Short-term Relative-Strength Strategies, Turnover, and the Connection between Winner Returns and the 52-week High*

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Abstract

We contribute with two principal findings that suggest a material role for a 52-week-high price anchor in understanding the short-run behavior of one-month stock returns. First, we find that short-term momentum in high-turnover stocks is only evident for stocks whose prices are relatively close to their 52-week high. Conversely, strong reversals are evident for high-turnover stocks whose prices are relatively far from their 52-week high. Second, we find that the apparent anchoring biases are asymmetric. Winner stocks that are near their 52-week-high strongly outperform winner stocks that are far from their 52-week-high; but the performance of past-loser stocks has little relation to this price anchor. We conduct five supplemental investigations that support an anchoring-bias interpretation for the relation between winner performance and this price anchor; also evaluating market sentiment, dispersion in analyst forecasted earnings, and the firm characteristics of size, market-to-book equity ratios, and idiosyncratic volatility.

JEL Classification: G11, G12, G14

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1. Introduction

Short-term reversals in one-month stock returns have been a well-known and widely-studied phenomenon in the finance literature since about 1990.[1] Yet, defying conventional wisdom that one-month equity returns are dominated by reversals, Medhat and Schmeling (2022) (hereafter MS) recently document that momentum is strongly evident in one-month stock returns for stocks with relatively high turnover, in contrast to the reversals of low to mid turnover stocks.[2] Their findings raise new implications for understanding price formation, equity market efficiency, and investor behavior. MS conclude that short-term momentum seems contradictory to models that assume strict rationality but is "suggestive of an explanation based on some traders underappreciating the information conveyed by prices".

We extend the MS (2022) empirical investigation by also evaluating the role of a stock's price to its 52-week-high ratio (PTH), which the literature has suggested can influence price formation through an anchoring bias channel.[3] We are interested both in understanding the channels behind MS's findings, specifically, and in the role of PTH anchoring biases in short-term strategies, more broadly. We evaluate short-term relative-return-strength strategies in multiple dimensions; including momentum strategies (buying winners and shorting losers), reversal strategies (buying losers and shorting winners), and winner-only or loser-only strategies based on a stock's relative 52-week PTH (e.g., buying high-PTH winners and shorting low-PTH winners).[4]

We contribute with two principal findings that establish new stylized facts for this literature and suggest a material role for price anchors in understanding short-run price behavior. Our first contribution bears on understanding and describing the short-term momentum in high turnover stocks. Specifically, we find that short-term momentum in high-turnover stocks is only evident for

[1]We refer to the reversal profits over month $t+1$ from a strategy that buys stocks that had relatively poor returns over month t (relative losers) and shorts stocks that had relatively strong returns over month t (relative winners). See Jegadeesh (1990) and Lehmann (1990) for early evidence. Much of the recent literature suggest a liquidity provision channel to explain reversals; see, e.g., Avramov, Chordia, and Goyal (2006), So and Wang (2014), Hameed and Mian (2015), and Cheng, Hameed, Subrahmanyam, and Titman (2017).

[2]Similarly, Chiang, Kirby, and Nie (2021) find that short-term reversals weaken and then move towards momentum as stocks' turnover increases. Since its discovery almost three decades ago by Jegadeesh and Titman (1993), momentum has become probably the most well-known financial market anomaly. Until MS (2022), momentum has generally been thought to be confined to the medium-run horizon from about three to twelve months in the U.S. equity market (e.g. Jegadeesh and Titman (1993) and Conrad and Kaul (1998)), whereas in the short horizon from one week to one month stock returns are known to exhibit reversals. Since reversal is the opposite of momentum, this suggests that momentum is a losing strategy in the short term.

[3]See, e.g., George and Hwang (2004), Huddart, Lang, and Yetman (2009), Birru (2015), George, Hwang, and Li (2018), and Zhu, Sun, and Stivers (2021).

[4]We broadly define short-term relative-return-strength strategies to include any long/short strategy where the positions are at least partially based on the relative returns (winners or losers) over a ranking month t, with the holding-period evaluation over month $t+1$.

stocks that are near their 52-week-high; conversely, high-turnover stocks that are far from their 52-week-high exhibit strong reversals. Our second contribution shows that the apparent anchoring role of a stock's 52-week PTH is asymmetric and concentrated in past winners. We find that winner stocks that are near their 52-week-high strongly outperform winner stocks that are far from their 52-week-high; conversely, there is little difference between the returns of high-PTH loser stocks and low-PTH loser stocks. This asymmetry is behind our first principal finding.

We next turn to further discussion of our first primary contribution. While examining past returns and turnover jointly, MS (2022) find that reversal and momentum actually coexist at the one month horizon. While unconditionally the reversal strategy dominates, momentum is the dominant behavior among high-turnover stocks. Over 1963 to 2018, they find stocks in the highest turnover decile have average momentum profits of 1.37% per month (versus average reversal profits of 1.41% per month for stocks in the lowest turnover decile).

However, we find that over our sample from July 1963 to December 2020, short-term momentum is only evident for high-turnover stocks if the stocks are also higher-PTH stocks. Conversely, high-turnover stocks with a lower PTH exhibit strong reversals. At first glance, our results and the results in MS (2022) seem inconsistent. How could momentum be evident in high-turnover stocks overall (as in MS), if momentum is only evident for high-turnover stocks with a high PTH but strong reversals are evident for high-turnover stocks with a low PTH (as in our results)?

We also contribute by reconciling this apparent puzzle. Both MS (2022) and we focus on value-weighted portfolio returns over the month $t+1$ holding period.[5] Thus, larger-cap stocks are more influential in the holding-period portfolio returns over month $t+1$. We document that high-PTH stocks tend to have a much larger market-capitalization, on average, relative to low-PTH stocks. Thus, in the high-turnover-based momentum strategy of MS with value-weighted portfolios, the high-turnover stocks with a high PTH (which exhibit momentum) dominate the overall result because these stocks are much larger, on average, relative to the high-turnover stocks with a low PTH (which exhibit reversals).

For our second principal contribution, we further investigate the apparent role played by the 52-week PTH in explaining short-run (one-month) price behavior by examining separately the performance of past winner stocks vs. past loser stocks. Intriguingly, we find that "it's all about the winners". By this, we mean that there is a strong PTH-based performance variation

[5]Our main analysis features value-weighted portfolio returns and omits low-priced stocks (less than \$1). These choices address concerns from Hou, Xue, and Zhang (2020), mitigates the impact of micro-cap and/or low-priced stocks, and makes our results more directly comparable to MS (2022).

where high-PTH winners strongly outperform low-PTH winners over the subsequent month $t+1$. However, there is relatively little difference between the subsequent performance of high-PTH losers versus low-PTH losers.

This asymmetry largely drives our first principal contribution regarding the momentum in high-turnover, high-PTH stocks and the reversals in high-turnover, low-PTH stocks. Specifically, this momentum is more driven by the sizable positive returns for high-turnover *winners* that also have a high PTH (with average excess returns of +1.51% per month for our quintile-based strategy of Table 1). And, the reversals are more driven by the sizable negative returns for the high-turnover *winners* that also have a low PTH (with average excess returns of -0.95%).[6] But, for the high-turnover loser stocks, there is almost no difference in performance based on PTH.

Thus, the above observations mean that a PTH-based winner-only strategy that goes 'long past-winner stocks with a high PTH and high turnover and short past-winner stocks with a low PTH and high turnover' had an average performance of +2.46% per month over our sample (Newey-West t-statistic of 5.83). These high profits exhibit quite large alphas too, with risk adjustments based on both the q-factor model and the Fama-French 5-factor model augmented with an additional momentum factor.

Further, we find that the strong performance of this PTH-based winner-only strategy (where high-PTH winners outperform low-PTH winners) is evident: (a) in subperiod analysis; (b) for each quintile subset of stocks based on turnover, (c) for both sequential and independent sorts on past returns, PTH, and turnover; and (d) when using an alternative Fama-MacBeth methodology. For example, across the five turnover quintiles analyzed in Table 1 (which features sequential sorts) and Table 3 (which features independent sorts), the average monthly returns for this PTH-based winner-only strategy have a mean of 1.85% per month and a range between 1.33% and 2.46% per month.[7] And, for each of the 10 evaluations of the strategy, the average returns and the risk-adjusted alphas are statistically significantly positive.

For past winners, the PTH-based variations behind our two main contributions fit well with the anchoring bias suggested in George and Hwang (2004) and Birru (2015). Our results are consistent with the following anchoring-bias channels. When a stock's price is near its 52-week high and many investors feel the stock might be nearing an overvaluation status, then these

[6] In our Table 1, we evaluate the performance in month $t+1$ for stocks based on three quintile-based sequential sorts: first on the 1-month relative return strength over month t, then on the 52-week PTH ratio from the end of month $t-1$, and finally on the turnover over month t.

[7] Each table evaluates the strategies separately across turnover quintile groupings, leading to a total of 10 cases.

investors tend to be pessimistic and underreact to the good news generally associated with the winner status for month t.[8] This underreaction, in turn, contributes to momentum profits for month $t+1$ as the prices correct to more fully incorporate the good news in month t. Conversely, when a stock's price is quite low relative to its 52-week high and many investors feel the stock might be nearing an undervaluation status, then these investors tend to overreact to the good news generally associated with the winner status for month t, implying a stronger reversal over month $t+1$ as the prices correct.

However, comparably, there is relatively little difference in the subsequent performance of past losers, when segmented by the stocks' lagged 52-week PTH. For past losers, the average difference in returns over month $t+1$ for high-PTH losers versus low-PTH losers is only -0.08% per month across the ten evaluations in Tables 1 and 3.

Since our analysis features value-weighted portfolios over the holding-period $t+1$ and our analysis omits low-priced stocks under $1, our results are not driven by small- and micro-cap stocks. Thus, our finding of a striking asymmetry between past winners and losers, in regard to how their performance varies with the past 52-week PTH ratio, presents a challenge for behavioral models of investor expectation. A satisfactory theory of price anchoring on investor expectation should address this puzzle.

We next turn to considering interpretation and the underlying economic channels behind our principal results. We conduct five supplemental investigations that are meant to: (1) either provide affirming or contradictory evidence regarding a PTH anchoring-bias interpretation; and (2) provide additional evidence that further describes and qualifies our main findings. This analysis broadly considers market conditions and/or firm characteristics where it seems intuitive that PTH anchoring biases might be relatively stronger.

For our first supplemental investigation, we use the market-wide sentiment indicator of Huang *et al.* (2015) and find sentiment-based variation in the apparent PTH biases. When market-wide sentiment is lower, then the apparent underreaction to good news for high-PTH winners is amplified. And, when market-wide sentiment is higher, then the apparent overreaction to good news of low-PTH winners is amplified.

For our second supplemental investigation, we evaluate whether the apparent PTH biases are stronger for stocks with a greater dispersion in analyst earnings forecasts, where this dispersion

[8] This bias might also contribute to a higher selling propensity by investors who hold stocks with large unrealized gains, consistent with the disposition literature. We revisit the link to the disposition literature in our Conclusions.

is interpreted as a measure of dispersion in beliefs or valuation uncertainty.[9] Consistent with this premise, we find that the returns of our new PTH-based winner-only strategy are markedly higher when implemented on stocks with greater analyst dispersion.

For our third to fifth supplemental investigation, we replace turnover with a stock's market capitalization (size), market-to-book ratio, or idiosyncratic volatility as the third factor. Sorting first on the firm characteristics, we find that our new PTH-based winner-only strategy has generally reliable positive returns for all five quintiles of the firm characteristics variables. However, the profits for our PTH-based winner-only strategy are appreciably greater for smaller-cap stocks, stocks with extreme market-to-book equity ratios, and stocks with higher idiosyncratic volatility. Under the view that these firm characteristics suggest relatively greater valuation uncertainty and dispersion in beliefs, these findings with our general theme.

In sum, we feel that the results of our five supplemental investigations provide consistent evidence to support a PTH-anchoring-bias interpretation of our main results. The apparent PTH biases are stronger: (1) when their directional bias aligns with the overall market sentiment (stronger underreaction to good news for high-PTH stocks in weak sentiment times, for example), and (2) for stocks that are likely to have greater valuation uncertainty or dispersion in beliefs.

This paper is organized as follows. Section 2 discusses related literature and how price-anchoring channels might influence short-run momentum. Section 3 describes the data and our empirical methodology. Sections 4 and 5 present our main empirical results. Section 6 discusses implications of our findings for related studies and possible alternative explanations. We offer concluding remarks in Section 7, including relating our findings to other recent related studies.

2. Discussion of Related Literature and Hypothesis Development

2.1. Related Literature on the 52-Week High as a Price Anchor

The notion that, under uncertainty, we tend to rely on heuristics such as reference points or anchors for decision making purpose has long been established, at least since Tversky and Kahneman (1974). They find that when making decisions under uncertainty, human beings often rely on three forms of heuristics, one of them being "adjustments from an anchor, which is usually employed in numerical prediction when a relevant value is available."[10]

[9]By 'dispersion in beliefs', we refer to the 'differences of opinion' concept in Harris and Raviv (1993).

[10]Please also see Kahneman, Slovic, and Tversky (1982) and the experimental evidence reported therein.

In the context of momentum investing, George and Hwang (2004) first identify the 52-week high as a remarkable price anchor that investors appear to rely on when reacting to news. They conjecture (p. 2146) that "when good news has pushed a stock's price near or to a new 52-week high, traders are reluctant to bid the price of the stock higher even if the information warrants it." In other words, nearness to the 52-week high induces investor underreaction, which in turn contributes to the success of momentum strategy.

Empirically, George and Hwang provide intriguing evidence that the momentum strategy based on the nearness to 52-week high performs well when compared with Jegadeesh and Titman's price momentum and Moskowitz and Grinblatt's (1999) industry momentum strategies. They show that a momentum strategy that is long in stocks trading near the 52-week high and short in stocks far away from the 52-week high outperforms traditional return momentum.[11]

The anchoring effect from the 52-week high has proven to be an important factor that has explanatory power for many interesting topics in finance that go beyond the momentum anomaly. For example, Huang, Lin, and Xiang (2021) find that the return predictability of economically linked firms can be explained by investors' to underreaction to news about customers, geographic neighbors, industry peers, or foreign industries when stocks trade near the 52-week high price. Li and Yu (2012) find that nearness to the Dow 52-week high positively predicts future equity-market returns. Driessen, Lin, and Hemert (2012) report that the 52-week high or low can impact option implied volatility. George, Hwang, and Li (2017) find that the post-earnings announcement drift anomaly is linked to the 52-week high. In the corporate finance literature, Baker, Pan, and Wurgler (2012) find that the 52-week high also exerts its impact on merger and acquisition activities by allowing the parties to simplify the complex task of valuation and negotiation. Heath, Huddart, and Lang (1999) discover that the 52-week high can influence the exercise of executive options.[12]

Relatedly, in Birru (2015), he suggests that a 52-week PTH anchoring bias can induce expectational errors among investors. When a stock's price is near its 52-week high, then investors might be hesitant to believe the price will continue upward, implying overly pessimistic expectations and potentially an underreaction to positive news and an overreaction to negative news. Conversely,

[11] George, Hwang, and Li (2018) show that returns from a medium-run momentum PTH strategy are no longer statistically significant when risk-adjusted with the q-factor model. They further show that the PTH is positively related with future profitability and investment growth, suggesting that the PTH momentum anomaly can be substantially explained by the investment CAPM. However, we will show that, among past winners, our PTH-based strategy strongly survive risk-adjustments with the q-factor asset pricing model as well as the Fama-French 6-factor model.

[12] Studies also find that the 52-week-high can explain retail investors' trading activities (Grinblatt and Keloharju (2001)), trading volume (Huddart, Lang, and Yetman (2009), and short term reversal (Zhu, Sun, and Stivers (2021)).

when a stock's price is far below its 52-week high, investors might feel that further downward price movements are unlikely, implying an upward biased expectation and potentially an underreaction to bad news and an overreaction to good news. The relative magnitudes of such anchoring biases, if they exist, is an empirical question. Also, it is an empirical question as to what might dominate when an anchoring-bias effect is in the opposite direction of typical reversal price movements due to the well-known liquidity provision.

In Della Vedova, Grant, and Westerholm (2022), the authors study investor-account level data on all trades from the Nasdaq Helsinki exchange over 2000 to 2009. They find that household investors sharply increase their selling as a stock approaches its 52-week high, with a sharp increase in limit-order selling. They argue that these selling patterns contribute to return continuation, as in George and Hwang (2004).[13]

2.2. Hypothesis Development

Thus, substantial evidence exists that investors view the 52-week high as a price anchor or psychological barrier. The anchoring-bias prediction is that the nearness of a stock's price to its 52-week high can induce expectational errors among investors. Specifically, we consider that investor's reaction to news for stocks trading near a 52-week high might be pessimistic (downward biased) and stocks trading far below a 52-week high might be optimistic (or upward biased).

Conditional upon these premises of the 52-week high as a price anchor, we consider the following predictions on the returns in month $t+1$ for past winners in month t with high or low PTH status in month $t-1$.

- Empirical Prediction I. - Past Winners with high PTH Status:[14] When the PTH is high at $t-1$, the anchoring-bias effect suggests that some investors might have a downward-biased pessimistic interpretation of news signals, since investors are concerned that the stock might be nearing an overvaluation status. When month t is a winner month, then the winner status generally means good news in month t. Then, under the anchoring bias, the high PTH should indicate an underreaction to the good news, on average. Thus, the high

[13]See Campbell and Sharpe (2009), Cen, Hilary, and Wei (2013), and Dougal *et al.* (2015) for additional evidence of the empirical relevance of anchoring bias; specifically, in economic forecasts, analyst firm earning forecasts, and credit spreads, respectively.

[14]We note that these empirical predictions might better be referred to as 'conditional empirical possibilities', conditional upon the associated anchoring bias being materially important (rather than 'empirical predictions' derived from a formal model). We use Roman numerals to list our Empirical Predictions here, to distinguish between our main Empirical Results in Section 4 that are listed with Arabic numerals.

PTH anchoring suggests a positive influence on returns in month $t+1$ as the good news from month t, to some extent, is incorporated in month $t+1$ as the initial underreaction is corrected. This positive influence should be offset by the normal tendency of 1-month reversals for month $t+1$ due to standard liquidity-provision arguments. The net effect is an empirical question, but PTH anchoring clearly suggests a more positive return in month $t+1$ for past Winner/High-PTH stocks relative to past Winner with a low-PTH (discussed next in II. below).

- Empirical Prediction II. - Past Winners with low PTH Status: With a low-PTH, an anchoring bias suggests that some investors might tend to have an upward-biased optimistic interpretation of news, because they feel the stock might be nearing an undervaluation status. Therefore, for low-PTH winners, if there is good news in month t, as suggested by the winner status, then investors would tend to overreact to the good information. If so, this suggests a reversal in the next period $t+1$ as the overreaction is corrected somewhat in month $t+1$. Thus, the low-PTH-anchoring-bias influence for the past winners suggests a negative influence on returns in month t+1. Further, the liquidity-provision reversal influences on a winner also suggests a negative return influence for month t+1. These two negative influences would reinforce each other and we would expect to see larger negative returns for past Winner/Low-PTH stocks (relative to past Winners with a high-PTH).

- Empirical Prediction III. Together, empirical predictions I. and II. suggest that a strategy that goes long past winners with high PTH and short past winners with low PTH should be profitable.

Similarly, an anchoring-bias perspective from the 52-week PTH suggests the following predictions on the returns in month $t+1$ for past losers in month t with high or low PTH status in month $t-1$.

- Empirical Prediction IV. - Past Losers with high PTH Status: We assume that the loser status in month t generally indicates bad news in month t for the loser. If some investors have a pessimistic downward-biased views for high-PTH stocks; this suggests an overreaction to the bad news in month t. This should impart a positive influence on month $t+1$ returns, as prices move to correct the bad-news overreaction in month t. Additionally, standard liquidity-provision reversal influences on a loser also suggests a positive return influence for month t+1. Therefore, there are two reinforcing positive influences for month t+1 returns, positive for both the PTH anchoring and the standard-liquidity provision-reversal effect. Together, this suggests more positive returns in month t+1, relative to Losers with a Low-PTH (discussed in V. next).

- Empirical Prediction V. - Past Losers with low PTH Status: Again, we assume that the loser status in month t generally indicates bad news in month t for the loser. If some investors have a optimistic upward-biased news interpretation for low-PTH stocks; this suggests an underreaction to the bad news in month t. Thus, this low-PTH anchoring bias should impart a negative influence on month $t+1$ returns, as the initial under-response to the bad news is corrected and prices more fully incorporate the bad news from month t. Conversely, standard liquidity-provision reversal influences on a loser suggests a positive return influence for month t+1. Therefore, there are opposing forces, negative from the PTH anchoring and positive from the liquidity-provision reversal. The net effect is an empirical question, but PTH anchoring suggests a more positive return in month $t+1$ for past Loser/High-PTH stocks (as in IV. above) as compared to past Loser/Low-PTH stocks here.

- Empirical Prediction VI. Together, empirical predictions #4 and #5 suggest that a strategy that goes long past losers with high PTH and short past losers with low PTH should be profitable.

Regarding short-term momentum, the impact of anchoring biases is unclear under the possible PTH biases discussed above. The high-PTH anchoring biases would impart a positive influence on month $t+1$ returns for both high-PTH winners and high-PTH losers. And, the low-PTH anchoring biases would impart a negative influence on month $t+1$ returns for both low-PTH winners and low-PTH losers. This suggests three possibilities:

- Empirical Prediction VII. - If the PTH-based biases are of comparable strength for both past winners and past losers, then we would not expect the strength of short-term momentum (or reversals) to vary with a stock's PTH.

- Empirical Prediction VIII - If the PTH-based biases are considerably stronger for past winners (more than for past losers) then we would expect that short-term momentum would be more strongly evident for high-PTH stocks and that short-term reversals would be more strongly evident for low-PTH stocks.

- Empirical Prediction IX. If the PTH-based biases are considerably stronger for past losers (more than for past winners) then we would expect that short-term momentum would be more strongly evident for low-PTH stocks and that short-term reversals would be more strongly evident for high-PTH stocks

Which of these predictions will hold in the data is an open empirical question. In Section 4, we will show that the possible anchor-based predictions about the past winners (I. to III.) are all evident. However, none of the possible anchor-based predictions about the past losers (IV. to VI.) are evident in our data. Given these results, this also means that Empirical Prediction VIII. is clearly evident in our data (but VII. and IX. are not). This asymmetry between past winners and past losers should be incorporated in theories about anchoring-bias influences on price formation.

3. Data, Methods, and Basic Short-Term Reversals in our Data

In Section 3.1, we discuss our data and portfolio construction methods. In Section 3.2, we report the performance of basic one-dimensional relative-strength strategies over our sample period. We evaluate portfolio returns in month $t+1$ based only on sorts on the relative-return strength over month t. This preliminary analysis is intended to provide perspective and help link the results in our subsequent main investigation to prior findings in the literature.

3.1. Data and Methodology

The stock returns and other related data such as stock prices, shares outstanding, volume, etc. are from the Center for Research in Security Prices (CRSP). We select all common stocks (share code 10 or 11) trading at the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association of Securities Dealers Automated Quotations (NASDAQ) from July 1963 to December 2020. Our sample period extends the MS (2022) study by two years. Following MS (2022), we exclude financial firms from our sample. We also adjust NASDAQ trading volume using the methodology of Gao and Ritter (2010), when computing share turnover defined as trading volume deflated by the number of shares outstanding.

Following from George and Hwang (2004), we compute PTH, the ratio of the current price of a stock to its highest price within the past 52 weeks, to measure nearness to the 52-week high. Stock prices are adjusted based on the cumulative factor to adjusted prices in CRSP to avoid price inconsistency due to stock splits. A higher PTH means that the price is close to the 52-week high, and *vice versa*. Relative to the holding-period evaluation return over month $t+1$ and the relative winner/loser status over month t, we evaluate the PTH as of the end-of-month prices from month $t-1$. Thus, the PTH status is set prior to the realization of the winner/loser status and also prior to the month t turnover.

Our initial empirical approach is to evaluate a set of 125 ($5 \times 5 \times 5$) portfolios, constructed from sequential quintile sorts on past 1-month (1M) returns first, then nearness to the 52-week high (PTH), and finally on share turnover. The choice of a sequential sorting procedure (rather than independent) follows MS (2022) and ensures a more similar number of stocks in each end-result portfolio. Later, in robustness checks, we also evaluate an alternative independent sorting procedure and find similar results.

The specific timing for our primary sequential sorting is as follows: At the end of month t, stocks are first sorted into quintiles based on their past 1M return over month t using NYSE breakpoints. Then, we further sort stocks into quintiles based on their PTH ranking as of the close of month $t-1$. Finally we sort stocks into quintiles based on their share turnover as of the close of month t.[15] This granularity of 125 portfolios is comparable to the double-decile-based sorts on relative-strength and turnover in MS (2022), which produces 100 portfolios.

We use the PTH as of the end of month $t-1$ to provide temporal separation from the other two sorting variables with past return and turnover both from month t. In this sense, the 'PTH condition' is set, before the month t information signal arrives. Empirically, however, we find that our results are similar if all sorting variables are ranked in the same month t.

Following Jegadeesh and Titman (1993), MS (2022), and many others, the momentum portfolio takes long positions in stocks from the top past return quintile (winner portfolio) and simultaneously takes short positions in stocks from the bottom past return quintile (loser portfolio). To minimize the influence of microstructure biases emanating from low-price stocks, we compute value-weighted portfolio returns and also exclude stocks whose prices are less than \$1 at the end of month $t-1$ for all of our portfolio formations. The zero-cost short-term momentum strategy profit is computed as the winner minus loser portfolio returns over month $t+1$.

While our main analysis focuses on triple-sorted portfolios, in some cases we also evaluate

[15] We use NYSE breakpoints for the past returns, following from MS (2022). Our main tabular results then use PTH and turnover breakpoints based on full-sample statistics. We choose full-sample breakpoints for PTH and turnover (and other sorting variables evaluated in later supplemental investigations) to end up with portfolios with a more similar number of total stocks. We have evaluated other breakpoint choices, using either NYSE breakpoints for all the sorting variables or full-sample breakpoints for all the sorting variables. Our principal results remain evident for all these breakpoint variations, with generally modestly stronger results when using full-sample breakpoints for all the variables. Results are available upon request.

various double-sorted portfolios to evaluate two conditional criteria jointly for the performance of the various strategies. Additionally, we use individual stock returns and other individual stock characteristics in our Fama and MacBeth (1973) cross-sectional regression analysis.

Following MS (2022), the following variables from COMPUSTAT are used as additional controls in the Fama-Macbeth regression analysis in Section 4.3.3: (1) logarithm of market capitalization as of prior June (Size), (2) logarithm of book-to-market ratio (BM Ratio), (3) cash-based operating profits-to-lagged assets (COP/A), and (4) asset growth ratio (dA/A).[16]

3.2. Establishing Baseline Short-term Strategy Results for Single Sorts on Past-Returns and Double-sorts on Past-Returns and Turnover

Before beginning our main analysis, we report results on relative-strengh strategies from prior literature, estimated over our sample period. Our purpose is to link our later findings to these simpler strategies from existing literature. First, to evaluate the simple short-term reversal/momentum behavior in our sample, we go long winners and short losers, using simple one-way sorts on stocks' prior 1-month return. Second, for comparison to Medhat and Schmeling's (2002) main results, we go long winners and short losers but implemented separately on subsets of stocks by turnover, using two-way sorts on stocks' prior 1-month return and turnover.

As previously discussed, past literature indicates that past losers tend to outperform past winners in short-term strategies based on 1-month returns. We confirm this short-run reversal tendency in our sample. Specifically, we evaluate holding-period portfolios over month $t+1$, with long/short strategies based on stocks' returns over month t; both for value-weighted and equal-weighted holding-period portfolios, for our full sample and approximate one-half subperiods; and for both decile and quintile sorts on past returns. Past losers always outperform past winners, on average, for all these investigations. For example, for decile-based reversal strategies with equal-weighted holding-period portfolios, the average loser-minus-winner return is 1.52% per month over our full sample. The reversal strategies have statistically significant average returns in all cases, except for the value-weighted strategy in the latter one-half subperiod. The weakening of reversal profits in recent years has been previously documented in the literature; see, e.g., Cheng, Hameed, Subrahmanyam, and Titman (2017). Tabular results are available in Appendix A.1.

[16]As in MS (2022), COP is total revenue (REVT) minus cost of goods sold (COGS), minus selling, general, and administrative expenses (XSGA), plus R&D expenditures (XRD), minus the change in accounts receivable (RECT), minus the change in inventory (INVT), minus the change in prepaid expenses (XPP), plus the change in deferred revenue (DRC + DRLT), plus the change in trade accounts payable (AP), plus the change in accrued expenses (XACC).

Next, we replicate the procedure from MS (2022) and report on the returns to short-term momentum strategies that are implemented on subsets of stocks based on turnover. More specifically, each month we form decile portfolios doubly-sorted on the previous month's return and turnover and compute value-weighted portfolio returns for the next month. In comparison with MS's sample, our sample includes two more years of data (2019 and 2020) and we also exclude stocks that trade below $1. The short-term momentum strategy then goes long (short) the stocks that had returns in the top-decile (bottom-decile) over the ranking-month t. We evaluate the average returns for this long/short position over the holding-month $t+1$.

We find comparable results to MS (2022) for a two-way sort on winner/loser and turnover. The profits to a short-term momentum strategy for low-turnover stocks is -1.68% per month, as compared to -1.41% reported in Table 1 of the MS (2022) paper. Further, consistent with MS (2022), we also find sizable and statistically-reliable profits to a momentum strategy implemented on high-turnover stocks. For the top turnover decile, we find an average profit of 1.15%, which is a little less but still similar to the 1.37% reported in the MS (2022) paper (this small difference is likely due to slight differences in the sample period and our implementation of the $1 price screen). The results from alphas of the Fama-French and q-factor models also yield similar comparisons to MS (2022). Tabular details are available in Appendix A.2.

4. Main Empirical Results: Portfolios Formed on Past Returns, 52-week PTH, and Turnover

This section presents our principal empirical findings that establish a striking role for the ratio of a stock's price to its 52-week high (PTH), in terms of the short-term reversal or momentum behavior of stocks sorted on their past 1-month return and turnover.

4.1. Full Sample Analysis

Table 1 provides our full-sample results, reporting average monthly excess returns of value-weighted portfolios triple-sorted on past return, PTH, and share turnover. Section 3.1 provides the sorting methodology details. Panels A to E of Table 1 present the results from low to high turnover quintiles, respectively; with average portfolio returns reported in columns 1 and 2. For each grouping of stocks by turnover quintile and extreme PTH quintiles, the table also reports on momentum-strategy results that goes long winners and shorts losers (columns 3 to 5 in rows 1 and 2). Additionally, for each grouping of stocks by turnover quintile, the table reports on: (1) a winner-only strategy that goes long high-PTH winners and shorts low-PTH winners (columns 3 to 5 in row 3); and (2) a loser-only strategy that goes long high-PTH losers and shorts low-PTH losers (columns 3 to 5 in row 4).

Our major findings from this table can be summarized as follows.

- *Empirical Result #1*: Consistent with MS (2022), we find evidence of short-term momentum among high-turnover stocks, but only if they are also higher PTH stocks. See results in Panel E, row 2. Here, the average monthly excess return is 1.02% for the momentum strategy, which is highly statistically significant and also has highly statistically significant alphas. This result is largely driven by the strong continuation of 1.51% for the past-winner/high-PTH/high-turnover stocks, which defies the conventional short-run reversal wisdom that past winners should tend to be losers over the next month.

- *Empirical Result #2*: However, at odds with MS (2022), we also find evidence of short-term reversals among high high-turnover stocks, if they are also lower-PTH stocks. See results in Panel E, row 1. In this case, a short-term reversal strategy earns an excess return of 1.49% in Panel E for the low-PTH stocks, with p-values of better than 1% for the average returns and the alphas also (or, equivalently, short-term momentum profits are -1.49% here.)

- *Empirical Result #3*: Following from the anchor-based Empirical Prediction III. in Section 2.2, we evaluate a new strategy implemented only on past winner stocks, which exploits the cross-sectional differences in PTH. This strategy goes long high-PTH Winners and short Low-PTH Winners, for each turnover grouping of stocks. Results for this strategy across the low to high turnover quintiles in Panels A to E indicate strong and consistent performance of 2.13%, 1.85%, 1.75%, 1.33%, and 2.46% per month, respectively (row-3 results). The average profit is 1.90% across the five panels, and the average strategy returns and its alphas are statistically significant with better than a 1% p-value in every case.

In addition, we highlight that the strongest performance of this strategy is in Panel E (at 2.46%) for the high-turnover stocks, which includes larger and more liquid stocks (see Section 4.4). We note that the strategy performance is appreciably stronger than any short-term momentum or reversal strategy from the MS (2002) paper, which has a maximum reversal/momentum strategy profit of 1.41% per month across their strategies in their Table 1.

In Table 1, we only report on the extreme PTH-quintiles; suppressing the results for the PTH mid-quintiles there and in subsequent tables for brevity and space considerations. Accordingly, for the high-turnover quintile results (which are of high interest), we summarize the results for the mid-PTH quintiles here. For the high-turnover quintile of results (expanding Panel E), we find that the reversals for the lower-PTH stocks give way to momentum for the higher-PTH stocks, with a monotonic directional change as the PTH quintile increases. The PTH quintile-4 of stocks exhibits momentum with an average return of +0.73% per month, with statistical significance for the average returns and the corresponding alphas. Conversely, the PTH quintile-2 of stocks exhibits reversals, with an average momentum return of -0.67% per month, with statistical significance for the average returns and the corresponding alphas. The PTH quintile-3 of stocks exhibits modest momentum of +0.54% per month, but the alphas are statistically insignificant.

- *Empirical Result #4*: Following from the anchor-based Empirical Prediction VI. in Section 2.2, we also evaluate a strategy implemented only on past loser stocks as segmented by cross-sectional differences in PTH. This strategy goes long high-PTH Losers and short Low-PTH Losers for each turnover grouping of stocks. We find that this PTH-based loser-only strategy exhibits near-zero and insignificant profits of 0.35%, 0.25%, -0.31%, -0.49%, and -0.05% across Panels A to E respectively (row-4 results), for an average of -0.05% across the five panels. Thus, together, our Empirical Results #3 and #4 here indicate a striking and strong asymmetry between past winners and past losers, in regard to how their performance varies with a stock's lagged 52-week PTH.

Our collective findings support the following conclusions. First, we conclude that Empirical Results #1 and #2 form a sharp contrast with MS (2022). For high-turnover stocks, we show that short-term momentum is only profitable among high-PTH stocks and short-term reversal still dominates among low-PTH stocks. These conclusions also hold if we judge the results based on alphas adjusted for the Fama-French and q-factor models. They also suggest that high turnover is not the unique determining factor for short-term momentum, with information from the PTH variable also playing a pivotal role in understanding short-term momentum and reversal. These observations provide clear support for Empirical Prediction VIII. of Section 2.2.

We note that Empirical Result #3 is consistent with our Empirical Predictions I. to III. from Section 2.2, regarding anchor-based prediction for past winners. A PTH-based strategy that 'goes long high-PTH winners and goes short low-PTH winners' is consistently profitable across all turnover quintiles. However, Empirical Result #4 is inconsistent with our Empirical Predictions IV. to VI. from Section 2.2, regarding anchor-based prediction for past losers.

This PTH-based asymmetry between winners and losers is quite striking and seems to pose a challenge to existing theories about the PTH anchoring effect. Since the 52-week PTH ratio captures the price anchoring effect, then our findings suggest that the strength of the price anchoring effect is conditional upon a stock's past return status (winner or loser). Why a stock's PTH seems to matter for past winners, but not for past losers, implies interesting differences in how investor expectations are influenced through the lens of price anchoring. These findings should be addressed in theories of investor behavior.

4.2. Analysis of One-Half Subperiods

While our principal empirical results #1 to #3 exhibit high statistical significance over our full sample in Table 1, our findings would be more impactful if they are also evident in subperiod analysis – especially if they are evident in recent times of higher liquidity since about 1990. In Table 2, we divide our sample into two one-half subperiods with approximately equal length. Panels A and B of this table report separate results for the sample periods from 07/1963 to 12/1991 and 01/1992 to 12/2020, respectively. In each panel, we redo our main analysis from Table 1 but separately for the respective period.

The results from Table 2 confirm that our main findings from Table 1 are largely intact in both subperiods. For example, when comparing results from the high turnover quintiles (Panel A.3 vs. Panel B.3), we find that high-PTH/winners exhibit strong return continuations in both subperiods with average excess returns of 1.06% (t-statistic = 2.41) and 1.96% (t-statistic = 3.32), respectively. It is interesting to note that the strongly positive returns for the high-PTH winner is even stronger in Panel B (for the more recent subperiod over 1992 to 2020), relative to Panel A (for the early subperiod from 1963 to 1991). In addition, the short-term momentum strategy implemented on the high-PTH and high-turnover quintile stocks is also appreciably stronger in Panel B (1.53%) than in Panel A (0.51%).

Strikingly, we find that the strategy of going long high-PTH winners and short low-PTH winners is highly reliably evident in both subperiods (main Empirical Finding #3). For example, the profits for this strategy when applied to high turnover stocks has an average profit of 2.56% per month in the second subperiod (row 4, Panel B.3) and 2.37% per month in the first subperiod (row 4, Panel A.3). The results from the new 'PTH-based winner-only' strategy are remarkably robust as its performance is consistently strong across all the turnover quintiles in both subperiods. The strategy's alphas are also positive and highly statistically significant in both subperiods.

We note that, for comparison purpose, standard short-term reversals are known to be appreciably weaker in more recent times, relative to older data. As we document in Appendix A.1, the general short-term reversal behavior is appreciably weaker over our recent one-half subperiod, relative to our earlier one-half subperiod. For value-weighted holding-period portfolios, the reversal returns are no longer statistically significant in our 1992-2020 subperiod. In our view, the 'subperiod reliability' contrast between the well-known reversal behavior and our new 'PTH-based winner only' strategy makes our new results more compelling.

Also consistent with results in Table 1, a strategy that buys high-PTH losers and short low-PTH losers exhibits insignificant profits across both subperiods and across turnover quintiles (our main Empirical Results #4). See the row-4 results in each panel. The asymmetry between past losers and past winners, in terms of the PTH implications for return behavior, remains an intriguing puzzle when evaluated with data from the two subsample periods.

4.3. Additional Robustness Checks

This subsection briefly reports on the results of two additional empirical evaluations that support the robustness of our main results.

4.3.1. Portfolios formed by the Intersection of Independent Sorts on Past-Returns, 52-week PTH, and Turnover

Recall that our main results in Tables 1 and 2 followed from the method in MS (2022), with sequential sorts on the three factors. A disadvantage of this sorting procedure is that the results could be susceptible to changes in sorting order. To address this concern, we redo Table 1 but adopt an alternative independent sorting procedure, which ensures that our results are not driven by the particular sorting orders that we use. Here, we formed portfolios based on the intersection of independent quintile sorts on the past return (NYSE breakpoints), the PTH, and turnover. A disadvantage of this approach is there might be cases where a few portfolios contain a relatively small number of stocks.

The independent-sorting results are presented in Table 3. We note that all the main findings from Table 1 are unchanged when switching to independent sorts. First, short-term momentum among high-turnover/high-PTH stocks has a mean return of +0.68% (t-statistic = 2.68). This result is modestly weaker than similar result from Table 1 but retains its statistical significance. Conversely, among high turnover and low PTH stocks, a short-term reversal strategy is profitable with an average return of 1.18% (t-statistic = 4.01). Thus, these results reaffirm our earlier findings that short-term momentum is only evident for high-PTH/high-turnover stocks, while high-turnover/low-PTH stocks exhibit reversals.

Further, across the five turnover quintiles, the strategy of going 'long high PTH winners and short low PTH winners' yields similarly impressive results as those reported in Table 1. We find that this strategy has average returns of 2.07%, 2.01%, 1.58%, 1.45%, and 1.91% across the five turnover quintiles shown in Panels A to E, respectively, of Table 3 (row-3 results). The Newey-West t-statistics range from 4.30 to 6.41. In contrast, the profits for the comparable strategy implemented on past losers only are near zero and lack statistical significance in all panels (row-4 results).

In sum, we conclude that all four of our main Empirical Results, as laid out in Section 4.1, are robust to using independent sorts.

4.3.2. Decile Sorts on Past Returns, and Tercile Sorts on PTH and Turnover

We next turn to evaluating alternative granularity in our sorting procedures. Recall that our main results from Table 1 are based on quintile sorts of past returns. Here, we provide additional robust checks by using decile-based sorting on past returns. Also, recall that the main results in MS (2022) feature such decile-based sorts. A potential problem that could arise from decile sorts of past returns is that if we continue to use quintile sorts on PTH and turnover, that would result in 250 portfolios ($10 \times 5 \times 5$), which will double the number of portfolios from Table 1 and substantially reduce the number of individual stocks within each portfolio. Therefore, as a compromise, we choose tercile sorts on PTH and turnover, which gives us 90 portfolios ($10 \times 3 \times 3$)), which is comparable to the 100 portfolios used in MS (2022) and 125 portfolios from Table 1.

With this alternative sorting granularity, we find that our conclusions from all four main Empirical Results of Section 4.1 remains intact. Specifically, we find that among the high-turnover stocks, short-term momentum is significantly profitable only among high-PTH stocks with an average return of 0.94% (t-statistic = 3.67). In contrast, for low-PTH/high-turnover stocks, a short-term reversal strategy has an average return of 1.58% (t-statistic = 4.37).

Further, we find that the strategy of being 'long high-PTH winners and short low-PTH winners' is consistently profitable among past winners across all the turnover groupings, with average returns of 1.63%, 1.74%, and 2.09% across the low-, mid-, and high-turnover terciles; all with better than 1% p-values (Empirical Result #3). By comparison, a strategy of being 'long high-PTH losers and short low-PTH losers' has insignificant profits for all three turnover groupings (Empirical Result #4). Overall, we conclude that the asymmetry across past winners and losers for the PTH-based strategy remains strikingly obvious with these alternative sorting breakpoints. Tabular details are available in Appendix A.3.

4.3.3. Return Predictability by Past-Returns, PTH, and Turnover with the Cross-sectional Fama-MacBeth Regression Approach

We next evaluate an alternative framework, the cross-sectional regression approach of Fama and MacBeth (1973), to take another look at the role of 52-week PTH and turnover in short-term relative strength strategies. As noted in Fama and French (2008) and MS (2022), cross-sectional regressions with continuous explanatory variables can impose a potentially misspecified functional form and are sensitive to outliers. In our setting, with three conditional factors, interactive terms with all three factors (in continuous variable form) seem likely to be especially subject to misspecification and outlier concerns.

Further, in a specification that uses the continuous lagged returns in the explanatory terms and assumes linear relations between the current and lagged return (and for the lagged return interacted with PTH and turnover variables), there would be no asymmetry allowed between past losers and past winners.[17] Our main results in Section 4 suggest that allowing for such asymmetry between past winners and losers is important. Thus, our Fama-MacBeth specifications will allow for asymmetry between past winners and past losers, in regard to the implications for the month $t + 1$ returns.

To mitigate such specification concerns and to provide a specification where the estimated coefficients are readily interpreted, our primary Fama-MacBeth specification uses explanatory terms that are dummy variables that equal one when a certain condition is met and zero otherwise (conditional on whether a stock is a relative winner or loser, has a high or low PTH, and/or has a high or low turnover). With this approach, we can evaluate the apparent incremental information from looking at relatively high and low turnover, and relatively high and low PTH; and evaluate

[17] In other words, an estimated coefficient of -0.2 on the past returns would imply the same magnitude reversal of -2% for positive past returns of 10% and +2% for negative past returns of -10%. We do later report on an alternative Fama-MacBeth specification that uses the lagged continuous returns as explanatory terms.

whether the incremental information is statistically significant.

Additionally, with the cross-sectional regression approach, we can also control for other well-known variables that have been shown to help explain cross-sectional variation in returns. Thus, this approach further allows us to evaluate the incremental role of our main conditional factors.

To summarize our results, we find that our Fama-MacBeth evidence provide consistent conclusions for all four of main Empirical Results highlighted in Section 4.1. First, short-term momentum for high-turnover stocks is only evident for high-PTH stocks; conversely, strong short-term reversals are evident for high-turnover/low-PTH stocks. Second, there is a strong PTH-based contrast between winners, with high-PTH winners strongly outperforming low-PTH winners (for both high-turnover and low-turnover cases); conversely there are only quite modest differences between the performance of losers, based on their PTH. The inclusion of the additional control variables (as used in Medhat and Schmeling (2022)) have little influence on the momentum and reversal results and do not change our conclusions. We also evaluate an alternative Fama-MacBeth specification that uses continuous lagged returns in the explanatory terms, but interactive dummy variables on the PTH or turnover levels, and find consistent results. For brevity, our Fama-MacBeth specifications and tabular details are available in Appendix A.4.

4.4. Differences in Firm Size across PTH & Turnover Quintile Portfolios

Recall that Tables 1 through 3 show that, among high turnover stocks, short-term momentum is only profitable when implemented on stocks with a high 52-week PTH (Empirical Result #1). Conversely, for high-turnover stocks, short-term reversals are dominant for stocks with a low 52-week PTH (Empirical Result #2). Thus, our results indicate that the existence of either short-term momentum or short-term reversals in high-turnover stocks is quite sensitive to cross-sectional variations in a stock's 52-week PTH.

Yet, in the analysis of MS (2022) (which does not differentiate by a stock's PTH), they find that short-term momentum is the dominant pattern for high-turnover stocks. On the surface, this comparison of our results to those of MS (2022) seems puzzling in the following sense: If short-term momentum is the overall dominant pattern in high-turnover stocks (as in MS), then how can both momentum and reversals be strongly evident for high-turnover stocks, dependent upon their PTH (as in our results)? And, in our Tables 1 and 3, we find that the short-term reversal profits for high-turnover/low-PTH stocks are greater in magnitude than the short-term momentum profits for high-turnover/high-PTH stocks.

To probe this apparent puzzle, here we investigate cross-sectional differences in stocks' market capitalization (size) across our various triple-sorted portfolio. Recall that both MS (2022) and we focus on value-weighted portfolio returns over the month $t + 1$ holding period.[18] This means that larger-cap stocks will be more influential in determining the portfolio returns in the holding period. Thus, if there are prominent differences in average stock size linked to a stock's 52-week PTH, size differences could help understand the apparent puzzle when comparing our main results to those in MS (2022).

In Table 4, we report the sample mean (in millions of dollars) of the market capitalization of the stocks that comprise the various portfolios across the 52-week PTH, past return, and turnover quintiles. Panel A of Table 4 shows that, among stocks in the high-turnover quintile, the low PTH/loser stocks have an average size of about 326 million; much smaller than the high-PTH/loser stocks that have an average size of 1,832 million.[19] Similarly, among stocks in the high-turnover quintile, the low PTH/winner stocks have an average size of about 478 million; much smaller than the high-PTH/winner stocks that have an average size of 2,049 million.

Further, for each month in our sample, we also calculate the ratio of the average market-cap of the high-PTH stocks to that of the low-PTH stocks (for each winner/loser and high-turnover/low-turnover grouping). Then, we calculate the time-series average of this size ratio and report it for the respective case in row 6 of each panel in the table. In the case of the high-turnover/losers, the high-PTH to low-PTH size ratio is 7.31. Similarly, for the high-turnover/winners, the high-PTH to low-PTH size ratio is 5.01.

Panel B of Table 4 comparably reports on the stocks in the low-turnover quintile. For this case, the low-PTH/loser stocks have an average size of about 54 million, whereas the high-PTH/loser stocks have an average size of 1,535 million. And, the low-PTH/winner stocks have an average size of about 105 million, whereas the high-PTH/winner stocks have an average size of 3,942 million. Thus, the differences in market cap for low vs. high PTH stocks are even larger for stocks in the low-turnover quintile in Panel B (relative to the high-turnover stocks in Panel A).

In sum, with PTH-based sorts, we document that high-PTH stocks tend to have a much larger market-capitalization, relative to low-PTH stocks. Thus, in a simple high-turnover momentum

[18] To address concerns from Hou, Xue, and Zhang (2020), to mitigate the impact of micro-cap and/or low-priced stocks, and to make our results more directly comparable to MS (2022); our main analysis features value-weighted portfolio returns and we omit low-priced stocks from our analysis (less than $1).

[19] Each month, we calculate the average market-capitalization (size) of the individual stocks that comprise a given triple-sorted portfolio. Then, the numbers in the table are the time-series average of the monthly average size of the stocks that comprise a given triple-sorted portfolio.

strategy with *value-weighted* portfolios (2-sort strategies on the lagged return and turnover, as in MS (2022)), the holding-period portfolio return in month $t + 1$ will generally be dominated by high-PTH stocks (which exhibit momentum) because the high-PTH stocks are of much larger size, on average, than the low-PTH stocks (which exhibit reversals). With these findings, we contribute by reconciling the apparent puzzle posited in the second paragraph of this subsection.

5. Supplemental Investigations: Evidence on Economic Channels

We feel that the strong, robust evidence in Section 4 establishes important new empirical stylized facts for the short-term return behavior in one-month stock returns, summarized as our Empirical Results #1 to #4 in Section 4.1. These empirical results align with Empirical Predictions I, II, III, and VIII from Section 2.2, which rely on the presumption of anchoring biases linked to a stock's 52-week high. It would be reassuring to provide related evidence that bolsters this view of PTH-based underreactions and overreactions for past winner stocks.

In this section, we present the results of five additional empirical investigations that are intended to: (1) either provide affirming or contradictory evidence to an anchoring-bias interpretation; and (2) provide additional evidence that further describes and qualifies our main findings. We evaluate market sentiment, dispersion in analyst forecasted earnings, and firm size in Sections 5.1 to 5.3, respectively. Section 5.4 briefly reports how our results vary with a firm's market-to-book equity ratio and idiosyncratic volatility.

5.1. Portfolios formed on Past-Returns, PTH, and Turnover: By Sentiment

If PTH anchoring biases are an important underlying channel for our results, then it seems intuitive and plausible that the biases might be amplified when the directional bias is aligned with the overall market sentiment. In other words, when the market sentiment is more negative, then it seems plausible that the downward-biased interpretation of good news for high-PTH stocks would be stronger. This intuition suggests that winners with high PTH would perform better in low market-sentiment times, because the stronger underreaction to the good news in month t implies higher returns over month $t + 1$ as the underreaction is corrected. And, conversely, when the market sentiment is more positive, then it seems plausible that any upward-biased interpretation of good news for low-PTH stocks would be stronger. If so, then winners with low PTH should perform worse in high market-sentiment times, because the stronger overreaction to the good news in month t implies lower returns over month $t+1$ as the overreaction is corrected.

To investigate this intuition, we repeat our main analysis as in Table 1 but separately for two subsamples based on market sentiment. Specifically, we segment the holding-period months $t+1$ based on whether the market-wide sentiment was above or below the median at the end of month $t-1$. With this timing, our interpretation is that the market sentiment in existence at the end of month $t-1$ might amplify the PTH-based anchoring biases to information flows over month t. We use the investor sentiment index of Huang *et al.* (2015), which is based on the six sentiment proxies of Baker and Wurgler (2006) but is argued to be more efficient as a stock market predictor. Table 5 reports the results, with the high-sentiment (more optimistic) periods in Panel A and the low-sentiment (more pessimistic) periods in Panel B.

We find results that align with our empirical conjecture above. We begin by reporting results for past-winner stocks with a high PTH. For the pessimistic periods, the past winner stocks with a high PTH and high turnover have average returns of 1.92% per month, appreciably higher than the 1.13% per month for this category of stocks over the optimistic periods. These relative comparisons are also evident for the mid- and low-turnover quintiles to a lesser degree.

We next report results for past-winner stocks with a low PTH. For the optimistic periods, the past winner stocks with a low PTH and high turnover exhibit stronger reversals with an average negative return of -1.55% per month; appreciably more negative than the -0.40% average return for this category of stocks over the pessimistic periods. Again, these relative comparisons are also evident for the mid- and low-turnover quintiles to a lesser degree.

We also observe variation in the performance of past-loser stocks, depending upon the market sentiment. Most prominently, we find that low-PTH losers perform stronger during pessimistic periods, relative to optimistic periods; a result observed for all the turnover groupings. When comparing the row-1 losers in Panels A.1 to A.3 to those in Panel B.1 to B.3, we note that the average returns have an average of about 1.7% over the pessimistic periods of Panel B versus essentially zero over the optimistic periods in Panel A. When factoring in that the typical reversal for these past losers implies subsequent positive returns (presumably largely attributable to liquidity provision), these results align with an anchoring-bias intuition. This is because if there is a stronger underreaction to bad-news for loser stocks with a low PTH in high-sentiment times, then one would expect weaker returns in month $t+1$ for these stocks as this stronger underreaction to bad news is somewhat corrected over month $t+1$ (relative to the same category of stocks in more pessimistic times).

To sum up, when bifurcating periods based on market sentiment, we find results consistent with the view that 52-week PTH anchoring biases tend to be amplified when the direction of the anchoring bias aligns with the overall market sentiment. In our view, this intuitive finding reinforces the premise that anchoring biases play an important role in understanding our main results in Section 4.

5.2. Dispersion in Analyst Earnings Forecasts, Past-Returns, and 52-week PTH

We next evaluate whether higher dispersion in analysts' earnings forecasts is associated with stronger profits for our new PTH-based winner strategy that is long high-PTH winners and short low-PTH winners. If so, then such findings would support a PTH-anchoring-bias interpretation of our main results, under the joint assertions that: (1) higher dispersion in forecasted earnings tends to reflect greater differences in opinion and valuation uncertainty, and (2) anchoring biases tend to be more influential on stocks with greater differences in opinion and valuation uncertainty.

Following from Garfinkel (2009) and others, we evaluate two scaled metrics for analyst dispersion (AD) in forecasted annual earnings. The unscaled AD is the cross-sectional standard deviation of the most recent analyst forecasts as of the end of month $t-1$. The first scaled AD metric takes the simple AD and divides by the absolute mean forecast. The second scaled AD takes the simple AD and divides by the mean monthly price. Data prior to 1982 is sparse and inadequate for this evaluation. Accordingly, we examine only the July 1982 to December 2020 period here. Over this period, our AD metrics are available for about 49% of the firms in our sample for a given month, on average.

Table 6 reports the results. Since only a subset of stocks has enough analyst coverage to form the analyst dispersion (AD) metric, here we use a tertile sort on the AD (rather than our usual quintile sort) to ensure a reasonable number of stocks in each portfolio. Panel A reports on the first scaled AD metric and Panel B on the second.

Consistent with an anchoring-bias channel, we find that the profits for our new PTH-based winner-only strategy are appreciably stronger for the high AD grouping. For the high-AD cases, the profits of the winner-only strategy are 1.96% per month in Panel A.3, row-3, and 1.65% in Panel B.3, row-3. Conversely, for the low-AD cases, the comparable profits are notably smaller at 0.64% and 1.05% in Panels A.1 and B.1, respectively. Further, in both panels, the high-PTH winners perform better and low-PTH winners perform worse for the high AD cases, relative to the low AD cases.

In sum, these AD results in Table 6 seem consistent with PTH-based anchoring biases being an important economic channel behind our main results, under the view that these biases are more influential on stocks with greater valuation uncertainty and differences of opinion. We also emphasize that the results in Table 6 are more oriented to larger-cap stocks, since many small- and micro-cap stocks do not have adequate analyst coverage to be included in this analysis.

5.3. Portfolios formed on Size, Past-Returns, and 52-week PTH

With greater analyst and press coverage, large-cap stocks generally have more readily available information and likely less valuation uncertainty, on average, as compared to small-cap stocks. If so, and if the influence of PTH-based anchoring biases are stronger for stocks with greater valuation uncertainty about the interpretation of a month's news, then PTH-based anchoring biases should be stronger for smaller-cap stocks, on average.

We perform an exercise comparable to that in Table 1, but we replace turnover with size, as the third factor in our triple-quintile-sorting procedure. In the sense of setting a stock's size grouping prior to the news that leads to a winner or loser status over month t, we first sort stocks based on their size as of the end of month $t-1$. Then, we next sort on the past-return over month t and finally sort stocks based on their 52-week PTH as of the end of month $t-1$. Table 7 reports the results.

We highlight the following findings. First, the pattern of our Empirical Result #3 for our new PTH-based winner-only strategy is evident in all five size quintiles. The average returns of the strategies that are 'long high-PTH winners and short low-PTH winners' are sizably positive with better than 1% p-values in every case. The values decline monotonically with size, from 4.32%, 3.18%, 2.04%, 1.27%, and 0.66% across the smallest to largest quintile of stocks. The alphas for these strategy returns are also positive and statistically significant in all cases, except for the Fama-French alpha for the results for the largest size quintile. Further, in each size quintile, the average excess return of past-winner stocks with a high PTH is always positive and statistically significant, which indicates a continuation in returns (at odds with the general 1-month reversal pattern that implies negative returns for past winners).

Next, the pattern of our Empirical Result #4 is also evident in all five size quintiles. The average returns of the strategy that 'goes long high-PTH losers and goes short low-PTH losers' are small, never statistically significant, and not monotonically increasing or decreasing with size. The average returns of this strategy are -0.13%, 0.19%, 0.49%, 0.17%, and 0.15% across the smallest to largest quintile of stocks.

We conclude that: (1) our Empirical Results #3 and #4 are reliability evident in both small- and large-cap stocks; and (2) the strength of our Empirical Result #3 is greater for smaller-cap stocks. Thus, the PTH-based asymmetry between winners and losers is quite robust to variation in a stock's size (Table 7), as well as to variation in a stock's turnover (Tables 1 and 3).

5.4. Firms' Market-to-Book Equity Ratio and Idiosyncratic Volatility

We also briefly report on two other firm characteristics, in a manner similar to how we investigated size in Section 5.3: (1) a stock's market-to-book equity ratio, and (2) idiosyncratic volatility. Our focus is on how the profits of our winner-only strategy (which is long high PTH winners and short low PTH winners) varies with these firm characteristics.

Firms with a high market-to-book (M/B) ratio are generally growth stocks with an appreciable component of their market value linked to option value. Firms with a low M/B ratio are more likely to include distressed firm with lower and poorer quality earnings; see, e.g., Fama and French (1995). Thus, in our view, both categories (high and low M/B ratios) suggest greater valuation uncertainty, relative to stocks with more typical M/B ratios. If so, this section's premise suggests greater profits with our winner-only strategy for stocks with an extreme M/B ratio.

Our evidence in Table 8 aligns with the above assertion. The average profits for our winner-only strategy are the highest for the lowest and highest M/B quintile of stocks (average of 2.12% for Panels A and E) versus the profits for the inner quintiles (average of 1.00% for Panels B, C, and D). Further, in Panels A and E, the average profits for the long position in the high-PTH winners and the short positions in the low-PTH winners are all relatively larger than any of the comparable values in Panels B, C, or D.

Next, as suggested in Huddart, Lang, and Yetman (2009), we also investigate idiosyncratic volatility (IV) as a firm characteristic, under the premise that a higher IV tends to indicate higher valuation uncertainty. To measure IV, we evaluate residuals from a 3-factor Fama-French model estimation on daily returns over months t-1 to t-12. For our winner-only strategy, we find that stocks in the top IV quintile have much larger profits (3.46% per month) than stocks in the bottom IV quintile (0.23% per month). Yet, we also find that stocks with higher IV tend to be smaller-cap stocks, so our IV results are substantially related to our firm-size results in Section 5.3. Accordingly, we only briefly summarize our IV results here, with tabular details available upon request.

5.5. Summary Remarks for our five Supplemental Investigations

Overall, we feel that the results of our five supplemental investigations in this section provide consistent evidence to support a PTH-anchoring-bias interpretation of our main results. Specifically, we highlight the following two results. First, the apparent PTH biases are stronger when their directional bias aligns with the overall market sentiment. For example, there appears to be stronger underreaction to good news for high-PTH stocks in weak sentiment times. Second, stocks that seem likely to have greater valuation uncertainty (or dispersion in beliefs) have greater profits for our new PTH-based winner-only strategy.

Finally, we point out that higher turnover might also indicate a greater difference of opinion or valuation uncertainty, see Harris and Raviv (1993) and Chordia, Huh, and Subrahmanyam (2007). If so, then our turnover-based results in Tables 1 to 3 fit with our general theme in this section: the PTH biases tend to be stronger for stocks with a greater difference in opinion about their valuation. This is because in those three tables: (1) the past-winner stocks with high PTH and high turnover always have more positive average returns over month $t + 1$, as compared to past-winner stocks with high PTH and lower turnover; and (2) the average momentum profits are always larger for high-turnover, high-PTH stocks; as compared to low-turnover, high-PTH stocks.

6. Discussion of other Related Literature

In this section, we briefly discuss our collective evidence from the context of other related literature. We focus primarily on theoretical perspectives that are consistent with the co-existence of momentum and reversals.[20] Sections 6.1 to 6.5 discuss theoretical frameworks that can generate momentum and/or reversals, without relying on a price anchoring bias. Section 6.6 discusses other recent empirical evidence that relates to our findings. Finally, Section 6.7 provides summary remarks.

6.1. Rational Expectations Equilibrium (REE) Models

Medhat and Schmeling (2022) argue that their evidence on the co-existence of short-run momentum and reversals behaviors, as related to turnover, is hard to reconcile with REE models. Similarly, Huddart, Lang, and Yetman (2009) argue that their findings of higher turnover and

[20] For brevity, our discussion here is more representative (rather than comprehensive), only addressing select papers that seem particularly relevant. See Medhat and Schmeling (2022), Chiang, Kirby, and Nie (2021), and Huddart, Lang, and Yetman (2009) for additional related literature discussion.

higher subsequent returns after a stock breaches a 52-week-high or low is hard to reconcile with REE models. In our setting, a rational framework would need to explain both the co-existence of short-run momentum and short-run reversals and their linkage to a stock's PTH ratio and turnover, seemingly raising the bar even higher for an REE framework.

We acknowledge that some REE models are consistent with the co-existence of momentum and reversals. For example, the risk-averse REE model of Wang (1994) can generate either return reversals or return continuations depending upon the nature of informed trading. In his framework, a high return accompanied by high volume implies: (1) higher future returns if the volume is more attributed to private valuation information, but (2) lower future returns if the volume is more attributed to non-informational reasons tied to changes in private investment opportunities. However, as discussed in Medhat and Schmeling (2022), this framework implies more momentum in smaller less-liquid stocks with greater informational asymmetry, which is at odds with the observation that the short-term momentum for high turnover stocks is more concentrated in larger-cap stocks. Further, for Wang's framework to explain our findings, it would require a systematic difference in the trading motivation between high-PTH winners and low-PTH winners, which seems implausible to us.

Seemingly more promising for explaining our findings, Andrei and Cujean (2017) propose a rational framework with information percolation through private word-of-mouth communications, which can generate either momentum or reversals depending upon the private meeting intensity. Their focus is more on jointly explaining medium-run momentum and longer-run reversals. However, it seems possible that their framework could generate behavior consistent with our findings if their meeting-intensity parameter is systematically related to a stock's PTH and its relative winner or loser status. Specifically, in their framework, momentum should be evident when the meeting intensity exceeds a certain threshold level (as long as the meeting intensity does not get too high). Conversely, if the meeting intensity is below this momentum threshold, then reversals are expected. To us, it seems plausible that past-winner stocks with a high PTH would be associated with strong word-of-mouth communications in the attention-grabbing sense of Barber and Odean (2008), implying perhaps a sufficiently high meeting intensity to generate momentum at the one-month horizon (consistent with our findings).[21] And, conversely, if the meeting intensity is relatively lower for past-winner stocks with low PTH and past-loser stocks with either high or low

[21] Further, we note that the most positive returns in month $t+1$ for past-winner stocks with high PTH are for those stocks that also had higher turnover in month t. If the higher turnover is another marker for higher meeting intensity, then this turnover pattern also seems to fit with the Andrei-Cujean framework.

PTH (with the meeting intensity falling below the Andrei-Cujean momentum threshold), then we would expect to see the well-known short-run reversals in these categories of stocks (also consistent with our findings). Thus, under the meeting-intensity assertions in the prior two sentences, our asymmetric findings about the strong winner-PTH relation versus the weak loser-PTH relation could fit with the Andrei-Cujean framework. Further research in this area might prove interesting.

6.2. Explaining Medium-run Momentum and Long-run Reversals Jointly

Other literature has proposed frameworks with bounded rationality that can explain both medium-run momentum and long-run reversals; i.e., the coexistence of momentum and reversals at different horizons (rather than the fixed 1-month horizon in our study).[22] For example, Daniel, Hirshleifer, and Subrahmanyam (1998) propose that investors tend to be overconfident about their private information signals with biased self-attribution towards their response to how public information reinforces their private signals. The combined effects imply short-run momentum and long-term reversals. One could argue that the short-run momentum in high-turnover stocks (as in Medhat and Schmeling (2022)) could fit with their framework if the high-turnover reflected more private information. However, recall that the high-turnover stocks tend to be larger-cap stocks, where private information would seem to be relatively less important. Further, regarding our findings, their framework does not predict our results of strong 1-month reversals in low-PTH winners, nor the asymmetric influence of PTH on winners versus losers. In general, frameworks that attempt to explain both medium-run momentum and long-run reversals do not seem to be a good fit to explain our findings focused on momentum and reversals in 1-month stock returns.

6.3. The Disposition Effect in Stock Selling Behavior

Our principal interpretation appeals to a 52-week-high price anchoring bias. Here, we briefly discuss our findings from the context of another bias, the asymmetric V-shaped selling disposition effect as documented in Ben-David and Hirshleifer (2012) and An (2016). These two papers indicate that investors are more likely to sell stocks with either sizable gains or sizable losses, but more so for gains (hence, the 'asymmetric' V-shape). And, for stocks with either large gains or large losses the selling distortion in month t should induce higher returns for month $t+1$; but, again, more so for large-gain stocks. In our findings, the relatively strong performance of past

[22]See, for example, Daniel, Hirshleifer, and Subrahmanyam (1993), Hong and Stein (1999) and Barberis, Shleifer, and Vishny (1998).

winners with higher turnover and high PTH (where a high PTH implies higher recent gains) seems consistent with their implications. Consistent with this disposition-selling view, Della Vedova, Grant, and Westerhold (2022) find evidence that household investors sharply increase their selling as a stock price moves towards its 52-week high, with a sharp increase in limit-order selling. However, this disposition effect also implies higher returns for losers with high turnover and a low-PTH (relative to losers, in general), because the low-PTH should indicate stocks with larger unrealized losses. But our findings indicate relatively little PTH-based difference in performance for losers. Nevertheless, we acknowledge that this selling disposition effect is another potential contributor to our findings.

6.4. Differences of Opinion about Public Information, Private Information, and Short-term Momentum and Reversals

Harris and Raviv (1993) assert that trading volume can also result from differences in opinion about the valuation implications from public news (rather than trading being driven by private information). One implication of their main results is that if speculators overestimate (underestimate) the quality of their signal, then consecutive returns should exhibit reversals (momentum). In our setting, a high PTH anchoring bias could presumably contribute to investors systematically underestimating the signal quality of positive public news for high-PTH stocks and overestimating the signal quality of positive public news for low-PTH stocks (in the spirit of Harris and Raviv). If so, then our findings could be considered to be consistent with these implications from Harris and Raviv. Further, the finding that the momentum in high turnover stocks is largely attributed to larger-cap stocks seems to align well with this perspective of a difference-of-opinion about public news, because private information is presumably less important in valuing larger-cap stocks relative to smaller-cap stocks.

6.5. High Subsequent Returns of Attention-Grabbing Stocks

Barber and Odean (2008) present evidence that the buying behavior of individual investors is more heavily influenced by attention than their selling behavior and that the attention effect is stronger for individual investors (relative to professional investors). Their proxies for attention-grabbing events are news, unusual trading volume, and extreme returns.

Relatedly, Huddart, Lang, and Yetman (HLY, 2009) examine a stock's return behavior after the stock's price either exceeds a 52-week-price high or falls below a 52-week-price low. Consistent with the Barber-Odean attention-grabbing assertion, they find that the trading volume spikes for stocks following the breach of such an anchoring price. They find that this volume effect is more pronounced for stocks with greater valuation uncertainty, as measured by return volatility and firm age. Further, these stocks that breach these 52-week price anchors (both high and low) experience higher risk-adjusted returns over the following week and month, especially for smaller firms where individual investor trading is likely to be more influential for price movements.[23]

Our findings that past-winner stocks with high-PTH and high-turnover have reliably positive returns over month $t+1$ seem consistent with such an attention-grabbing premise. Yet, analysis in both Medhat and Schmeling (2022) and our study indicate that the high-turnover stocks that exhibit momentum tend to be larger-cap stocks (at odds with the smaller-firm emphasis noted in HLY (2009)). Further, such an attention-grabbing hypothesis would also imply that loser stocks with a low-PTH and high turnover would have especially more positive returns (when taking into account both the attention-grabbing influence and the normal reversals expected from losers to due liquidity provision).[24] Yet, we find that the average returns in month $t+1$ for past loser stocks with a low PTH and high turnover is less positive than past losers on average (without conditioning on the PTH or turnover).

Further, a view that attention-driven buying from individual investors contributes towards momentum for stocks near their 52-week-price high seems at odds with Della Vedova, Grant, and Westerhold (2022). They find evidence that household investors sharply increase their selling as a stock price moves towards its 52-week high, with a sharp increase in limit-order selling.

Finally, under the assumption that more optimistic periods are likely to experience greater attention-grabbing behavior, our sentiment results in Section 5.1 seem at odds with an attention-grabbing influence. In other words, under an attention-grabbing premise, past-winner stocks with a high PTH and high turnover during more *optimistic* times seem likely to have higher subsequent returns due to attention-grabbing behavior, relative to this stock category during more *pessimistic* times. However, we find exactly the opposite pattern; the subsequent returns for this grouping of stocks has an average return of 1.92% in pessimistic times versus 1.13% in optimistic times (compare the row-2 results in Table 5, Panel B.3 versus Panel A.3).

[23]Chen et al. (2022) find that their investor-attention index reliably predicts stock-market returns. Over their 1980 to 2017 sample, a 1-standard-deviation increase in their primary attention index predicts a 0.64% decrease in next month's excess stock-market return. This negative relation to market returns seems at odds with the positive returns for individual stocks following attention-grabbing price movements, as found in HLY (2009).

[24]This view presumes that the combination of being a relative loser over month t, being far from a 52-week high at the end of month t (implying being relatively close to a 52-week low), and having relative high turnover in month t are together indicative of a high-attention stock.

6.6. Other Recent Empirical Evidence

In results reminiscent of MS (2022); Chiang, Kirby, and Nie (CKN, 2021) find that short-term reversals give way to momentum as turnover increases, with the top decile of stocks by turnover exhibiting short-term momentum. They present evidence that suggests this turnover pattern is because: (1) higher turnover indicates more liquidity (so the reversal influence due to liquidity-provision is smaller); and (2) returns with high turnover are more likely indicative of news-driven trading. Their premise is that news can generate continuations if it takes multiple trading sessions to be fully incorporated into prices.

In Zhu, Sun, and Stivers (ZSS, 2021), the authors find that one-month reversal strategies perform better for low-PTH stocks, also suggesting a role for anchoring biases in understanding short-term return behavior. Their findings align with the stronger reversals for low-PTH stocks that we document in our Tables 1 to 3 for the different turnover-segmented results (the row-1 results). However, ZSS do not: (1) sort on turnover as a conditional factor; (2) find short-term momentum in any of their strategies; (3) investigate our new PTH-based winner-only strategy; and (4) evaluate variation in strategy performance based on market-level sentiment or on a stock' dispersion in analysts' forecasted earnings or market-to-book equity ratio.

6.7. Summary Remarks

In sum, the other frameworks discussed in Sections 6.1 to 6.5 seem incapable of explaining our findings, unless augmented by some role for a 52-week-price-high in how investors assess or process news. In Section 6.1, we argued that the rational information-percolation perspective of Andrei and Cujean (2017) could be consistent with our findings, if past-winner stocks with high turnover and high PTH were also associated with a higher private meeting intensity in their sense (relative to other categories of stocks in our analysis).

Other interpretations fall into the bounded rationality camp, with some bias or deviation from strict rationality. The disposition effect (Section 6.3) and attention-grabbing buying behavior (Section 6.5) could promote momentum in past winner stocks with high PTH and high turnover (as we find), but seem inconsistent with other aspects of our findings and other related literature. Next, if a stock's nearness to its 52-week-price-high can systematically influence how investors regard the quality of their news signal in the sense of Harris and Raviv (1993) (Section 6.4), then our findings seem consistent with aspects of their difference-of-opinion perspective.

Finally, our anchoring-bias interpretation seems consistent with aspects of CKN's (2021) interpretation (Section 6.6) in that our analysis also suggests that prices can need multiple trading sessions to fully incorporate news; implying momentum in their underreaction case, which is consistent with the evidence for winners with high PTH and high turnover in our analysis. Along these lines, MS (2022) argue that their momentum findings suggests a boundedly-rational perspective, where some traders systematically underinfer information from prices; implying underreaction with multiple trading periods being required for prices to fully incorporate information. Our extension beyond CKN (2021) and MS (2022) is that our findings also imply that a low PTH can induce a systematic overreaction to good news (rather than underreaction) through an anchoring-bias influence. Such an overreaction implies reversals, as we observe for past-winner stocks with a low PTH. This apparent overreaction still implies multiple trading sessions are required for prices to fairly incorporate the information signal.

7. Conclusions

We contribute with two principal findings that establish new stylized facts regarding short-term (one-month) return behavior and the empirical relevance of a stock's 52-week high as a price reference point. First, we find that short-term momentum in high-turnover stocks (as recently documented in the literature) is only evident for stocks whose prices are relatively close to their 52-week high. On the other hand, high-turnover stocks whose prices are far from their 52-week high exhibit strong reversals. Thus, we find the co-existence of momentum and reversals among high-turnover stocks, depending on a stock's 52-week-price-to-high ratio (PTH). Since high-PTH stocks tend to be larger (in a market-capitalization sense), the dominant result when evaluating value-weighted portfolios is that high-turnover stocks exhibit momentum, consistent with results in Medhat and Schmeling (2022) and Chiang, Kirby, and Nie (2021).

Our second contribution shows that the apparent anchoring role of a stock's 52-week PTH is asymmetric and concentrated in past winners. We document that high-PTH winners strongly outperform low-PTH winners; across a variety of different turnover, size, and market-to-book segmentations for the stock portfolios. The difference in average returns is striking, about 1.86% per month, on average, for our quintile-based segmentations on these firm characteristics.[25]

[25]This average value is referring to the average of the 20 different results in row-3 of the five panels in Tables 1, 3, 7, and 8. We note that the 1.86% per month is appreciably greater than the 1.37% per month for the momentum in high-turnover stocks as documented in MS (2022), despite that we use quintile-based sorts and MS use decile-based sorts. CKN (2021) find short-term momentum profits of 0.40% per month, using quintile-based sorts and when excluding micro-cap stocks.

Further, regarding the performance of our strategy that buys high-PTH winners and shorts low-PTH winners, the continuation of high-PTH winners is generally the more important contributor for higher-turnover and larger-cap stocks. So, our results are not dependent upon taking short positions in small-cap illiquid stocks (as is sometimes the case for relative-strength strategies); which we feel is an intriguing feature of our findings.

To probe interpretation, we supplement our principal investigation with five supplementary empirical evaluations. First, when market-wide sentiment is lower (higher), then the apparent underreaction (overreaction) to good news for high-PTH winners (low-PTH winners) is stronger. Second, we find that the average returns of our new PTH-based winner-only strategy are markedly stronger for stocks with greater analyst dispersion in forecasted earnings. Third, we find that the performance of our PTH-based winner-only strategy is reliably evident for both small-cap and large-cap stocks, but stronger for small-cap stocks. Finally, we find that the profits of our PTH-based winner-only strategy are stronger for stock with extreme market-to-book equity ratios and higher idiosyncratic volatility.

In sum, for past winners, the PTH-based variations behind our two main contributions align well with the anchoring bias suggested by past literature. Our results fit with the following premise. When a stock's price is near its 52-week high, then investors tend to underreact to the good news associated with stocks that are relative winners over month t, which in turn contributes to higher returns over month $t+1$ as the prices correct to the underreaction from the good news in month t. Conversely, when a stock's price is low relative to its 52-week high, then investors tend to overreact to good news associated with stocks that are relative winners over month t, implying weaker returns over month $t+1$. The results from our five supplementary investigations reinforce such an anchoring-bias role, where the strength of the bias varies with market sentiment over time and with a stock's valuation uncertainty (or difference of opinion in the Harris and Raviv (1993) sense) in the cross-section.

However, comparably, there is relatively little difference in the subsequent performance of past losers, depending upon the loser stock's 52-week PTH. Thus, our findings emphasize a striking asymmetry between winners and losers, regarding their relation to the stock's PTH.

To close, we contribute with two new stylized facts on short-term return behavior, both suggesting a compelling role for a stock's 52-week-high-price as a reference point that can induce price-formation anchoring biases. Future theories of price formation and investor expectations should incorporate these stylized facts. We look forward to this future work.

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Table 1: Portfolios formed on Past-Returns, 52-Week Price-to-High Ratio, and Turnover

This table reports on the average monthly excess returns (in percentage) over month $t+1$ for portfolios created by sequential quintile-based stock sorts on lagged information, as follows: first sorted into quintiles on the NYSE breakpoints of past returns over month t, then into quintiles based on the price to 52-week high ratio (PTH) as of the end of month $t-1$, and finally into quintiles based on turnover over month t. Portfolios are value-weighted and rebalanced at the end of each month. Panels A to E report the results from low to high stock turnover quintiles, respectively; with the average portfolio returns reported in columns 1 and 2. Section 3.1 explains our stock selection and screening methods. In columns 3 to 5, we also report average excess returns (μ^e) and risk-adjusted alphas for long-short strategies across quintiles relative to Fama and French's (2015) five-factor model plus the momentum factor (FF6) and Hou, Xue, and Zhang's (2015) q-factor model. In columns 3 to 5, rows 1 and 2 report on momentum strategies, defined as the winner-minus-losers of the respective row; and rows 3 and 4 report on long/short strategies as defined at the beginning of each row. The sample period is from July 1963 to December 2020, except for the q-factors, which are available from January 1967. Newey and West (1987) heteroscedasticity and autocorrelation consistent t-statistics are reported in parentheses.

	Past return		Strategy Performance (winners-losers for rows 1 & 2) (as denoted for rows 3 & 4)		
	1. Losers ($\leq$ 20%)	2. Winners ($\geq$ 80%)	3. μ^e	4. α_{FF6}	5. α_Q
Panel A: Low Turnover Quintile					
1. Low PTH	0.74	-1.90	-2.64	-3.01	-2.86
	(1.67)	(-5.15)	(-7.25)	(-6.71)	(-5.54)
2. High PTH	1.09	0.23	-0.85	-0.87	-0.74
	(5.19)	(1.19)	(-4.72)	(-4.47)	(-3.26)
3. High PTH winners - Low PTH winners			2.13	1.86	1.93
			(7.55)	(7.51)	(6.77)
4. High PTH losers - Low PTH losers			0.35	-0.29	-0.18
			(0.90)	(-0.79)	(-0.41)
Panel B: 2nd Turnover Quintile					
1. Low PTH	0.72	-1.40	-2.12	-2.29	-2.24
	(1.58)	(-3.60)	(-6.64)	(-6.72)	(-5.71)
2. High PTH	0.97	0.45	-0.52	-0.47	-0.17
	(4.87)	(2.46)	(-2.72)	(-2.24)	(-0.68)
3. High PTH winners - Low PTH winners			1.85	1.54	1.80
			(5.58)	(6.43)	(5.48)
4. High PTH losers - Low PTH losers			0.25	-0.28	-0.27
			(0.67)	(-1.09)	(-0.73)

Table 1: (continued)

	Past return		Strategy Performance		
	1. Losers	2. Winners	3. μ^e	4. α_{FF6}	5. α_Q
	($\leq$ 20%)	($\geq$ 80%)	(winners-losers for rows 1 & 2)		
			(as denoted for rows 3 & 4)		
Panel C: 3rd Turnover Quintile					
1. Low PTH	1.26	-1.16	-2.42	-2.37	-2.35
	(2.48)	(-3.02)	(-6.53)	(-5.35)	(-4.38)
2. High PTH	0.95	0.59	-0.36	-0.41	-0.29
	(4.42)	(2.74)	(-1.84)	(-1.99)	(-1.09)
3. High PTH winners			1.75	1.11	1.33
- Low PTH winners			(5.47)	(3.81)	(3.67)
4. High PTH losers			-0.31	-0.85	-0.73
- Low PTH losers			(-0.76)	(-2.45)	(-1.52)
Panel D: 4th Turnover Quintile					
1. Low PTH	1.29	-0.43	-1.72	-1.73	-1.71
	(2.73)	(-1.06)	(-4.81)	(-4.12)	(-3.45)
2. High PTH	0.80	0.89	0.09	0.14	0.32
	(3.03)	(3.56)	(0.39)	(0.55)	(1.04)
3. High PTH winners			1.33	0.89	1.03
- Low PTH winners			(3.95)	(3.16)	(3.02)
4. High PTH losers			-0.49	-0.98	-1.01
- Low PTH losers			(-1.22)	(-2.89)	(-2.40)
Panel E: High Turnover Quintile					
1. Low PTH	0.54	-0.95	-1.49	-1.51	-1.42
	(1.12)	(-2.26)	(-3.89)	(-3.50)	(-3.22)
2. High PTH	0.49	1.51	1.02	0.98	1.28
	(1.62)	(4.08)	(3.52)	(3.41)	(3.33)
3. High PTH winners			2.46	1.85	2.18
- Low PTH winners			(5.83)	(4.72)	(3.73)
4. High PTH losers			-0.05	-0.64	-0.52
- Low PTH losers			(-0.14)	(-1.93)	(-1.34)

Table 2: Portfolios formed on Past-Returns, 52-Week PTH, and Turnover: Subperiods

This table repeats the analysis of Table 1, but separately for approximate one-half subperiods. Panel A reports the results over July 1963 to December 1991, and Panel B reports the results over January 1992 to December 2020. Panels A.1 to A.3 (B.1 to B.3) report the results from low, mid, and high turnover quintiles, respectively, for the two subperiods. Other tabular details and methodology are as explained with Table 1. For brevity, results for the second and fourth turnover quintile are suppressed.

Panel A: July 1963 to December 1991

	Past return		Strategy Performance		
	1. Losers ($\leq 20\%$)	2. Winners ($\geq 80\%$)	3. μ^e	4. α_{FF6}	5. α_Q
			(winners-losers for rows 1 & 2) (as denoted for rows 3 & 4)		
Panel A.1: Low Turnover Quintile					
1. Low PTH	1.06	-2.22	-3.28	-3.27	-3.17
	(1.85)	(-4.73)	(-7.41)	(-6.54)	(-5.91)
2. High PTH	1.17	0.01	-1.15	-1.23	-1.34
	(4.22)	(0.06)	(-5.24)	(-4.93)	(-4.43)
3. High PTH winners - Low PTH winners			2.23	1.89	1.89
			(6.07)	(5.00)	(4.43)
4. High PTH losers - Low PTH losers			0.10	-0.15	0.06
			(0.22)	(-0.36)	(0.13)
Panel A.2: 3rd Turnover Quintile					
1. Low PTH	1.28	-1.68	-2.96	-2.56	-2.99
	(1.97)	(-4.08)	(-6.30)	(-5.17)	(-5.39)
2. High PTH	1.15	0.42	-0.73	-0.90	-0.91
	(3.63)	(1.39)	(-3.00)	(-3.15)	(-2.75)
3. High PTH winners - Low PTH winners			2.11	1.62	1.69
			(6.56)	(4.75)	(3.69)
4. High PTH losers - Low PTH losers			-0.13	-0.04	-0.40
			(-0.27)	(-0.10)	(-0.83)
Panel A.3: High Turnover Quintile					
1. Low PTH	0.56	-1.31	-1.88	-2.20	-2.24
	(0.90)	(-2.48)	(-3.83)	(-4.33)	(-3.73)
2. High PTH	0.54	1.06	0.51	0.11	0.18
	(1.21)	(2.41)	(1.53)	(0.28)	(0.42)
3. High PTH winners - Low PTH winners			2.37	1.66	1.62
			(5.70)	(3.65)	(2.84)
4. High PTH losers - Low PTH losers			-0.02	-0.64	-0.80
			(-0.05)	(-1.40)	(-1.33)

Table 2: (continued)

Panel B: January 1992 to December 2020

	Past return		Strategy Performance		
	1. Losers ($\leq$ 20%)	2. Winners ($\geq$ 80%)	3. μ^e	4. α_{FF6}	5. α_Q
			(winners-losers for rows 1 & 2) (as denoted for rows 3 & 4)		
Panel B.1: Low Turnover Quintile					
1. Low PTH	0.42	-1.59	-2.01	-2.57	-2.48
	(0.63)	(-2.80)	(-3.55)	(-3.84)	(-3.40)
2. High PTH	1.01	0.45	-0.56	-0.64	-0.40
	(3.20)	(1.52)	(-1.97)	(-2.22)	(-1.22)
3. High PTH winners			2.03	1.82	1.96
- Low PTH winners			(4.75)	(5.09)	(5.17)
4. High PTH losers			0.58	-0.11	-0.13
- Low PTH losers			(0.97)	(-0.21)	(-0.21)
Panel B.2: 3rd Turnover Quintile					
1. Low PTH	1.25	-0.64	-1.88	-1.74	-1.65
	(1.60)	(-1.00)	(-3.35)	(-2.61)	(-2.18)
2. High PTH	0.75	0.76	0.00	-0.05	0.12
	(2.61)	(2.48)	(0.01)	(-0.17)	(0.32)
3. High PTH winners			1.39	0.74	1.04
- Low PTH winners			(2.55)	(1.55)	(2.00)
4. High PTH losers			-0.49	-0.94	-0.73
- Low PTH losers			(-0.73)	(-1.97)	(-1.07)
Panel B.3: High Turnover Quintile					
1. Low PTH	0.51	-0.60	-1.11	-0.82	-0.66
	(0.70)	(-0.92)	(-1.90)	(-1.30)	(-1.05)
2. High PTH	0.43	1.96	1.53	1.59	1.85
	(1.05)	(3.32)	(3.26)	(3.95)	(3.68)
3. High PTH winners			2.56	2.08	2.20
- Low PTH winners			(3.49)	(3.73)	(2.67)
4. High PTH losers			-0.08	-0.33	-0.30
- Low PTH losers			(-0.14)	(-0.63)	(-0.54)

Table 3: Portfolios formed on Past-Returns, 52-Week PTH, and Turnover: Indep. Sorts

This table reports on a similar empirical sorting exercise as in Table 1, except that the portfolios are formed from the *intersection* of *independent* sorts on relative-strength, price-to-52-week-high ratio (PTH), and turnover (rather than the conditional sequential sorts of Table 1). Specifically, this table reports on the average monthly excess returns (in percentage) over month $t+1$ for portfolios created by the intersection of independent quintile sorts on the NYSE breakpoints of past returns over month t, on the 52-week PTH as of the end of month $t-1$, and into turnover over month t. Portfolios are value-weighted and rebalanced at the end of each month. Thus, here with the intersection of independent sorts, each triple-factor portfolio does not necessarily contain approximately the same number of stocks. Panels A to E report the results from low to high stock turnover quintiles, respectively. The remainder of the portfolio details and tabular details are as for Table 1.

	Past return		Strategy Performance		
	1. Losers ($\leq 20\%$)	2. Winners ($\geq 80\%$)	3. μ^e	4. α_{FF6}	5. α_Q
			(winners-losers for rows 1 & 2) (as denoted for rows 3 & 4)		
Panel A: Low Turnover Quintile					
1. Low PTH	0.91	-2.02	-2.93	-2.90	-2.87
	(2.13)	(-4.95)	(-7.59)	(-7.59)	(-7.37)
2. High PTH	1.05	0.02	-1.03	-1.16	-1.05
	(4.60)	(0.06)	(-3.56)	(-3.73)	(-2.97)
3. High PTH winners - Low PTH winners			2.07	1.72	1.85
			(5.29)	(4.82)	(4.46)
4. High PTH losers - Low PTH losers			0.10	-0.10	-0.12
			(0.26)	(-0.31)	(-0.34)
Panel B: 2nd Turnover Quintile					
1. Low PTH	1.04	-1.56	-2.58	-2.64	-2.45
	(2.32)	(-3.90)	(-7.12)	(-7.34)	(-6.07)
2. High PTH	1.22	0.42	-0.80	-0.72	-0.53
	(5.97)	(1.82)	(-3.61)	(-3.02)	(-2.10)
3. High PTH winners - Low PTH winners			2.01	1.62	1.66
			(5.79)	(5.42)	(4.62)
4. High PTH losers - Low PTH losers			0.18	-0.31	-0.27
			(0.44)	(-1.01)	(-0.67)

Table 3: (continued)

	Past return		Strategy Performance		
	1. Losers	2. Winners	3. μ^e	4. α_{FF6}	5. α_Q
	($\leq$ 20%)	($\geq$ 80%)	(winners-losers for rows 1 & 2)		
			(as denoted for rows 3 & 4)		
Panel C: 3rd Turnover Quintile					
1. Low PTH	1.35	-1.07	-2.42	-2.55	-2.48
	(2.98)	(-2.96)	(-7.05)	(-5.88)	(-5.11)
2. High PTH	1.09	0.52	-0.58	-0.54	-0.23
	(4.62)	(2.60)	(-2.63)	(-2.31)	(-0.87)
3. High PTH winners			1.58	1.09	1.33
- Low PTH winners			(5.14)	(3.92)	(4.45)
4. High PTH losers			-0.26	-0.92	-0.91
- Low PTH losers			(-0.68)	(-2.76)	(-2.20)
Panel D: 4th Turnover Quintile					
1. Low PTH	1.16	-0.82	-1.98	-1.93	-1.87
	(2.54)	(-2.19)	(-5.94)	(-5.37)	(-4.34)
2. High PTH	0.57	0.63	0.06	0.02	0.24
	(2.27)	(2.64)	(0.27)	(0.06)	(0.81)
3. High PTH winners			1.45	0.86	1.02
- Low PTH winners			(4.30)	(3.15)	(2.90)
4. High PTH losers			-0.61	-1.10	-1.10
- Low PTH losers			(-1.57)	(-3.33)	(-2.54)
Panel E: High Turnover Quintile					
1. Low PTH	0.55	-0.63	-1.18	-1.31	-1.20
	(1.31)	(-1.67)	(-4.01)	(-3.73)	(-3.16)
2. High PTH	0.61	1.28	0.68	0.66	0.84
	(2.07)	(4.22)	(2.62)	(2.39)	(2.45)
3. High PTH winners			1.91	1.42	1.71
- Low PTH winners			(6.41)	(5.69)	(4.70)
4. High PTH losers			0.06	-0.54	-0.31
- Low PTH losers			(0.20)	(-1.85)	(-0.87)

Table 4: Average Stock's Size in Portfolios formed on Past-Returns, 52-week PTH, and Turnover

This table reports how a stock's market capitalization (size) varies across stock portfolios formed from triple sorts on relative-strength, the price-to-52-week high ratio (PTH), and turnover. We form the same conditional triple-sort portfolios as in Table 1, and then compute the average size for the stocks that comprise each portfolio each month, measured as of the end of month t. The table below then reports the time-series average for the monthly average sizes (in millions of dollars) of the stocks that comprise the respective denoted portfolios. The final column similarly reports on the average size of the stocks that comprise the momentum strategy of going long winners and shorting losers, for the respective PTH grouping in that row. In row 6, we report the time-series average of the monthly ratios of the high-PTH average size to the low-PTH average size of the denoted portfolio for the column (winners, losers, and the momentum portfolios). Panels A and B report the results for high- and low-turnover stocks, respectively. We use all NYSE/AMEX/NASDAQ common stocks (share codes 10 or 11) from CRSP monthly file except that financial firms are excluded from the sample. We also exclude stocks that trade below $1 per share at month t–1. The sample period is from July 1963 to December 2020.

	Past return		Momentum Strategies
Price to 52-week high	Losers ($\leq 20\%$)	Winners ($\geq 80\%$)	(Winners-minus-Losers)
Panel A: High Turnover Quintile			
1. Low PTH	325.85	477.52	401.69
2. 2nd PTH	825.55	1141.49	983.52
3. 3rd PTH	1318.02	1545.85	1431.94
4. 4th PTH	1619.31	2032.52	1825.92
5. High PTH	1831.76	2048.83	1940.30
6. High-PTH-to-Low-PTH Ratio	7.31	5.01	5.05
Panel B: Low Turnover Quintile			
1. Low PTH	54.33	104.72	79.53
2. 2nd PTH	129.74	225.43	177.58
3. 3rd PTH	213.27	556.45	384.86
4. 4th PTH	534.64	1810.70	1172.67
5. High PTH	1534.54	3942.12	2738.33
6. High-PTH-to-Low-PTH Ratio	32.16	54.75	41.08

Table 5: Portfolios formed on Past-Returns, 52-Week PTH, and Turnover: By Sentiment

This table repeats the analysis as in Table 1, but reports separate results for the more optimistic periods in Panel A and the more pessimistic periods in Panel B; based on Huang et al (2014)'s orthogonal sentiment index from month t-1. Panels A.1 to A.3 (Panels B.1 to B.3) report the results of the stocks in the corresponding low, mid, and high turnover quintiles, respectively. For brevity, results for the second and fourth turnover quintile are suppressed. Other tabular details are as explained in Table 1.

Panel A: More Optimistic Periods (333 months)

	Past return		Strategy Performance		
	1. Losers ($\leq$ 20%)	2. Winners ($\geq$ 80%)	3. μ^e (winners-losers for rows 1 & 2) (as denoted for rows 3 & 4)	4. α_{FF6}	5. α_Q
Panel A.1: Low Turnover Quintile					
1. Low PTH	0.10	-2.23	-2.33	-2.91	-2.84
	(0.13)	(-3.78)	(-4.05)	(-4.19)	(-3.64)
2. High PTH	1.16	0.22	-0.94	-0.99	-0.86
	(3.52)	(0.71)	(-3.55)	(-3.43)	(-2.56)
3. High PTH winners			2.45	1.86	2.02
- Low PTH winners			(5.68)	(4.89)	(4.62)
4. High PTH losers			1.07	-0.07	0.04
- Low PTH losers			(1.70)	(-0.12)	(0.06)
Panel A.2: 3rd Turnover Quintile					
1. Low PTH	0.12	-1.54	-1.66	-1.84	-1.86
	(0.15)	(-2.20)	(-3.15)	(-2.72)	(-2.33)
2. High PTH	0.81	0.44	-0.37	-0.55	-0.43
	(2.35)	(1.21)	(-1.21)	(-1.67)	(-1.04)
3. High PTH winners			1.98	0.94	1.28
- Low PTH winners			(3.51)	(1.89)	(2.25)
4. High PTH losers			0.69	-0.35	-0.15
- Low PTH losers			(1.06)	(-0.65)	(-0.21)
Panel A.3: High Turnover Quintile					
1. Low PTH	-0.40	-1.55	-1.15	-1.48	-1.37
	(-0.53)	(-2.17)	(-1.88)	(-2.21)	(-2.09)
2. High PTH	-0.12	1.13	1.25	1.42	1.67
	(-0.25)	(1.84)	(2.65)	(2.92)	(2.73)
3. High PTH winners			2.69	1.95	2.41
- Low PTH winners			(3.71)	(2.92)	(2.45)
4. High PTH losers			0.28	-0.95	-0.64
- Low PTH losers			(0.47)	(-1.93)	(-1.18)

Table 5: (continued)

Panel B: More Pessimistic Periods (333 months)

	Past return		Strategy Performance		
	1. Losers	2. Winners	3. μ^e	4. α_{FF6}	5. α_Q
	($\leq$ 20%)	($\geq$ 80%)	(winners-losers for rows 1 & 2)		
			(as denoted for rows 3 & 4)		
Panel B.1: Low Turnover Quintile					
1. Low PTH	1.29	-1.68	-2.97	-3.02	-2.75
	(2.30)	(-3.44)	(-6.27)	(-5.47)	(-4.84)
2. High PTH	0.96	0.29	-0.67	-0.63	-0.66
	(3.52)	(1.10)	(-2.63)	(-2.31)	(-2.29)
3. High PTH winners			1.97	2.07	1.84
- Low PTH winners			(4.97)	(6.29)	(5.29)
4. High PTH losers			-0.33	-0.32	-0.25
- Low PTH losers			(-0.70)	(-0.76)	(-0.56)
Panel B.2: 3rd Turnover Quintile					
1. Low PTH	2.39	-0.89	-3.28	-2.82	-2.71
	(3.54)	(-2.23)	(-6.35)	(-5.34)	(-5.27)
2. High PTH	1.07	0.76	-0.32	-0.19	-0.05
	(3.77)	(2.76)	(-1.17)	(-0.67)	(-0.16)
3. High PTH winners			1.65	1.34	1.45
- Low PTH winners			(4.63)	(3.95)	(3.52)
4. High PTH losers			-1.32	-1.28	-1.21
- Low PTH losers			(-2.49)	(-2.97)	(-2.75)
Panel B.3: High Turnover Quintile					
1. Low PTH	1.47	-0.40	-1.87	-1.48	-1.30
	(2.20)	(-0.70)	(-3.85)	(-2.81)	(-2.42)
2. High PTH	0.98	1.92	0.94	0.60	0.67
	(2.49)	(4.42)	(2.76)	(1.56)	(1.65)
3. High PTH winners			2.32	1.75	1.76
- Low PTH winners			(4.77)	(3.69)	(3.46)
4. High PTH losers			-0.49	-0.33	-0.22
- Low PTH losers			(-0.97)	(-0.79)	(-0.42)

Table 6: Portfolios formed on Analyst Dispersion, Past-Returns, and 52-Week PTH

This table reports on the average monthly excess returns (in percentage) over month $t+1$ for portfolios created by sequential percentile-based stock sorts on lagged information, as follows: first sorted into terciles on the 'analyst dispersion in earnings forecast' as of month t-1, then into quintiles on the NYSE breakpoints of the return over month t, and finally into quintiles on lagged price to 52-week high ratio as of the end of month t-1. Panels A and B evaluate different measures of scaled analyst dispersion. We scale the analyst forecast dispersion by absolute mean forecast in Panel A and by the mean monthly price in Panel B. Dispersion is the cross-sectional standard deviation of the analyst forecasts. Other tabular details are as explained in Table 1.

Panel A: Analyst forecast dispersion scaled by absolute mean forecast

	Past return		Strategy Performance		
	1. Losers ($\leq$ 20%)	2. Winners ($\geq$ 80%)	3. μ^e	4. α_{FF6}	5. α_Q
			(winners-losers for rows 1 & 2) (as denoted for rows 3 & 4)		
Panel A.1: Low analyst dispersion					
1. Low PTH	1.48	-0.04	-1.52	-1.58	-1.65
	(3.37)	(-0.10)	(-4.42)	(-3.72)	(-3.47)
2. High PTH	0.89	0.61	-0.29	-0.32	-0.23
	(3.59)	(2.47)	(-1.21)	(-1.42)	(-0.87)
3. High PTH winners			0.64	0.26	0.53
- Low PTH winners			(2.11)	(0.93)	(1.57)
4. High PTH losers			-0.59	-1.00	-0.90
- Low PTH losers			(-1.63)	(-3.01)	(-2.01)
Panel A.2: Mid-level analyst dispersion					
1. Low PTH	0.86	-0.26	-1.12	-1.14	-1.04
	(1.46)	(-0.72)	(-2.58)	(-2.70)	(-2.45)
2. High PTH	0.55	0.73	0.13	0.27	0.37
	(1.77)	(2.52)	(0.52)	(1.04)	(1.27)
3. High PTH winners			0.99	0.54	0.68
- Low PTH winners			(2.92)	(1.71)	(1.65)
4. High PTH losers			-0.30	-0.89	-0.76
- Low PTH losers			(-0.65)	(-2.40)	(-1.68)
Panel A.3: High analyst dispersion					
1. Low PTH	0.95	-0.69	-1.64	-1.46	-1.38
	(1.39)	(-1.19)	(-3.21)	(-2.32)	(-2.12)
2. High PTH	0.98	1.27	0.29	0.47	0.57
	(2.66)	(3.20)	(0.83)	(1.20)	(1.30)
3. High PTH winners			1.96	1.45	1.63
- Low PTH winners			(3.72)	(3.33)	(2.71)
4. High PTH losers			0.03	-0.48	-0.33
- Low PTH losers			(0.05)	(-0.75)	(-0.47)

Table 6: (continued)

Panel B: Analyst forecast dispersion scaled by mean monthly price

	Past return		Strategy Performance		
	1. Losers	2. Winners	3. μ^e	4. α_{FF6}	5. α_Q
	($\leq$ 20%)	($\geq$ 80%)	(winners-losers for rows 1 & 2)		
			(as denoted for rows 3 & 4)		
Panel B.1: Low analyst dispersion					
1. Low PTH	1.28	-0.33	-1.61	-1.55	-1.63
	(3.13)	(-0.93)	(-5.11)	(-4.08)	(-3.94)
2. High PTH	1.12	0.72	-0.40	-0.48	-0.34
	(4.65)	(2.96)	(-1.87)	(-2.31)	(-1.36)
3. High PTH winners			1.05	0.67	0.93
- Low PTH winners			(3.42)	(2.40)	(2.61)
4. High PTH losers			-0.17	-0.40	-0.37
- Low PTH losers			(-0.52)	(-1.50)	(-1.10)
Panel B.2: Mid-level analyst dispersion					
1. Low PTH	0.89	-0.52	-1.41	-1.31	-1.27
	(1.65)	(-1.41)	(-3.60)	(-3.31)	(-3.26)
2. High PTH	0.35	0.76	0.37	0.48	0.64
	(1.24)	(2.48)	(1.44)	(1.73)	(2.01)
3. High PTH winners			1.28	0.87	1.08
- Low PTH winners			(3.58)	(2.38)	(2.47)
4. High PTH losers			-0.53	-0.94	-0.85
- Low PTH losers			(-1.20)	(-2.82)	(-2.01)
Panel B.3: High analyst dispersion					
1. Low PTH	1.45	-0.62	-2.07	-1.98	-2.09
	(2.06)	(-1.10)	(-4.04)	(-3.09)	(-3.08)
2. High PTH	0.64	1.03	0.39	0.79	0.75
	(1.73)	(3.04)	(1.11)	(1.97)	(1.71)
3. High PTH winners			1.65	1.15	1.24
- Low PTH winners			(3.23)	(2.64)	(2.02)
4. High PTH losers			-0.81	-1.63	-1.60
- Low PTH losers			(-1.32)	(-2.51)	(-2.11)

Table 7: Returns of Portfolios formed on Firm Size, Past-Returns, and 52-week PTH

This table reports the average monthly excess returns (in percentage) over month $t+1$ for portfolios created by sequential quintile-based stock sorts on lagged information, as follows: first sorted into quintiles based on the stock's market capitalization (size) as of the end of month $t-1$; then into quintiles on the NYSE breakpoints of past returns over month t, and finally into quintiles based on the price to 52-week high ratio (PTH) as of the end of month $t-1$. Portfolios are value-weighted and rebalanced at the end of each month. Panels A to E report the results from the smallest to the largest size stocks by quintile, respectively; with rows 1 and 2 reporting the denoted average returns. See Section 3.1 for details on stock selection and screens. In columns 3 to 5, we report average excess returns (μ^e) and risk-adjusted alphas for long-short portfolios across quintiles relative to Fama and French's (2015) five-factor model plus the momentum factor (FF6) and Hou, Xue, and Zhang's (2015) q-factor model, respectively. In columns 3 to 5, rows 1 and 2 report on momentum strategies, defined as the winner-minus-losers of the respective row; and rows 3 and 4 report on long/short strategies as defined at the beginning of the row. The sample period is from July 1963 to December 2020, except for the q-factors, which are available from January 1967. Newey and West (1987) heteroscedasticity and autocorrelation consistent t-statistics are reported in parentheses.

	Past return		Strategy Performance		
	1. Losers	2. Winners	3. μ^e	4. α_{FF6}	5. α_Q
	($\leq$ 20%)	($\geq$ 80%)	(winners-losers for rows 1 & 2)		
			(as denoted for rows 3 & 4)		
Panel A: Smallest Quintile of Market Capitalization (Size)					
1. Low PTH	2.48	-3.02	-5.50	-5.69	-5.82
	(4.49)	(-5.83)	(-11.28)	(-8.86)	(-7.90)
2. High PTH	2.35	1.30	-1.05	-0.98	-0.98
	(6.19)	(3.87)	(-3.25)	(-2.85)	(-2.52)
3. High PTH winners			4.32	3.77	3.75
- Low PTH winners			(10.19)	(9.49)	(9.21)
4. High PTH losers			-0.13	-0.93	-1.09
- Low PTH losers			(-0.29)	(-1.93)	(-1.81)
Panel B: 2nd Smallest Quintile of Market Capitalization (Size)					
1. Low PTH	1.22	-1.93	-3.15	-3.34	-3.36
	(2.58)	(-4.34)	(-8.59)	(-6.42)	(-5.63)
2. High PTH	1.41	1.25	-0.16	-0.28	-0.30
	(4.78)	(3.75)	(-0.60)	(-0.94)	(-0.86)
3. High PTH winners			3.18	2.55	2.57
- Low PTH winners			(8.92)	(8.31)	(7.07)
4. High PTH losers			0.19	-0.51	-0.49
- Low PTH losers			(0.58)	(-1.39)	(-1.04)

Table 7: (continued)

	Past return		Strategy Performance		
	1. Losers	2. Winners	3. μ^e	4. α_{FF6}	5. α_Q
	($\leq$ 20%)	($\geq$ 80%)	(winners-losers for rows 1 & 2)		
			(as denoted for rows 3 & 4)		
Panel C: Middle Quintile of Market Capitalization (Size)					
1. Low PTH	0.99	-1.01	-2.00	-2.01	-2.07
	(2.23)	(-2.63)	(-6.74)	(-6.27)	(-5.25)
2. High PTH	1.48	1.03	-0.45	-0.33	-0.24
	(5.41)	(3.92)	(-2.25)	(-1.56)	(-0.97)
3. High PTH winners			2.04	1.50	1.60
- Low PTH winners			(6.76)	(5.82)	(4.93)
4. High PTH losers			0.49	-0.19	-0.23
- Low PTH losers			(1.51)	(-0.70)	(-0.65)
Panel D: 2nd Largest Quintile of Market Capitalization (Size)					
1. Low PTH	0.98	-0.41	-1.39	-1.49	-1.33
	(2.50)	(-1.24)	(-5.82)	(-4.97)	(-3.96)
2. High PTH	1.15	0.86	-0.30	-0.17	0.05
	(4.74)	(3.68)	(-1.55)	(-0.83)	(0.21)
3. High PTH winners			1.27	0.77	1.02
- Low PTH winners			(4.86)	(3.76)	(3.21)
4. High PTH losers			0.17	-0.56	-0.36
- Low PTH losers			(0.61)	(-2.36)	(-1.08)
Panel E: Largest Quintile of Market Capitalization (Size)					
1. Low PTH	0.61	-0.15	-0.75	-0.80	-0.76
	(1.89)	(-0.58)	(-3.44)	(-3.17)	(-2.60)
2. High PTH	0.75	0.52	-0.24	-0.30	-0.12
	(3.95)	(2.63)	(-1.49)	(-1.80)	(-0.57)
3. High PTH winners			0.66	0.14	0.39
- Low PTH winners			(3.32)	(0.91)	(1.66)
4. High PTH losers			0.15	-0.36	-0.25
- Low PTH losers			(0.61)	(-1.74)	(-0.90)

Table 8: Returns of Portfolios formed on Market-to-Book, Past-Returns, and 52-week PTH

This table reports the average monthly excess returns (in percentage) over month $t+1$ for portfolios created by sequential quintile-based stock sorts on lagged information, as follows: first sorted into quintiles based on a stock's market-to-book equity ratio as of the end of month $t-1$; then into quintiles on the NYSE breakpoints of past returns over month t, and finally into quintiles based on the price to 52-week high ratio (PTH) as of the end of month $t-1$. Portfolios are value-weighted and rebalanced at the end of each month. Panels A to E report the results from the lowest to highest market-to-book stocks by quintile, respectively; with rows 1 and 2 reporting the denoted average returns. See Section 3.1 for details on stock selection and screens. In columns 3 to 5, we report average excess returns (μ^e) and risk-adjusted alphas for long-short portfolios across quintiles relative to Fama and French's (2015) five-factor model plus the momentum factor (FF6) and Hou, Xue, and Zhang's (2015) q-factor model, respectively. In columns 3 to 5, rows 1 and 2 report on momentum strategies, defined as the winner-minus-losers of the respective row; and rows 3 and 4 report on long/short strategies as defined at the beginning of the row. The sample period is from July 1963 to December 2020, except for the q-factors, which are available from January 1967. Newey and West (1987) heteroscedasticity and autocorrelation consistent t-statistics are reported in parentheses.

	Past return		Strategy Performance		
	1. Losers ($\leq$ 20%)	2. Winners ($\geq$ 80%)	3. μ^e	4. α_{FF6}	5. α_Q
			(winners-losers for rows 1 & 2) (as denoted for rows 3 & 4)		
Panel A: Lowest Market-to-Book Quintile					
1. Low PTH	1.37	-0.86	-2.23	-2.01	-1.73
	(2.59)	(-1.79)	(-4.94)	(-3.85)	(-3.12)
2. High PTH	1.28	0.80	-0.48	-0.40	-0.24
	(4.35)	(3.28)	(-1.77)	(-1.29)	(-0.76)
3. High PTH winners - Low PTH winners			1.67	1.11	1.08
			(3.90)	(2.81)	(2.51)
4. High PTH losers - Low PTH losers			-0.09	-0.51	-0.41
			(-0.19)	(-1.23)	(-0.89)
Panel B: 2nd Lowest Market-to-Book Quintile					
1. Low PTH	1.12	-0.43	-1.56	-1.53	-1.49
	(2.37)	(-1.18)	(-4.62)	(-4.23)	(-3.50)
2. High PTH	0.88	0.51	-0.38	-0.21	0.03
	(3.53)	(2.61)	(-1.73)	(-0.97)	(0.11)
3. High PTH winners - Low PTH winners			0.94	0.56	0.81
			(3.01)	(2.25)	(2.66)
4. High PTH losers - Low PTH losers			-0.24	-0.76	-0.71
			(-0.60)	(-2.06)	(-1.44)

Table 8: (continued)

	Past return		Strategy Performance		
	1. Losers	2. Winners	3. μ^e	4. α_{FF6}	5. α_Q
	($\leq$ 20%)	($\geq$ 80%)	(winners-losers for rows 1 & 2)		
			(as denoted for rows 3 & 4)		
Panel C: Middle Market-to-Book Quintile					
1. Low PTH	1.30	-0.43	-1.73	-1.67	-1.77
	(3.03)	(-1.22)	(-4.99)	(-4.22)	(-3.93)
2. High PTH	0.99	0.50	-0.48	-0.41	-0.30
	(4.39)	(2.46)	(-2.49)	(-1.86)	(-1.27)
3. High PTH winners			0.93	0.38	0.52
- Low PTH winners			(3.17)	(1.45)	(1.73)
4. High PTH losers			-0.32	-0.88	-0.96
- Low PTH losers			(-0.83)	(-2.44)	(-2.15)
Panel D: 2nd Highest Market-to-Book Quintile					
1. Low PTH	0.85	-0.60	-1.45	-1.62	-1.62
	(2.02)	(-1.77)	(-4.44)	(-4.51)	(-4.08)
2. High PTH	0.99	0.51	-0.48	-0.44	-0.27
	(4.73)	(2.39)	(-2.64)	(-2.23)	(-1.14)
3. High PTH winners			1.12	0.55	0.63
- Low PTH winners			(3.91)	(2.17)	(1.72)
4. High PTH losers			0.15	-0.62	-0.72
- Low PTH losers			(0.42)	(-1.98)	(-1.86)
Panel E: Highest Market-to-Book Quintile					
1. Low PTH	0.95	-1.92	-2.87	-3.15	-3.09
	(2.07)	(-5.26)	(-8.01)	(-7.91)	(-6.58)
2. High PTH	0.78	0.65	-0.13	-0.23	-0.07
	(3.18)	(2.79)	(-0.66)	(-1.13)	(-0.27)
3. High PTH winners			2.57	2.13	2.39
- Low PTH winners			(8.13)	(7.64)	(6.93)
4. High PTH losers			-0.17	-0.79	-0.63
- Low PTH losers			(-0.49)	(-2.40)	(-1.57)

A. External Appendix

This appendix reports results that are secondary and supportive to our main empirical findings. For brevity in the main text, we relegate these results to the appendix.

A.1. Baseline Results for Short-term Reversals (single sort)

This appendix supports discussion in Sections 3.2 and 4.2. Here, we document the basic short-run reversal behavior in our sample, with portfolios sorted only on past returns. We report portfolio returns in month $t+1$ that are based on sorts on returns over month t. Table A1 reports the results. Panels A and B report results based on quintile and decile sorts, respectively. We reports results for both value-weighted and equal-weighted holding-period portfolio returns in each panel. Further, we report separate results over our full sample (columns 1 to 5), over the approximate first one-half subperiod (columns 6 to 10), and over the approximate second one-half subperiod (columns 11 to 15).

Consistent with the literature on short-term reversals, we find that unconditionally 1-month returns are dominated by short-term reversals. For example, in Panel A, the average monthly excess returns for reversal strategies with quintile portfolios are 0.30% and 1.13% over our full sample, for value-weighted and equal-weighted portfolios, respectively. The results based on decile-portfolios are similar. Importantly, we report that short-term reversals are appreciably weaker during the second-half of our sample. For example, in the case of value-weighted portfolios, short-term reversals have average returns of 0.18% (quintile portfolios) and 0.09% (decile portfolios), both of which are statistically insignificant.

Recall that our subperiod results from Table 2 find that the strategy of going 'long winner/ high-PTH stocks and short winner/low-PTH stocks' is strongly evident in both one-half subperiods. For the high-turnover stocks, this 'PTH-based winner only' strategy actually performs better in the second half of our sample than in the first half. In light of the evidence here that short-term reversals are appreciably weaker in the recent one-half subperiod, the subperiod results reported in Table 2 seem even more intriguing.

A.2. Comparative Results with 2-way Relative-Strength and Turnover Sorts

This appendix supports discussion in Section 3.2. Here, we approximately replicate the double-sort method in Table 1 of Medhat and Schmeling (2022), forming portfolios in month $t+1$ based on sorts on stocks' returns and turnover over month$t$. Table A2 reports our findings for the resulting 100 portfolios, with the sample that we employ in this study. We note that there two main difference between our sample and that from MS (2022). First, our sample ends in 2020 whereas MS's sample ends in 2018. Second, we use a \$1 price screen to filter out low-priced stocks that are more likely to be influenced by illiquidity and related microstructural biases. MS (2022) does not mention using any comparable price screens in their portfolio formations. As discussed in Section 3.2, we find our results closely match those from MS (2022).

A.3. Alternative Granularity for Relative-Strength, PTH, and Turnover Sorts

This appendix reports tabular details for the robustness results that evaluate alternative granularity for the portfolio sorts, as summarized in Section 4.3.2.

Recall that the main results from Table 1 are based on quintile sorts of past returns. Here, we provide additional robust checks by using decile-based sorting on past returns (following from the main results in MS (2022) that feature such decile-based sorts). To ensure that the number of stocks per portfolio is similar to that in MS (2022), we use tercile sorts on PTH and turnover here. This gives us 90 portfolios ($10 \times 3 \times 3$)), which is comparable to the 100 portfolios used in MS (2022) in their 10 by 10 double-sort on past-returns and turnover.

Table A3 reports the results with this alternative sorting granularity. We find that our conclusions from all four empirical results discussion in Section 4.1 remains intact. Specifically, we find that among the high-turnover stocks, short-term momentum is significantly profitable only among high-PTH stocks with an average return of 0.94% (t-statistic = 3.67; Panel C, row 2). In contrast, for low-PTH/high-turnover stocks, the short-term momentum strategy has an average return of -1.58% (t-statistic = -4.37; Panel C, row 1). These negative momentum returns for the low-PTH stocks indicates the existence of reliable reversal behavior for the low-PTH stocks.

For our new strategy of going 'long high PTH and short low PTH' winner stocks, we find consistent profitability among past winners across all turnover terciles with average returns of 1.63%, 1.74%, and 2.09% in Panels A to C, respectively (row 3 results). By contrast, a similar PTH-based strategy implemented on past-losers has insignificant returns of 0.17%, -0.49%, and -0.43% across the three panels, which are all statistically insignificant (row 4 results). Overall, we conclude that the asymmetry between past winners and past losers for the PTH-based strategy remains strongly evident with this alternative sorting breakpoints.

A.4. Return Predictability by Past-Returns, PTH, and Turnover with the Cross-sectional Fama-MacBeth Regression Approach

This appendix reports the details for our Fama-MacBeth cross-sectional approach, as summarized in Section 4.3.3.

A.4.1. Discussion and Overview

We next evaluate an alternative framework, the cross-sectional regression approach of Fama and MacBeth (1973), to take another look at the role of 52-week PTH and turnover in short-term relative strength strategies. As noted in Fama and French (2008) and MS (2022), cross-sectional regressions with continuous explanatory variables can impose a potentially misspecified functional form and are sensitive to outliers. In our setting, with three conditional factors, interactive terms with all three factors (in continuous variable form) seem likely to be especially subject to misspecification and outlier concerns.

To mitigate such specification concerns and to provide a specification where the estimated coefficients are readily interpreted, we instead estimate a specification where the primary explanatory terms are dummy variables that equal one when a certain condition is met and zero otherwise (conditional on whether a stock is a relative winner or loser, has a high or low PTH, and/or has a high or low turnover). With this approach, we can evaluate the apparent incremental information from looking at relatively high and low turnover, and relatively high and low PTH; and evaluate whether the incremental information is statistically significant.

Further, in a specification that uses the continuous lagged returns in the explanatory terms and assumes linear relations between the current and lagged return (and for the lagged return interacted with PTH and turnover variables), there is no asymmetry allowed between past losers and past winners. Thus, another important feature of our specification is that it allows for asymmetry between past winners and past losers (and their interaction terms), in regard to the implications for the month $t + 1$ returns. Our main results in Section 4 suggest that allowing for such asymmetry between past winners and losers is important.

Additionally, with the cross-sectional regression approach, we can also control for other well-known variables that have been shown to help explain cross-sectional variation in returns. Thus, this approach further allows us to evaluate the incremental role of our main conditional factors.

A.4.2. Main Fama-MacBeth Specifications

Using the Fama-MacBeth methodology, we first evaluate a simple specification to establish the baseline reversal behavior. We estimate cross-sectional regressions for every calendar month $t+1$, as follows:

$$Rt_{i,t+1} = \beta_0 + \lambda_1 \, Dm_{i,t}^{Ls} + \gamma_1 \, Dm_{i,t}^{Wn} + \epsilon_{i,t+1} \tag{A1}$$

where $Rt_{i,t+1}$ is the return of stock i over month $t+1$; $Dm_{i,t}^{Ls}$ is a dummy variable that equals one if the return of stock i was a relative Loser (Ls) over month t and is zero otherwise; $Dm_{i,t}^{Wn}$ is a dummy variable that equals one if the return of stock i was a relative Winner (Wn) over month t and is zero otherwise; the β_0, λs and γs are coefficients to be estimated; and $\epsilon_{i,t+1}$ is the residual. We then retain the estimated coefficients for each monthly cross-sectional regression and report on the average coefficients in our tabular results, in the usual Fama-MacBeth way. A stock is a relative winner (loser) if it is in the top-quintile (bottom-quintile) of return performance.

Next, following from MS (2022), we add turnover into the analysis and estimate cross-sectional regressions for every calendar month $t+1$, as follows:

$$\begin{gathered} Rt_{i,t+1} = \beta_0 + \lambda_1 \, Dm_{i,t}^{Ls} + \lambda_2 \, Dm_{i,t}^{Ls\&Ltv} + \lambda_3 \, Dm_{i,t}^{Ls\&Htv} \\ \gamma_1 \, Dm_{i,t}^{Wn} + \gamma_2 \, Dm_{i,t}^{Wn\&Ltv} + \gamma_3 \, Dm_{i,t}^{Wn\&Htv} + \epsilon_{i,t+1} \end{gathered} \tag{A2}$$

where $Dm_{i,t}^{Ls\&Ltv}$ is a dummy variable that equals one if the return of stock i was both a relative Loser (Ls) over month t (first sort) and had Low Turnover (Ltv) over month t (second sort) and is zero otherwise; $Dm_{i,t}^{Ls\&Htv}$ is a dummy variable that equals one if the return of stock i was both a relative Loser (Ls) over month t (first sort) and had High Turnover (Htv) over month t (second sort) and is zero otherwise; $Dm_{i,t}^{Wn\&Ltv}$ and $Dm_{i,t}^{Wn\&Htv}$ are the comparable variables but for Winners (Wn) rather than losers; and the other terms are as defined for equation (A1). High (low) turnover is defined as being in the top (bottom) quintile of turnover.

Finally, we extend the Fama-MacBeth approach to also consider the 52-week PTH, in conjunction with past returns and turnover. We estimate cross-sectional regressions for every calendar month $t+1$, as follows:

$$\begin{gathered} Rt_{i,t+1} = \beta_0 + \lambda_1 \, Dm_{i,t}^{Ls} + \lambda_2 \, Dm_{i,t}^{Ls\&Lpth\&Ltv} + \lambda_3 \, Dm_{i,t}^{Ls\&Lpth\&Htv} + \\ \lambda_4 \, Dm_{i,t}^{Ls\&Hpth\&Ltv} + \lambda_5 \, Dm_{i,t}^{Ls\&Hpth\&Htv} + \gamma_1 \, Dm_{i,t}^{Wn} + \gamma_2 \, Dm_{i,t}^{Wn\&Lpth\&Ltv} + \end{gathered} \tag{A3}$$

$$\gamma_3\, Dm_{i,t}^{Wn\&Lpth\&Htv} + \gamma_4\, Dm_{i,t}^{Wn\&Hpth\&Ltv} + \gamma_5\, Dm_{i,t}^{Wn\&Hpth\&Htv} + \epsilon_{i,t+1}$$

where $Dm_{i,t}^{Ls\&Lpth\&Ltv}$ is a dummy variable that equals one if the return of stock i was a relative Loser (Ls) over month t (first sort), was also a Low-PTH stock (Lpth) from the end of month $t-1$ (second sort), and was also a Low Turnover (Ltv) stock over month t (third sort) and is zero otherwise; the other 3-way-dummy variables are defined similarly with superscript Wn indicating a relative winner, superscript $Hpth$ indicating a high 52-week PTH value, and superscript Htv indicating a high turnover; and the other terms are as defined for equations (A1) and (A2). For each sort, relatively high (low) indicates a value in the top quintile (bottom quintile).

As a robustness check, we also estimate a fourth specification, using an augmented version of equation (A3) that includes a set of commonly used firm characteristics as control variables. These variables are described in Section 3 and are the same control variables used in MS (2022) in their Fama-MacBeth approach.

A.4.3. Empirical Results for our main Fama-MacBeth Specifications

Results for Equation (A1). Table A4, the Model-1 column, report the results for equation (A1). Here, our results depict the well-known reversal behavior in one-month returns, with a sizably positive λ_1 on the past loser-dummy of 0.58% and a sizably negative γ_1 on the past winner-dummy of -0.55%.

Results for Equation (A2). Table A4, the Model-2 column, reports the results for equation (A2), with the addition of the high and low turnover conditioning. The results are broadly consistent with Table 1 of MS (2022) in that reversals are much stronger for the low-turnover stocks, relative to the high-turnover stocks. Specifically, a direct interpretation of the estimated coefficients for equation (A2) suggests a strong reversal profits from buying low-turnover losers and shorting low-turnover winners at 1.57% per month, on average. Conversely, there is a much lower reversal profit from buying high-turnover losers and shorting high-turnover winners at 0.33%, on average. While this near-zero reversal profit for the high-turnover stocks is less striking than the momentum in the Medhat-Schmeling paper, we remind readers that our approach here is equal-weighted with conditional dummies based on high and low quintiles. Chiang, Kirby, and Nie (2021) find that the short-term momentum is stronger when excluding micro-cap stocks and MS (2022) note that short-term momentum is stronger among the larger and more liquid stocks. Further, recall that Table 1 of the Medhat-Schmeling paper features decile sorts, rather than quintile. Thus, it is not surprising that our high-turnover results here (with an equal-weighted approach and quintile sorts rather than decile) are weaker, in terms of not observing short-term momentum for the high-turnover stocks.

Results for Equation (A3). Table A4, the Model-3 column, reports the results for equation (A3), here with both extreme 52-week PTH and turnover investigated. First, we discuss what our results imply about short-term momentum for high-turnover stocks. Consistent with our main results in Table 1, the results indicate more positive returns for Winner/High-PTH/High-Turnover stocks with a sizably positive estimated γ_5 coefficient of 1.14% and more negative returns for Loser/High-PTH/High-Turnover stocks with a negative estimated λ_5 coefficient of -0.59%. A direct interpretation of all the estimated coefficients indicates a short-term momentum profit of +0.64%, on average, when buying Winner/high-PTH/high-Turnover stocks and shorting Loser/high-PTH/high-Turnover stocks. Conversely, the implied short-term momentum profits from buying Winner/low-PTH/high-Turnover stocks and shorting Loser/low-PTH/high-Turnover stocks is -1.81%. Thus, these Fama-MacBeth results reinforce our main Empirical Results #1 and #2 in Section 4.1: short-term momentum in high-turnover stocks is only evident for stocks that are also high-PTH stocks; conversely stocks with low-PTH and high-turnover exhibit sizable reversals.

Next, we shift to discussing the difference in performance between high-PTH Winners and low-PTH Winners, and between high-PTH losers and low-PTH losers. For winner-only strategies, our Fama-MacBeth results indicate that: (1) Winner/high-PTH/high-Turnover stocks outperform Winner/low-PTH/high-Turnover stocks by about 2.6% per month, on average; and (2) Winner/high-PTH/low-Turnover stocks outperform Winner/low-PTH/low-Turnover stocks by about 2.2% per month, on average. However, for loser-only strategies, our result indicate that the difference between high-PTH losers and low-PTH losers is only about 0.13% for high-turnover stocks and -0.47% for low-turnover stocks, on average. Thus, these Fama-MacBeth results reinforce our main Empirical Results #3 and #4 in Section 4.1.

A.4.4. Results with Additional Control Variables

Finally, Table A4, the Model-4 column, reports on the augmented version of equation (A3), which include a set of control variables that are firm characteristics known for their predictive power in explaining cross-sectional variation in returns. We use the same set of four control variables as in MS (2022), and find that three of the four control variables are statistically significant at better than a 1% p-value. However, we find the inclusion of these controls does not change statistical inferences on our primary results-of-interest, as the estimated λ and γ coefficients are very similar to those for model (A3). Hence, our conclusions remain intact when including the control variables.

A.4.5. Alternative Fama-MacBeth Specification Using the Continuous Lagged Stock Returns in the Explanatory Terms

We also estimate an alternative Fama-MacBeth specification that uses the continuous lagged return as explanatory terms, by themselves, and when interacted with conditional dummy variables based on high or low turnover and/or high or low 52-week PTH. This approach addresses the criticism of Bandarchuk and Hilscher (BH, 2013) while still mitigating outliers by using dummy variables based on percentile groupings of stock's turnover and/or 52-week PTH.[26]

Table A5 reports the results. Models 1 and 2 of the table report on variations of the following specification, with cross-sectional regressions estimated for every calendar month $t + 1$:

$$Rt_{i,t+1} = \beta_0 + \lambda_1\, Rt_{i,t} + \lambda_2\, Rt_{i,t}\, D^{Ltv}_{i,t} + \lambda_3\, Rt_{i,t}\, D^{Htv}_{i.t} + \lambda_6\, D^{Ltv}_{i.t} + \lambda_7\, D^{Htv}_{i.t} + \epsilon_{i.t+1} \tag{A4}$$

where $Rt_{i,t}$ is the return for stock i in month t; $D^{Ltv}_{i,t}$ is a dummy variable that equals one if turnover was in the low-quintile grouping; $D^{Htv}_{i,t}$ is a dummy variable that equals one if turnover was in the high-quintile grouping; the β_0, and λs are coefficients to be estimated; and $\epsilon_{i,t+1}$ is the residual. We then retain the estimated coefficients for each monthly cross-sectional regression and report on the average coefficients in our tabular results, in the usual Fama-MacBeth way. High turnover (low turnover) is defined in the second sort, as being in the top quintile (bottom quintile) of turnover in month t for the respective group of winner or loser stocks.

Model 3 of Table A5 reports on the following specification, with cross-sectional regressions estimated for every calendar month $t + 1$, as follows:

$$Rt_{i,t+1} = \beta_0 + \lambda_1\, Rt_{i,t} + \lambda_2\, Rt_{i,t}\, D^{Lpth\&Ltv}_{i,t} + \lambda_3\, Rt_{i,t}\, D^{Lpth\&Htv}_{i,t} + \lambda_4\, Rt_{i,t}\, D^{Hpth\&Ltv}_{i,t} + \lambda_5\, Rt_{i,t}\, D^{Hpth\&Htv}_{i,t}$$
$$+ \lambda_6\, D^{Lpth\&Ltv}_{i,t} + \lambda_7\, D^{Lpth\&Htv}_{i,t} + \lambda_8\, D^{Hpth\&Ltv}_{i,t} + \lambda_9\, D^{Hpth\&Htv}_{i,t} + \epsilon_{i,t+1} \tag{A5}$$

where $D^{Lpth\&Ltv}_{i,t}$ is one if stock i was both a Low-PTH stock (Lpth) from the end of month $t - 1$ (second sort) and a Low Turnover (Ltv) stock over month t (third sort) and is zero otherwise;

[26]BH (2013) study medium-run momentum with 6-month ranking periods and show that double-sorting on the relative returns and other firm characteristic can serve to identify more extreme returns, within a given return percentile grouping. And, when taking the return magnitude into consideration (rather than using percentile groupings), the firm characteristics add little to explaining medium-run momentum performance.

the other 2-way-dummy variables are defined similarly with superscript $Hpth$ indicating a high 52-week PTH value, and superscript Htv indicating a high turnover; and the other terms are as defined for equations (A5). For each sort, relatively high (low) indicates a value in the top quintile (bottom quintile).

As a robustness check, we also estimate a fourth specification, using an augmented version of equation (A5) that includes a set of commonly used firm characteristics as control variables. These variables are described in Section 3 and are the same control variables used in MS (2022) in their Fama-MacBeth approach.

To summarize, when estimating our alternative Fama-MacBeth specification, we find results that are consistent with our main results in Section 4 and our primary Fama-MacBeth results in Section A.4.3. The estimated λ_1 coefficients on the past returns (by themselves when not interacted with another condition) are always sizably negative and statistically significant (row-2 results), indicating the tendency for well-known one-month reversals.

However, when interacting the past returns with the high-PTH&high-turnover condition, the total coefficient on the lagged returns becomes positive; consistent with the continuation of high-PTH/high-turnover winners in our main results. The estimated λ_5 coefficients (row-6 results) are large and highly statistically significant at 5.06 and 5.24 for models 3 and 4, respectively.

Further, when interacting the lagged returns with the low-PTH&low-turnover condition in Models 3 and 4, then reversals are much stronger; consistent with the strong reversals seen in low-PTH, low-turnover stocks in our main results. The estimated λ_2 coefficients (row-3 results) are sizably negative at -8.28 and -7.72 in models 3 and 4, respectively.

Addition of the four other control variables (as used in Model 4 of Table A4) has very little impact on our results of interest. We conclude that our key results of interest are consistently evident in this alternative Fama-MacBeth specification.

A.4.6. Concluding Remarks - Fama-MacBeth Results

In sum, our Fama-MacBeth results provide consistent results for all four of main Empirical Results highlighted in Section 4.1. First, short-term momentum for high-turnover stocks is only evident for high-PTH stocks; conversely, strong short-term reversals are evident for low-PTH stocks with high turnover. Second, there is a strong PTH-based contrast between winners, with high-PTH winners strongly outperforming low-PTH winners; conversely there are only quite modest differences between the performance of losers, based on their PTH.

Table A1: Portfolios Sorted on Past-Returns Only: Basic Short-term Reversal Behavior

This appendix table reports average monthly excess returns (in percentage) at month $t + 1$ for portfolios sorted on past returns (at month t) only. Here, for comparison to the literature, we report on the basic short-term reversal phenomenon over our sample, without any additional sorts on other stock characteristics. Columns 1 and 2 report on past Losers (Lsr) and past Winners (Wnr), respectively. In columns three through five in each sample grouping, we also report the average excess returns (μ^e) of winner minus loser portfolios as well as alphas from the Fama and French's (2015) five-factor model plus the momentum factor (FF6) and Hou, Xue, and Zhang's (2015) q-factor model. Portfolios are rebalanced at the end of each month and we report both value-weighted and equal weighted. Panels A and B show results for quintile-based and decile-based portfolios, respectively. We use all NYSE/AMEX/NASDAQ common stocks (share codes 10 or 11) from CRSP monthly file except that financial firms are excluded from the sample. We also exclude stocks that trade below $1 per share at month t–1. The full sample period is from July 1963 to December 2020, except for the q-factors, which are available from January 1967. Newey and West (1987) heteroscedasticity and autocorrelation consistent t-statistics are reported in parentheses.

Panel A: Relative-Strength portfolios based on past return quintiles

Full Sample					July 1963 to December 1991					January 1992 to December 2020				
		Wnr-minus-Lsr					Wnr-minus-Lsr					Wnr-minus-Lsr		
Lsr	Wnr	μ^e	α_{FF6}	α_Q	Lsr	Wnr	μ^e	α_{FF6}	α_Q	Lsr	Wnr	μ^e	α_{FF6}	α_Q
Value-weighted portfolios														
0.72	0.42	-0.30	-0.31	-0.19	0.65	0.23	-0.41	-0.60	-0.60	0.79	0.61	-0.18	-0.04	0.10
(3.22)	(2.15)	(-2.06)	(-1.91)	(-0.90)	(2.12)	(0.89)	(-2.21)	(-3.04)	(-2.38)	(2.43)	(2.10)	(-0.84)	(-0.15)	(0.31)
Equal-weighted portfolios														
1.34	0.22	-1.13	-1.23	-1.18	1.46	-0.11	-1.57	1.66	-1.81	1.23	0.54	-0.69	-0.66	-0.60
(4.52)	(0.81)	(-7.96)	(-6.59)	(-4.77)	(3.40)	(-0.30)	(-7.83)	(-8.70)	(-7.40)	(2.97)	(1.43)	(-3.73)	(-2.44)	(-1.83)

Panel B: Relative-Strength portfolios based on past return deciles

Value-weighted portfolios														
0.75	0.44	-0.31	-0.33	-0.15	0.69	0.17	-0.52	-0.73	-0.76	0.80	0.70	-0.09	0.09	0.29
(2.84)	(1.99)	(-1.86)	(-1.76)	(-0.61)	(1.95)	(0.62)	(-2.35)	(-3.40)	(-2.63)	(2.06)	(2.09)	(-0.39)	(0.31)	(0.87)
Equal-weighted portfolios														
1.59	0.06	-1.52	-1.64	-1.60	1.73	-0.35	-2.08	-2.17	-2.39	1.44	0.47	-0.97	-0.92	-0.86
(4.86)	(0.21)	(-8.35)	(-7.02)	(-5.21)	(3.72)	(-0.90)	(-8.14)	(-9.26)	(-7.82)	(3.15)	(1.12)	(-4.03)	(-2.66)	(-2.07)

Table A2: Portfolios formed from decile-double-sorts on Past-Returns and Turnover: Comparison to MS (2022)

This appendix table reports average monthly excess returns (in percentage) at month $t+1$ for portfolios double-sorted on past returns (at month t) and turnover (month t). Excess returns are computed by subtracting 1-month Treasury yields. We also report risk-adjusted returns for long-short portfolios across quintiles relative to Fama and French's (2015) five-factor model plus the momentum factor (FF6) and Hou, Xue, and Zhang's (2015) q-factor model. We use conditional portfolios sorts, first into deciles on the NYSE breakpoints of past returns, then into deciles on turnover. Portfolios are value-weighted and rebalanced at the end of each month. We use all NYSE/AMEX/NASDAQ common stocks (share codes 10 or 11) from CRSP monthly file except that financial firms are excluded from the sample. We also exclude stocks that trade below $1 per share at month t–1. The sample period is from July 1963 to December 2020, except for the q-factors, which are available from January 1967. Newey and West (1987) heteroscedasticity and autocorrelation consistent t-statistics are reported in parentheses.

	Past return deciles										Winners-minus-Losers		
	Losers	2	3	4	5	6	7	8	9	Winners			
Turnover											μ^e	α_{FF6}	α_Q
low	1.05	0.97	0.33	0.55	0.21	0.11	0.08	0.45	-0.09	-0.63	-1.68	-1.75	-1.92
	(3.47)	(4.06)	(1.47)	(2.69)	(0.88)	(0.50)	(0.38)	(2.06)	(-0.39)	(-2.13)	(-5.36)	(-5.28)	(-4.97)
2	0.95	1.19	0.76	0.66	0.55	0.81	0.26	0.09	0.19	-0.20	-1.15	-1.16	-1.14
	(3.51)	(4.60)	(3.32)	(3.10)	(2.63)	(3.79)	(1.18)	(0.44)	(0.92)	(-0.77)	(-4.60)	(-4.45)	(-3.97)
3	1.09	0.89	0.86	0.81	0.71	0.51	0.27	0.41	0.28	-0.02	-1.12	-1.18	-1.06
	(3.86)	(3.72)	(4.06)	(3.82)	(3.82)	(2.90)	(1.46)	(2.09)	(1.40)	(-0.09)	(-4.23)	(-4.61)	(-3.42)
4	1.53	1.24	0.84	0.46	0.72	0.61	0.32	0.43	0.26	0.35	-1.18	-1.18	-1.13
	(5.10)	(5.55)	(3.96)	(2.35)	(3.85)	(3.19)	(1.65)	(2.31)	(1.30)	(1.39)	(-4.75)	(-4.25)	(-3.59)
5	0.91	0.90	0.90	0.97	0.79	0.71	0.47	0.58	0.45	0.10	-0.80	-0.96	-0.83
	(3.11)	(3.92)	(4.36)	(5.07)	(4.40)	(3.68)	(2.59)	(2.91)	(2.07)	(0.45)	(-3.25)	(-3.47)	(-2.35)
6	1.19	0.87	1.00	0.78	0.71	0.71	0.59	0.68	0.53	0.35	-0.84	-0.83	-0.70
	(3.99)	(3.36)	(4.54)	(3.74)	(3.67)	(3.54)	(3.18)	(3.25)	(2.41)	(1.36)	(-3.28)	(-2.96)	(-1.88)
7	0.92	0.80	0.88	0.66	0.62	0.67	0.54	0.69	0.64	0.66	-0.26	-0.23	-0.08
	(3.09)	(3.21)	(3.70)	(3.01)	(2.96)	(3.07)	(2.55)	(3.18)	(2.63)	(2.22)	(-0.98)	(-0.72)	(-0.22)
8	1.06	0.66	0.92	0.71	0.90	0.83	0.85	0.62	0.51	0.57	-0.49	-0.34	-0.27
	(3.30)	(2.43)	(3.50)	(2.73)	(3.73)	(3.60)	(3.66)	(2.51)	(1.92)	(1.89)	(-1.82)	(-1.14)	(-0.82)
9	0.60	0.99	0.97	0.86	0.86	0.70	0.68	0.85	0.76	0.84	0.24	0.13	0.38
	(1.75)	(3.42)	(3.46)	(3.14)	(3.26)	(2.78)	(2.42)	(3.24)	(2.87)	(2.41)	(0.90)	(0.49)	(0.95)
High	-0.09	0.72	0.94	0.91	0.55	0.44	0.90	0.94	0.71	1.06	1.15	1.16	1.53
	(-0.23)	(2.30)	(2.62)	(2.49)	(1.77)	(1.29)	(2.76)	(2.78)	(2.07)	(3.02)	(3.91)	(3.39)	(3.74)
High-Low Turnover Strategies													
μ^e	-1.14	-0.25	0.61	0.35	0.34	0.33	0.82	0.49	0.80	1.70			
	(-3.34)	(-0.92)	(2.01)	(1.04)	(1.15)	(1.05)	(2.83)	(1.58)	(2.40)	(4.68)			
α_{FF6}	-1.04	-0.16	0.55	0.23	0.39	0.44	0.72	0.54	0.98	1.87			
	(-3.28)	(-0.57)	(1.96)	(0.79)	(1.51)	(1.50)	(2.90)	(1.97)	(3.27)	(5.14)			
α_Q	-1.26	0.00	0.52	0.24	0.32	0.49	0.66	0.38	1.05	2.18			
	(-3.71)	(-0.01)	(1.66)	(0.68)	(1.10)	(1.51)	(2.36)	(1.18)	(2.72)	(4.85)			

Table A3: Portfolios formed on Past-Returns, 52-Week PTH, and Turnover: Altern. Sort

This appendix table reports on a similar empirical exercise as in Table 1, but with alternative breakpoints for the portfolio construction (in place of the quintile breakpoints in Table 1). This table reports on the average monthly excess returns (in percentage) over month $t+1$ for portfolios created by sequential percentile-based stock sorts on lagged information, as follows: first sorted into deciles based on the NYSE breakpoints of past returns over month t, then into terciles based on the price to 52-week high ratio (PTH) as of the end of month $t-1$, and finally into terciles based on turnover over month t. The remainder of the portfolio details and tabular details are the same as for Table 1.

	Past return		Strategy Performance		
	1. Losers ($\leq$ 10%)	2. Winners ($\geq$ 90%)	3. μ^e	4. α_{FF6}	5. α_Q
			(winners-losers for rows 1 & 2) (as denoted for rows 3 & 4)		
Panel A: Low Turnover Tercile					
1. Low PTH	0.94	-1.45	-2.39	-2.54	-2.45
	(2.40)	(-4.14)	(-8.48)	(-7.66)	(-6.47)
2. High PTH	1.11	0.19	-0.92	-0.95	-0.92
	(4.64)	(0.91)	(-4.39)	(-4.49)	(-3.50)
3. High PTH winners			1.63	1.35	1.38
- Low PTH winners			(5.94)	(6.08)	(4.97)
4. High PTH losers			0.17	-0.24	-0.16
- Low PTH losers			(0.60)	(-0.93)	(-0.50)
Panel B: Middle Turnover Tercile					
1. Low PTH	1.63	-1.03	-2.66	-2.68	-2.74
	(3.70)	(-3.01)	(-7.88)	(-6.43)	(-5.34)
2. High PTH	1.14	0.71	-0.43	-0.38	-0.19
	(4.61)	(2.99)	(-2.00)	(-1.69)	(-0.61)
3. High PTH winners			1.74	1.37	1.51
- Low PTH winners			(6.32)	(6.05)	(4.75)
4. High PTH losers			-0.49	-0.93	-1.04
- Low PTH losers			(-1.50)	(-3.21)	(-2.73)
Panel C: High Turnover Tercile					
1. Low PTH	0.96	-0.63	-1.58	-1.65	-1.58
	(2.00)	(-1.61)	(-4.37)	(-4.43)	(-3.67)
2. High PTH	0.53	1.46	0.94	0.87	1.16
	(1.81)	(4.44)	(3.67)	(3.32)	(3.03)
3. High PTH winners			2.09	1.66	1.99
- Low PTH winners			(5.82)	(5.13)	(4.27)
4. High PTH losers			-0.43	-0.86	-0.76
- Low PTH losers			(-1.27)	(-2.91)	(-2.32)

Table A4: Fama-MacBeth Cross-sectional Regressions on Return Predictability

This table reports the estimation results from Fama-MacBeth (1973) cross-sectional regressions on return predictability, based on winner/loser status, turnover, and the price-to-52-week-high ratio. See equations (A1), (A2), and (A3), for the full specifications. The dependent variable is a stock's return (in percentage) in month $t+1$. We define our dummy (Dm) explanatory terms based on if the stock is in Loser (Ls)/ Winner (Wn), Low-Turnover (Ltv)/ High-Turnover (Htv), and Low-PTH (Lpth)/ High-PTH (Hpth) quintiles as denoted by each dummy's superscript. In Model 2, the Ltv and Htv are defined based on 5×5 conditional double sorts (previous month's return $\times$ turnover). In Models 3 and 4, Ltv, Htv, Lpth, and Hpth are defined based on our conditional triple sorts as for Table 1. We use all NYSE/AMEX/NASDAQ common stocks (share codes 10 or 11) from CRSP monthly file except that financial firms are excluded. We also exclude stocks priced below \$1 at month t–1. In Model 4, we include a set of control variables as described in Section 3 (the ψ coefficients). The sample is over July 1963 to December 2020. Newey and West (1987) heteroscedasticity and autocorrelation consistent t-statistics are in parentheses.

	Model 1		Model 2		Model 3		Model 4	
β_0:	Inter.	1.13 (4.94)	Inter.	1.13 (4.94)	Inter.	1.13 (4.94)	Inter.	1.65 (4.51)
λ_1:	Dm^{Ls}	0.58 (5.23)	Dm^{Ls}	0.77 (6.65)	Dm^{Ls}	0.63 (5.67)	Dm^{Ls}	0.69 (6.96)
λ_2:			$Dm^{Ls\&Ltv}$	-0.29 (-2.69)	$Dm^{Ls\&Lpth\&Ltv}$	0.35 (1.65)	$Dm^{Ls\&Lpth\&Ltv}$	0.25 (1.24)
λ_3			$Dm^{Ls\&Htv}$	-0.65 (-5.89)	$Dm^{Ls\&Lpth\&Htv}$	-0.72 (-2.67)	$Dm^{Ls\&Lpth\&Htv}$	-0.78 (2.87)
λ_4:					$Dm^{Ls\&Hpth\&Ltv}$	-0.12 (-0.68)	$Dm^{Ls\&Hpth\&Ltv}$	-0.18 (1.02)
λ_5:					$Dm^{Ls\&Hpth\&Htv}$	-0.59 (-3.50)	$Dm^{Ls\&Hpth\&Htv}$	-0.63 (4.07)
γ_1:	Dm^{Wn}	-0.55 (-6.16)	Dm^{Wn}	-0.48 (-5.21)	Dm^{Wn}	-0.46 (-5.26)	Dm^{Wn}	-0.64 (8.05)
γ_2:			$Dm^{Wn\&Ltv}$	-0.61 (-4.98)	$Dm^{Wn\&Lpth\&Ltv}$	-2.00 (-10.21)	$Dm^{Wn\&Lpth\&Ltv}$	-1.92 (10.47)
γ_3:			$Dm^{Wn\&Htv}$	0.27 (1.97)	$Dm^{Wn\&Lpth\&Htv}$	-1.44 (-4.95)	$Dm^{Wn\&Lpth\&Htv}$	-1.37 (5.48)
γ_4:					$Dm^{Wn\&Hpth\&Ltv}$	0.21 (1.42)	$Dm^{Wn\&Hpth\&Ltv}$	0.24 (1.94)
γ_5:					$Dm^{Wn\&Hpth\&Htv}$	1.14 (5.89)	$Dm^{Wn\&Hpth\&Htv}$	1.13 (5.97)
ψ_1:							Size	-0.065 (1.69)
ψ_2:							BM Ratio	0.21 (2.99)
ψ_3:							COP/A	0.43 (5.11)
ψ_4:							dA/A	-0.32 (4.81)

Table A5: Alternative Fama-MacBeth Cross-sectional Specification on Return Predictability

This appendix table reports the results from estimating our alternative specification for the monthly Fama-MacBeth (1973) cross-sectional regressions on return predictability. Again, the dependent variable is a stock's return (in percentage) in month $t + 1$. The explanatory terms are the lagged returns ($Rt_{i,t}$) from month t in row 2 (in continuous form, by themselves without conditional interactive terms) and the lagged returns interacted with different dummy variables indicating high or low PTH status and/or high or low turnover in rows 3 through 6. We define our dummy (D) explanatory terms based on if the stock is in Low-Turnover (Ltv)/ High-Turnover (Htv), or Low-PTH (Lpth)/ High-PTH (Hpth) quintiles as denoted by each dummy's superscript; using the same quintile sorts to create these dummy variables as defined in Table A4. We also include the conditional dummy variables as stand-alone explanatory terms in rows 7 to 10. Model 4 includes other control variables in rows 11 through 14. See equations A4 and A5 for the detailed specification. The sample is over July 1963 to December 2020. The λ_1 through λ_5 coefficient values in the table below are scaled up by 100 for easy of presentation. Other data construction, methods, and tabular details are as defined for Table A4.

Model 1		Model 2		Model 3		Model 4	
1. β_o Inter.	1.15 (4.54)	Inter.	1.26 (5.06)	Inter.	1.20 (4.82)	Inter.	1.80 (4.65)
2. λ_1x100: $Rt_{i,t}$	-3.68 (-8.55)	$Rt_{i,t}$	-4.49 (-8.95)	$Rt_{i,t}$	-3.50 (-7.62)	$Rt_{i,t}$	-4.42 (-9.38)
3. λ_2x100:		$Rt_{i,t}\, D^{Ltv}$	-2.35 (-5.81)	$Rt_{i,t}\, D^{Lpth\&Ltv}$	-8.28 (-10.51)	$Rt_{i,t}\, D^{Lpth\&Ltv}$	-7.72 (-9.80)
4. λ_3x100:		$Rt_{i,t}\, D^{Htv}$	3.26 (7.17)	$Rt_{i,t}\, D^{Lpth\&Htv}$	-0.63 (-0.98)	$Rt_{i,t}\, D^{Lpth\&Htv}$	0.18 (0.29)
5. λ_4x100:				$Rt_{i,t}\, D^{Hpth\&Ltv}$	-0.21 (-0.32)	$Rt_{i,t}\, D^{Hpth\&Ltv}$	-0.17 (-0.24)
6. λ_5x100:				$Rt_{i,t}\, D^{Hpth\&Htv}$	5.06 (8.18)	$Rt_{i,t}\, Dm^{Hpth\&Htv}$	5.24 (8.32)
7. λ_6:		D^{Ltv}	-0.42 (-4.59)	$D^{Lpth\&Ltv}$	-0.78 (-4.90)	$D^{Lpth\&Ltv}$	-0.95 (-7.95)
8. λ_7:		D^{Htv}	-0.14 (-1.27)	$D^{Lpth\&Htv}$	-0.90 (-4.43)	$D^{Lpth\&Htv}$	-0.83 (-4.59)
9. λ_8:				$D^{Hpth\&Ltv}$	-0.02 (-0.18)	$D^{Hpth\&Ltv}$	0.03 (0.25)
10. λ_9: .				$D^{Hpth\&Htv}$	0.24 (1.71)	$D^{Hpth\&Ltv}$	0.25 (2.05)
11. λ_{10}:						Size	-0.08 (-2.16)
12. λ_{11}:						BM Ratio	0.21 (3.05)
13. λ_{12}:						COP/A	0.44 (5.19)
14. λ_{13}:						dA/A	-0.31 (-4.68)