Salience and Short-term Momentum and Reversals

by*

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Abstract

We measure firm-level deviation salience (DS) as the normalized return divergence between individual stocks and their peers. We find that the predictive ability of the past month's stock performance for future returns strongly depends on the level of DS. High-DS stocks exhibit short-term *reversals* with a return spread of -1.30% per month, whereas low-DS stocks display return *continuation* with a return spread of 1.41% per month. The result is robust after controlling for the effects of size, illiquidity, volatility, and turnover. Our finding is consistent with the story that investors are prone to overreact to salient information but underreact to non-salient information.

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1 Introduction

Psychological studies suggest that individuals tend to underreact to news because of conservatism, anchoring bias, or limited attention. On the other hand, prior studies also find that individuals tend to overreact to news because of representativeness or overweighing of salient/extreme events. To unify conservatism and representativeness, Griffin and Tversky (1992) suggest that individuals might underreact to ordinary news but overreact to a salient/extreme performance.[1] The insight that *salience* shapes attention is established in the psychology and cognitive science literature (Treisman and Gelade, 1980; Taylor and Thompson, 1982), and has been recently introduced into financial economics (Bordalo et al., 2012, 2013a,b, 2022).

In this study, we explore the implications of salience-induced distortion in attention and its subsequent effect on stock prices. Figure 1 presents a visual illustration of salience from computational neuroscience (Itti, 2005, 2008). Attention is often allocated to choices that are salient in a given context, and the subjective evaluation would be affected by the contrast with surroundings (Bordalo et al., 2022). Excessive attention to salient events could lead to probability overweighting of these events in decision making. Thus, individuals tend to overreact to news on these stocks. In particular, if a stock's recent performance is perceived to be salient relative to a set of representative peer firms, then investors would be inclined to overreact to price changes or the underlying news for these price changes, probably because of the distorted attention-induced probability overweighting. If a stock's payoff is perceived to be less salient and subjectively indistinguishable relative to alternatives, however, then investors would tend to underreact to value-relevant information, probably because of limited attention or conservatism bias, leading to delayed price reactions.

We measure deviation salience (DS) as the degree of divergence in the monthly performance between a given stock and its peers, inspired by the salience function of Bordalo et al. (2012, 2013a,b). Specifically, DS is calculated as the absolute difference between the monthly excess stock return and the contemporaneous average excess return of peer stocks, normalized by the sum of absolute excess returns of the focal stock and its peers.[2] This

[1] In earlier influential studies, Barberis et al. (1998), Daniel et al. (1998), and Hong and Stein (1999) attempt to reconcile underreaction and overreaction in financial markets.

[2] While we adopt the functional form proposed by Bordalo et al. (2012, 2013a,b) for salience measurement, this paper does not directly implement their full model or test its specific theoretical predictions. Rather, we draw motivation from the core psychological and economic principles underlying their work to formulate our research hypothesis.

construction captures the notion that a stock may grab attention when it deviates from comparable alternatives; salience also diminishes for larger return magnitudes, reflecting the idea that payoff differences are easier to perceive at lower levels.[3] In addition, the sign of returns does not affect the magnitude of deviation salience. For our main analysis, we define peers as firms covered by common analysts, as in Ali and Hirshleifer (2020), who show that analyst linkage can account for most of the existing economic linkages between firms.

Our result reveals a striking pattern in the predictive ability of short-horizon returns. By double-sorting stocks based on lagged deviation salience and the one-month return, we find that high-DS stocks display short-term *reversals* with a return spread of -1.30% per month, whereas low-DS stocks exhibit short-term return *continuation* with a return spread of 1.41% per month. This finding aligns with our hypothesis that a higher (lower) level of deviation salience attracts (distracts) attention, generating overreaction (underreaction) to price changes or the information/news underlying the price changes. We also confirm the pattern in Fama-MacBeth regressions and find that the result is robust to value-weighted regressions and to controlling for interaction effects of size, illiquidity, volatility, turnover, and attention proxies. While the traditional explanation for short-term reversal is based on liquidity demands, our results suggest that investors tend to underreact even at the monthly horizon. In addition, we show that salience can also lead to overreaction and thus reversal in the short horizon.

We conduct several tests to inspect the mechanism underlying the documented variation in short-term return predictive ability. First, DS is positively correlated with abnormal trading volume and retail investor attention, measured by abnormal Google search volume (Da et al., 2011). This result supports our hypothesis that deviation salience induces a distorted allocation of attention, which in turn affects pricing efficiency. It also helps distinguish between our findings and the findings of Medhat and Schmeling (2022), who show that high-turnover stocks display short-term *momentum*. In sharp contrast, we find that DS is positively correlated with turnover, but high-DS stocks display short-term *reversals*. Moreover, our short-term momentum effect among firms with low DS is also different from the traditional post-earnings announcement drift (PEAD) effect of Ball and Brown (1968). In particular, we find that the effect of salience on the predictive ability of short-term returns remains significant among firms without any earnings announcements in the last month, suggesting that our short-term momentum is not purely driven by underreaction to earnings

[3]This property is a form of the Weber-Fechner law, which states that the saliency of a stimulus is inversely related to its size. In a related study, Karolyi et al. (2025) find that investors exhibit stronger underreaction to earnings news for stocks with high earnings per share magnitudes.

announcement news. Lastly, by controlling for a factor based on industry momentum, we show that our short-term momentum among low salience firms is not driven by the well-known industry momentum effect.

Our salience-based explanation for the short-term reversal effect is also considerably different from the conventional liquidity-based story. Intuitively, the liquidity provision channel suggests that slow-moving capital or liquidity providers' inventory risks could cause excess liquidity demands to temporarily drive up stock prices and lead to subsequent reversals.[4] While perfect isolation of the salience effect from liquidity provision is almost impossible, we find that our results remain valid for highly liquid stocks and mega caps. The salience-induced reversal and continuation in returns even exist among the largest 500 stocks, in which the unconditional reversal strategy does not earn any profits. For example, among the largest 500 stocks, winners actually earn slightly higher average returns than losers by 0.04% per month (t-stat=0.13). However, among high-salience firms, there is still a significant short-term reversal effect with a return spread of -0.90% per month (t-stat= -3.04), whereas, among low-salience firms, there is a significant short-term momentum effect with a return spread of 0.98% per month (t-stat= 2.10). In addition, by directly controlling for a factor based on industry-adjusted return reversals, our reversal effect among salient firms remains significant. Overall, our result is unlikely to be solely driven by liquidity provision.

We also inspect the long-horizon performance of the short-term winners-minus-losers strategy. It turns out that the return reversal observed in high-DS stocks is transient and disappears quickly. The return spread becomes insignificant after two months. By contrast, we find that the return continuation of low-DS stocks persists for up to 12 months, which is in line with the underreaction interpretation. In addition, we explore the extent to which market expectations for recent winners and losers are affected by deviation salience. Specifically, we find that the interaction between the one-month return and the high-DS dummy negatively predicts analyst forecast errors, suggesting that analyst forecasts are biased relatively upward (downward) for recent winner stocks with a high (low) level of deviation salience. The predictability of forecast errors is consistent with the explanation that market participants tend to overreact (underreact) to recent performance for stocks with high (low) deviation salience. Moreover, we also find that a higher level of deviation salience reduces the predictive ability of short-term returns for future fundamentals, which

[4]See, for example, Avramov et al. (2006); Nagel (2012); Da et al. (2014b); So and Wang (2014); Cheng et al. (2017); and Dai et al. (2024).

is suggestive of overinference when the stock is salient among its peers.

In a series of portfolio analyses, we show that the effect of DS on short-term return predictive ability is robust after controlling for a battery of compounding effects. For example, Wang (1994) and Llorente et al. (2002) argue that informed trading due to private information could cause persistent price movements that could counteract temporary price pressure and potentially lead to momentum. Hence, among stocks with a high degree of information asymmetry, returns should reverse less and may even continue. High-information-asymmetry stocks should be small, illiquid, and volatile, and have low analyst coverage and low institutional ownership. Thus, we construct the orthogonal deviation salience by taking residuals of cross-sectional regressions of DS on firm characteristics such as size, illiquidity, idiosyncratic volatility, institutional ownership, analyst coverage, and turnover. We find that our findings are still valid using the orthogonalized DS.

Lastly, we also consider alternative benchmark returns in the construction of DS. Using various industry definitions and stocks with similar characteristics (He et al., 2023), we find consistent results of short-term return predictability under alternative context choices. Thus, our short-term momentum among firms with low DS is unlikely driven by the short-run industry momentum of Moskowitz and Grinblatt (1999). In addition, to highlight the necessity of the salience function and contrast in the definition of salience, we perform several placebo tests. Specifically, we (1) use the absolute return difference and (2) use the market return or randomly matched peers to calculate deviation salience. We find that these constructions fail to generate variations in short-term return predictive ability, which in turn supports our empirical design. Moreover, we also repeat the same exercise in 28 international markets and find a similar pattern as well, suggesting that salience-driven distortion in stock pricing is an international phenomenon.

In terms of related literature, in a series of influential studies, Bordalo et al. (2012, 2013a,b) propose salience theory and its asset pricing implications. Subsequent studies test the salience theory in the stock market (Cosemans and Frehen, 2021; Cakici and Zaremba, 2022; Sun et al., 2023) and the bond market (Lin and Zhang, 2022). These studies typically use firm-level salience measures to predict future stock/bond returns. Here, we do not use salience itself to predict stock returns. Instead, we focus on the interaction effect between salience and past stock returns in predicting future returns. More important, the salience measures in these studies capture the distortion in return expectations caused by salient thinking, whereas our salience captures the degree of deviation in returns from the stock's peers and is non-directional. In addition, our study suggests that context matters for asset pricing, as in Hartzmark and Shue (2018); He and Li (2020); Antoniou et al. (2021); Ben-David et al. (2022, 2024); and Meyer and Hundtofte (2023). However, our firm-level salience measure is different from earlier studies. Among others, the context and measurement in our paper are different from those in these studies. Our results also accord with recent theoretical work in behavioral economics that emphasizes the context-dependency of attention and decision making (Bordalo et al., 2020; Wachter and Kahana, 2024).

Our study is obviously also related to short-term reversals.[5] Typically, liquidity provision is the leading explanation for the short-term reversal effect. Notable recent studies include Avramov et al. (2006); Nagel (2012); Da et al. (2014b); So and Wang (2014); Cheng et al. (2017); and Dai et al. (2024). Different from these studies, apart from short-term reversals, we also find price continuation at the monthly horizon. Moreover, we show that beyond liquidity provision, salience-induced overreaction could also be the driving force behind short-term reversals.

In addition, our study is related to early studies on underreaction and overreaction, which are too vast to cite here. Typically, early studies find that investors tend to overreact to news in the long run (De Bondt and Thaler, 1985) and underreact to news in the short run (Ball and Brown, 1968; Foster et al., 1984; Bernard and Thomas, 1989, 1990). Recent studies on underreaction to news in the short run includes Jiang and Zhu (2017) and Jiang et al. (2021). On the other hand, there is increasing evidence that investors also overreact to news in the short run (Klos et al., 2020; Kumar et al., 2021; Mohrschladt, 2021; Da et al., 2021; Bahcivan et al., 2023; Gulen and Woeppel, 2025). Different from these studies, we find a coexistence of overreaction and underreaction to past news at the monthly horizon, depending on the degree of news salience. In addition, we focus on the interaction effect between salience and short-term returns, whereas the above studies tend to focus on the predictive power of firm-level news or news salience directly, rather than the interaction term.

Lastly, our paper is closely related to studies on the coexistence of momentum and reversal at short horizons. Among others, Medhat and Schmeling (2022) document that there is short-term momentum (reversals) among firms with high (low) turnover. Chan (2003) finds that stocks with news exhibit momentum, while stocks without news do not. Kwon and Tang (2025) document overreaction to more extreme event-types, such as leadership changes, M&A, and customer announcements, and underreaction to less extreme event-types such as earnings announcements. Huang et al. (2018) define salience as the number of quantitative

[5]Early seminal work on short-term reversal includes Jegadeesh (1990); Lehmann (1990); Kaul and Nimalendran (1990); Lo and MacKinlay (1990); and Campbell et al. (1993).

items in an earnings press release headline and show that higher salience is associated with a stronger announcement reaction and subsequent reversal. Frank and Sanati (2018) show that the stock market overreacts to good news and underreacts to bad news. We differ from these studies by measuring salience based on the return of the focal firm relative to its peers, in line with the theoretical work of Bordalo et al. (2012, 2013a,b), rather than some special events/news. In addition, our results are robust after controlling for the turnover effect on short-term momentum/reversals.

The rest of the paper is organized as follows. Section 2 provides descriptions of data sources, variable definitions, and summary statistics. Section 3 presents the main empirical results. Section 4 provides examinations of the underlying mechanisms. Section 5 presents additional robustness tests. Section 6 concludes.

2 Data and variable constructions

2.1 Data source

Our sample consists of all NYSE/NASDAQ/AMEX common stocks (share codes 10 or 11). Stock market and firm accounting data are obtained from CRSP and Compustat, respectively. We also obtain analyst forecast data from the Institutional Brokers Estimate System (IBES) detail file. Data on institutional holdings are obtained from Thomson Reuters. Monthly time series of asset pricing factors are downloaded from Kenneth French's website. The sample period is from December 1983 to December 2021. To control for the effect of microcaps, we require a share price of at least $1 at the portfolio formation date and at least 10 available trading days in the last month.

We obtain firm-level news data from various sources. Earnings announcement data is obtained from the Compustat Fundamentals Quarterly. An earnings announcement is identified using the report date of quarterly earnings (Compustat quarterly item RDQ). Data on major corporate event announcement dates is acquired from the Capital IQ Key Developments. Following Kwon and Tang (2025), we keep observations that can be merged with CRSP and focus on events that are related to firms' real economic activities. We obtain media stories data from the Dow Jones edition of Ravenpack. Following previous studies (Gao et al., 2018; Jiang et al., 2021; Chen et al., 2023), we filter news stories using a "relevance score" and an "event novelty score" of 100 and exclude news primarily pertaining to market movements.

2.2 Deviation salience

Our key variable is the subjective divergence in stock returns with their peers, which should reflect psychological features in the formation of bottom-up stimulus-driven attention (Bordalo et al., 2022). To this end, we make use of the salience function developed by Bordalo et al. (2012, 2013a,b). At the end of each month, we define deviation salience (DS) as the absolute difference between stock i's return and the average return of its peer firms, divided by the sum of absolute excess returns:

$$DS_{i,t} = \frac{|r_{i,t} - r_{i,t}^{p}|}{|r_{i,t} - r_{f,t}| + |r_{i,t}^{p} - r_{f,t}|}, \tag{1}$$

where $r_{i,t}$ and $r_{f,t}$ are stock i's return and risk-free rate in month t, respectively, and $r_{i,t}^{p}$ is the average peer stock return, serving as the context to which the stock is in contrast. The choice of the context (i.e., $r_{i,t}^{p}$) is not arbitrary and should be representative to sufficiently summarize peer stocks' performance and relevant information. We use the shared analyst coverage of Ali and Hirshleifer (2020) as the benchmark returns. The main reason we use analyst linkage to measure peers is that Ali and Hirshleifer (2020) have shown that analyst linkage can account for almost all of the existing economic linkages documented in the literature in terms of return predictability.[6] Specifically, each month, two firms are identified as peers if at least one analyst issued FY1 or FY2 earnings forecasts for both firms in the past 12 months. Then, the average peer stock return of focal stock i is calculated as

$$r_{i,t}^{p} = \frac{1}{\sum_{j=1}^{N_{i,t}} n_{i,j}} \sum_{j=1}^{N_{i,t}} n_{i,j} r_{j,t}, \tag{2}$$

where $r_{j,t}$ is the monthly return of stock j, $N_{i,t}$ is the total number of peer stocks of firm i, and $n_{i,j}$ is the number of shared analysts between firms i and j. In robustness tests, we also consider other benchmark returns such as industry peers and stocks with similar characteristics (He et al., 2023). Our results are robust to these alternative context choices.

[6] It's essential to clarify that our assertion is not that shared analyst coverage precisely serves as a proxy for the context (i.e., peer firms) perceived by investors. Instead, our argument is that what investors perceive as peer firms is highly likely to be covered by shared analyst coverage. This is because of the superior ability of shared analyst coverage to unify economic links, as demonstrated by Ali and Hirshleifer (2020). Nevertheless, we also explore several alternative choices for defining the context and find results that consistently support our conclusions.

The definition of deviation salience is motivated by various properties of bottom-up and stimulus-driven attention as described in Bordalo et al. (2012, 2013a,b, 2022): First, salience emerges when the stock is in contrast to comparable alternatives. This is captured by the numerator that a stock's payoff tends to be salient when it is very different from peers' average performance.[7] Second, the normalization (denominator) implies that DS tends to decrease for larger magnitudes of returns, which reflects diminishing sensitivity. For example, consider return pairs $(0.10, 0.15)$ and $(0.50, 0.55)$. The distance in returns is 0.05 for both cases; however, the latter would be perceived as less pronounced. Third, DS satisfies the reflection condition: deviation salience only depends on the magnitude of excess returns, irrespective of signs.[8]

We note that equation (1) is an imperfect proxy for salience, and its functional form may exhibit undesirable properties in empirical applications. Nevertheless, DS remains arguably the most reasonable and widely used metric, as it explicitly captures the context-dependent, contrast-driven forces that shape salience. In Section 3.1, we report a series of robustness checks on the implementation of this measure following our baseline results.

2.3 Control variables

We control for a battery of firm characteristics in our analysis, including the log of market capitalization (Size), the log of the book-to-market ratio (LogBM), and the cumulative return from $t-12$ to $t-2$ (Mom). Illiquidity (Illiq) is measured using the method of Amihud (2002), averaged over all trading days in a month. Idiosyncratic volatility (IVol) is estimated using daily stock returns in a month, based on the Fama-French (1996) three-factor model (Ang et al., 2006). Monthly turnover ratio (TO) is calculated as the total volume of trades divided by the number of shares outstanding (Medhat and Schmeling, 2022). Analyst coverage (AC) is defined as the log number of analysts covering the firm, where a firm is considered to be covered by an analyst if the analyst issues at least one FY1 or FY2 earnings forecast for the

[7]This property is defined as the ordering condition of the salience function. Intuitively, salience tends to increase in the percentage difference between stock i's return and its peers' performance. For example, consider two stocks outperforming their peers. If interval $[r^p_{i,t}, r_{i,t}]$ contains interval $[r^p_{j,t}, r_{j,t}]$, then it suggests that stock i is more salient than stock j. Refer to Bordalo et al. (2012, 2013a,b) for formal definitions of ordering.

[8]In our robustness tests, we show that both the *context* and the *function form* of equation (1) are necessary to unveil the salience-induced mispricing. Specifically, the return predictability pattern disappears if the market return or random portfolio return is used as the benchmark; the result is also muted when directly using the return distance (i.e., the numerator) as a measure of DS. Further discussions on the salience measure are provided in Section 3.1.5.

firm in the preceding 12 months (Ali and Hirshleifer, 2020). Institutional ownership (Inst) is calculated as the log of the proportion of shares held by institutional investors (Nagel, 2005).[9] As a comparison to our deviation salience measure, we also control for the salience theory value (ST), following the construction of Cosemans and Frehen (2021).

2.4 Summary statistics of DS-sorted portfolios

Table 1 reports summary statistics of portfolios sorted by deviation salience. We present equal-weighted averages of firm characteristics in each DS quintile and the time-series average of correlations with DS.[10] We find that the contemporaneous one-month return (RET) and the absolute return (|RET|) are smaller in extreme DS quintiles relative to the other quintiles. This pattern comes from the construction of DS, especially reflecting the ordering and the diminishing sensitivity properties. Stocks with high deviation salience are associated with more trading and are more volatile. High-DS stocks are also smaller and less liquid than low-DS stocks. Accordingly, high-DS stocks tend to be covered by fewer analysts and held by fewer institutional investors. Although the correlations of DS with other firm characteristics might affect the analysis, our results are robust after purging out these confounding factors.

In addition, the correlation between DS and the salience theory value (ST) is close to zero. This finding is natural given the fact that ST measures the distortion in return expectation and thus mispricing caused by salient thinking (Cosemans and Frehen, 2021), whereas DS captures the degree of deviation in returns or the underlying news from the stock's peers and is non-directional. The correlation between DS and turnover is positive but close to zero as well. Overall, our DS measure is only weakly correlated with other variables that potentially confound the short-term reversal effect.

[9] Specifically, $Inst_{i,t} = \log(1 + IO_{i,t})$, where $IO_{i,t}$ is the proportion of shares held by institutional investors. Following Nagel (2005), IO below 0.01% and above 99.99% are replaced with 0.01% and 99.99%, respectively.

[10] We observe that the average book-to-market ratio (BM) exceeds 1 for all quintile portfolios. This occurs because DS and BM are nearly uncorrelated and our use of equal weights in computing portfolio-level characteristics. Consequently, the average BM value for each DS quintile is influenced by extremely large BM values.

3 Empirical results

This section presents our main results regarding deviation salience and the predictive ability of short-horizon returns. We first perform portfolio analysis by double sorting based on DS and the stock return, along with a series of robustness tests. Then, we use Fama-MacBeth regressions to control for other firm characteristics. In particular, we consider a list of confounding variables studied in previous research that potentially affect short-term return predictability.

3.1 Double sorts on deviation salience and one-month return

3.1.1 Baseline result

Each month, we first sort stocks into five groups based on deviation salience; within each group, we further divide stocks into decile portfolios based on one-month returns. Portfolios are then held for one month, and value-weighted average returns are calculated.[11] Figure 2 presents our main result graphically. We find that the predictive ability of short-horizon performance for future returns strongly depends on the contrast with peer firms. In particular, stocks with a high level of deviation salience exhibit *short-term reversals*: for stocks in the top DS quintile, past one-month winners underperform losers, and the corresponding high-minus-low strategy generates a monthly return of -1.30% (t=-4.18). For stocks with a low level of deviation salience, however, there exists a significant *short-term return continuation*. The strategy that buys the past month's winners and shorts the past losers earns a monthly return of 1.41% (t=3.14) for stocks in the bottom DS quintile.

Table 2 reports the returns of double-sorted portfolios based on DS and one-month performance in more detail. We also calculate risk-adjusted returns using the momentum-augmented factor model of Fama and French (2015). Overall, we find that salience-induced bias leads to significant variation in the pricing of short-term returns. In particular, the difference in the winners-minus-losers (WML) strategy performance between high-DS stocks and low-DS stocks is statistically and economically large, with a monthly return of -2.71%

[11] Our findings remain robust when we first sort by one-month return and then by deviation salience. The results hold significant when using NYSE breakpoints, excluding financial firms, and are even stronger for equal-weighted portfolios. The two-regime pattern also persists when excluding stocks in the bottom two deciles of the monthly market capitalization distribution using NYSE breakpoints. These robustness tests are summarized in Appendix Table A1.

(t=-4.40) and a six-factor alpha of -2.90% (t= -4.10). In addition, although DS is not associated with expected stock returns unconditionally, we find that DS positively predicts future returns for past losers but negatively predicts future returns for past winners. The intuition behind this finding is that bad (good) news tends to be overlooked (overvalued) for stocks with a low (high) DS; as a result, past losers with low DS and past winners with high DS are prone to be overpriced, leading to the return predictive ability of deviation salience among these subsets of firms.

Da et al. (2014a) also find that investors tend to underreact to non-salient news, and the traditional medium-term momentum effect is stronger among firms with non-salient news. Different from Da et al. (2014a), we focus on the predictive power of past one-month return among firms with different levels of salience, whereas Da et al. (2014a) focus on the predictive power of past 12-month return, skipping the most recent month. It is well known that there is a medium-term momentum and Da et al. (2014a) find a stronger medium-term momentum effect among firms with non-salient news. On the other hand, it is also well known that there is a short-term reversal effect. However, we show that the short-term reversal effect is reversed and becomes short-term momentum among firms with non-salient news. In addition, our salience measure is only weakly correlated with the information discreteness measure of Da et al. (2014a), and double sorting on information discreteness and one-month stock return does not give rise to the two-regime pattern documented in Table 2.[12]

3.1.2 Placebo test on the salience measure

Our construction of deviation salience features two crucial elements: (1) the salience functional form (Bordalo et al., 2012, 2013a,b) and (2) a set of representative peer firms as the context for contrast. We show that both elements are necessary by conducting several placebo tests. To examine the role of the salience function, we remove the denominator of equation (1) and directly use the absolute difference component, $|r_{i,t} - r^p_{i,t}|$, to measure deviation salience; to examine the role of context, we consider two alternative benchmark returns without "peer" identifications. Precisely, we use (1) the market and (2) randomly selected peer stocks as the context and calculate DS based on equation (1). We expect that DS does not generate significant pricing effects if the salience functional form is not satisfied

[12]Specifically, we follow Da et al. (2014a) and calculate monthly information discreteness (ID) as $ID = sgn(RET) \times [\%neg - \%pos]$, where $sgn(RET)$ denotes the sign of monthly stock return, and $\%neg$ ($\%pos$) represents the percentage of days during the month with negative (positive) returns. The time-series average of cross-sectional correlation between ID and deviation salience is merely 0.07.

or the context is not pinned down to specific peer definitions.

Table 3 presents the results of placebo tests. In Panel A, we find that high-DS stocks do not exhibit short-term reversals when DS is calculated solely based on the numerator. While the continuation effect occurs among low-DS stocks, the magnitude is only around half of our baseline result. More importantly, the difference in the winners-minus-losers strategy return between low- and high-DS groups is insignificant. This result indicates that the return distance alone is not a proper measure of perceived divergence in stock performance.

In Panel B and Panel C, we use the market and randomly matched stocks as the context, respectively, while preserving the salience functional form. We find that the WML strategy does not generate significant returns across DS groups. Both the continuation and reversal in stock returns disappear if the contrast is not built on inter-peer comparisons. Overall, we find evidence supporting the necessity of our construction of deviation salience.

3.1.3 Control for industry-related effects

It is well-documented that industry is an important dimension of momentum and reversal in stock returns. For instance, prior research demonstrates that industry returns display momentum (Moskowitz and Grinblatt, 1999; Hou, 2007), and the traditional short-term reversal effect can be enhanced by adjusting stock returns for industry performance (Da et al., 2014b; Hameed and Mian, 2015). Given that security analysts tend to specialize by industry, the stock returns of peers with shared analyst coverage could be highly related to industry returns, and thus a concern arises that our findings may be driven by traditional industry momentum and industry-adjusted reversals.

If our momentum among low-salience firms and reversals among high-salience firms are indeed driven by industry momentum and industry-adjusted reversals, respectively, then our results should be stronger when DS is measured with the numerator only, since the numerator is more related to these industry effects. However, Panel A of Table 3 shows that the two-regime pattern is much weaker without diminishing sensitivity (i.e., the denominator) in our salience function. Thus, it is unlikely that our two-regime results are mainly driven by the industry-related momentum and reversals. Nonetheless, in the following tests, we still directly control for industry-related factors to evaluate the robustness of salience-induced momentum and reversals.

We construct two factors to capture industry momentum and industry-adjusted short-term reversals. Specifically, we calculate the industry-peer return using the value-weighted average return of other stocks within the same industry. We also define the industry-adjusted return as the focal stock's monthly return minus the industry-peer return. Then, stocks are sorted into quintiles each month based on either the industry-peer return or the industry-adjusted return. The industry momentum factor is defined as the strategy that longs stocks in the top industry-peer return quintile and shorts those in the bottom quintile. Similarly, the industry-adjusted reversal factor longs stocks in the top industry-adjusted return quintile and shorts those in the bottom quintile. All portfolio returns are value-weighted.

Table 4 reports the alphas of portfolios sorted by DS and one-month stock return. We report the returns to the winners-minus-losers strategy that controls for industry momentum (column (1)), industry-adjusted reversal (column (2)), or both (column (3)). We find that the salience-induced two-regime pattern, i.e., the low-salience momentum and high-salience reversal, is qualitatively similar after controlling for these two industry-related factors.

3.1.4 Trade-off between the numerator and the denominator

In our previous placebo tests, we have shown that using only the absolute value of return difference, i.e., the numerator of deviation salience, fails to generate the two-regime pattern of the short-term return's predictive ability. The main reason is that the numerator and the denominator *jointly* determine the level of salience. For example, a low salience level arises from both a small return difference and a large return magnitude, while a high salience level results from both a large return difference and a small return magnitude.

One concern regarding our main findings is that the variation in the predictive ability of short-horizon returns might potentially stem from mechanical relationships between the focal stock's return and the benchmark return. In particular, one might worry that the short-term momentum among low-DS stocks is mainly driven by the small difference between focal stocks' returns and the context. Thus, sorting by low-DS stocks' monthly returns seems to be similar to sorting by their benchmark returns, and the momentum effect reflects underreaction to peer-wide information instead of salience distortion.

We address this concern by examining our results across subgroups based on different levels of the numerator and denominator of DS. Table 5 reports the results. In Panel A, we find that the short-term momentum of low-DS stocks exists for all numerator levels, even for stocks with large return difference (i.e., a high $|r_{i,t} - r^p_{i,t}|$). Therefore, our momentum result is not solely determined by the distance between the focal stock's return and the benchmark return. Panel B also shows that DS-driven short-term reversal holds for all denominator groups.[13] More importantly, the performance difference of the winner-minus-loser strategy between low- and high-DS stocks always remains statistically significant and economically large.

3.1.5 Further discussion on the salience function

Trade-off between the numerator and the denominator also reflects the joint role of ordering and diminishing sensitivity in determining salience (Bordalo et al., 2013a,b). A more general characterization of the salience function is given as follows:

$$DS^{\theta}_{i,t} = \frac{|r_{i,t} - r^p_{i,t}|}{|r_{i,t} - r_{f,t}| + |r^p_{i,t} - r_{f,t}| + \theta}, \tag{3}$$

where $\theta \geq 0$ is a constant. In our baseline specification, we have followed Bordalo et al. (2013a,b) and set $\theta = 0$, meaning that DS is homogenous of degree zero.[14] This section examines our main results under different θ values. Importantly, a strictly positive θ implies a weaker form of diminishing sensitivity, as a larger θ tends to dominate the variation in the denominator component of DS. In the extreme case where θ is sufficiently large, the denominator would be indifferent from a constant, making DS primarily determined by the numerator.

To illustrate this property, we calculate the Spearman's rank correlation between $DS^{\theta}_{i,t}$ and its numerator (i.e., $|r_{i,t} - r^p_{i,t}|$). A high correlation implies that the ordering condition tends to dominate diminishing sensitivity in determining salience. We consider θ ranging from 1 basis point to 10%. Our expectation is that the salience effect will be preserved for

[13] Table 5 also reveals two supplementary patterns: (1) the low-DS momentum vanishes when the denominator is not large enough; (2) the high-DS reversal effect disappears when the focal stock's performance is nearly indistinguishable from that of its peers. We discuss these findings below. First, when the denominator is small and DS is low, the distance between the focal stock's return and the benchmark return should be minimal as well. If our main results are merely mechanical (e.g., driven by peer-wide information spillover), one would expect to observe stronger momentum and mitigated reversal, yet we see the opposite. Second, when the numerator is small and DS is high, the denominator should be relatively small as well. In this case, returns are close to the risk-free rate, compressing the spread of the sorting variable and naturally dampening the reversal effect. Collectively, these findings confirm that the documented short-term momentum and reversals arise primarily from salience-induced distortion, while artifacts from mechanical factors are unlikely to underlie the stark two-regime pattern.

[14] That is, $DS(\alpha(r_{i,t} - r_{f,t}), \alpha(r^p_{i,t} - r_{f,t})) = DS(r_{i,t} - r_{f,t}, r^p_{i,t} - r_{f,t})$ for any $\alpha > 0$.

positive but small θ values. However, the effect will be less evident for large θ values, since in those cases, DS no longer proxies for salience but merely reflects the return distance, as examined in our placebo tests (Table 3).

Table 6 presents the results. First, we find that the influence of the numerator becomes more prominent as θ increases. As θ approaches 5%, DS closely resembles the numerator, with the correlation between $DS^{\theta}_{i,t}$ and $|r_{i,t} - r^{p}_{i,t}|$ exceeding 90%. Second, our main results remain quantitatively similar for small positive values of θ. For instance, when $\theta = 0.001$, we observe a momentum effect of 1.32% (t-stat=2.95) for low-DS stocks and a reversal effect of -1.25% (t-stat=-3.58) for high-DS stocks. Consistent with our expectations, for larger values of θ, both the momentum and reversal effects tend to diminish, especially the reversal effect. This is primarily because a higher value of θ weakens the role of diminishing sensitivity in determining salience.[15] Overall, these findings suggest that both the ordering condition (governed by the numerator) and the diminishing sensitivity condition (governed by the denominator) are necessary to reveal the pricing implications of salience distortion.

3.1.6 Portfolio characteristics

In addition, one might worry that the characteristic distribution mechanically drives our result. For example, it is possible that the difference in the predictive power of short-term returns is a direct consequence of the fact that the spread of the past one-month stock return in the high-DS group is larger. While this is likely to be the case, we find that the two-regime pattern still holds if we reverse the order of our double sorting. Furthermore, while trading in stocks with more extreme past returns might lead to a stronger short-term reversal effect, the difference in the return spreads among low- and high-DS firms cannot explain why low-DS stocks exhibit return continuation.

In Table 7, we report the average characteristics of the double-sorted portfolios, including deviation salience (Panel A), the contemporaneous monthly return (Panel B), and the

[15] We note that the experiments by Bordalo et al. (2012) suggest a value of $\theta \sim 0.1$. Notice that they use *dollar* payoffs in their experiments, whereas we calculate salience based on *returns*. Notably, a positive θ implies that the salience function no longer satisfies homogeneity of degree zero, making the *unit* used to measure payoffs crucial. Given that monthly stock returns are of much smaller magnitude than dollar payoffs, it is reasonable to infer that a plausible value of θ in our context should be significantly smaller as well. In this sense, our results actually align with the calibrations of Bordalo et al. (2012). In fact, Bordalo et al. (2012) also acknowledge that $\theta \sim 0.1$ is not a formal calibration, but rather a value employed only to illustrate the role of salience in affecting risk preferences. Therefore, our results indicate that an appropriate choice of θ should be of smaller magnitude when examining the impact of salience on the predictive power of short-term stock returns.

monthly turnover ratio (Panel C). In particular, Panel B illustrates that the medium DS group exhibits the largest one-month return spread (0.521), yet we find that the difference in future returns between winners and losers is minor (0.27% with a t-statistic of 0.70), as suggested in Table 2. In addition, Panel C shows that the average turnover ratio and the spread in turnover tend to be larger for high-DS stocks, which is consistent with our hypothesis that salience-induced trading and overreaction lead to short-term reversals. More importantly, the distribution of the turnover ratio also helps to differentiate between our results and the short-term momentum effect documented by Medhat and Schmeling (2022), where high-volume stocks display momentum instead of reversal. We formally examine the relationship between deviation salience and trading volume in a later analysis.

3.2 Fama-MacBeth regressions

Although the above portfolio-sorting approach is simple and intuitive, it cannot explicitly control for other variables that could influence returns. Since salience is potentially correlated with other firm-level characteristics such as volatility and shares turnover, concern could arise that the results in Table 2 are driven by effects other than salience. To address this important concern, we perform a series of Fama and MacBeth (1973) cross-sectional regressions, which allow us to conveniently control for additional variables.

Specifically, we control for other confounding factors in Fama-MacBeth regressions to assess the robustness of our results. For example, the conventional explanation for the reversal effect at short horizons ascribes the returns to the compensation for providing liquidity (Avramov et al., 2006; Nagel, 2012; Da et al., 2014b; So and Wang, 2014; Cheng et al., 2017; Dai et al., 2024). Therefore, we control for the effects of firm size and stock illiquidity (Amihud, 2002). Most recently, Medhat and Schmeling (2022) show that the pricing of short-horizon returns varies significantly by the turnover ratio. They find that low-turnover stocks exhibit short-term reversal, while high-turnover stocks display short-term momentum. Dai et al. (2024) find that the short-term reversal is also stronger among high-volatility stocks. We take these patterns into account in our regressions. Finally, we also consider attention proxies using analyst coverage and institutional ownership since earlier research (e.g., Chen et al. (2023)) has shown that underreaction-related anomalies such as medium-term price momentum tend to be stronger among firms with lower investor attention.

Table 8 shows the average coefficients from monthly cross-sectional regressions. The main independent variable of interest is the interaction between deviation salience (DS) and the one-month stock return (RET). We find that the estimated coefficient on DS×RET is negative and highly significant; in terms of magnitude, the predictive ability of the interaction term is comparable and even stronger than RET itself. This finding is consistent with the portfolio results and suggests that short-term returns tend to reverse (continue) for stocks with high (low) deviation salience. In addition, the coefficient on the interaction term between turnover and one-month returns is significantly positive, consistent with the findings in Medhat and Schmeling (2022). In columns (4) and (8), we also find that including the salience theory value (ST) of Cosemans and Frehen (2021) hardly affects our estimates. This result is expected since DS and ST are conceptually different.[16]

We also separate good news and bad news to investigate the potential asymmetry of the salience effect. A large literature in psychology suggests that there is a positive-negative asymmetry effect generally in various events. In particular, Baumeister et al. (2001) demonstrate that negative news receives more processing and contributes more strongly to the final impression. Therefore, we conjecture that the salience distortion would be more pronounced for bad news than for good news. Table 9 examines this hypothesis through a series of Fama-MacBeth regressions, in which we estimate the interaction effect of salience separately for negative returns (bad news) and positive returns (good news). Across various specifications, it shows that the estimated coefficient on DS×bad news has a larger magnitude than that on DS×good news. Notably, this result seems to contradict the result of Frank and Sanati (2018), where they find underreaction to negative news but overreaction to positive news. We differ from Frank and Sanati (2018) in that we focus on the interaction effect of salience, rather than the direct price reaction to news. Our testing result suggests that salience-induced distortion in stock returns is relatively more evident for the negative part, which appears to be not driven by prior findings on market response to information. We shall formally examine the influence of news in a later analysis.

3.3 Long-horizon portfolio returns

Figure 3 shows the cumulative returns to the winners-minus-losers strategies for high- and low-DS stocks. For stocks in the bottom DS quintile, the return continuation effect tends to drift upward and persist for 12 months. As a comparison, the reversal effect among

[16] In Appendix Table A2, we also control for the potential influence of ST by using (1) the absolute value of ST, and (2) the square of ST. We find quantitatively similar results.

stocks in the top DS quintile becomes insignificant 2 months after portfolio formation. This result suggests that the underreaction-induced mispricing among low-DS firms gets corrected slowly over the next 12 months, whereas transient price pressure from overreaction among high-DS firms gets corrected quickly in the next month. To further explore the underlying mechanisms, we shall explore the subsequent earnings forecast errors and fundamental performance in the next section.

4 Inspecting the mechanisms

In this section, we perform several tests to examine the mechanism underlying the variation in return predictability associated with DS. We first examine the contemporaneous relationship between deviation salience, abnormal trading volume, and retail investor attention. Then, we explore DS-induced distortion in belief updating by examining analysts' forecast errors and subsequently realized fundamentals. We also address illiquidity-related concerns by testing our main results in different subsamples. Lastly, we control for the potential influence of event-driven under-and-overreaction by examining the salience effect among firms without news.

4.1 Evidence from trading volume and retail investor attention

Our primary hypothesis builds on the concept of salience-induced attention bias. In particular, when a stock's performance is perceived as close to its peers, measured by a low level of DS, then value-relevant news would be less attractive. This effect leads to underreaction and hence return continuation at short horizons. By contrast, when a stock is perceived to deviate significantly from its peers, represented by a high level of DS, then investors would tend to overweight such information, probably because of excessive attention, leading to overreaction and short-term reversals.

We examine this hypothesis by testing the contemporaneous relationships between deviation salience, trading volume, and attention. Abnormal trading volume is calculated as the log difference between monthly turnover and the average turnover in the past three months. This definition follows a manner similar to prior studies such as Kandel and Pearson (1995) and Chae (2005). We also measure retail investors' attention using abnormal Google search volume, as in Da et al. (2011). Panel A and Panel B of Table 10 report the results from panel regressions. Consistent with our hypothesis, we find that deviation salience positively and significantly correlates with contemporaneous abnormal volume and retail investor attention. Note that, by construction, DS measures the degree of return divergence and hence is *non-directional*. Therefore, one potential interpretation of our estimations is that higher salience attracts more trading and attention to the stock, which may in turn lead to overreaction among high-salience firms. It is also possible that excess attention and trading lead to more salient returns. In either case, investors might have overreacted to high-salience firms.

As a robustness check, we also examine two additional variables related to trading volume and retail investor attention. First, rather than using total trading volume, we focus specifically on trades made by retail investors (Boehmer et al., 2021). Second, we consider an alternative measure of retail investor attention based on social media activity (Cookson et al., 2024).[17] Aligning with our earlier findings, Panel C of Table 10 shows that deviation salience positively correlates with retail trading volume. In Panel D, we also find that deviation salience significantly attracts attention revealed by social media activities, i.e., highly salient stocks are mentioned more frequently on social media platforms. In Appendix Table A3, we use account-level data from a large U.S. discount brokerage (Barber and Odean, 2000, 2001, 2002) to further investigate the role of deviation salience in trading decisions.[18] We find evidence that individual investors are indeed more likely to trade salient stocks.

We show that there is a positive association between our salience measure and proxies for attention, lending support to the salience-induced attention channel in affecting asset prices. However, salience can affect the asset price through channels other than pure attention. For example, it is possible that salience can induce probability overweighting for salient news, as in the prospect theory of Kahneman and Tversky (1979). Since it is almost impossible to directly measure the probability weighting function, we are not trying to distinguish these alternative channels in this paper. Rather, we focus on examining how salience influences short-term return predictive ability in general.

4.2 Evidence from forecast errors and subsequent fundamentals

Next, we examine whether security analysts' forecasts are distorted by deviation salience. If a high (low) level of DS leads to overweighting (underweighting) of short-term performance

[17]We thank the authors for making their data available.
[18]We thank Terrance Odean for sharing the data with us.

in belief formations, then the forecast would tend to be too optimistic (pessimistic) for stocks that have recently performed well (poorly). We calculate the forecast error as the difference between realized earnings and the consensus forecast, normalized by the share price (DellaVigna and Pollet, 2009).

Table 11 shows the results from regressions of analyst forecast error on the lagged short-term return (RET), a dummy variable indicating a high deviation salience ($I_{\text{High DS}}$), and their interaction. In Panel A, we find that the estimated coefficient on RET$\times I_{\text{High DS}}$ is significant and negative, suggesting that market expectations tend to be biased upward (downward) for recent winners (losers) when the deviation salience is high. In contrast, for stocks that are subjectively indistinguishable from their peers (low DS), market participants are inclined to fail to learn from prices, which leads to the return continuation. Panel B re-estimates the regressions using the placebo DS measures examined in Section 3.1.2. It shows that, when DS is defined (1) directly as the return distance, (2) relative to the market return, or (3) against randomly assigned context, the link between short-term returns and analysts' forecast errors does not exhibit significant variations across salience levels. This result echoes our previous robustness tests on double-sorted portfolios in Section 3.1.2, which suggest that these placebo DS measures fail to generate overreaction/underreaction patterns in the pricing of short-horizon returns.

To further validate our hypothesis, we also examine how stock returns can predict subsequent fundamentals. Since stock prices are forward looking, current increases in prices are suggestive of better fundamentals in the future. However, if investors pay excessive attention to the focal firm because of its salience, then the predictive ability of past returns for future fundamentals could be mitigated, probably because of the overreaction of stock prices in the current period. Similarly, if investors partially neglect the information content of non-salient returns, then the association between past price changes and future fundamentals should be stronger. That is, a small price increase could indicate a relatively large fundamental improvement in the future when current investor attention is limited.

We consider various fundamental variables to test this prediction, including return-on-equity (ROE), return-on-assets (ROA), changes in earnings per share (ΔEPS), profit growth (PG), and gross profitability (GP). Table 12 reports the results. Consistent with previous analysis, the slope on the interaction term (RET$\times I_{\text{High DS}}$) is significantly negative, and the estimated coefficient on the past short-term return (RET) is positive. This result suggests that a lower (higher) level of deviation salience amplifies (reduces) the predictive ability of returns for future fundamentals. It also, in turn, supports our estimation regarding forecast errors, as analysts are subject to underinference when returns are not salient.

4.3 Evidence based on large and liquid firms

Our result suggests that *overreaction* to salient information contributes to the return reversal at short horizons. This channel is considerably different from the prevailing explanation that the short-term reversal primarily represents compensation for liquidity provision (Avramov et al., 2006; Nagel, 2012; Da et al., 2014b; So and Wang, 2014; Cheng et al., 2017; Dai et al., 2024). While it is challenging to isolate the effects of salience-induced overreaction and liquidity provision, we can show that the latter is unlikely to be the main driving force of our results. Specifically, we partition stocks into subsamples based on size or liquidity and examine the double-sorted portfolios within each group.

Table 13 reports returns to the winners-minus-losers strategy for each subsample and DS group. We also calculate the overall WML strategy return for each subsample, based on the direct one-sort portfolios. Panel A and Panel B show that the unconditional short-term reversal effect is nonexistent among these large and liquid firms. In sharp contrast, the two-regime pattern remains intact for these highly liquid stocks, and the difference in the WML strategy return between low-DS stocks and high-DS stocks is significant. In Panel C, we find that the salience-induced pricing effect even applies to the most liquid stocks. For example, the largest 1,000 firms, which account for around 90% of the total market capitalization, exhibit *both* short-term reversal and momentum, depending on the level of deviation salience.[19] In addition, this finding also distinguishes our mechanism from that of Medhat and Schmeling (2022), where the short-term reversal of low-volume stocks disappears for mega caps. In contrast, the salience-induced coexistence of reversal and momentum applies to all size and liquidity subsamples.[20] Therefore, although we cannot completely rule

[19] In untabulated results, we also form value-weighted one-sort portfolios among these large stocks based on the salience theory value (ST) of Cosemans and Frehen (2021). It turns out that ST does not exhibit significant predictive ability for future returns within mega caps. Note that we also control the potential influence of ST in Fama-MacBeth regressions (Table 8) and find that it does not alter our results. Therefore, the interaction effect of deviation salience and stock return documented in this paper is related to but distinct from the mechanism studied in Cosemans and Frehen (2021).

[20] We also examine the robustness of our results by replacing the raw monthly return with industry-adjusted return, since previous studies such as Da et al. (2014b) and Hameed and Mian (2015) find that the return reversal is stronger after accounting for industry information. In untabulated results, we find that even the industry-adjusted return does not guarantee a significant reversal effect for mega caps. When directly sorting large stocks based on industry-adjusted returns and forming value-weighted portfolios, the average return of the resulting winners-minus-losers strategy is only marginally significant or insignificant. However, a strong short-term reversal effect is still present in high-salience stocks when using industry-

out the effect of liquidity provision, the results suggest that salience is more likely to be the dominant factor behind our findings.

4.4 Evidence based on firms with and without news

We have shown that there is short-term price continuation among firms with low salience. It is possible that this price continuation is driven by the traditional PEAD effect among these firms. In addition, earlier studies also find that investors tend to overreact to extreme news and there are reversals after extreme news (Kwon and Tang, 2025). Thus, it is also possible that the overreaction among firms with high salience is also driven by overreaction to extreme earnings announcement news or other corporate events. If low-salience firms is more likely to experience earnings news in the past month, then our short-term momentum could be completely driven by the traditional PEAD effect. On the other hand, if high-salience firms is more likely to experience extreme corporate news in the past month, then our stronger reversal effect among high-salience firms could just be driven by the effect documented by earlier studies such as Huang et al. (2018), Frank and Sanati (2018), and Kwon and Tang (2025). To investigate these possibilities, we examine the impact of firm-level event news on the effect of salience on short-term return predictive ability with subsample analysis among firms with and without news in the previous month.

Novy-Marx (2015) finds that the traditional medium-term price momentum is mainly driven by the traditional PEAD effect. First, if our short-term price continuation among low-salience firms is also mainly driven by the traditional PEAD effect, we should observe much weaker price continuation among firms without earnings announcements in the previous month. Panel A and Panel B of Table 14 report the double-sorted portfolio returns for firms with and without earnings announcements, respectively. We find that the coexistence of short-horizon momentum and reversal remains evident regardless of whether there is an earnings announcement. Thus, earnings news is not the only driver for our documented salience effect. In addition, the high-salience return reversal effect is much stronger when returns are not associated with earnings news. For example, the winners-minus-losers strategy among high-DS stocks generates a monthly return of -2.15% when there are no earnings announcements, whereas the strategy yields a return of -1.01% per month in the presence of earnings news. This result is consistent with the finding from early studies that

adjusted returns. While the low-salience momentum effect is weaker than our baseline result, we find that the salience-induced two-regime pattern remains highly significant. In robustness tests, we directly control for industry-related momentum and reversal effects and find that our results are hardly influenced.

reversals tend to be stronger if one excludes earning announcement returns from the return in the previous month. Moreover, we find that the low-salience momentum effect is similarly strong among these two groups of firms, suggesting that our short-term momentum among low-salience firms is not driven by the traditional PEAD effect. Panel C reports the difference across two groups of firms. The results indicate that the differences are mostly insignificant, suggesting that the role of salience on the predictive ability of short-term returns does not crucially depend on investor responses to past earnings announcement news.

While earnings announcements constitute vital information for firms, concerns persist regarding the influence of alternative corporate events on our findings. For instance, Kwon and Tang (2025) find that there is underreaction to less extreme events beyond earnings news, such as product announcements and annual general meetings; Jiang et al. (2021) find that stock prices generally drift in the same direction as the initial market response after publications of media news. Thus, the short-term momentum among low-salience stocks might be partially driven by underreaction to these events. On the other hand, Kwon and Tang (2025) find that investors tend to overreact to more extreme events such as M&A and leadership changes. Therefore, the short-term reversal within high-salience stocks might be potentially driven by the overreaction to firm news with salient attributes.

To address these concerns, we further complement our tests by incorporating two additional sources of firm news. Firstly, we utilize major corporate event news retrieved from the Capital IQ Key Developments. We focus on the 24 major event types related to the real economic activities of firms, as studied in Kwon and Tang (2025). These events include earnings, mergers and acquisitions, leadership changes, product and client-related announcements, labor activities, and business reorganizations. Then, a firm is defined as having news if there was an earnings announcement or at least one major corporate event in the preceding month. Secondly, we incorporate media news from the Ravenpack database, which covers an extensive repository of firm-related information. Similarly, we define a firm as having news if there is at least one media-reported story or an earnings announcement within the preceding month.

In Panel D to Panel F of Table 14, we repeat our portfolio analysis as in Panel A to Panel C using major corporate events. It shows that salience-induced momentum and reversal still exist even if there was no major corporate event news in the portfolio formation month. The difference in the salience effect (DS5-DS1) between firms with/without news is also insignificant. Therefore, our result is not simply driven by event extremeness-related over- and under-reaction. Panel G to Panel I of Table 14 report the results using Ravenpack news. As the media news data spans a much shorter period (beginning in 2000) compared to our baseline sample, the statistical significance is reduced. Nevertheless, we find that the salience effect remains after excluding a wide range of firm-specific news. Overall, our results support the story that investors tend to overreact (underreact) to salient (non-salient) information, which does not seem to stem solely from the channels documented by earlier studies.[21] Therefore, the deviation salience measure constructed in this paper captures salience distortion as depicted by Bordalo et al. (2012, 2013a,b) in a general sense, rather than merely reflecting market responses to special events or news.

5 Additional robustness tests

5.1 Orthogonalized deviation salience

High-DS stocks tend to be smaller, less liquid, held by fewer institutional investors, more volatile, and covered by fewer analysts. Although we have accounted for these effects in Fama-MacBeth regressions and show that our results hold for large stocks, we further assess the robustness of our results using orthogonalized deviation salience measures and portfolio-sorting analysis. Specifically, we perform monthly cross-sectional regressions of DS on a set of firm-level characteristics including firm size, illiquidity, institutional ownership, idiosyncratic volatility, and analyst coverage, and then take the residuals. To further rule out the effect of turnover, as in Medhat and Schmeling (2022), we also orthogonalize our salience measure against turnover.

Table 15 reports double-sorted portfolios by orthogonal DS and one-month stock performance. We find that the pricing pattern of short-term returns documented in Table 2 still holds. Among stocks with high orthogonalized DS (DS5), there is a significant short-term reversal effect; for low-orthogonalized DS stocks (DS1), however, past winners continue to outperform past losers in the future. For example, Panel D reports the result when all characteristics are taken into account. It shows that the momentum effect among low-salience firms is 1.70% (t=3.76) per month, whereas the reversal effect is -1.00% (t=-3.88) per month among high-salience firms.

[21] One might worry that our result could be driven by differences in firm size between those with and without news, as firms experiencing major events or high media coverage tend to be larger than firms without such events. However, in untabulated results, we find that the salience effect remains highly significant for firms without news, even when restricting attention to observations above the bottom two or three deciles of NYSE size distributions. Hence, the size effect alone cannot explain our findings.

5.2 Alternative benchmark returns

We have thus far used shared analyst coverage (Ali and Hirshleifer, 2020) as the context for constructing deviation salience. In this section, we show that our main findings hold for other choices of benchmark. A natural context for investors to evaluate a stock is other stocks' performance in the same industry. We thus construct alternative DS measures using various industry definitions. Specifically, we consider the Fama-French 49 industry classification, the three-digit SIC codes industry classification, and the text-based industry classification (Hoberg and Phillips, 2016, 2018).[22] In addition, we also use stocks with similar characteristics (He et al., 2023) as an alternative benchmark. In particular, we measure the similarity between two stocks by the Euclidean distance between their characteristics, including price, size, book-to-market ratio, profitability, and investment rates. For each stock, we calculate the value-weighted average return of its 50 nearest stocks.

Table 16 reports the double-sorted portfolios based on alternative DS measures and one-month return. Across all constructions, we find that short-horizon returns tend to continue for low-DS stocks but reverse for high-DS stocks. Take the context of the SIC codes industry as an example. Panel B of Table 16 shows that the winners-minus-losers strategy earns a monthly return of 82 bps (t=3.59) for stocks in the low DS group, whereas the strategy generates a negative return of -1.38% (t=-5.18) for stocks in the high DS group. Since our results still hold when we use industry return as our benchmark, it is unlikely that the short-term momentum effect among low-salience firms is driven by the well-known industry momentum, as in Moskowitz and Grinblatt (1999).

5.3 Earlier sample periods

In our main analysis, we use the shared analyst coverage of Ali and Hirshleifer (2020) as the benchmark returns, and thus we limit our sample to the post-1983 period because of the availability of IBES analyst-forecast data. We extend our sample back to 1926 by using the Fama-French 49 industry returns as context and re-calculate deviation salience based on equation (1). Table 17 presents the double-sorted portfolio results for four intervals: 1926 to 1963, 1926 to 1983, 1963 to 1983, and 1926 to 2021. Across all sample periods, the low-DS momentum and high-DS reversal remains evident.

[22]Data on text-based industry classification are downloaded from the Hoberg-Phillips Data Library.

5.4 International evidence

Lastly, we examine the pricing effect of deviation salience in other markets to further assess the external validity of our findings. We obtain international stock market data from the Compustat Global Security database. We start with common stocks traded on major stock exchanges from the countries (markets) studied by Gao et al. (2018) and apply several filters to mitigate the influence of noise in the international sample. First, we require a stock to have a minimum of 12 monthly observations to be included in the sample (Hou et al., 2011). Second, we drop extreme return values, following the procedure of Ince and Porter (2006). Third, we exclude firm observations with a stock price or market value below the 5th percentile of the market each month. Finally, a country/market is included only if at least 150 stocks have non-missing values for double sorting and the average number of available stocks is at least 200 over the sample period.

We use Global Industry Classification Standard (GICS) codes to assign stocks into sectors (Ali and Hirshleifer, 2020). The benchmark return for each stock is the value-weighted average monthly return of other stocks in the same sector. Then, the deviation salience is calculated in each market analogously, based on equation (1). We use the 30-day U.S. T-bill rate as the risk-free rate, and all returns and market values are in U.S. dollars. Figure 4 shows the annualized Sharpe ratios of the WML strategies within different deviation salience groups. Across 28 markets, we find that the returns of low DS stocks tend to continue, whereas high DS stocks exhibit short-term reversals. There are only three exceptions: low DS stocks exhibit a reversal effect in Japan and Turkey, while high DS stocks exhibit minor momentum in Malaysia. Moreover, on average, the short-term momentum effect among low-salience firms is 0.62% per month (t=3.21), whereas the short-term reversal effect among high-salience firms is -1.18% per month (t=-5.40). The difference between these two effects is also highly significant with a t-statistic of 7.12 in absolute value. Overall, the result suggests that the two-regime pricing pattern from deviation salience generally holds in a broad set of international markets.

6 Conclusion

Earlier studies suggest that investors tend to underreact to ordinary news but overreact to salient news. Using a firm-level salience measure based on the relative distance of the focal firm's return in the past month to its peers' return in the past month, we find that there is indeed short-term momentum among low-salience firms, whereas there is a strong short-term reversal among high-salience firms. These results are robust after controlling for a battery of compounding effects. Our study highlights the importance of salience in asset pricing. In future research, it would be interesting to study the role of salience in other markets such as the bond market or the foreign exchange market. It would also be fruitful to build salience into otherwise standard models to account for asset pricing phenomena.

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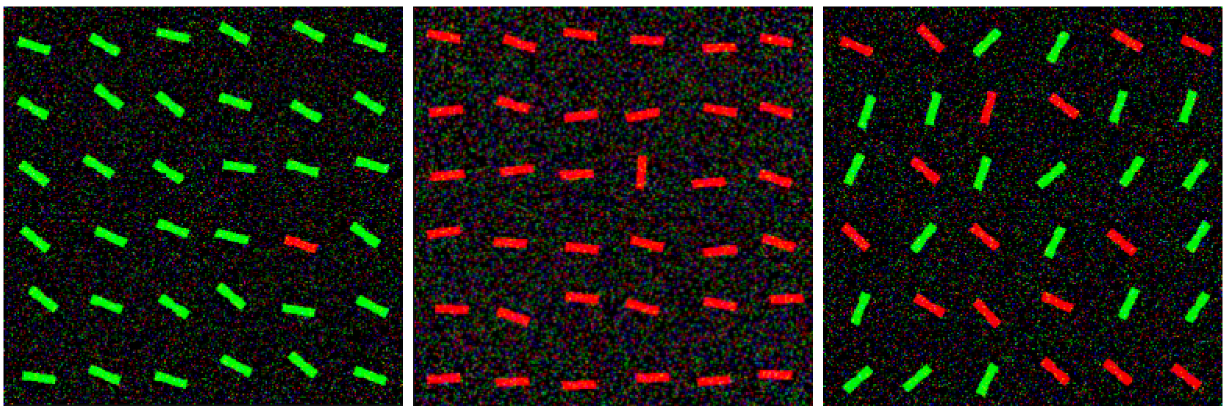

Figure 1: Visual illustration of salience

This figure presents examples of visual salience (Itti, 2005, 2008), illustrating the stimulus-driven attention theory pioneered by Treisman and Gelade (1980). In the left panel, the red bar attracts immediate attention because of its high salience from the sharp contrast with other green bars. Similarly, the vertical bar in the middle panel stands out conspicuously against its surroundings. In the right panel, the red right-oriented bar (row 2, column 3) is unique among all elements, yet requires greater cognitive effort to detect due to interference from bars with similar features.

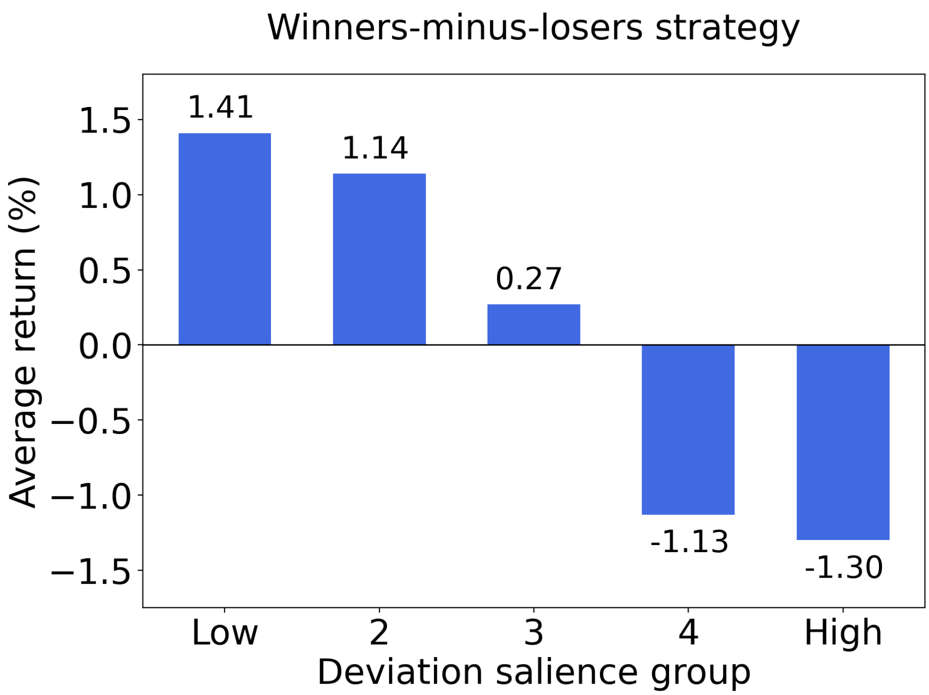

Figure 2: Deviation salience and winners-minus-losers strategy returns. The figure plots the average returns to strategies that buy the past month's winners and short the past month's losers. Each month, stocks are sorted into quintile portfolios based on deviation salience (DS) and then split into deciles based on one-month return. The winners and losers are defined as stocks in the top and bottom deciles, respectively. Monthly value-weighted returns are reported. The sample period is from December 1983 to December 2021.

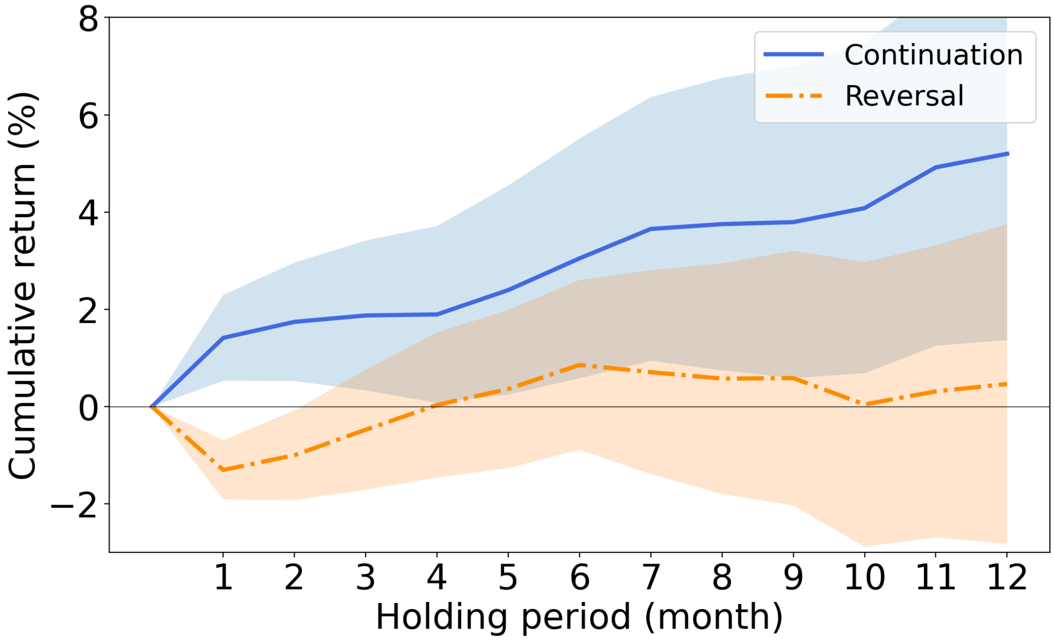

Figure 3: Long-run returns of DS-based winners-minus-losers strategies.
The figure plots the value-weighted average cumulative returns of winners-minus-losers portfolios within the low-DS group (solid blue line) and the high-DS group (dash-dotted orange line). The shadow areas represent the 95% confidence intervals. The sample period is from December 1983 to December 2021.

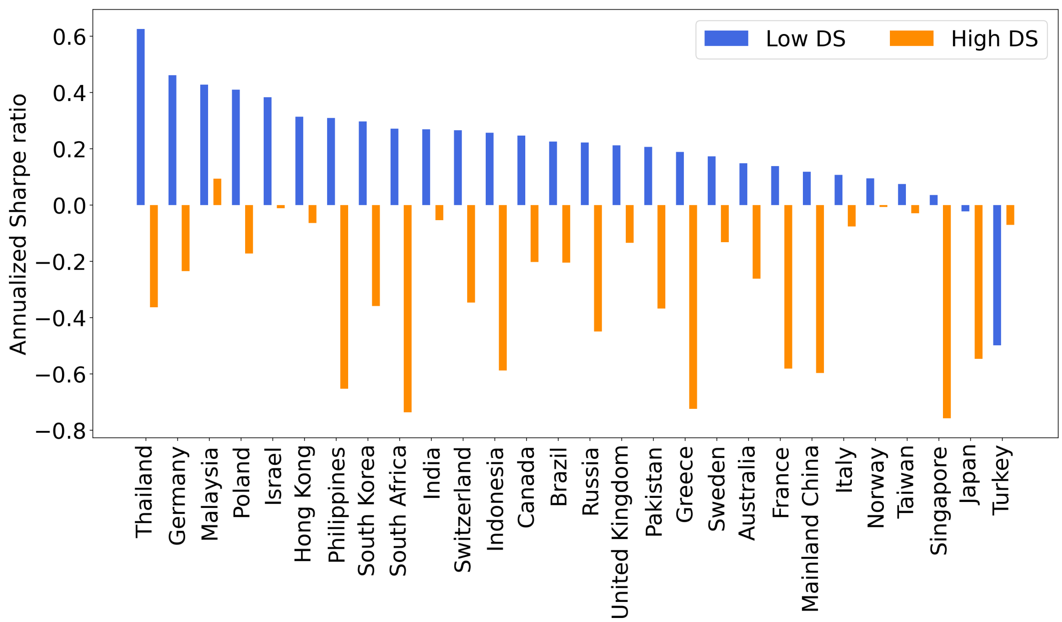

Figure 4: Deviation salience and international stock returns.
The figure presents the annualized Sharpe ratios of the winners-minus-losers (WML) strategies within low- and high-DS groups in each market. At the end of each month, we form 3×10 portfolios by sequentially sorting stocks based on deviation salience (DS) and monthly return. The WML strategy returns are calculated as the difference in future returns between the top and bottom decile portfolios within each DS group. All returns and market values are in U.S. dollars, and portfolios are value weighted. The sample ends in December 2021.

Table 1: Summary statistics

This table reports summary statistics of portfolios formed on deviation salience (DS). DS is calculated as the absolute difference between the stock return and peer stocks' average return, divided by the sum of absolute excess returns. Each month, we sort stocks into quintile portfolios based on DS and calculate equal-weighted averages of firm characteristics. The table shows for each DS quintile the time-series averages of monthly characteristics. Also reported are time-series averages of cross-sectional correlations between DS and firm characteristics. RET and |RET| are a stock's return (in %) and the absolute return (in %) in a month. ST is the salience theory value (in %), calculated using daily returns in a month (Cosemans and Frehen, 2021). Mom is the cumulative 11-month return (in %), skipping the most recent month. Size is the log of market capitalization. BM is the book-to-market ratio. Illiq is the illiquidity measure of Amihud (2002) with a one-month calculation window. TO is the turnover ratio, defined as the monthly total trading volume divided by the shares outstanding (Medhat and Schmeling, 2022). IVol is the idiosyncratic volatility (Ang et al., 2006), estimated using daily stock returns in a month (in %). AC is the analyst coverage, computed as the log number of analysts covering a firm. Inst is the institutional ownership, defined as the log transformation of the proportion of shares held by institutional investors. The sample period is from December 1983 to December 2021.

	DS	RET	|RET|	ST	Mom	Size	BM	Illiq	TO	IVol	AC	Inst
Low DS	0.13	1.27	7.57	0.46	15.31	13.37	1.23	1.29	0.11	2.00	2.07	0.40
2	0.38	1.69	10.17	0.53	15.58	13.20	1.22	1.36	0.11	2.19	2.03	0.40
3	0.64	2.92	13.90	0.71	15.21	12.89	1.43	1.86	0.13	2.61	1.92	0.38
4	0.93	0.17	9.93	0.38	13.84	12.71	1.45	2.47	0.12	2.62	1.83	0.36
High DS	0.99	-0.43	7.78	0.31	14.27	12.72	1.42	2.60	0.12	2.55	1.83	0.36
High-Low	0.86	-1.70	0.21	-0.16	-1.04	-0.65	0.20	1.31	0.02	0.55	-0.25	-0.04
Corr. DS	1.00	-0.01	0.05	-0.01	-0.02	-0.15	0.01	0.03	0.02	0.14	-0.12	-0.10

Table 2: Double sorts on deviation salience and one-month return

This table presents double-sorted portfolio results based on deviation salience (DS) and one-month stock return (RET). DS is calculated as the absolute difference between the stock return and peer stocks' average return, divided by the sum of absolute excess returns. Each month, stocks are sorted into quintiles based on DS; within each quintile, stocks are further divided into deciles. Portfolios are held for one month. Then, value-weighted returns and the six-factor alphas (Fama and French, 2015) are calculated. Returns and alphas are reported in percentage points. The sample ranges from December 1983 to December 2021. The t-statistics are calculated based on Newey-West adjusted standard errors and reported in parentheses.

Panel A. Excess returns

DS \RET	Low	2	3	4	5	6	7	8	9	High	High-Low
Low	-0.30	0.56	0.65	0.54	0.84	0.87	0.62	0.88	0.74	1.12	1.41
	(-0.84)	(2.21)	(2.16)	(2.07)	(3.42)	(3.40)	(2.42)	(3.64)	(3.40)	(3.12)	(3.14)
2	0.02	0.38	0.87	0.88	0.73	0.77	0.76	0.71	0.85	1.16	1.14
	(0.05)	(1.23)	(3.32)	(3.37)	(2.83)	(2.87)	(2.99)	(2.68)	(3.01)	(3.62)	(2.90)
3	0.51	0.71	0.83	0.64	0.52	0.79	0.77	0.60	0.63	0.78	0.27
	(1.31)	(2.20)	(2.77)	(2.43)	(2.12)	(3.30)	(3.19)	(2.22)	(2.04)	(2.41)	(0.70)
4	1.34	1.32	1.43	1.30	1.16	0.90	0.96	0.73	0.46	0.22	-1.13
	(3.42)	(4.04)	(5.38)	(5.57)	(5.60)	(3.77)	(4.14)	(3.03)	(1.56)	(0.71)	(-3.64)
High	1.27	1.46	1.46	1.23	0.88	0.81	1.02	0.60	0.47	-0.03	-1.30
	(3.09)	(5.00)	(5.78)	(5.14)	(3.93)	(3.49)	(4.26)	(2.51)	(1.54)	(-0.10)	(-4.18)
High-Low	1.57	0.91	0.81	0.70	0.04	-0.06	0.40	-0.28	-0.27	-1.15	-2.71
	(4.28)	(3.49)	(2.71)	(3.49)	(0.23)	(-0.40)	(1.98)	(-1.52)	(-1.13)	(-3.00)	(-4.40)

Panel B. Six-factor alphas

DS \RET	Low	2	3	4	5	6	7	8	9	High	High-Low
Low	-1.03	-0.07	-0.09	-0.31	0.12	0.11	-0.09	0.19	-0.00	0.48	1.51
	(-3.82)	(-0.33)	(-0.49)	(-2.18)	(0.90)	(0.92)	(-0.61)	(1.20)	(-0.03)	(1.56)	(2.94)
2	-0.72	-0.42	0.07	0.17	-0.13	0.01	0.02	-0.05	0.18	0.62	1.34
	(-2.13)	(-2.26)	(0.39)	(1.02)	(-0.89)	(0.05)	(0.12)	(-0.28)	(1.02)	(2.67)	(2.94)
3	-0.43	-0.04	-0.24	-0.13	-0.26	-0.04	0.02	-0.14	-0.05	0.21	0.64
	(-1.39)	(-0.16)	(-1.19)	(-0.79)	(-1.89)	(-0.28)	(0.14)	(-0.81)	(-0.24)	(0.85)	(1.44)
4	0.57	0.49	0.66	0.50	0.41	0.04	0.15	-0.07	-0.22	-0.41	-0.98
	(2.22)	(2.30)	(3.74)	(3.22)	(3.53)	(0.33)	(1.46)	(-0.52)	(-1.21)	(-1.83)	(-2.90)
High	0.72	0.79	0.80	0.50	0.13	-0.05	0.26	-0.19	-0.21	-0.66	-1.39
	(2.51)	(4.58)	(4.81)	(3.36)	(1.38)	(-0.41)	(2.22)	(-1.56)	(-1.09)	(-3.09)	(-4.41)
High-Low	1.76	0.86	0.89	0.81	0.01	-0.16	0.35	-0.38	-0.21	-1.14	-2.90
	(3.76)	(2.94)	(2.90)	(3.70)	(0.08)	(-0.99)	(1.70)	(-1.76)	(-0.74)	(-2.65)	(-4.10)

Table 3: Placebo tests

This table presents double-sorted portfolio results based on deviation salience (DS) and one-month stock return (RET). In Panel A, DS is calculated directly using the absolute difference between the focal stock's monthly return and peer stocks' average return, where peer stocks are defined identically as in Table 1. In Panel B, DS is calculated according to equation (1), while the CRSP value-weighted market return is used as the context. In Panel C, we randomly select 100 other stocks for each focal stock, use the value-weighted return of these random portfolios as the context, and apply equation (1) to compute DS. Each month, stocks are sorted into quintile portfolios based on the DS; within each quintile, stocks are further divided into deciles based on monthly returns. Portfolios are held for one month, and value-weighted returns are calculated. The column RET10-RET1 refers to the winners-minus-losers portfolio, and the column FF6 alpha reports the corresponding factor-adjusted return (Fama and French, 2015). Returns and alphas are reported in percentage points. The sample ranges from December 1983 to December 2021. The t-statistics are calculated based on Newey-West adjusted standard errors and reported in parentheses.

	RET1	RET5	RET10	RET10-RET1	FF6 alpha
Panel A. DS constructed solely based on the absolute difference					
DS1	0.23	0.85	0.98	0.76	0.80
	(0.72)	(4.01)	(3.56)	(2.23)	(1.94)
DS3	0.32	1.37	0.72	0.41	0.43
	(0.89)	(5.25)	(2.55)	(1.34)	(1.21)
DS5	0.59	1.17	0.58	-0.02	0.26
	(1.15)	(3.33)	(1.43)	(-0.03)	(0.59)
DS5-DS1	0.37	0.32	-0.41	-0.77	-0.53
	(0.86)	(1.29)	(-1.19)	(-1.45)	(-0.97)
Panel B. Market return as the context					
DS1	0.79	0.93	0.62	-0.17	-0.11
	(3.38)	(4.18)	(2.73)	(-1.07)	(-0.63)
DS3	0.52	0.61	0.55	0.02	0.15
	(1.49)	(2.07)	(1.97)	(0.07)	(0.38)
DS5	1.10	0.92	0.54	-0.56	-0.49
	(2.96)	(3.67)	(1.68)	(-1.53)	(-1.47)
DS5-DS1	0.31	-0.01	-0.09	-0.39	-0.38
	(0.88)	(-0.03)	(-0.33)	(-0.96)	(-1.05)
Panel C. Random portfolio return as the context					
DS1	0.85	0.92	0.59	-0.26	-0.28
	(3.21)	(4.50)	(2.53)	(-1.40)	(-1.20)
DS3	0.46	0.70	0.55	0.08	0.32
	(1.38)	(2.79)	(1.88)	(0.28)	(1.01)
DS5	0.75	1.05	0.35	-0.40	-0.36
	(1.87)	(4.77)	(1.35)	(-1.17)	(-1.12)
DS5-DS1	-0.10	0.13	-0.24	-0.14	-0.08
	(-0.38)	(0.79)	(-1.18)	(-0.41)	(-0.30)

Table 4: Control for industry-related effects in portfolio analysis

This table presents the performance of winners-minus-losers (WML) strategy based on deviation salience (DS) and one-month stock return (RET). Each month, stocks are sorted into quintile portfolios based on DS; within each quintile, stocks are further divided into deciles based on RET. We then calculate value-weighted average returns of each portfolio. The table reports average returns (in percentage) to the WML strategy that longs stocks within the top RET decile and shorts those within the bottom RET decile. Strategy returns are adjusted by industry-augmented factor models. In column (1), factors include the Fama-French six factors and the industry momentum factor; in column (2), factors include the Fama-French six factors and the industry-adjusted reversal factor; in column (3), factors include the Fama-French six factors, the industry momentum factor, and the industry-adjusted reversal factor. We calculate average industry-peer return by the value-weighted average return of other stocks within the same industry. The industry momentum factor is defined as the strategy that longs stocks within the top industry-peer return quintile and shorts those within the bottom industry-peer return quintile. To construct the industry-adjusted reversal factor, we first define industry-adjusted return (RETX) for each stock as the the raw monthly stock return minus the average industry-peer return. Then, the industry-adjusted reversal factor is defined as the strategy that longs stocks within the top RETX quintile and shorts those within the bottom RETX quintile. In all specifications, the Fama-French 49 industry classifications are used to classify stocks. The sample ranges from December 1983 to December 2021. The t-statistics are calculated based on Newey-West adjusted standard errors and reported in parentheses.

DS quintiles	(1) Control for industry momentum	(2) Control for industry-adjusted revesal	(3) Control for industry momentum and industry-adjusted revesal
Low DS	0.93	2.04	1.34
	(2.46)	(4.65)	(3.55)
2	0.71	1.96	1.25
	(2.09)	(5.70)	(4.35)
3	0.13	1.26	0.78
	(0.34)	(3.62)	(2.32)
4	-0.96	-0.84	-0.70
	(-2.95)	(-2.28)	(-2.01)
High DS	-1.28	-1.36	-1.14
	(-4.30)	(-4.06)	(-3.60)
High-Low	-2.21	-3.41	-2.48
	(-3.95)	(-5.03)	(-4.14)

Table 5: Trade-off between the numerator and the denominator in determining salience distortion

This table reports the performance of the winners-minus-losers (WML) strategy. In Panel A, stocks are sorted into three groups based on the numerator of deviation salience (DS), i.e., $|r_{i,t} - r^p_{i,t}|$; in Panel B, stocks are sorted into three groups based on the denominator of DS, i.e., $|r_{i,t} - r_{f,t}| + |r^p_{i,t} - r_{f,t}|$. The large (small) group contains stocks with a numerator or a denominator above (below) the 70th (30th) percentile each month, and the remaining stocks are classified as the medium group. Within each group, 3×10 portfolios are formed based on DS and contemporaneous one-month return (RET). The WML strategy longs stocks within the top RET decile and shorts those within the bottom RET decile. We report the average returns and six-factor (Fama and French, 2015) alphas of the WML strategy within low-DS (below the 25th percentile) stocks and high-DS (above the 75th percentile) stocks, as well as the difference between the two DS groups (High-Low). All portfolios are value weighted. The sample period is from December 1983 to December 2021. The t-statistics are calculated based on Newey-West adjusted standard errors and reported in parentheses.

Panel A. Subgroups by the numerator $|r_{i,t} - r^p_{i,t}|$

	Small		Medium		Large	
	Return	FF6 alpha	Return	FF6 alpha	Return	FF6 alpha
Low DS	1.40	1.59	0.97	1.18	1.07	1.40
	(2.91)	(2.93)	(2.08)	(2.24)	(1.99)	(2.53)
High DS	-0.14	-0.13	-0.75	-0.73	-1.27	-1.27
	(-0.69)	(-0.50)	(-2.78)	(-2.78)	(-3.15)	(-2.90)
High-Low	-1.55	-1.72	-1.72	-1.91	-2.34	-2.67
	(-2.76)	(-2.83)	(-3.16)	(-3.20)	(-3.70)	(-3.85)

Panel B. Subgroups by the denominator $|r_{i,t} - r_{f,t}| + |r^p_{i,t} - r_{f,t}|$

	Small		Medium		Large	
	Return	FF6 alpha	Return	FF6 alpha	Return	FF6 alpha
Low DS	0.27	0.19	0.10	0.12	1.48	1.55
	(0.97)	(0.53)	(0.35)	(0.33)	(2.98)	(3.14)
High DS	-0.85	-1.04	-1.23	-1.16	-1.32	-1.30
	(-3.33)	(-3.60)	(-3.45)	(-2.96)	(-2.10)	(-2.00)
High-Low	-1.11	-1.23	-1.33	-1.28	-2.80	-2.85
	(-2.86)	(-2.77)	(-2.58)	(-2.15)	(-3.45)	(-3.04)

Table 6: θ and salience distortion

This table reports the performance of the winners-minus-losers (WML) strategy based on deviation salience (DS) with positive θ:

$$DS_{i,t}^{\theta} = \frac{|r_{i,t} - r_{i,t}^{p}|}{|r_{i,t} - r_{f,t}| + |r_{i,t}^{p} - r_{f,t}| + \theta}$$

The second column reports the time-series average of cross-section Spearman's rank correlation between $DS_{i,t}^{\theta}$ and its numerator (i.e., $|r_{i,t} - r_{i,t}^{p}|$). Each month, stocks are sorted into quintile portfolios based on DS; within each quintile, stocks are further divided into deciles based on one-month return. The WML strategy within each DS group longs stocks within the top decile and shorts those within the bottom decile. The table reports the average returns of the WML strategy within low-DS stocks and high-DS stocks, as well as the difference between the two DS groups (High-Low). Also reported is the six-factor alpha of the difference (FF6 alpha). Returns and alphas are reported in percentage points. The sample period is from December 1983 to December 2021. The t-statistics are calculated based on Newey-West adjusted standard errors and reported in parentheses.

θ	$\mathrm{Corr}\big(DS_{i,t}^{\theta}, \lvert r_{i,t} - r_{i,t}^{p}\rvert\big)$	Low DS	High DS	High-Low	FF6 alpha
0.0001	0.694	1.41	-1.37	-2.79	-2.87
		(3.14)	(-3.91)	(-4.64)	(-4.07)
0.0002	0.695	1.40	-1.34	-2.74	-2.81
		(3.11)	(-3.84)	(-4.58)	(-4.01)
0.0005	0.699	1.41	-1.35	-2.76	-2.83
		(3.12)	(-3.88)	(-4.58)	(-4.00)
0.001	0.706	1.32	-1.25	-2.57	-2.62
		(2.95)	(-3.58)	(-4.31)	(-3.74)
0.002	0.717	1.34	-1.18	-2.52	-2.58
		(2.98)	(-3.31)	(-4.18)	(-3.64)
0.005	0.746	1.37	-1.01	-2.38	-2.46
		(3.12)	(-2.67)	(-4.01)	(-3.55)
0.01	0.783	1.31	-1.01	-2.32	-2.28
		(2.98)	(-2.61)	(-3.76)	(-3.15)
0.02	0.831	1.21	-0.96	-2.17	-2.09
		(2.87)	(-2.34)	(-3.57)	(-2.98)
0.05	0.901	0.89	-0.43	-1.32	-1.19
		(2.15)	(-0.91)	(-2.16)	(-1.68)
0.1	0.946	0.95	-0.30	-1.26	-1.07
		(2.45)	(-0.64)	(-2.17)	(-1.55)

Table 7: Contemporaneous portfolio characteristics

This table reports the characteristics of portfolios formed by deviation salience (DS) and monthly stock return. Each month, we sequentially sort stocks into 5×10 portfolios based on DS and one-month stock return. DS is calculated as the absolute difference between the stock return and peer stocks' average return, divided by the sum of absolute excess returns. We then calculate equal-weighted averages of characteristics of each portfolio, including DS (Panel A), monthly stock return (Panel B), and monthly turnover ratio (Panel C). Column "H-L" reports the difference in characteristics between the top and bottom return decile portfolios. The sample period is from December 1983 to December 2021.

DS quintiles	Monthly return deciles										
	Low	2	3	4	5	6	7	8	9	High	H-L
Panel A. Deviation salience											
Low	0.150	0.133	0.128	0.123	0.121	0.120	0.123	0.127	0.135	0.154	0.004
2	0.399	0.387	0.377	0.371	0.368	0.369	0.373	0.380	0.388	0.403	0.004
3	0.668	0.655	0.641	0.632	0.630	0.630	0.633	0.639	0.650	0.672	0.004
4	0.938	0.938	0.936	0.936	0.941	0.941	0.935	0.931	0.936	0.936	-0.002
High	0.989	0.990	0.992	0.994	0.996	0.997	0.997	0.996	0.994	0.994	0.005
Panel B. One-month return											
Low	-0.087	-0.040	-0.021	-0.006	0.006	0.018	0.030	0.045	0.065	0.117	0.203
2	-0.136	-0.070	-0.041	-0.018	0.003	0.024	0.046	0.071	0.103	0.186	0.322
3	-0.203	-0.106	-0.067	-0.035	0.000	0.034	0.071	0.111	0.164	0.318	0.521
4	-0.211	-0.103	-0.064	-0.039	-0.019	0.001	0.022	0.045	0.088	0.260	0.471
High	-0.190	-0.086	-0.051	-0.029	-0.013	0.001	0.016	0.035	0.069	0.214	0.405
Panel C. Turnover											
Low	0.124	0.101	0.096	0.095	0.095	0.096	0.098	0.100	0.110	0.136	0.012
2	0.141	0.107	0.100	0.098	0.096	0.098	0.100	0.105	0.118	0.155	0.014
3	0.179	0.116	0.104	0.100	0.097	0.099	0.105	0.118	0.137	0.211	0.033
4	0.179	0.115	0.105	0.097	0.093	0.092	0.095	0.100	0.112	0.241	0.063
High	0.174	0.112	0.104	0.096	0.093	0.092	0.094	0.099	0.109	0.234	0.060

Table 8: Fama-MacBeth regressions

This table reports time-series averages of coefficients from monthly cross-sectional regressions. DS is the deviation salience, and RET is the one-month stock return. We control for potential interaction effects of firm size (Size), illiquidity (Illiq), turnover ratio (TO), idiosyncratic volatility (IVol), analyst coverage (AC), institutional ownership (Inst), and the salience theory value (ST) of Cosemans and Frehen (2021). Independent variables are winsorized at 1% and 99% each month and standardized to have zero mean and unit variance. Control variables include the interaction variables as well as past one-year return (skipping the most recent month) and the log of the book-to-market ratio. The sample ranges from December 1983 to December 2021. The t-statistics are calculated based on Newey-West adjusted standard errors and reported in parentheses.

	Panel A. Equal weighted				Panel B. Value weighted			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RET	-0.206	-0.277	-0.375	-0.311	-0.288	-0.312	-0.558	-0.474
	(-2.82)	(-3.64)	(-4.86)	(-4.06)	(-2.86)	(-3.09)	(-5.25)	(-4.66)
DS	0.075	0.066	0.056	0.033	0.019	0.010	-0.003	-0.006
	(2.90)	(2.67)	(2.14)	(1.31)	(0.62)	(0.32)	(-0.10)	(-0.18)
DS × RET	-0.569	-0.559	-0.627	-0.663	-0.320	-0.324	-0.409	-0.446
	(-7.16)	(-7.16)	(-7.76)	(-8.02)	(-3.61)	(-3.74)	(-4.56)	(-4.80)
Size × RET		-0.006	-0.056	0.070		-0.044	0.044	0.132
		(-0.17)	(-1.51)	(1.43)		(-0.89)	(0.88)	(2.10)
Illiq × RET		-0.382	-0.340	-0.344		-0.320	-0.036	-0.264
		(-4.51)	(-4.00)	(-4.14)		(-2.01)	(-0.22)	(-1.93)
TO × RET			0.141	0.166			0.227	0.281
			(4.99)	(5.63)			(6.30)	(7.50)
IVol × RET			0.060	0.024			0.136	0.091
			(2.43)	(0.87)			(3.09)	(1.75)
AC × RET				-0.145				-0.130
				(-3.08)				(-1.58)
Inst × RET				-0.114				-0.183
				(-3.52)				(-3.39)
ST × RET				0.087				0.040
				(3.36)				(0.91)
Controls	√	√	√	√	√	√	√	√
Intercept	0.945	0.938	0.923	0.871	0.939	0.926	0.901	0.865
	(3.43)	(3.39)	(3.33)	(3.07)	(3.37)	(3.32)	(3.18)	(2.96)
Avg. R^2(%)	5.698	5.867	6.087	6.299	12.790	13.019	13.501	14.014
Avg. # Obs	3117	3117	3117	3117	3117	3117	3117	3117

Table 9: Fama-MacBeth regressions: good news and bad news

This table reports time-series averages of coefficients from monthly cross-sectional regressions. DS is the deviation salience, and RET is the one-month stock return. We separate good news and bad news based on the sign of the focal stock's monthly return (in excess of the risk-free rate, R_f). $\mathbf{I}_{POS}$ is a dummy variable that takes a value of 1 if $RET - R_f > 0$ and zero otherwise; $\mathbf{I}_{NEG}$ is a dummy variable that takes a value of -1 if $RET - R_f < 0$ and zero otherwise. RET^+ and RET^- are the positive and negative parts of the focal stock's monthly excess return, respectively. Specifically, $RET^+ = \max\{RET - R_f, 0\}$ and $RET^- = \min\{RET - R_f, 0\}$. Control variables include size, the log of the book-to-market ratio, past one-year return (skipping the most recent month), illiquidity, turnover ratio, idiosyncratic volatility, analyst coverage, institutional ownership, and the salience theory value (Cosemans and Frehen, 2021). Continuous variables (i.e., independent variables except for $\mathbf{I}_{POS}$, $\mathbf{I}_{NEG}$, RET^+, and RET^-) are winsorized at 1% and 99% each month and standardized to have zero mean and unit variance. The last two rows report the difference between estimated coefficients on interaction terms. The sample ranges from December 1983 to December 2021. The t-statistics are calculated based on Newey-West adjusted standard errors and reported in parentheses.

	Panel A. Equal weighted		Panel B. Value weighted	
	(1)	(2)	(3)	(4)
DS × $\mathbf{I}_{POS}$	-0.279		-0.067	
	(-2.91)		(-0.77)	
DS × $\mathbf{I}_{NEG}$	-0.529		-0.314	
	(-5.73)		(-3.65)	
DS × RET^+		-1.653		-0.859
		(-3.73)		(-1.29)
DS × RET^-		-5.489		-3.440
		(-8.37)		(-3.93)
RET	-0.321	-0.275	-0.295	-0.348
	(-4.77)	(-3.79)	(-2.95)	(-3.59)
DS	-0.010	-0.000	-0.050	0.009
	(-0.13)	(-0.01)	(-0.68)	(0.29)
Controls	√	√	√	√
Intercept	0.902	0.928	0.894	0.924
	(3.25)	(3.34)	(3.18)	(3.30)
Avg. R^2(%)	5.613	5.791	12.765	13.026
Avg. # Obs	3117	3117	3117	3117
DS × $\mathbf{I}_{NEG}$ − DS × $\mathbf{I}_{POS}$	-0.250		-0.247	
	(-1.63)		(-1.71)	
DS × RET^- − DS × RET^+		-3.837		-2.581
		(-5.51)		(-2.53)

Table 10: Deviation salience, trading volume, and attention

This table reports estimated coefficients from panel regressions. In Panel A, the dependent variable is abnormal trading volume, defined as the log difference between monthly turnover and the average turnover in the past three months. In Panel B, the dependent variable is retail investor attention (Da et al., 2011), measured as the log difference between the current Google search volume index and the medium index level over the past six months. In Panel C, the dependent variable is abnormal retail trading volume, defined as the log difference between monthly retail trading volume and the average value in the past three months. Retail trading is identified based on the Boehmer et al. (2021) algorithm. Daily retail trading volume is defined as the total number of retail-traded shares divided by shares outstanding. For our analysis, we calculate the monthly retail trading volume by averaging the daily retail trading volumes. In Panel D, the dependent variable is social media attention (Cookson et al., 2024), measured as the first principal component of attention across *StockTwits*, *Twitter*, and *Seeking Alpha*. For each platform, attention to a specific stock is defined as the number of messages mentioning the stock divided by the total number of stock-related messages on that platform. We use average social media attention within each month in our regressions. The main independent variable of interest is DS, the deviation salience. Control variables include the absolute value of one-month stock returns, analyst coverage, maximum daily return of the month (Bali et al., 2011), idiosyncratic volatility (Ang et al., 2006), log of the book-to-market ratio, log of market capitalization, past 11-month return (skipping the most recent month), and institutional ownership. Independent variables are winsorized at 1% and 99% each month and standardized to have zero mean and unit variance. We include firm fixed effects, month fixed effects, and industry fixed effects. The sample period is from December 1983 to December 2021 for Panel A, from July 2004 to December 2020 for Panel B, from January 2007 to December 2021 for Panel C, and from January 2012 to December 2021 for Panel D. Standard errors are clustered by firm and month, and t-statistics are reported in parentheses.

	Panel A. Abnormal volume			Panel B. Retail investor attention		
	(1)	(2)	(3)	(4)	(5)	(6)
DS	0.029	0.021	0.022	0.010	0.003	0.003
	(19.05)	(16.90)	(15.55)	(8.70)	(2.96)	(2.60)
Controls		√	√		√	√
Firm FE	√	√		√	√	
Industry FE			√			√
Time FE	√	√	√	√	√	√
N	1546660	1431145	1376047	625183	591985	551647
Adj. R^2	0.38	0.49	0.32	0.02	0.02	0.01
	Panel C. Retail trading volume			Panel D. Social media attention		
	(1)	(2)	(3)	(4)	(5)	(6)
DS	0.044	0.023	0.023	0.017	0.007	0.007
	(24.43)	(16.20)	(14.83)	(12.22)	(5.26)	(3.96)
Controls		√	√		√	√
Firm FE	√	√		√	√	
Industry FE			√			√
Time FE	√	√	√	Yes	Yes	√
N	526424	500755	452558	52034	49064	38306
Adj. R^2	0.05	0.25	0.21	0.51	0.56	0.34

Table 11: Analyst forecast errors

This table reports estimated coefficients from panel regressions. The dependent variable is the forecast error (multiplied by 100), defined as the difference between the actual earnings per share and the consensus forecast, normalized by the stock price at the end of the corresponding quarter. To mitigate the noise in the calculation of forecast error and ensure the consistency of comparison, the sample is restricted to firms with a share price of at least $5 and fiscal quarters ending in March, June, September, and December. Panel A reports baseline results using deviation salience (DS). The main independent variable of interest is the interaction term RET$\times$I$_{\text{High DS}}$, where I$_{\text{High DS}}$ is a dummy variable that takes a value of one if DS is above the 70th percentile in the cross section; RET is the corresponding monthly stock return. Control variables include firm size, past 11-month stock return (skipping the most recent month), book-to-market ratio, institutional ownership, analyst coverage, and turnover ratio. Continuous variables are winsorized at 1% and 99% each quarter, and independent variables (except for I$_{\text{High DS}}$) are standardized to have zero mean and unit variance. We include quarter fixed effects and industry fixed effects. Panel B reports results based on placebo deviation salience measures. In the first two columns, DS is calculated directly using the numerator component of equation (1); in the middle two columns, DS is calculated according to equation (1), while the market return is used as the context; in the last two columns, we randomly select 100 other stocks for each focal stock, use the value-weighted return of these random portfolios as the context, and apply equation (1) to compute DS. The sample ranges from December 1983 to December 2021. Standard errors are clustered by firm and quarter, and *t*-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Deviation salience						
RET$\times$I$_{\text{High DS}}$	-0.044	-0.025	-0.051	-0.024	-0.059	-0.030
	(-2.28)	(-2.30)	(-2.47)	(-2.25)	(-2.71)	(-2.75)
I$_{\text{High DS}}$	-0.034	-0.028	-0.021	-0.019	-0.019	-0.016
	(-3.73)	(-2.75)	(-2.23)	(-1.94)	(-2.00)	(-1.60)
RET	0.052	0.046	0.058	0.047	0.058	0.049
	(5.06)	(5.11)	(5.41)	(5.26)	(5.46)	(5.43)
Controls			√	√	√	√
Time FE		√		√		√
Industry FE		√			√	√
N	275480	262117	258856	258856	248142	248142
Adj. R^2	0.00	0.03	0.01	0.03	0.01	0.04
Panel B. Placebo deviation salience measures						
	DS constructed using solely the numerator		Market return as the context		Random portfolio return as the context	
RET$\times$I$_{\text{High DS}}$	0.002	-0.001	-0.005	-0.004	-0.016	-0.015
	(0.16)	(-0.11)	(-0.28)	(-0.23)	(-1.14)	(-1.05)
I$_{\text{High DS}}$	-0.068	-0.068	-0.008	-0.010	-0.008	-0.009
	(-4.27)	(-3.97)	(-0.74)	(-0.87)	(-0.73)	(-0.81)
RET	0.040	0.042	0.041	0.040	0.046	0.045
	(3.27)	(3.40)	(4.74)	(4.64)	(5.53)	(5.52)
Controls	√	√	√	√	√	√
Time FE	√	√	√	√	√	√
Industry FE		√		√		√
N	258856	248142	258856	248142	258856	248142
Adj. R^2	0.04	0.04	0.03	0.04	0.03	0.04

Table 12: Subsequent fundamentals

This table reports estimated coefficients from panel regressions. The dependent variables are one-quarter-ahead fundamentals (multiplied by 100). Return-on-equity (ROE) is the net income before extraordinary items scaled by one-quarter-lagged book equity; return-on-assets (ROA) is the net income before extraordinary items scaled by one-quarter-lagged total assets; changes in earnings per share (ΔEPS) is the change in split-adjusted quarterly earnings per share from its value four quarters ago divided by lagged price; profit growth (PG) is the quarterly operating income before depreciation minus its value four quarters ago divided by one-quarter-lagged total assets; gross profitability (GP) is the total revenue minus cost of goods sold divided by one-quarter-lagged total assets. The sample is restricted to firms with a share price of at least $5 and fiscal quarters ending in March, June, September, and December. The main independent variable of interest is the interaction term RET$\times$I$_{\text{High DS}}$, where I$_{\text{High DS}}$ is a dummy variable that takes a value of one if the deviation salience (DS) is above the 70th percentile of DS in the cross section; RET is the corresponding monthly stock return. Control variables include firm size, past 11-month stock return (skipping the most recent month), book-to-market ratio, institutional ownership, analyst coverage, and turnover ratio. Continuous variables are winsorized at 1% and 99% each quarter, and independent variables (except for I$_{\text{High DS}}$) are standardized to have zero mean and unit variance. We include quarter fixed effects, industry fixed effects, and firm fixed effects. The sample ranges from December 1983 to December 2021. Standard errors are clustered by firm and quarter, and t-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ROE		ROA		ΔEPS		PG		GP	
RET$\times$I$_{\text{High DS}}$	-0.090	-0.163	-0.050	-0.092	-0.109	-0.125	-0.040	-0.062	-0.068	-0.158
	(-1.77)	(-1.76)	(-2.03)	(-1.91)	(-2.52)	(-2.82)	(-1.97)	(-2.61)	(-2.11)	(-2.25)
I$_{\text{High DS}}$	-0.019	-0.011	-0.006	-0.001	0.060	0.064	0.014	0.009	0.008	0.131
	(-0.51)	(-0.20)	(-0.37)	(-0.06)	(2.22)	(2.24)	(1.00)	(0.56)	(0.36)	(2.95)
RET	0.334	0.331	0.153	0.158	0.325	0.337	0.251	0.267	0.346	0.417
	(7.60)	(4.35)	(7.19)	(4.11)	(7.80)	(8.05)	(14.16)	(13.31)	(13.84)	(8.09)
Controls	√	√	√	√	√	√	√	√	√	√
Time FE	√	√	√	√	√	√	√	√	√	√
Firm FE	√		√		√		√		√	
Industry FE		√		√		√		√		√
N	253068	243597	257475	247636	256623	246954	232458	223135	227235	218442
Adj. R^2	0.42	0.13	0.55	0.15	0.06	0.06	0.17	0.08	0.74	0.31

Table 13: Deviation salience and winners-minus-losers return: subsample results

This table reports the performance of the winners-minus-losers (WML) strategy. In Panel A and Panel B, stocks are sorted into three groups based on liquidity and size, respectively. The Liquid (Illiquid) group consists of stocks with the Amihud (2002) illiquidity measure above (below) the 70th (30th) percentile each month. The breakpoints for size are based on the 30th and 70th percentiles for NYSE stocks. Panel C reports the result among the 1,500, 1,000, or 500 largest stocks by market capitalization. Within each group, 3×10 portfolios are formed based on deviation salience (DS) and contemporaneous one-month return. We report the average returns and six-factor (Fama and French, 2015) alphas of the WML strategy within low-DS (below the 25th percentile) stocks and high-DS (above the 75th percentile) stocks, as well as the difference between the two DS groups (High-Low). For comparison, each panel also reports the unconditional WML strategy performance of the overall subsample (Overall). All portfolios are value weighted. Returns and alphas are reported in percentage points. The sample period is from December 1983 to December 2021. The t-statistics are calculated based on Newey-West adjusted standard errors and reported in parentheses.

	Return	FF6 alpha	Return	FF6 alpha	Return	FF6 alpha
Panel A. Liquidity						
	Illiquid		Medium		Liquid	
Low DS	2.24	1.99	2.21	2.10	1.18	1.32
	(4.30)	(3.52)	(5.43)	(4.04)	(2.52)	(2.55)
High DS	-2.67	-2.75	-2.41	-2.52	-0.66	-0.75
	(-5.12)	(-4.82)	(-7.01)	(-6.67)	(-2.33)	(-2.40)
High-Low	-4.91	-4.75	-4.62	-4.63	-1.85	-2.06
	(-6.25)	(-5.87)	(-7.63)	(-6.84)	(-2.95)	(-3.00)
Overall	-2.00	-2.00	-0.83	-0.84	0.20	0.24
	(-5.76)	(-5.00)	(-3.26)	(-2.49)	(0.76)	(0.86)
Panel B. Size						
	Small		Medium		Big	
Low DS	2.50	2.47	1.30	1.43	0.87	1.11
	(5.71)	(4.31)	(3.07)	(2.89)	(2.18)	(2.41)
High DS	-1.80	-1.83	-1.41	-1.34	-0.94	-1.01
	(-5.77)	(-5.47)	(-5.43)	(-4.74)	(-3.00)	(-2.91)
High-Low	-4.30	-4.30	-2.71	-2.78	-1.81	-2.12
	(-7.17)	(-6.26)	(-4.60)	(-4.11)	(-3.09)	(-3.32)
Overall	-0.61	-0.55	-0.29	-0.11	0.00	0.07
	(-2.22)	(-1.62)	(-1.14)	(-0.37)	(-0.01)	(0.25)
Panel C. N largest stocks						
	Largest 1,500		Largest 1,000		Largest 500	
Low DS	0.90	1.09	0.87	1.05	0.76	0.98
	(2.16)	(2.26)	(2.17)	(2.24)	(1.94)	(2.10)
High DS	-0.97	-1.03	-0.88	-0.98	-0.84	-0.90
	(-3.41)	(-3.24)	(-3.16)	(-3.14)	(-3.19)	(-3.04)
High-Low	-1.87	-2.12	-1.75	-2.03	-1.60	-1.89
	(-3.15)	(-3.11)	(-3.10)	(-3.16)	(-3.06)	(-3.30)
Overall	0.05	0.11	-0.04	0.02	-0.02	0.04
	(0.17)	(0.39)	(-0.15)	(0.08)	(-0.09)	(0.13)

Table 14: Double sorts on deviation salience and monthly return: firm news

This table presents double-sorted portfolios based on deviation salience (DS) and monthly stock return (RET). We report the results of two subsamples: (1) stock-month observations *with* news and (2) stock-month observations *without* news. Also reported is the difference in portfolio returns between the two subsamples. In Panel A to Panel C, firm news is defined as earnings announcements; In Panel D to Panel F, firm news is defined as earnings announcements or major corporate events; In Panel G to Panel I, firm news is defined as earnings announcements or Ravenpack news stories. Portfolios are held for one month, and value-weighted returns are calculated. The column RET10-RET1 refers to the winners-minus-losers portfolio, and the column FF6 alpha reports the corresponding factor-adjusted return. Returns and alphas are reported in percentage points. The sample in Panel A to Panel F ranges from December 1983 to December 2021, whereas the sample period in Panel G to Panel I is from January 2000 to December 2021. The *t*-statistics are calculated based on Newey-West adjusted standard errors and reported in parentheses.

	RET1	RET5	RET10	RET10-RET1	FF6 alpha
Panel A. Stock-month *with* earnings announcements					
DS1	-0.56	0.44	1.15	1.71	1.97
	(-1.28)	(1.44)	(3.22)	(3.34)	(3.64)
DS3	0.66	0.37	1.22	0.57	0.81
	(1.49)	(1.28)	(3.10)	(1.38)	(1.80)
DS5	1.16	0.72	0.15	-1.01	-1.38
	(2.76)	(2.74)	(0.40)	(-2.67)	(-3.13)
DS5-DS1	1.72	0.28	-1.00	-2.72	-3.35
	(3.91)	(1.10)	(-2.40)	(-3.98)	(-4.33)
Panel B. Stock-month *without* earnings announcements					
DS1	-0.26	0.81	1.22	1.49	1.54
	(-0.64)	(2.87)	(3.09)	(2.89)	(2.65)
DS3	0.56	0.58	0.42	-0.14	0.31
	(1.30)	(2.47)	(1.20)	(-0.31)	(0.61)
DS5	1.76	0.98	-0.39	-2.15	-2.30
	(4.06)	(3.86)	(-1.21)	(-5.11)	(-5.08)
DS5-DS1	2.03	0.17	-1.61	-3.64	-3.83
	(4.54)	(0.91)	(-3.66)	(-4.78)	(-4.42)
Panel C. Difference: *without*-minus-*with* (earnings announcements)					
DS1	0.30	0.37	0.08	-0.22	-0.43
	(0.98)	(1.35)	(0.31)	(-0.58)	(-1.01)
DS3	-0.10	0.21	-0.81	-0.71	-0.51
	(-0.29)	(0.84)	(-2.71)	(-1.59)	(-1.04)
DS5	0.60	0.26	-0.54	-1.14	-0.92
	(1.63)	(1.31)	(-2.03)	(-2.45)	(-1.80)
DS5-DS1	0.31	-0.10	-0.61	-0.92	-0.49
	(0.70)	(-0.33)	(-1.56)	(-1.47)	(-0.69)

	RET1	RET5	RET10	RET10-RET1	FF6 alpha
Panel D. Stock-month *with* major events or earnings announcements					
DS1	-0.52	0.78	1.13	1.65	1.86
	(-1.32)	(3.01)	(3.14)	(3.40)	(3.64)
DS3	0.34	0.43	1.08	0.74	1.12
	(0.91)	(1.33)	(3.13)	(1.81)	(2.54)
DS5	1.10	0.77	-0.04	-1.14	-1.35
	(2.77)	(3.07)	(-0.13)	(-3.39)	(-3.85)
DS5-DS1	1.62	-0.00	-1.17	-2.79	-3.21
	(4.21)	(-0.01)	(-2.99)	(-4.48)	(-4.66)
Panel E. Stock-month *without* major events and earnings announcements					
DS1	-0.02	0.83	1.23	1.24	1.27
	(-0.04)	(2.81)	(3.31)	(2.35)	(2.13)
DS3	0.11	0.62	0.35	0.24	0.49
	(0.23)	(2.21)	(0.86)	(0.46)	(0.84)
DS5	1.41	1.01	-0.57	-1.97	-2.13
	(3.11)	(4.09)	(-1.66)	(-4.93)	(-4.85)
DS5-DS1	1.42	0.18	-1.79	-3.22	-3.40
	(3.27)	(0.80)	(-4.07)	(-4.35)	(-3.94)
Panel F. Difference: *without*-minus-*with* (major events & earnings announcements)					
DS1	0.51	0.06	0.10	-0.41	-0.59
	(1.53)	(0.28)	(0.42)	(-1.00)	(-1.24)
DS3	-0.23	0.19	-0.73	-0.50	-0.63
	(-0.60)	(0.63)	(-2.11)	(-0.91)	(-1.06)
DS5	0.31	0.23	-0.52	-0.83	-0.79
	(0.97)	(1.12)	(-2.01)	(-2.20)	(-1.77)
DS5-DS1	-0.20	0.18	-0.62	-0.42	-0.19
	(-0.49)	(0.59)	(-1.71)	(-0.83)	(-0.36)
Panel G. Stock-month *with* RP news or earnings announcements					
DS1	-0.18	0.73	0.53	0.71	0.98
	(-0.36)	(2.15)	(1.30)	(1.49)	(1.73)
DS3	0.66	0.51	0.84	0.18	0.35
	(1.17)	(1.29)	(1.91)	(0.41)	(0.69)
DS5	1.17	0.55	0.07	-1.11	-1.17
	(2.06)	(1.69)	(0.14)	(-2.62)	(-2.86)
DS5-DS1	1.35	-0.18	-0.46	-1.81	-2.15
	(2.90)	(-0.71)	(-1.04)	(-2.81)	(-2.81)
Panel H. Stock-month *without* RP news and earnings announcements					
DS1	-0.98	1.10	0.62	1.59	1.57
	(-1.42)	(2.32)	(1.27)	(2.32)	(2.13)
DS3	0.40	0.56	0.51	0.12	0.83
	(0.52)	(1.00)	(0.74)	(0.13)	(0.84)
DS5	0.85	0.82	-1.00	-1.85	-1.81
	(1.04)	(1.89)	(-1.65)	(-2.35)	(-2.40)
DS5-DS1	1.82	-0.28	-1.62	-3.44	-3.38
	(2.26)	(-0.74)	(-2.29)	(-3.14)	(-3.11)

	RET1	RET5	RET10	RET10-RET1	FF6 alpha
Panel I. Difference: *without*-minus-*with* (RP news & earnings announcements)					
DS1	-0.79	0.37	0.09	0.89	0.59
	(-1.79)	(1.05)	(0.28)	(1.63)	(1.07)
DS3	-0.27	0.06	-0.33	-0.06	0.49
	(-0.48)	(0.14)	(-0.62)	(-0.08)	(0.54)
DS5	-0.33	0.27	-1.07	-0.74	-0.64
	(-0.50)	(1.00)	(-2.29)	(-0.94)	(-0.84)
DS5-DS1	0.47	-0.10	-1.16	-1.63	-1.23
	(0.62)	(-0.25)	(-2.04)	(-1.80)	(-1.52)

Table 15: Double sorts on orthogonal deviation salience and one-month return

This table presents double-sorted portfolio results based on orthogonal deviation salience (DS) and one-month stock return (RET). Orthogonal deviation salience is the residual from the cross-sectional regression of DS on firm characteristics, including Size, Illiq, Inst, IVol, AC, and TO. Each month, stocks are sorted into quintile portfolios based on the orthogonal DS; within each quintile, stocks are further divided into deciles based on monthly returns. Portfolios are held for one month, and value-weighted returns are calculated. The column RET10-RET1 refers to the winners-minus-losers portfolio, and the column FF6 alpha reports the corresponding factor-adjusted return (Fama and French, 2015). The sample ranges from December 1983 to December 2021. The *t*-statistics are calculated based on Newey-West adjusted standard errors and reported in parentheses.

	RET1	RET5	RET10	RET10-RET1	FF6 alpha
Panel A. Orthogonal to Size					
DS1	-0.22	1.00	1.45	1.68	1.97
	(-0.56)	(3.79)	(4.14)	(3.88)	(4.01)
DS3	0.35	0.66	0.95	0.60	1.11
	(0.92)	(2.47)	(2.64)	(1.53)	(2.50)
DS5	1.13	1.02	0.21	-0.92	-0.92
	(3.26)	(4.21)	(0.74)	(-3.31)	(-3.26)
DS5-DS1	1.35	0.02	-1.24	-2.59	-2.89
	(3.82)	(0.12)	(-3.39)	(-4.48)	(-4.43)
Panel B. Orthogonal to Size, Illiq, and Inst					
DS1	-0.32	0.97	1.39	1.72	1.93
	(-0.82)	(3.88)	(3.83)	(3.95)	(3.91)
DS3	0.33	0.55	0.98	0.65	1.01
	(0.84)	(1.99)	(2.74)	(1.64)	(2.21)
DS5	1.16	0.99	0.26	-0.90	-0.97
	(3.28)	(4.00)	(0.89)	(-3.31)	(-3.45)
DS5-DS1	1.48	0.01	-1.14	-2.61	-2.90
	(4.18)	(0.07)	(-3.17)	(-4.49)	(-4.48)
Panel C. Orthogonal to Size, Illiq, Inst, and IVol					
DS1	-0.14	0.99	1.35	1.49	1.76
	(-0.37)	(3.76)	(3.70)	(3.35)	(3.61)
DS3	0.39	0.61	0.68	0.29	0.66
	(0.97)	(2.11)	(1.95)	(0.70)	(1.43)
DS5	1.26	0.89	0.31	-0.95	-0.97
	(3.95)	(3.70)	(1.07)	(-3.64)	(-3.37)
DS5-DS1	1.41	-0.10	-1.04	-2.45	-2.73
	(4.31)	(-0.59)	(-2.68)	(-4.07)	(-4.12)
Panel D. Orthogonal to Size, Illiq, Inst, IVol, AC, and TO					
DS1	-0.32	1.02	1.37	1.70	1.94
	(-0.83)	(4.08)	(3.64)	(3.76)	(3.88)
DS3	0.53	0.69	0.72	0.19	0.55
	(1.29)	(2.61)	(2.13)	(0.48)	(1.26)
DS5	1.29	0.88	0.29	-1.00	-1.02
	(4.00)	(3.70)	(1.04)	(-3.88)	(-3.68)
DS5-DS1	1.61	-0.13	-1.08	-2.70	-2.96
	(4.78)	(-0.77)	(-2.73)	(-4.47)	(-4.48)

Table 16: Double sorts on alternative deviation salience and one-month return

This table presents double-sorted portfolio results based on alternative-context deviation salience (DS) and one-month stock return (RET). The context in constructing DS is defined based on the Fama-French 49 industries (Panel A), the three-digit SIC codes industries (Panel B), the text-based industries (Panel C), and the similarities of He et al. (2023) (Panel D). Portfolios are held for one month, and value-weighted returns are calculated. The column RET10-RET1 refers to the winners-minus-losers portfolio, and the column FF6 alpha reports the corresponding factor-adjusted return (Fama and French, 2015). The sample period is from July 1963 to December 2021 for Panel A, Panel B, and Panel D, and from June 1989 to June 2021 for Panel C. The t-statistics are calculated based on Newey-West adjusted standard errors and reported in parentheses.

	RET1	RET5	RET10	RET10-RET1	FF6 alpha
Panel A. Fama-French 49 industries					
DS1	0.26	0.58	0.82	0.56	0.49
	(1.18)	(2.78)	(3.81)	(2.79)	(2.13)
DS3	0.53	0.81	0.40	-0.14	-0.08
	(1.73)	(4.06)	(1.54)	(-0.50)	(-0.28)
DS5	1.29	0.89	-0.07	-1.35	-1.43
	(3.81)	(4.56)	(-0.26)	(-5.61)	(-5.76)
DS5-DS1	1.03	0.30	-0.89	-1.91	-1.92
	(4.02)	(2.00)	(-4.94)	(-6.12)	(-6.01)
Panel B. Three-digit SIC codes industries					
DS1	-0.02	0.47	0.79	0.82	0.82
	(-0.09)	(2.19)	(3.89)	(3.59)	(3.19)
DS3	0.73	0.78	0.36	-0.37	-0.37
	(2.34)	(3.84)	(1.33)	(-1.35)	(-1.38)
DS5	1.30	0.92	-0.08	-1.38	-1.43
	(3.82)	(4.78)	(-0.33)	(-5.18)	(-5.19)
DS5-DS1	1.33	0.45	-0.87	-2.20	-2.25
	(5.41)	(2.76)	(-5.21)	(-6.93)	(-6.20)
Panel C. Text-based industries					
DS1	-0.05	0.93	1.06	1.11	1.30
	(-0.13)	(3.49)	(2.61)	(2.70)	(2.97)
DS3	0.46	0.68	0.88	0.42	0.81
	(1.02)	(2.47)	(2.13)	(0.99)	(1.81)
DS5	1.11	0.93	-0.02	-1.13	-1.15
	(2.30)	(3.53)	(-0.05)	(-2.79)	(-2.90)
DS5-DS1	1.16	0.00	-1.07	-2.24	-2.44
	(3.27)	(0.02)	(-2.48)	(-3.73)	(-3.90)
Panel D. Similar stocks					
DS1	0.09	0.74	1.03	0.95	0.72
	(0.34)	(3.13)	(3.50)	(3.42)	(2.06)
DS3	0.98	0.78	0.54	-0.43	-0.36
	(3.57)	(3.92)	(1.94)	(-1.53)	(-1.04)
DS5	0.92	0.87	0.08	-0.84	-0.73
	(2.85)	(4.24)	(0.33)	(-3.40)	(-3.33)
DS5-DS1	0.83	0.13	-0.96	-1.79	-1.46
	(3.57)	(0.72)	(-4.35)	(-5.13)	(-3.73)

Table 17: Salience distortion in earlier sample periods

This table reports the performance of the winners-minus-losers (WML) strategy. We define deviation salience (DS) using the Fama-French 49 industry return as the context. The sample periods examined include 1926 to 1963 (Panel A), 1926 to 1983 (Panel B), 1963 to 1983 (Panel C), and 1926 to 2021 (Panel D). Each month, stocks are sorted into quintiles based on DS; within each quintile, stocks are further divided into deciles. A WML strategy for each DS quintile longs stocks within the top monthly return decile and shorts those within the bottom decile. Portfolios are held for one month. We calculate value-weighted average returns (Return) and the corresponding Fama and French (1996) three-factor alphas (FF3 alpha). The *t*-statistics are calculated based on Newey-West adjusted standard errors and reported in parentheses.

	Panel A. Jun 1926 - Dec 1963		Panel B. Jun 1926 - Dec 1983	
	Return	FF3 alpha	Return	FF3 alpha
Low DS	0.87	0.67	0.86	0.72
	(2.43)	(2.08)	(3.31)	(3.01)
High DS	-2.79	-2.69	-2.63	-2.51
	(-6.08)	(-6.25)	(-8.02)	(-8.17)
High-Low	-3.67	-3.36	-3.48	-3.22
	(-7.24)	(-6.59)	(-9.42)	(-8.79)
	Panel C. Jun 1963 - Dec 1983		Panel D. Jun 1926 - Dec 2021	
	Return	FF3 alpha	Return	FF3 alpha
Low DS	0.82	1.04	0.68	0.63
	(2.65)	(3.17)	(3.66)	(3.45)
High DS	-2.23	-2.17	-1.93	-1.77
	(-6.06)	(-5.94)	(-8.07)	(-7.50)
High-Low	-3.05	-3.21	-2.62	-2.41
	(-6.56)	(-6.90)	(-9.22)	(-8.67)

Appendix for
"Salience and Short-term Momentum and Reversals"

This Appendix provides additional empirical results. Table A1 reports robustness tests of our baseline result using various portfolio specifications. Table A2 shows the results of controlling for alternative salience theory value effects. Table A3 examines the role of deviation salience in individual investors' trading decisions using account-level data.

Table A1: Robustness on portfolio specifications

This table reports the performance of winners-minus-losers (WML) strategy based on different portfolio specifications. In the baseline specification, stocks are sorted into quintile portfolios based on deviation salience (DS) each month; within each quintile, stocks are further divided into deciles based on one-month return (RET). The WML strategy within each DS group longs stocks within the top RET decile and shorts those within the bottom RET decile. We consider five alternative specifications: (1) Instead of sequentially sorting stocks by DS and RET, we first sort stocks into deciles based on RET and then sort stocks into quintiles based on DS within each RET group. (2) We use NYSE breakpoints to define DS quintiles and RET deciles. (3) Exclude financial firms. (4) Exclude stocks in the bottom two deciles of the monthly market capitalization distribution using NYSE breakpoints. (5) We use equal-weighted instead of value-weighted portfolios. The table reports the average returns of the WML strategy within low-DS stocks and high-DS stocks, as well as the difference between the two DS groups (High-Low). Also reported is the six-factor alpha of the difference (FF6 alpha). Returns and alphas are reported in percentage points. The sample period is from December 1983 to December 2021. The t-statistics are calculated based on Newey-West adjusted standard errors and reported in parentheses.

Specification	Low DS	High DS	High-Low	FF6 alpha
Reverse the order of sorts	1.04	-1.22	-2.26	-2.38
	(2.51)	(-3.19)	(-3.86)	(-3.63)
NYSE breakpoints	0.90	-1.08	-1.98	-2.19
	(2.74)	(-3.84)	(-4.02)	(-3.96)
Exclude financial firms	1.67	-1.21	-2.88	-3.08
	(3.32)	(-4.05)	(-4.14)	(-3.94)
Exclude smallest 20% stocks	1.29	-1.01	-2.30	-2.57
	(3.05)	(-3.42)	(-3.76)	(-3.71)
Equal-weighted portfolios	2.04	-1.97	-4.02	-4.12
	(5.11)	(-6.51)	(-7.01)	(-6.60)

Table A2: Control for alternative salience theory value effects

This table reports time-series averages of coefficients from monthly cross-sectional regressions. DS is the deviation salience, and RET is the one-month stock return. We account for the potential influence of the salience theory value (ST) of Cosemans and Frehen (2021) by controlling for interaction effects based on the absoulte value of ST (|ST|) and the square of ST (ST^2). Other controlled interaction effects include firm size, illiquidity, turnover ratio, idiosyncratic volatility, analyst coverage, and institutional ownership. Independent variables are winsorized at 1% and 99% each month and standardized to have zero mean and unit variance. Control variables include the interaction variables as well as past one-year return (skipping the most recent month) and the log of the book-to-market ratio. The sample ranges from December 1983 to December 2021. The *t*-statistics are calculated based on Newey-West adjusted standard errors and reported in parentheses.

	Panel A. Equal weighted		Panel B. Value weighted	
	(1)	(2)	(3)	(4)
DS × RET	-0.665	-0.643	-0.453	-0.442
	(-8.15)	(-7.91)	(-4.80)	(-4.77)
RET	-0.248	-0.241	-0.387	-0.377
	(-3.44)	(-3.37)	(-4.35)	(-4.29)
DS	0.045	0.044	-0.006	-0.006
	(1.67)	(1.66)	(-0.18)	(-0.19)
|ST|× RET	0.086		0.021	
	(3.38)		(0.33)	
|ST|	0.006		0.068	
	(0.18)		(1.03)	
ST^2× RET		0.029		-0.106
		(1.30)		(-1.90)
ST^2		0.018		0.077
		(0.29)		(0.78)
Controls	√	√	√	√
Intercept	0.906	0.909	0.889	0.899
	(3.29)	(3.30)	(3.14)	(3.17)
Avg. R^2(%)	6.246	6.300	13.923	13.818
Avg. # Obs	3117	3117	3117	3117

Table A3: Deviation salience and investor trading behavior

This table shows the results of households' trading behavior based on account-level data from a large U.S. discount brokerage (Barber and Odean, 2000, 2001, 2002). The data set consists of transactions from around 78,000 household accounts between January 1991 and December 1996. Given computational capacity limitations, we rely on 10,000 randomly selected accounts for our tests. We follow the steps of Ben-David and Hirshleifer (2012) in cleaning and preparing the data. The table reports the estimated coefficients from panel regressions: $\mathbf{I}(Trade)_{i,j,t} = \alpha + \beta DS_{i,t-1} + \text{Controls} + \varepsilon_{i,j,t}$. The dependent variable, $\mathbf{I}(Trade)_{i,j,t}$, is a dummy equal to one if investor j trades stock i on day t. The main independent variable of interest is the deviation salience of stock i ($DS_{i,t-1}$), scaled by 100. Deviation salience is measured at the end of the most recent month. The coefficient β represents the marginal effect of salience on investors' trading decisions. Firm-level control variables include the absolute stock return, the volatility of daily stock returns over the month, and the log of market capitalization. To ensure consistency with the timing of deviation salience, firm-level controls are all measured at the end of the most recent month. We also control for the square root of the number of days since investor j purchased stock i. Various fixed effects are included in the regression. Columns (1) and (2) present our baseline specifications, which include day, account, and stock or industry fixed effects. In the remaining columns, we further incorporate high-dimensional fixed effects from interactions of indicators to mitigate the influence of other potentially omitted confounding factors. The number of observations varies across columns due to singleton observations from fixed effect estimations. Observations are at the account-stock-day level. The sample period is from January 1991 to December 1996. Standard errors are clustered by account (Ben-David and Hirshleifer, 2012; An et al., 2024), and t-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)
DS	0.021	0.024	0.021	0.029
	(3.39)	(3.93)	(2.51)	(4.11)
Controls	√	√	√	√
Day FE	√	√		
Account FE	√	√		√
Stock FE	√		√	√
Industry FE		√		
Account×Day FE			√	
Industry×Day FE				√
N	21,963,594	21,815,510	16,058,963	21,815,186
Adj. R^2	0.02	0.02	0.15	0.02