0.51***	0.61***	0.47***	0.55***
	(4.75)	(5.39)	(4.70)	(5.53)
Non-updating PTH momentum: (12) – (13)	-0.04	0.03	-0.08	-0.04
	(-0.30)	(0.22)	(-0.60)	(-0.29)

Notes: Here, $R_{i,t}$ and $Size_{i,t}$ are respectively the return and the logged market capitalization of stock *i* in month *t*. *PTHH* (*PTHL*) is a dummy variable that equals 1 if stock *i* is ranked in the top (bottom) 30% based on the ratio of price to the 52-week high ranking criterion and 0 otherwise. All other variables are dummy variables constructed via the corresponding ranking measures. The coefficients are the average of the month-by-month estimates. The raw returns and adjusted returns by Fama & French's (2015) five-factor model are reported herein; t-statistics in parentheses are adjusted for autocorrelation using the Newey & West (1987) method. *, **, and *** denote the significant levels at 0.1, 0.05, and 0.01, respectively.

This paper further reports the value-at-risk (VaR) with a 99% level of confidence to estimate any extreme downside risk using the Cornish-Fisher expansion method. The 99% VaR of the non-price PTH strategy is -13.24%, indicating that its extreme downside risk is smaller than those of the other two strategies. Another measure for extreme downside risk is the maximum drawdown, defined as the maximum loss from a peak to a trough of a portfolio's equity. The non-price PTH strategy experiences the smallest maximum drawdown of -44.08%, but the non-updating PTH strategy has the largest maximum drawdown of -50.33%. Thus, these measures consistently point out that the non-price PTH strategy is the best in terms of downside risks.

The last two rows of Table 7 list the maximum and minimum rolling returns with continuous twelve months, respectively. These two measures separately illustrate the best and worst performances of a trading strategy in successive twelve months, implying that they can capture the stability of a strategy. The non-price PTH strategy presents both the highest maximum and minimum rolling returns with 50.87% and -34.39%, respectively. In addition, the non-updating PTH strategy shows the lowest maximum rolling return with 47.11%, while the conventional PTH strategy is the worst one in regards to minimum rolling return with -35.15%.

In conclusion, Table 7 echoes the findings shown in sections 4.1 and 4.2. Here, the non-price PTH strategy reports the most substantial risk-adjusted return among three PTH-based strategies. Furthermore, Table 7 confirms that the non-price PTH strategy has the lowest investment risk, meaning that removing the price change component from the PTH measure is useful.

Table 7: Some reward-risk measures for the three strategies

	PTH strategy	Non-price PTH strategy	Non-updating PTH strategy
Annualized return (%)	7.53	7.63	7.08
Annualized standard deviation	16.88	15.84	17.05
Sharpe ratio	0.45	0.48	0.42
Sharpe ratio – January excluded	0.47	0.51	0.44
Sortino ratio	0.72	0.81	0.67
Sortino ratio – January excluded	0.85	0.97	0.79
99%VaR (%)	-14.62	-13.24	-14.61
99%VaR – January excluded (%)	-13.21	-11.63	-13.37
% of positive months	57.53	59.41	58.33
Maximum drawdown (%)	-48.64	-44.08	-50.33
Top 3 drawdown in average (%)	-43.22	-38.09	-44.44
Max 12-month rolling return (%)	49.27	50.87	47.11
Min 12-month rolling return (%)	-35.15	-34.39	-35.03

Note: The three strategies sort stocks into 3 portfolios (with top and bottom classes using 30% cutoffs) based on the PTH, PTH_nonP, and PTH_nonU ratios, respectively. The Sortino ratio measures the risk-adjusted return of a portfolio using downside deviation. Here, 99%VaR is calculated by the Cornish-Fisher expansion method. Maximum drawdown denotes the maximum loss from a peak to a trough of a portfolio's equity.

5.2 Mean Reversion and Updating of the 52-week High

As we note beforehand, a downward updating of the 52-week high implies that the stock price has not set a higher 52-week high for a long period. This paper supposes that the longer period a stock has undergone in which its price has not set a higher 52-week high, the higher the stock's sequential return will generate. Thus, this paper proposes a measure s defined by the last upward updating of the 52-week high being formed s months ago. Moreover, s can denote the duration between two consecutive upward updating events. This measure is straightforward, i.e. finding the minimum value of s that satisfies the following conditional for each month t:

$$High_{t-s-1} < High_{t-s} \leq High_t, \quad s \geq 0. \quad (6)$$

Table 8: Mean-reverting and updating effect

	(1) January incl.	(2) January excl.	(3) January incl.	(4) January excl.
Intercept	1.34	0.94	1.30	0.88
	(1.22)	(0.81)	(1.18)	(0.76)
$R_{i,t-1}$	-0.01	0.00	-0.01	0.00
	(-0.99)	(0.33)	(-0.85)	(0.29)
$Size_{i,t-1}$	-0.09	-0.06	-0.09	-0.06
	(-1.04)	(-0.67)	(-1.04)	(-0.68)
JTH	-0.30***	-0.33***	-0.30***	-0.32***
	(-2.70)	(-2.85)	(-2.71)	(-2.80)
JTL	-0.20**	-0.24***	-0.19**	-0.23***
	(-2.55)	(-3.14)	(-2.47)	(-3.06)
MGH	0.01	-0.00	0.01	-0.00
	(0.09)	(-0.04)	(0.09)	(-0.06)
MGL	-0.05	-0.07	-0.06	-0.08
	(-0.70)	(-0.90)	(-0.81)	(-1.02)
PTHH	0.18*	0.24**	0.19*	0.26**
	(1.88)	(2.44)	(1.67)	(2.05)
PTHL	-0.49***	-0.61***	-0.38***	-0.44***
	(-4.82)	(-5.11)	(2.71)	(-3.00)
s	-0.00	-0.01	-0.01	-0.02
	(-0.35)	(-1.06)	(-0.75)	(-1.18)
PTHH × s			0.05*	0.05*
			(1.89)	(1.85)
PTHL × s			-0.00	-0.00
			(-0.21)	(-0.22)

Notes: Here, s denotes the duration between two consecutive upward updating events, while $R_{i,t}$ and $Size_{i,t}$ are respectively the return and the logged market capitalization of stock i in month t. *PTHH* (*PTHL*) is a dummy variable that equals 1 if stock i is ranked in the top (bottom) 30% based on the ratio of price to the 52-week high ranking criterion and 0 otherwise. All other variables are dummy variables constructed via the corresponding ranking measures. Lastly, t-statistics in parentheses are adjusted for autocorrelation using the Newey & West (1987) method. *, **, and *** denote the significant levels at 0.1, 0.05, and 0.01, respectively.

Here, $High_t$ is the corresponding 52-week high at the end of month t, and s is equal to zero if the price breaks through its previous 52-week high in current month t. The descriptive statistics show that the mean (median) of s is 11.10 (7) and the maximum value is 132, meaning that a certain stock price does not experience an upward updating of its 52-week high for 11 years. This paper further applies the Fama-MacBeth cross-sectional regression to discuss the effect of s.

Table 8 reports the estimation results. Models (1) and (2) set s as an independent variable, and Models (3) and (4) further add two interaction terms to examine the effects of s on the winner and loser portfolios based on the PTH ratio. The coefficients of s in all models are near zero and insignificant, indicating that the duration between two consecutive upward updating events would not directly affect stock returns. However, the coefficients of (PTHH×s) are positively significant at the 10% significance level, meaning that when a stock is classified into a winner portfolio, the longer the duration is between two consecutive upward updating events, the higher a stock's future return will be. This finding also implies that the profits from winner portfolios can be enhanced if we further choose stocks with a larger s from winners to construct a new winner portfolio. Nevertheless, the coefficients of (PTHL×s) are statistically insignificant. According to Table 8, this test verifies that the updating effect can be explained by a mean reversion assumption. Specifically, a stock with a downward updated 52-week high should have a larger s than that with an upward updated 52-week high.

6. Conclusions

The finance literature has commonly accepted the 52-week high stock price as a reference or anchoring point that can

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influence investors' trading psychology. The profitability of the 52-week high momentum investing strategy is also verified by a large number of empirical studies, but they lack any discussion on the implications and effects from movement in 52-week high prices within the scope of a 52-week high momentum strategy. Based on behavioral perspectives, this paper considers that the updating of 52-week high prices can influence investors' attention and further affect the corresponding momentum profitability. This paper thus decomposes the ratio of price to 52-week high and investigates the internal engine of 52-week high momentum profits. More specifically, this paper denotes two components of the ratio of stock price to 52-week high: one is the price change component (return within the current period) and the other is the updating component (52-week high price updating). The literature on behavioral finance considers that the updating component would dominate the price change component in terms of 52-week high momentum profits. Accordingly, this paper presents consistent evidence that the price change component is redundant after we utilize a portfolio approach and Fama-MacBeth regression. Moreover, we find that if a high ratio of stock price to 52-week high is driven by a downward updating event, then the subsequent positive momentum for a winner portfolio is more substantial.

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