Short-Term Moving Average Distance and the Cross-Section of Stock Returns

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Abstract
In this study, we propose a new predictor of stock returns based on the distance between the end-of-month price and past 10-day moving average, which we term short-term moving-average distance (SMAD). Our measure is motivated by the recency bias and the belief-adjustment model that decision makers are prone to the recency bias in updating their beliefs. While extreme short-term prices are salient to investors, they tend to overreact to the information embedded in SMAD, resulting in a negative return predictability. We empirically confirm this prediction. We next show that the return predictability of SMAD is stronger among stocks with higher salient payoffs, thus providing the supportive evidence for the salience theory in explaining the SMAD premium. Finally, we show that an advantage of SMAD is its effectiveness in predicting the return premia of ten mispricing anomalies.

JEL Classification: G11; G12; G14
Keywords: Moving averages; Recency bias; Return predictability; Anchoring bias

1. Introduction

Technical analysis, with its effectiveness often been viewed as violation of the weak-form market efficiency, has recently become one of the important issues that attracts substantial attention from academic researchers. Unlike Lo and MacKinlay (1988) who propose that prices follow random walks because they aggregate all publicly available information, Brock, LeBaron, and Lakonishok (1992), Lo, Mamaysky, and Wang (2000), Han, Yang, and Zhou (2013), and Neely, Rapach, Tu, and Zhou (2014) all verify that technical trading rules provide useful information in forecasting future stock returns and equity risk premium.

By exploring a broad set of moving averages calculated on the basis of historical prices, Han, Zhou, and Zhu (2016) develop a trend factor to incorporate simultaneously the information embedded in short-, intermediate-, and long-term prices on the moving averages. Avramov, Kaplanski, and Subrahmanyam (2021), by contrast, focus exclusively on the distance between moving averages of prices in short (21 days) and long terms (200 days), which is termed long-term moving-average distance (LMAD), in explaining the cross-section of stock returns. They attribute the explanatory power of LMAD to investors' underreaction to news because their trading decisions are anchored by the long-term moving average of the stock.

The empirical evidence of Han, Zhou, and Zhu (2016) and Avramov, Kaplanski, and Subrahmanyam (2021) motivates us to examine the possibility of incorporating short-term moving-average prices to construct a predictor of stock returns. We consider short-term moving-average prices because Tversky and Kahneman's (1973) theory of recency bias and Hogarth and Einhorn's (1992) belief-adjustment model suggest that decision makers are prone to the recency bias in updating their beliefs.[1] This leads us in hypothesizing that short-term

[1] Supportive evidence for the recency bias and the belief-adjustment model includes Ashton and Ashton (1988), Tubbs, Messier Jr., and Knechel (1990), Pei, Reckers, and Wyndelts (1990), Bamber, Ramsay, and Tubbs (1997) in

moving-average price could be a recent anchor to investors when making trading decisions. Specifically, we propose a measure based on the distance between one-day price and 10-day moving average of price at the end of the month, which we term short-term moving-average distance (SMAD), and we hypothesize that SMAD shall negatively predict future stock returns.

Why is SMAD negatively correlated with future stock returns? When making investment decisions, the recency effect implies that information embedded in recent short-term prices is the most salient to investors (Nofsinger and Varma, 2013). Hence, when the end-of-month price substantially exceeds (falls below) past 10-day moving average, the stock is positioned in an upward (downward) trend, causing such short-term moving-average signal to be salient to investors. If this upward (downward) trend reflects investors' overreaction to positive (negative) information in the short term, the stock is overvalued (undervalued) as predicted by Bordalo, Gennaioli, and Shleifer's (2012, 2013, 2021) salience theory. As a result, subsequent reversals reveal to reflect price corrections of these overvalued (undervalued) stocks.

Confirming our conjecture, we empirically show that a trading strategy of buying stocks with the highest values of SMAD and show selling those with the lowest values of SMAD generates significantly negative returns under both equal and value weights. By contrasting the relative power between SMAD and LMAD for future stock returns, we find that the negative return predictability of SMAD and the positive return predictability of LMAD coexist in the U.S. markets when penny stocks are excluded. When penny stocks are included, LMAD largely loses its explanatory power for stock returns, especially under value weights and risk adjustments. The explanatory power of SMAD, instead, remains consistently significant regardless of the weighting scheme and/or risk adjustments.

the auditing context and Nofsinger and Varma (2013) and Chakrabarty, Moulton, and Trzcinka (2017) for trading behavior of retail and institutional investors.

We confirm the robustness of the significantly negative SMAD premium in several aspects. First, SMAD remains effective in explaining stock returns when it is constructed based on alternative anchors of 5- and 20-day moving averages, indicating that our results are not limited to a specific short-term anchor. Second, the negative relation between SMAD and stock returns is significant in the Fama-MacBeth (1973) cross-sectional regressions that control LMAD, a variety of firm characteristics, and mispricing proxies, indicating that the negative SMAD premium is unlikely to be subsumed by other determinants of stock returns. Finally, the negative SMAD premium remains significant following both high and low sentiment periods, suggesting that its profitability is not caused by sentiment-driven traders.

In our study, the return predictability of SMAD is built on the assumption that the short-term moving-average price represents an anchor to investors and that information embedded in recent short-term prices is the most salient to investors as implied by the recency effect. If our argument is true, the SMAD premium should be stronger among stocks whose prices are the most salient to investors. To this end, we apply Cosemans and Frehen's (2021) approach to empirically construct the salience measure that is based on Bordalo, Gennaioli, and Shleifer's (2012, 2013) concept. We show that the negative SMAD premium is significantly stronger among stocks with higher magnitude of salient payoffs than those with lower magnitude of salient payoffs. Our result is in support of the salience theory as a plausible explanation for the return predictability of SMAD.

Existing studies have examined the effectiveness of employing moving-average signals in forecasting future stock returns and equity risk premium, and Han, Huang, Zhou (2021) further demonstrate the value of moving-average signals when stock returns are mispriced. They show that considering the difference between 50- and 200-day moving-averages monthly is beneficial to enhance the profits of eight accounting-based asset pricing anomalies. While an extreme value of SMAD signifies a large price divergence in the short term, the magnitude of mispricing would be substantially enhanced in such situation, further leading to higher return premia of the mispricing anomalies. To explore our conjecture, we apply the SMAD measure to form enhanced long and short positions for ten mispricing anomalies. Specifically, the enhanced long (short) position is constructed by buying (short selling) stocks that are the most undervalued (overvalued) as predicted by each anomaly that have the lowest (highest) SMAD values simultaneously. We show that the ten anomaly returns are all significantly higher when SMAD signals are taken into consideration, with remarkably higher returns for all long positions and remarkably lower returns for most of the short positions. This finding indicates that SMAD is useful in predicting not only future stock returns but also mispricing anomalies.

The remaining of this paper is organized as follows. We provide literature review and hypothesis development in Section 2. Section 3 describes the constructions of variables and data. We present the empirical results in Section 4, and the last section concludes.

2. Literature review and hypothesis development

According to the efficient market hypothesis, prices are assumed to follow random walks because current price shall have reflected all publicly available information (Lo and MacKinlay, 1988). Brock, LeBaron, and Lakonishok (1992) and Lo, Mamaysky, and Wang (2000) develop the foundations of technical analysis and show that technical trading rules are applicable to practitioners. In recent studies, Han, Yang, and Zhou (2013) and Neely, Rapach, Tu, and Zhou (2014) show that technical trading rules based on moving-average signals predict future stock returns and equity risk premium.

Han, Zhou, and Zhu (2016) construct a trend factor by incorporating multiple price signals based on the moving averages of past prices ranging from three to 1,000 days. This factor, by its construction, contains information associated with short-term reversals, intermediate-term momentum, and long-term reversals in stock returns. In Han, Zhou, and Zhu's (2016) study, they use the closing price on the last trading day of the month as normalization for each moving averages, and they claim that the purpose of this normalization is to make moving average signals stationary. In other words, Han, Zhou, and Zhu (2016) do not particular focus on any trading signal implied by the relative strength between different lengths of moving averages.

Avramov, Kaplanski, and Subrahmanyam (2021) develop the moving-average distance as the ratio of short- to long-term moving averages based on 21- and 200-day average prices, denoted as LMAD, and they show that stocks with higher LMADs outperform those with lower LMADs. They propose that the predictive power of LMAD is induced because investors use past 200-day moving average as an anchor when making investment decisions. Furthermore, they show that the return predictability of LMAD persists up to one year, and that LMAD provides better predictive power than price momentum, the 52-week high, profitability, and several prominent predictors of stock returns.

While the technical trading rule based on the relative strength between short- and long-term moving-average prices is investigated in Avramov, Kaplanski, and Subrahmanyam (2021), our proposed measure of SMAD, which is based on very short-term moving-average prices, is expected to provide information that is distinct from that embedded in LMAD. Motivated by Tversky and Kahneman's (1973) theory of recency bias and Hogarth and Einhorn's (1992) belief-adjustment model that decision makers are prone to the recency bias in updating their beliefs, we propose that short-term moving-average price serve as a recent anchor to investors when making trading decisions. SMAD thus reflects investors' perception of information when they are anchored by the short-term price that occurs recently.

Nofsinger and Varma (2013) propose that according to the recency effect, the information embedded in recent short-term prices is the most salient to investors when making investment decisions. In particular, when SMAD is extremely high (low), the stock price is in a steeply upward (downward) trend in the short term, causing investors pay more attention to this salient and recent price pattern. When short-term traders' attention is drawn to higher (lower) SMAD, they might be overconfident with the information, resulting in overreaction behavior. We thus expect subsequent reversals to occur for stocks with both extremely higher and lower SMADs, reflecting the price corrections to the overreaction phenomenon.

The above discussions lead to the following hypothesis regarding the predictive ability of SMAD on the cross-sectional variations of stock returns:

Hypothesis 1: Stocks with higher values of SMAD tend to underperform those with lower values of SMAD.

3. Construction of variables and data

In this study, we mainly examine two technical trading signals based on different lengths of moving-average prices. The first measure, which is the main variable proposed in our study, is designed to capture the very short-term information embedded in short-term moving averages. At the beginning of each moth t, we calculate a stock's short-term moving-average price, denoted as $MA(10)$, based on past 10 days ending in month $t-1$. Here we use 10 days to differentiate from the short-term moving average price used in LMAD. We define the short-term technical trading signal, SMAD, as $\frac{P_{t-1}}{MA(10)_{t-1}}$, where P_{t-1} is the closing price of the last trading day in month $t-1$. In further investigations, we will consider alternative lengths of 5 and 20 days to compute short-term moving averages to verify the robustness of our results.

Our second measure of technical trading signal, the distance between moving averages of prices in short and long terms (denoted as LMAD), is proposed by Avramov, Kaplanski, and Subrahmanyam (2021). At the beginning of each moth t, we calculate a stock's short-term moving-average price, denoted as $MA(21)$, based on past 21 days ending in month $t-1$ and its long-term moving-average price, denoted as $MA(200)$, based on past 200 days ending in month $t-1$. LMAD in month t is then defined as $\frac{MA(21)_{t-1}}{MA(200)_{t-1}}$. Here the stock prices are adjusted for splits and dividend distributions.

By its construction, LMAD measures the relative strength of price information contained in recent period compared with the information contained in a prolonged period by using the 200-day average price as a psychological anchor. Our proposed variable of SMAD, however, measures the relative strength of the most recent price shock compared with the short-term price information. Avramov, Kaplanski, and Subrahmanyam (2021) claim that LMAD captures the degree of investor underreaction to information, while we propose that SMAD captures the degree of investor overreaction to information.

In addition to SMAD and LMAD, we also include several firm characteristics and mispricing proxies. We include firm size (SIZE), past-month return (REV), and maximum daily return (MAX) as controls to ensure that the return predictability of SMAD is not induced by the size, short-term reversal, or lottery effects. Following Fama and French (1992, 1993) and the vast literature, for each July of year Y to June of year Y+1, SIZE is defined as the value of a stock's market capitalization at the end of June in year Y. For each month t, REV is defined as a stock's monthly return in month $t-1$. Finally, following Bali, Cakici, and Whitelaw (2011), for each month t we compute MAX as $Max\{r_{i,d}\}$, in which $r_{i,d}$ is stock i's return on day d within month $t-1$.

To measure the magnitude of mispricing, we follow Stambaugh, Yu, and Yuan (2012) and Chu, Hirshleifer, and Ma (2020) to consider ten mispricing anomalies. To be consistent with the literature, we define and construct the above variables in the same way as in the corresponding initial studies. We list these anomalies, along with the major initial studies and corresponding definitions as follows:

- Momentum (Jegadeesh and Titman, 1993): We calculate a stock's cumulative return from months $t-11$ to $t-2$ as past return performance to capture its momentum effect.
- Gross profitability (Novy-Marx, 2013): For each July of year Y to June of year $Y+1$, a stock's gross profitability is measured as the ratio of its total revenue minus cost of goods sold to total assets at the end of fiscal year Y.
- Asset growth (Cooper, Gulen, and Schill, 2008): For each July of year Y to June of year $Y+1$, a stock's asset growth is measured as the annual change in total assets divided by lagged total assets at the end of fiscal year Y.
- Investment-to-assets (Titman, Wei, and Xie, 2004): For each July of year Y to June of year $Y+1$, a stock's investment-to-assets is measured as the annual change in gross property, plant, and equipment plus the annual change in inventories, divided by lagged total assets at the end of fiscal year Y.
- Return on assets (ROA) (Fama and French, 2006): For each quarter, a stock's return on assets is measured as its quarterly earnings scaled by quarterly total assets in the previous quarter.
- Net operating assets (Hirshleifer, Hou, Teoh, and Zhang, 2004): For each July of year Y to June of year $Y+1$, a stock's net operating assets is measured as the difference between all operating assets and all operating liabilities on the balance sheet, scaled by lagged total assets at the end of fiscal year Y.

- Accruals (Sloan, 1996): For each July of year *Y* to June of year *Y*+1, we measure a stock's accruals as the change in noncash working capital minus depreciation expense, scaled by lagged total assets at the end of fiscal year *Y*.
- Net stock issues (Ritter, 1991; Loughran and Ritter, 1995): We measure a stock's net stock issues on an annual basis, which is calculated as the change in the natural logarithm of the stock's adjusted shares over the last year.
- Composite equity issues (Daniel and Titman, 2006): For each July of year *Y* to June of year *Y*+1, we follow Daniel and Titman (2006) by using the COMPUSTAT data to compute a stock's log difference between its market value of equity minus the log difference between its share price at the end of fiscal year *Y*.
- Bankruptcy probability measured by O-score (Ohlson, 1980): For each July of year *Y* to June of year *Y*+1, we follow Ohlson's (1980) procedure to calculate the probability of bankruptcy in a static model using accounting variables at the end of fiscal year *Y*.

Our sample consists of the ordinary common stocks of all firms (with share codes of 10 and 11) listed on NYSE, AMEX, and NASDAQ for the period from July 1964 to December 2021. We obtain market data, including daily and monthly returns and share prices, from the Center for Research in Security Prices database. We retrieve accounting data from the Compustat database. A stock must have sufficient market and accounting data to be included in the final sample. Following Avramov, Kaplanski, and Subrahmanyam (2021), we exclude penny stocks whose ending price in the previous month fall below $5 to make our results comparable to their results.[2]

4. Empirical analyses

[2] In follow-up analyses, we show that the SMAD premium is robust to the inclusion of penny stocks while the LMAD premium is largely attenuated without this price filter.

4.1. Portfolio returns formed by long- and short-term moving-average signals

We first apply portfolio-based analyses to observe exactly how profitable investors can benefit from using SMAD and LMAD to form their trading strategies. At the beginning of each month *t*, we allocate individual stocks into decile portfolios according to their vales of SMAD (or LMAD) calculated at the end of month $t-1$. We next calculate equally- and value-weighted returns for each decile portfolio for month *t*. We then define the SMAD (LMAD) premium as the difference between highest and lowest decile portfolios classified by SMAD (LMAD). Avramov, Kaplanski, and Subrahmanyam (2021) have demonstrated significantly positive LMAD premium, and our **Hypothesis 1** predicts that the SMAD premium is significantly negative.

Panel A of Table 1 reports the average raw returns for decile portfolios formed on SMAD. Consistent with **Hypotheses 1**, we show that the return differences between the highest and lowest SMAD deciles are significantly negative at -2.230% and -1.287% per month with corresponding *t*-statistics of -13.11 and -6.95 under equal and value weights, respectively. It should be noted that the average returns of SMAD deciles decrease monotonically, and that the highest SMAD decile has an average monthly returns of -0.424% and 0.021% under equal and value weights. This evidence suggests that stocks whose most recent prices substantially exceed past 10-day moving average prices are overpriced while those with the lowest SMAD values are underpriced, resulting in an overall negative SMAD premium.

In Panel B, we verify the existence of the LMAD premium. The average LMAD premia are 1.378% and 1.106% per month with corresponding *t*-statistics of 5.87 and 3,79 when portfolios are constructed based on equal and value weights, a finding that is consistent with Avramov, Kaplanski, and Subrahmanyam's (2021) evidence of significant LMAD premium. However, the LMAD premium is less robust while the SMAD premium is enhanced when the $5 price filter is moved. As presented in Panel C, the SMAD premia with penny stocks included are higher and more significant compared with the numbers reported in Panel A. The LMAD premium under equal weight, as presented in Panel D, becomes insignificant at 0.161% when penny stocks are included, whereas the value-weighted LMAD premium remains significant and quantitatively similar to the number reported in Panel B. The findings indicate that the return predictability of LMAD seems to be substantially attenuated by extremely low-priced stocks, and that the return predictability of SMAD is pervasively existent among the universe of listed common stocks.

[Insert Table 1 here]

4.2. Abnormal returns

We next examine the abnormal risk premia for SMAD and LMAD using various factor models. The factor models considered in this study include Fama and French's (2015) five-factor model, an augmented six-factor model that augments Fama and French's (2015) five factors with the momentum factor, Hou, Xue, and Zhang's (2015) Q4-factor model, and Hou, Mo, Xue, and Zhang's (2021) Q5-factor model.[3] We regress the time-series of SMAD or LMAD premia on each set of factor models and obtain the intercepts from the regressions as the abnormal returns.

We report the abnormal returns in Table 2. For the SMAD strategy presented in Panel A, its abnormal returns are all significantly negative at the 1% significance level, regardless of the weighting scheme and factor models used. This evidence suggests that the SMAD premia are less likely to be induced by the exposure to factor risks. For the LMAD strategy presented in Panel B, it has significantly positive abnormal returns in four (two) out of the six factor models for portfolio returns calculated using equal (value) weights. In particular, the Q5 and DHS

[3] We obtain the data on Fama and French's (2015) five factors and the momentum factor from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. We also obtain Q4 and Q5 factors from Lu Zhang's website: http://global-q.org/factors.html.

models can fully explain the LMAD premia computed using either equal or value weights. Hence, the LMAD premia are less robust to the control of risk factor models.

[Insert Table 2 here]

We next include penny stocks in the constructions of SMAD and LMAD premia, and report their abnormal returns in Panels C and D. Again, we obtain significantly negative abnormal returns for the SMAD strategy. For the LMAD strategy, we only observe significantly positive abnormal returns for both equal and value schemes under the liquidity-augmented six-factor model. Overall, our results from Table 2 reveal that the SMAD premia are unexplained by the six sets of factor models, while the LMAD premia are more likely to be attributed to risk exposures.

4.3. Robustness based on alternative lengths of short-term moving averages

So far, our SMAD signal is constructed based on the 10-day moving average as a short-term price anchor, but we are unaware of exactly how short-term traders set up the anchor. To ensure the robustness of SMAD in predicting stock returns, we construct SMAD in an alternative way by using 5- or 20-day moving averages as the potential anchor. That is, we define SMAD as $\frac{P_{t-1}}{MA(5)_{t-1}}$ or $\frac{P_{t-1}}{MA(20)_{t-1}}$ for each month t. We next form decile portfolios using the two alternative measures and observe their return predictability.

As presented in Table 3, we show that the SMAD premia are all negative at the 1% significance level using the two alternative measures, and that the abnormal returns are also significant in all model specifications. It should be noted that the SMAD premia are enhanced when the 5-day moving average is used and are slightly weakened when the 20-day moving average is used. This observation suggests that the price correction is more pronounced when investors overreact more to the very short-term price information. It is also consistent with our conjecture that investors tend to use more recent short-term prices as an anchor to make investment decisions.

[Insert Table 3 here]

4.4. Cross-sectional regressions

We next apply the Fama-MacBeth cross-sectional regressions to control for a variety of variables that have been documented to explain stock returns. More importantly, the cross-sectional regressions enable us to compare the relative power of SMAD and LMAD simultaneously. The regression takes the following form:

$$R_{i,t} = \alpha_0 + \alpha_1 SMAD_{i,t-1} + \alpha_2 LMAD_{i,t-1} + \sum_{l=1}^{L} \beta_l X_{i,l,t-1} + \varepsilon_{i,t}, \quad (1)$$

where $R_{i,t}$ is stock i's return in month t; $SMAD_{i,t-1}$ and $LMAD_{i,t-1}$ are short- and long-term moving average signals as defined in Section 2; $X_{i,l,t-1}$ is stock i's lth control variable identified at the end of month $t-1$. We include SIZE, REV, MAX as the control variables for the basic model. We test the time-series averages of the monthly estimated coefficients from the Fama-MacBeth (1973) cross-sectional regressions using t-statistics calculated with Newey and West's (1987) robust standard errors. Our **Hypothesis 1** predicts a significantly negative coefficient of α_1, while a significantly positive coefficient of α_2 is predicted by Avramov, Kaplanski, and Subrahmanyam (2021).

Table 4 reports the estimation results of cross-sectional regressions. In Panel A where penny stocks are excluded, we show that SMAD always exhibits significantly negative coefficients while LMAD always exhibits significantly positive coefficients regardless of the inclusion of control variables. When included in the regressions simultaneously, the coefficients of SMAD have remarkably larger t-statistics compared with the coefficients of LMAD, a finding that provides a potential support for the superior explanatory ability of SMAD over LMAD on stock returns.

In Panel B, we exclude penny stocks from the sample. We show that the SMAD coefficients still remain negative with significance, while the LMAD coefficients are insignificant when included as the sole explanatory variable or included together with SMAD. The significance of the LMAD coefficient appears when control variables are incorporated.

[Insert Table 4 here]

Next, we examine whether the explanatory ability of SMAD is robust to the consideration of the mispricing anomalies. To this end, we include the ten mispricing variables described in Section 3 in the cross-sectional regressions as follows:

$$R_{i,t} = \alpha_0 + \alpha_1 SMAD_{i,t-1} + \alpha_2 LMAD_{i,t-1} + \sum_{l=1}^{L} \beta_l X_{i,l,t-1} + \sum_{k=1}^{K} \gamma_k Mis_{i,k,t-1} + \varepsilon_{i,t}, \tag{2}$$

Where $Mis_{i,k,t-1}$ is stock i's kth mispricing variable identified at the end of month $t-1$. In Table 5, we provide ten specifications from Models (1) to (10) by including each of the ten mispricing variables in the regressions and a complete specification of Model (11) that incorporates all variables in one regression simultaneously. In Panel A where penny stocks are excluded, we show that the coefficients of SMAD and LMAD are significantly negative and positive in Models (1) to (10). When all variables are included in Model (11), the significance of the LMAD coefficient disappears while SMAD remains powerful in explaining stock returns.

When penny stocks are included, as shown in Panel B, we obtain consistently negative coefficients of SMAD and slightly weaker positive relation between LMAD and stock returns compared with Panel A. Overall, our results from Tables 4 and 5 suggest that SMAD has stronger explanatory ability for the cross-sectional variations of stock returns compared with

LMAD, and that the SMAD effect cannot be explained by the pricing ability of various firm characteristics or mispricing.

[Insert Table 5 here]

4.5. Investor sentiment

By analyzing the impact of investor sentiment on the performance of 22 technical indicators, Feng, Wang, and Zychowicz (2017) show that the effectiveness of technical indicators in predicting future returns is stronger when investor sentiment is high, and that this sentiment effect is more pronounced among small stocks. Feng, Wang, and Zychowicz's (2017) study motivates us to examine whether the SMAD premium is related to investor sentiment. A major difference between our study and Feng, Wang, and Zychowicz (2017) is that we analyze individual stocks while their analyses focus on technical indicators at the index level. We follow the majority of prior studies, including Feng, Wang, and Zychowicz (2017), by employing Baker and Wurgler's (2006, 2007) sentiment index (denoted as BW index) for the period from July 1965 to December 2021.[4] For a given month *t*, we define it as high sentiment if the BW index in month $t-1$ is higher than the median of the sample period; otherwise month *t* is classified as low sentiment. In Table 6, we report raw and abnormal returns of the value-weighted SMAD strategy separately for periods of high and low sentiment, respectively.

Table 6 clearly shows that the negative raw and abnormal SMAD premia are indistinguishable between periods of high and low sentiment. In particular, the raw SMAD premia are -1.330% and -1.244%, respectively, for high and low sentiment periods, resulting in an insignificant difference of -0.087% with a *t*-statistic of -0.22. The differences in abnormal

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[4] We obtain the sentiment index from Jeffrey Wurgler's website: http://pages.stern.nyu.edu/~jwurgler/. We use the first principal component of six sentiment proxies that is orthogonalized to a set of business cycle variables.

returns between high and low sentiment periods are mostly insignificant across factor models, with the only exception of the DHS model, which has a marginally significant difference of -0.674% with a *t*-statistic of -1.65. Overall, the significance of the SMAD premia following both high and low sentiment periods suggests that the profitability of the SMAD strategy is less likely to be caused by sentiment-driven traders.

[Insert Table 6 here]

4.6. Explanation based on the salience theory

In this study, we propose that the return predictability of SMAD is induced because short-term moving-average price represents an anchor to investors. As predicted by the recency effect, information embedded in recent short-term prices is the most salient to investors. This implies that the SMAD premium should be stronger among stocks whose prices are the most salient to investors. Hence, it is important to examine whether the salience theory explains the SMAD effect. The salience theory is proposed by Bordalo et al. (2012, 2013), who develop a theoretical framework to characterize investors' attention drawn to stocks with salient upside (downside) payoffs relative to their benchmarks. Cosemans and Frehen (2021) further develop the empirical measure of salience payoffs, denoted as ST, which negatively predicts future returns with statistical significance. We thus follow Cosemans and Frehen's (2021) approach to construct ST and apply this measure to explain our results.

We construct the ST measure in the following way. First, while the salience of a stock's payoff on day d ($r_{i,d}$) depends on its distance from the benchmark, the salience of the daily payoff is defined as:

$$\sigma\left(r_{i,d}-\overline{r}_d\right)=\frac{\left|r_{i,d}-\overline{r}_d\right|}{\left|r_{i,d}\right|+\left|\overline{r}_d\right|+\theta}, \tag{3}$$

where $\bar{r}_d$ is the average payoff of the market on day *d*. Here we follow Cosemans and Frehen (2021) by using equal weights to calculate the benchmark returns. Based on Bordalo et al.'s (2012) calibration, Cosemans and Frehen (2021) set $\theta = 1$ to match experimental evidence on long-shot lotteries.

The next step is to sort each stock's daily payoffs $r_{i,d}$ within the previous month, and then assign ranks $k_{i,d}$, ranging from 1 for the most salient to *D* for the least salient, in which *D* is the number of trading days in the previous month. Each payoff $r_{i,d}$ may occur with an equal probability π_d, i.e., $\pi_d = 1/d$. We next define the salience weight as:

$$\omega_{i,d} = \frac{\delta^{k_{i,d}}}{\sum_{d'} \delta^{k_{i,d'}} \times \pi_{d'}}, \tag{4}$$

where parameter δ captures the degree to which salience distorts decision weights and proxies for the decision-maker's cognitive ability. We follow Cosemans and Frehen (2021) by setting $\delta = 0.7$ based on Bordalo et al.'s (2012) calibration.

Once $\omega_{i,d}$ is obtained, we define the ST measure as $ST_{i,t-1} = Cov\left[\omega_{i,d}, r_{i,d}\right]$ for each individual stock *i*, which is again estimated using daily observations in month *t*–1. This ST measure thus captures the salience of the stock's past returns distributions. To examine the salience explanation for the SMAD premium, we adopt a double-sorting procedure based on the values of SMAD and the ST measures. We first sort individual stocks into deciles based on their SMAD values. Within each decile, we sort individual stocks into quintiles according to their values of the ST measure. We next calculate the return premia using value weights between the highest and lowest deciles for each of the five ST subgroups. If the salience theory explains the SMAD premium, the negative SMAD premium should be more pronounced in high ST groups than in low ST groups.

We show in Table 7 that the negative SMAD premium is the strongest in the highest ST quintile than in other ST quintiles. Specifically, the SMAD premia are -1.167%, -1.385%, -1.344%, -1.345%, and -1.938% for the lowest to highest ST quintiles. The difference in the SMAD premia between the highest and lowest ST quintiles is significant at -0.770% with a *t*-statistic of -2.37. This return pattern is robust to most factor models as the differences in abnormal returns between the highest and lowest ST quintiles are all negative in the six model specifications, with four out of them being significant. Overall, our results confirm that the saliency theory accounts for the return predictability of SMAD.

[Insert Table 7 here]

4.7. SMAD signals and mispricing anomalies

The final task of this study is to examine whether applying SMAD signals to the mispricing anomalies could enhance the profits of these anomalies. This analysis is motivated by Han, Huang, Zhou (2021), who demonstrate the value of moving-average signals by using the difference between 50- and 200-day moving-averages to enhance the profits of eight accounting-based asset pricing anomalies. Here we consider the ten mispricing anomalies mentioned in Section 3.

We first construct the standard mispricing strategies by sorting individual stocks into decile portfolios according to their values of each mispricing variable. We buy the decile portfolio that contains containing the most undervalued stocks and short sell the decile portfolio containing the most overvalued stocks. For momentum, gross profitability, and return on assets anomalies, the long position is the highest decile and the short position is the lowest decile. For asset growth, investment-to-assets, net operating assets, accruals, net stock issues, composite equity issues, and O-score anomalies, the long position is the lowest decile and the short position is the highest decile. For each anomaly, we calculate the difference in value-weighted returns between the most undervalued and overvalued decile as its return premium. We use this premium as the benchmark to examine whether the consideration of the SMAD signal leads to significantly higher return premium.

To examine the effectiveness of SMAD, we construct the enhanced anomalies based on the following procedures. We first allocate individual stocks into quintiles according to their values of each mispricing variables. Within each mispricing quintiles, we further allocate individual stocks into quintiles according to their values of SMAD. As stocks with high (low) SMAD are likely to be over- (under-)valued in the short term, the magnitude of mispricing would be enhanced if over- (under-)valued stocks identified by the mispricing variable are in a short-term down- (up-)ward trend. Hence, we construct long position of the enhanced mispricing anomaly by buying stocks classified as the most undervalued stocks that are allocated in the lowest SMAD quintile simultaneously. The short position of the enhanced mispricing anomaly thus involves short selling stocks classified as the most overvalued stocks that are allocated in the highest SMAD quintile simultaneously. We calculate value-weighted returns for both long and short positions of the enhanced mispricing anomaly and obtain the difference as the return premium of the enhanced mispricing anomaly.

In Table 8, we report the average returns of enhanced and standard mispricing anomalies, as well as their differences. The average premia of the ten enhanced mispricing anomalies are all significantly positive with *t*-statistics greater than 3 under the critique of Harvey, Liu, and Zhu (2016). The differences between enhanced and standard mispricing anomalies are also significantly positive with *t*-statistics greater than 3 for all of the ten anomalies. This finding confirms our conjecture that incorporating SMAD signals in the mispricing anomalies is beneficial to enhance their profits.

[Insert Table 8 here]

In Table 8, we also report the returns of long and short positions for the standard and enhanced anomalies. Then differences in returns between the enhanced and standard long positions are significantly positive for all of the ten anomalies, and only the accruals anomaly fails to exhibit significance at the 1% level. For the enhanced and standard short positions, only the asset growth anomaly fails to exhibit significant difference. Hence, the effectiveness of SMAD signals in enhancing the profits of the mispricing anomalies is overall existent for under- and over-valued stocks.

We next examine whether LMAD signals are useful to enhance the mispricing by repeating a similar procedure to construct LMAD-enhanced mispricing anomalies. That is, we construct long position of the enhanced mispricing anomaly by buying stocks classified as the most undervalued stocks that are allocated in the highest LMAD quintile simultaneously. The short position of the enhanced mispricing anomaly short sells stocks classified as the most overvalued stocks that are allocated in the lowest LMAD quintile simultaneously. We show in Table 9 that two (investment-to-assets and accruals) out of the ten mispricing anomalies exhibit significantly positive difference between LMAD-enhanced and standard mispricing anomalies. In addition, only four (two) long (short) positions exhibit significantly positive (negative) differences in returns between LMAD-enhanced and standard mispricing anomalies. Overall, our findings suggest that one advantage of our SMAD measure over Avramov, Kaplanski, and Subrahmanyam's (2021) LMAD measure is that it better differentiates the return performance of highly mispriced stocks.

[Insert Table 9 here]

5. Conclusions

Motivated by the recency effect that information embedded in recent short-term prices is the most salient to investors, we propose that short-term moving-average prices is an anchor that affects investors' trading decisions. We accordingly propose the SMAD measure based on the distance between one-day price and 10-day moving average of price at the end of the month, and we demonstrate a significantly negative relation between SMAD and future stock returns. More importantly, this negative SMAD premium is robust to various controls and is unrelated to investor sentiment. We further show that the saliency theory provides a plausible explanation for the SMAD premium, consistent with our main argument that information embedded in recent short-term prices is the most salient to investors. Finally, we show that one advantage of SMAD is to substantially enhance the profits of mispricing anomalies. Overall, our study provides important implications to the literature on asset pricing and technical analyses.

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Table 1: Returns of portfolios formed on moving-average indicators

This table reports the average monthly returns of portfolios formed on moving-average indicators. Our sample consists of the ordinary common stocks of all firms listed on NYSE, AMEX, and NASDAQ for the period from July 1964 to December 2021. At the beginning of each month *t*, we allocate individual stocks into decile portfolios according to their vales of SMAD (or LMAD) calculated at the end of month *t*−1. We next calculate equally- and value-weighted returns for each decile portfolio for month *t*. We then define the SMAD (LMAD) premium as the difference between highest and lowest decile portfolios classified by SMAD (LMAD). We calculate the time-series average of returns for each decile and the long-short position. In Panels A and B, we exclude penny stocks whose ending price in the previous month fall below $5 to form the decile portfolios according to the vales of SMAD and LMAD, respectively. In Panels C and D, we include penny stocks and form the decile portfolios according to the vales of SMAD and LMAD, respectively. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Low	2	3	4	5	6	7	8	9	High	High−Low
Panel A: Portfolios formed on SMAD											
EW	1.807 ***	1.351 ***	1.196 ***	1.097 ***	1.036 ***	0.929 ***	0.810 ***	0.607 ***	0.355	-0.424	-2.230 ***
	(5.94)	(5.37)	(5.19)	(5.19)	(5.04)	(4.52)	(3.86)	(2.78)	(1.49)	(-1.51)	(-13.11)
VW	1.308 ***	1.426 ***	1.243 ***	1.066 ***	0.988 ***	0.809 ***	0.696 ***	0.613 ***	0.369 *	0.021	-1.287 ***
	(5.12)	(6.47)	(6.53)	(5.78)	(5.87)	(4.62)	(3.99)	(3.49)	(1.92)	(0.09)	(-6.95)
Panel B: Portfolios formed on LMAD											
EW	0.027	0.486 *	0.767 ***	0.832 ***	0.930 ***	1.001 ***	1.030 ***	1.084 ***	1.177 ***	1.405 ***	1.378 ***
	(0.08)	(1.79)	(3.21)	(3.84)	(4.52)	(5.00)	(5.16)	(5.16)	(5.06)	(4.91)	(5.87)
VW	0.212	0.816 ***	0.904 ***	0.864 ***	0.818 ***	0.912 ***	0.875 ***	0.931 ***	1.020 ***	1.318 ***	1.106 ***
	(0.62)	(3.30)	(4.34)	(4.60)	(4.51)	(5.46)	(5.40)	(5.22)	(5.03)	(5.13)	(3.79)
Panel C: Portfolios formed on SMAD with penny stocks included											
EW	3.338 ***	1.760 ***	1.487 ***	1.300 ***	1.197 ***	1.100 ***	0.988 ***	0.892 ***	0.566 **	-0.254	-3.593 ***
	(8.88)	(6.07)	(5.81)	(5.50)	(5.35)	(4.88)	(4.35)	(3.62)	(2.15)	(-0.78)	(-15.14)
VW	1.582 ***	1.526 ***	1.374 ***	1.212 ***	1.115 ***	0.894 ***	0.737 ***	0.675 ***	0.503 **	0.132	-1.451 ***
	(5.61)	(6.79)	(7.17)	(6.78)	(6.48)	(5.23)	(4.26)	(3.81)	(2.58)	(0.53)	(-7.57)
Panel D: Portfolios formed on LMAD with penny stocks included											
EW	1.537 ***	0.931 ***	0.911 ***	1.042 ***	1.106 ***	1.190 ***	1.243 ***	1.278 ***	1.417 ***	1.698 ***	0.161
	(3.51)	(2.84)	(3.30)	(4.20)	(4.88)	(5.42)	(5.75)	(5.77)	(5.76)	(5.68)	(0.54)
VW	0.303	0.775 **	0.896 ***	0.933 ***	0.962 ***	0.947 ***	0.948 ***	0.977 ***	1.132 ***	1.426 ***	1.122 ***
	(0.78)	(2.58)	(3.85)	(4.46)	(5.29)	(5.40)	(5.66)	(5.57)	(5.76)	(5.58)	(3.48)

Table 2: Abnormal returns based on various factor models

This table reports the abnormal monthly returns of the long-short strategy formed on SMAD (LMAD). Our sample consists of the ordinary common stocks of all firms listed on NYSE, AMEX, and NASDAQ for the period from July 1964 to December 2021. At the beginning of each month *t*, we allocate individual stocks into decile portfolios according to their vales of SMAD (or LMAD) calculated at the end of month *t*−1. We next calculate equally- and value-weighted returns for each decile portfolio for month *t*. We then define the SMAD (LMAD) premium as the difference between highest and lowest decile portfolios classified by SMAD (LMAD). We regress the time-series of SMAD or LMAD premia on various factor models to obtain the intercepts from the regressions as the abnormal returns. The factor models include Fama and French's (2015) five-factor model, an augmented six-factor model that augments Fama and French's (2015) five factors with the momentum factor, Hou, Xue, and Zhang's (2015) Q4-factor model, and Hou, Mo, Xue, and Zhang's (2021) Q5-factor model. In Panels A and B, we exclude penny stocks whose ending price in the previous month fall below $5 to form the decile portfolios according to the vales of SMAD and LMAD, respectively. In Panels C and D, we include penny stocks and form the decile portfolios according to the vales of SMAD and LMAD, respectively. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	FF5 alpha	FF5+MOM alpha	Q4 alpha	Q5 alpha
Panel A: Portfolios formed on SMAD				
EW	-2.269 ***	-2.389 ***	-2.409 ***	-2.331 ***
	(-11.45)	(-11.51)	(-10.62)	(-9.64)
VW	-1.414 ***	-1.519 ***	-1.543 ***	-1.452 ***
	(-6.78)	(-7.33)	(-7.16)	(-6.45)
Panel B: Portfolios formed on LMAD				
EW	1.403 ***	0.585 ***	0.800 **	0.298
	(4.45)	(3.09)	(2.16)	(0.85)
VW	1.274 ***	0.307	0.670	0.003
	(3.49)	(1.40)	(1.56)	(0.01)
Panel C: Portfolios formed on SMAD with penny stocks included				
EW	-3.638 ***	-3.880 ***	-3.956 ***	-3.841 ***
	(-11.95)	(-11.05)	(-9.84)	(-8.84)
VW	-1.578 ***	-1.707 ***	-1.777 ***	-1.674 ***
	(-7.09)	(-7.52)	(-7.55)	(-6.76)
Panel D: Portfolios formed on LMAD with penny stocks included				
EW	0.144	-0.795 **	-0.776	-1.114 **
	(0.36)	(-2.52)	(-1.53)	(-2.22)
VW	1.266 ***	0.206	0.587	-0.148
	(3.23)	(0.89)	(1.30)	(-0.36)

Table 3: SMAD premium based on alternative anchors

This table reports raw and abnormal monthly returns of the long-short strategy formed on SMAD that is constructed using alternative anchors of MA(5) or MA(20). Our sample consists of the ordinary common stocks of all firms listed on NYSE, AMEX, and NASDAQ for the period from July 1964 to December 2021. We exclude penny stocks whose ending price in the previous month fall below $5. At the beginning of each month *t*, we first calculate SMAD as $P_{t-1}/MA(5)_{t-1}$ or $P_{t-1}/MA(20)_{t-1}$. We next allocate individual stocks into decile portfolios according to their vales of SMAD calculated at the end of month $t-1$. We next calculate equally- and value-weighted returns for each decile portfolio for month *t*. We then define the SMAD premium as the difference between highest and lowest decile portfolios classified by SMAD. We calculate the time-series average of returns for the long-short position. We also regress the time-series of SMAD premia on various factor models to obtain the intercepts from the regressions as the abnormal returns. The factor models include Fama and French's (2015) five-factor model, an augmented six-factor model that augments Fama and French's (2015) five factors with the momentum factor, Hou, Xue, and Zhang's (2015) Q4-factor model, and Hou, Mo, Xue, and Zhang's (2021) Q5-factor model. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	MA(5) as the anchor		MA(20) as the anchor	
	EW	VW	EW	VW
Low	1.914 ***	1.490 ***	1.733 ***	1.183 ***
	(6.28)	(5.72)	(5.15)	(3.98)
High	-0.583 **	-0.127	-0.173	0.357
	(-2.06)	(-0.51)	(-0.57)	(1.40)
High−Low	-2.497 ***	-1.618 ***	-1.906 ***	-0.826 ***
	(-14.72)	(-8.24)	(-9.65)	(-4.02)
FF5 alpha	-2.483 ***	-1.687 ***	-1.800 ***	-0.650 ***
	(-12.73)	(-7.34)	(-7.62)	(-2.90)
FF5+MOM alpha	-2.575 ***	-1.767 ***	-1.973 ***	-0.816 ***
	(-13.28)	(-8.11)	(-8.21)	(-3.79)
Q4 alpha	-2.587 ***	-1.852 ***	-1.957 ***	-0.835 ***
	(-12.31)	(-7.60)	(-6.74)	(-3.26)
Q5 alpha	-2.408 ***	-1.578 ***	-2.071 ***	-0.908 ***
	(-11.42)	(-6.89)	(-6.61)	(-3.29)

Table 4: Cross-sectional regressions

This table reports the estimation results of the Fama-MacBeth cross-sectional regressions. Our sample consists of the ordinary common stocks of all firms listed on NYSE, AMEX, and NASDAQ for the period from July 1964 to December 2021. For each month t, we perform the cross-sectional regressions in the following form:

$$R_{i,t} = \alpha_0 + \alpha_1 SMAD_{i,t-1} + \alpha_2 LMAD_{i,t-1} + \sum_{l=1}^{L} \beta_l X_{i,l,t-1} + \varepsilon_{i,t},$$

where $R_{i,t}$ is stock i's return in month t; $SMAD_{i,t-1}$ and $LMAD_{i,t-1}$ are short- and long-term moving average signals; $X_{i,l,t-1}$ is stock i's lth control variable identified at the end of month $t-1$. We include SIZE, REV, MAX as the control variables for the basic model. We test the time-series averages of the monthly estimated coefficients from the cross-sectional regressions using t-statistics calculated with Newey and West's (1987) robust standard errors, which is reported in the parentheses. In Panel A, we exclude penny stocks whose ending price in the previous month fall below \$5. In Panel B, penny stocks are included. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Model (1)	Model (2)	Model (3)	Model (4)
Panel A: Penny stocks excluded				
SMAD	-12.717 ***		-13.482 ***	-12.875 ***
	(-15.64)		(-16.99)	(-15.25)
LMAD		1.792 ***	1.927 ***	1.723 ***
		(5.57)	(5.99)	(6.17)
SIZE				-0.025
				(-0.89)
REV				-0.004
				(-1.32)
MAX				-0.059 ***
				(-6.36)
Panel B: Penny stocks included				
SMAD	-16.954 ***		-17.749 ***	-16.899 ***
	(-18.83)		(-19.66)	(-17.87)
LMAD		0.407	0.628	0.847 ***
		(1.07)	(1.63)	(2.64)
SIZE				-0.113 ***
				(-3.28)
REV				-0.019 ***
				(-5.42)
MAX				-0.010
				(-1.17)

Table 5: Cross-sectional regressions including mispricing variables

This table reports the estimation results of the Fama-MacBeth cross-sectional regressions. Our sample consists of the ordinary common stocks of all firms listed on NYSE, AMEX, and NASDAQ for the period from July 1964 to December 2021. For each month *t*, we perform the cross-sectional regressions in the following form:

$$R_{i,t} = \alpha_0 + \alpha_1 SMAD_{i,t-1} + \alpha_2 LMAD_{i,t-1} + \sum_{l=1}^{L} \beta_l X_{i,l,t-1} + \sum_{k=1}^{K} \gamma_k Mis_{i,k,t-1} + \varepsilon_{i,t},$$

where $R_{i,t}$ is stock *i*'s return in month *t*; $SMAD_{i,t-1}$ and $LMAD_{i,t-1}$ are short- and long-term moving average signals; $X_{i,l,t-1}$ is stock *i*'s *l*th control variable identified at the end of month $t-1$; $Mis_{i,k,t-1}$ is stock *i*'s *k*th mispricing variable identified at the end of month $t-1$. We include SIZE, REV, MAX as the control variables for the basic model. We test the time-series averages of the monthly estimated coefficients from the cross-sectional regressions using *t*-statistics calculated with Newey and West's (1987) robust standard errors, which is reported in the parentheses. In Panel A, we exclude penny stocks whose ending price in the previous month fall below $5. In Panel B, penny stocks are included. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)	Model (10)	Model (11)
Panel A: Penny stocks excluded											
SMAD	-13.287 ***	-12.617 ***	-12.644 ***	-12.389 ***	-14.450 ***	-12.413 ***	-12.582 ***	-12.317 ***	-13.300 ***	-11.760 ***	-13.525 ***
	(-15.84)	(-14.93)	(-15.07)	(-14.46)	(-7.93)	(-14.04)	(-12.98)	(-14.60)	(-14.77)	(-12.60)	(-11.64)
LMAD	0.909 ***	1.783 ***	1.713 ***	1.726 ***	1.392 ***	1.660 ***	1.737 ***	1.713 ***	1.213 ***	1.614 ***	0.427
	(2.95)	(6.30)	(6.11)	(6.16)	(2.79)	(5.89)	(4.91)	(6.02)	(4.04)	(5.00)	(1.08)
SIZE	-0.018	-0.024	-0.028	-0.019	0.023	-0.028	-0.017	-0.025	-0.040	-0.044	-0.035
	(-0.66)	(-0.86)	(-0.97)	(-0.66)	(0.43)	(-1.00)	(-0.56)	(-0.84)	(-1.48)	(-1.42)	(-1.18)
REV	0.000	-0.007 **	-0.007 **	-0.007 **	-0.014 **	-0.006 *	-0.003	-0.006 **	-0.009 ***	-0.006 *	-0.010 **
	(-0.15)	(-2.24)	(-2.14)	(-2.13)	(-2.45)	(-1.92)	(-0.83)	(-2.10)	(-2.74)	(-1.72)	(-2.47)
MAX	-0.058 ***	-0.058 ***	-0.057 ***	-0.054 ***	-0.006	-0.053 ***	-0.063 ***	-0.054 ***	-0.044 ***	-0.053 ***	-0.037 ***
	(-6.34)	(-6.26)	(-6.38)	(-6.31)	(-0.16)	(-5.98)	(-5.97)	(-6.11)	(-4.65)	(-4.91)	(-3.85)
PR12	0.435 ***										0.262 *
	(3.72)										(1.82)
GP		0.360 ***									0.023
		(3.13)									(0.16)
AG			-0.247 ***								0.358
			(-4.41)								(1.00)
IVA				-0.614 ***							-0.325
				(-6.31)							(-0.72)
ROA					0.383						0.031
					(0.79)						(1.22)
NOA						-0.289 ***					0.203
						(-4.73)					(0.97)
AC							-1.075 ***				-0.865
							(-4.15)				(-1.57)
NSI								-0.542 ***			-0.867 *
								(-5.73)			(-1.89)
CEI									-0.429 ***		-0.416 ***
									(-5.97)		(-4.10)
OSCORE										-0.134 ***	-0.073 **
										(-4.97)	(-2.44)

Table 5 continued

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)	Model (10)	Model (11)
Panel B: Penny stocks included											
SMAD	-17.452 ***	-16.900 ***	-16.888 ***	-16.680 ***	-18.247 ***	-16.839 ***	-18.086 ***	-16.595 ***	-18.110 ***	-17.420 ***	-18.187 ***
	(-18.24)	(-18.28)	(-18.16)	(-17.63)	(-13.65)	(-17.95)	(-15.25)	(-17.63)	(-17.48)	(-15.88)	(-15.48)
LMAD	0.023	0.843 ***	0.849 ***	0.815 **	0.350	0.865 ***	0.655 *	0.784 **	0.786 **	0.649 *	-0.495
	(0.07)	(2.62)	(2.67)	(2.54)	(0.81)	(2.69)	(1.92)	(2.43)	(2.42)	(1.81)	(-1.35)
SIZE	-0.110 ***	-0.121 ***	-0.120 ***	-0.123 ***	-0.087 **	-0.125 ***	-0.126 ***	-0.132 ***	-0.103 ***	-0.177 ***	-0.144 ***
	(-3.21)	(-3.49)	(-3.50)	(-3.48)	(-2.05)	(-3.64)	(-3.45)	(-3.67)	(-3.36)	(-5.41)	(-4.70)
REV	-0.015 ***	-0.019 ***	-0.019 ***	-0.020 ***	-0.025 ***	-0.019 ***	-0.018 ***	-0.020 ***	-0.020 ***	-0.016 ***	-0.016 ***
	(-4.46)	(-5.42)	(-5.43)	(-5.62)	(-3.60)	(-5.18)	(-4.67)	(-5.51)	(-5.53)	(-4.66)	(-4.14)
MAX	-0.010	-0.009	-0.009	-0.008	0.025	-0.008	-0.008	-0.006	-0.006	-0.002	0.009
	(-1.17)	(-1.10)	(-1.01)	(-0.94)	(0.89)	(-0.98)	(-0.91)	(-0.70)	(-0.62)	(-0.22)	(0.99)
PR12	0.434 ***										0.334 **
	(3.41)										(2.49)
GP		0.360 ***									0.014
		(3.41)									(0.10)
AG			-0.301 ***								-0.044
			(-5.42)								(-0.23)
IVA				-0.632 ***							-0.298
				(-7.37)							(-1.15)
ROA					0.923						0.027
					(1.36)						(1.46)
NOA						-0.321 ***					0.054
						(-5.75)					(0.35)
AC							-0.723 ***				-0.919 ***
							(-3.14)				(-3.18)
NSI								-0.704 ***			-0.709 **
								(-6.91)			(-2.48)
CEI									-0.397 ***		-0.308 ***
									(-5.28)		(-3.56)
OSCORE										-0.159 ***	-0.090 ***
										(-5.68)	(-2.78)

Table 6: SMAD premium and investor sentiment

This table reports the average monthly returns of portfolios formed on SMAD conditional on investor sentiment. Our sample consists of the ordinary common stocks of all firms listed on NYSE, AMEX, and NASDAQ for the period from July 1965 to December 2021. At the beginning of each month *t*, we allocate individual stocks into decile portfolios according to their vales of SMAD calculated at the end of month $t-1$. We next calculate value-weighted returns for each decile portfolio for month *t*. We then define the SMAD premium as the difference between highest and lowest decile portfolios classified by SMAD. We calculate the time-series average of returns for the highest and lowest deciles and the long-short position. For a given month *t*, we define it as high sentiment if the BW index in month $t-1$ is higher than the median of the sample period; otherwise month *t* is classified as low sentiment. We obtain raw and abnormal returns of the value-weighted SMAD strategy separately for periods of high and low sentiment, respectively. We also calculate the differences between high and low sentiment periods. The factor models include Fama and French's (2015) five-factor model, an augmented six-factor model that augments Fama and French's (2015) five factors with the momentum factor, Hou, Xue, and Zhang's (2015) Q4-factor model, and Hou, Mo, Xue, and Zhang's (2021) Q5-factor model. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

SMAD portfolio	Low sentiment	High sentiment	High−Low sentiment
Low	1.599 ***	1.022 ***	-0.577
	(4.56)	(2.64)	(-1.11)
High	0.356	-0.308	-0.664
	(1.09)	(-0.91)	(-1.42)
High−Low	-1.244 ***	-1.330 ***	-0.087
	(-5.47)	(-4.22)	(-0.22)
FF5	-1.167 ***	-1.645 ***	-0.478
	(-4.49)	(-4.52)	(-1.06)
FF5+MOM	-1.264 ***	-1.763 ***	-0.499
	(-5.01)	(-4.76)	(-1.11)
Q4	-1.263 ***	-1.848 ***	-0.585
	(-4.82)	(-5.08)	(-1.29)
Q5	-1.226 ***	-1.669 ***	-0.442
	(-4.12)	(-4.95)	(-0.99)

Table 7: SMAD premium and salience theory

This table reports raw and abnormal monthly returns of the long-short strategy formed on SMAD conditional on individual stocks' measure of salience theory. Our sample consists of the ordinary common stocks of all firms listed on NYSE, AMEX, and NASDAQ for the period from July 1964 to December 2021. We exclude penny stocks whose ending price in the previous month fall below $5. For each month *t*, we first sort individual stocks into deciles based on their SMAD values. Within each decile, we sort individual stocks into quintiles according to their values of the ST measure. We next calculate the return premia using value weights between the highest and lowest deciles for each of the five ST subgroups. We obtain raw and abnormal returns of the value-weighted SMAD strategy separately for the five ST subgroups. The factor models include Fama and French's (2015) five-factor model, an augmented six-factor model that augments Fama and French's (2015) five factors with the momentum factor, Hou, Xue, and Zhang's (2015) Q4-factor model, and Hou, Mo, Xue, and Zhang's (2021) Q5-factor model. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Salience theory quintile					
	1	2	3	4	5	5−1
Low	0.666 **	1.605 ***	1.496 ***	1.543 ***	1.497 ***	0.830 ***
	(2.00)	(5.89)	(5.65)	(5.30)	(4.06)	(3.29)
High	-0.501 *	0.220	0.152	0.198	-0.441	0.060
	(-1.93)	(0.90)	(0.59)	(0.70)	(-1.34)	(0.25)
High−Low	-1.167 ***	-1.385 ***	-1.344 ***	-1.345 ***	-1.938 ***	-0.770 **
	(-4.56)	(-5.35)	(-6.05)	(-5.66)	(-6.18)	(-2.37)
FF5	-1.229 ***	-1.524 ***	-1.376 ***	-1.435 ***	-2.163 ***	-0.934 **
	(-4.87)	(-5.04)	(-5.84)	(-5.35)	(-6.11)	(-2.58)
FF5+MOM	-1.276 ***	-1.684 ***	-1.515 ***	-1.524 ***	-2.215 ***	-0.939 **
	(-4.89)	(-5.49)	(-6.61)	(-5.58)	(-6.26)	(-2.55)
Q4	-1.256 ***	-1.706 ***	-1.493 ***	-1.504 ***	-2.282 ***	-1.025 ***
	(-4.63)	(-5.24)	(-6.05)	(-5.28)	(-6.23)	(-2.68)
Q5	-1.106 ***	-1.668 ***	-1.423 ***	-1.446 ***	-1.924 ***	-0.818 **
	(-3.80)	(-4.93)	(-5.21)	(-4.99)	(-4.90)	(-2.08)

Table 8: SMAD indicator and mispricing anomalies

This table reports the raw monthly returns of the SMAD-enhanced mispricing anomalies. For each month *t*, we allocate individual stocks into quintiles according to their values of each mispricing variables. For momentum, gross profitability, and return on assets anomalies, the long position is the highest quintile and the short position is the quintile. For asset growth, investment-to-assets, net operating assets, accruals, net stock issues, composite equity issues, and O-score anomalies, the long position is the lowest quintile and the short position is the highest quintile. Within each mispricing quintiles, we further allocate individual stocks into quintiles according to their values of SMAD. We construct long position of the enhanced mispricing anomaly by buying stocks classified as the most undervalued stocks that are allocated in the lowest SMAD quintile simultaneously. The short position of the enhanced mispricing anomaly involves short selling stocks classified as the most overvalued stocks that are allocated in the highest SMAD quintile simultaneously. We calculate value-weighted returns for both long and short positions of the enhanced mispricing anomaly and obtain the difference as the return premium of the enhanced mispricing anomaly. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Long−Short			Long position			Short position		
	SMAD enhanced	Original	Difference	SMAD enhanced	Original	Difference	SMAD enhanced	Original	Difference
MOM	2.877 ***	1.867 ***	1.009 ***	1.880 ***	1.446 ***	0.434 ***	-0.996 ***	-0.421	-0.575 ***
	(9.53)	(5.85)	(3.87)	(7.73)	(5.38)	(3.20)	(-2.77)	(-1.08)	(-2.72)
GP	1.734 ***	0.601 ***	1.133 ***	1.723 ***	1.081 ***	0.641 ***	-0.012	0.480	-0.492 **
	(6.65)	(3.37)	(4.27)	(6.68)	(4.21)	(3.90)	(-0.04)	(1.56)	(-2.09)
AG	1.919 ***	0.742 ***	1.177 ***	1.862 ***	0.843 ***	1.020 ***	-0.056	0.101	-0.157
	(6.66)	(4.84)	(4.55)	(6.14)	(2.71)	(5.06)	(-0.20)	(0.31)	(-0.89)
IVA	2.010 ***	0.645 ***	1.365 ***	1.880 ***	1.092 ***	0.788 ***	-0.130	0.447 *	-0.577 ***
	(8.06)	(4.12)	(5.36)	(6.62)	(5.61)	(4.10)	(-0.47)	(1.67)	(-3.42)
ROA	1.962 ***	0.917 ***	1.046 ***	1.518 ***	1.018 ***	0.500 ***	-0.445	0.101	-0.546 *
	(5.60)	(3.10)	(3.15)	(6.21)	(4.75)	(3.25)	(-1.08)	(0.26)	(-1.87)
NOA	1.788 ***	0.754 ***	1.034 ***	1.598 ***	1.087 ***	0.512 ***	-0.190	0.333	-0.522 ***
	(7.31)	(4.69)	(4.33)	(5.20)	(4.58)	(2.74)	(-0.68)	(1.29)	(-3.23)
ACC	1.508 ***	0.425 **	1.084 ***	1.262 ***	0.808 ***	0.454 *	-0.246	0.384	-0.630 ***
	(5.28)	(2.34)	(3.67)	(3.71)	(2.60)	(1.95)	(-0.82)	(1.24)	(-3.61)
NSI	1.925 ***	0.738 ***	1.187 ***	1.728 ***	1.146 ***	0.583 ***	-0.197	0.407	-0.604 ***
	(7.07)	(4.08)	(5.03)	(7.88)	(6.96)	(4.22)	(-0.60)	(1.58)	(-3.13)
CEI	1.711 ***	0.516 ***	1.195 ***	1.654 ***	1.170 ***	0.485 ***	-0.057	0.654 ***	-0.711 ***
	(8.96)	(4.25)	(6.03)	(7.46)	(6.69)	(3.71)	(-0.23)	(3.11)	(-4.60)
OS	2.290 ***	0.827 ***	1.463 ***	1.425 ***	1.009 ***	0.417 ***	-0.864 **	0.182	-1.047 ***
	(6.66)	(3.65)	(4.73)	(5.30)	(4.01)	(2.94)	(-2.07)	(0.47)	(-3.79)

Table 9: LMAD indicator and mispricing anomalies

This table reports the raw monthly returns of the LMAD-enhanced mispricing anomalies. For each month *t*, we allocate individual stocks into quintiles according to their values of each mispricing variables. For momentum, gross profitability, and return on assets anomalies, the long position is the highest quintile and the short position is the quintile. For asset growth, investment-to-assets, net operating assets, accruals, net stock issues, composite equity issues, and O-score anomalies, the long position is the lowest quintile and the short position is the highest quintile. Within each mispricing quintiles, we further allocate individual stocks into quintiles according to their values of LMAD. We construct long position of the enhanced mispricing anomaly by buying stocks classified as the most undervalued stocks that are allocated in the highest LMAD quintile simultaneously. The short position of the enhanced mispricing anomaly involves short selling stocks classified as the most overvalued stocks that are allocated in the lowest LMAD quintile simultaneously. We calculate value-weighted returns for both long and short positions of the enhanced mispricing anomaly and obtain the difference as the return premium of the enhanced mispricing anomaly. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Long−Short			Long position			Short position		
	LMAD enhanced	Original	Difference	LMAD enhanced	Original	Difference	LMAD enhanced	Original	Difference
MOM	1.573 ***	1.867 ***	-0.295	1.665 ***	1.446 ***	0.219 *	0.093	-0.421	0.514 **
	(3.65)	(5.85)	(-1.12)	(5.83)	(5.38)	(1.79)	(0.19)	(-1.08)	(2.40)
GP	0.909 **	0.601 ***	0.308	1.332 ***	1.081 ***	0.251	0.423	0.480	-0.057
	(2.37)	(3.37)	(0.80)	(5.22)	(4.21)	(1.44)	(0.99)	(1.56)	(-0.19)
AG	1.148 ***	0.742 ***	0.407	1.175 ***	0.843 ***	0.332 *	0.026	0.101	-0.075
	(3.52)	(4.84)	(1.43)	(4.23)	(2.71)	(1.84)	(0.07)	(0.31)	(-0.39)
IVA	1.337 ***	0.645 ***	0.692 **	1.223 ***	1.092 ***	0.131	-0.114	0.447 *	-0.561 **
	(4.28)	(4.12)	(2.31)	(4.85)	(5.61)	(0.84)	(-0.30)	(1.67)	(-2.48)
ROA	1.416 ***	0.900 ***	0.516	1.422 ***	0.999 ***	0.423 ***	0.006	0.098	-0.092
	(3.11)	(3.02)	(1.28)	(5.28)	(4.59)	(2.85)	(0.01)	(0.25)	(-0.25)
NOA	1.100 ***	0.754 ***	0.347	1.074 ***	1.087 ***	-0.012	-0.026	0.333	-0.359 *
	(3.36)	(4.69)	(1.13)	(4.01)	(4.58)	(-0.07)	(-0.07)	(1.29)	(-1.67)
ACC	1.023 ***	0.425 **	0.598 *	1.305 ***	0.808 ***	0.497 **	0.283	0.384	-0.101
	(3.06)	(2.34)	(1.93)	(4.37)	(2.60)	(2.49)	(0.73)	(1.24)	(-0.48)
NSI	1.082 ***	0.738 ***	0.343	1.235 ***	1.146 ***	0.090	0.154	0.407	-0.253
	(2.84)	(4.08)	(0.99)	(6.06)	(6.96)	(0.67)	(0.36)	(1.58)	(-0.86)
CEI	0.628 **	0.516 ***	0.112	1.043 ***	1.170 ***	-0.127	0.415	0.654 ***	-0.239
	(2.14)	(4.25)	(0.42)	(5.35)	(6.69)	(-1.28)	(1.20)	(3.11)	(-1.06)
OS	1.460 ***	0.827 ***	0.633	1.201 ***	1.009 ***	0.193	-0.258	0.182	-0.441
	(3.04)	(3.65)	(1.49)	(4.46)	(4.01)	(1.14)	(-0.49)	(0.47)	(-1.28)