Attention-grabbing trading in overnight and intraday

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Abstract

I examine how investor attention, triggered by stock returns that deviate significantly from the market average, differentially influences overnight and intraday trading behavior. To quantify attention effects, I introduce salience deviation as a novel measure of the extent to which a stock's return diverges from overall market performance. This analysis reveals that overnight investors, drawn to stocks exhibiting large deviations from market-wide returns, exhibit systematic trading distortions, resulting in a significant overnight premium that varies with market conditions. In contrast, intraday traders engage in arbitrage strategies, generating an intraday discount in the opposite direction, yet remain largely insensitive to market fluctuations. These findings provide robust evidence that investor heterogeneity plays a crucial role in shaping attention-driven trading dynamics, offering new insights into the behavioral mechanisms underlying return anomalies across trading sessions.

1. Introduction

The salience function quantifies the extent to which a stock's return deviates from the market average, to model cognitive distortions in decision-making. This study examines how extreme salience deviations in stock returns influence investor behaviour in the presence of investor heterogeneity.

The hypothesis is that high salience deviation attracts excessive attention from overnight investors, resulting in a buy-sell imbalance and subsequently causing mispricing in overnight trading. A potential explanation for this phenomenon is that overnight investors tend to focus on stocks that attract attention due to extreme information, rather than relying on fundamental valuations or disciplined investment frameworks. Overnight traders tend to purchase stocks with extremely positive or negative returns, which maximizes their attention. In contrast, intraday traders—often institutional, informed, or sophisticated investors—possess greater expertise and engage in arbitrage activities.

The hypothesis mainly developed from Barber and Odean (2008) and Cosemans and Frehen (2021). Barber and Odean (2008) find that retail investors 'reactions to extreme returns, often used as a proxy for attention, are influenced by the extent to which the stock's return deviates from its historical returns. Cosemans and Frehen (2021) define salience deviation as a measure of how much a stock's return divergence from the market average return. Unlike individual stock extreme return, salience deviation considers the impact of market-wide average returns. This measure provides a broader context for understanding how investors evaluate individual stock performance.

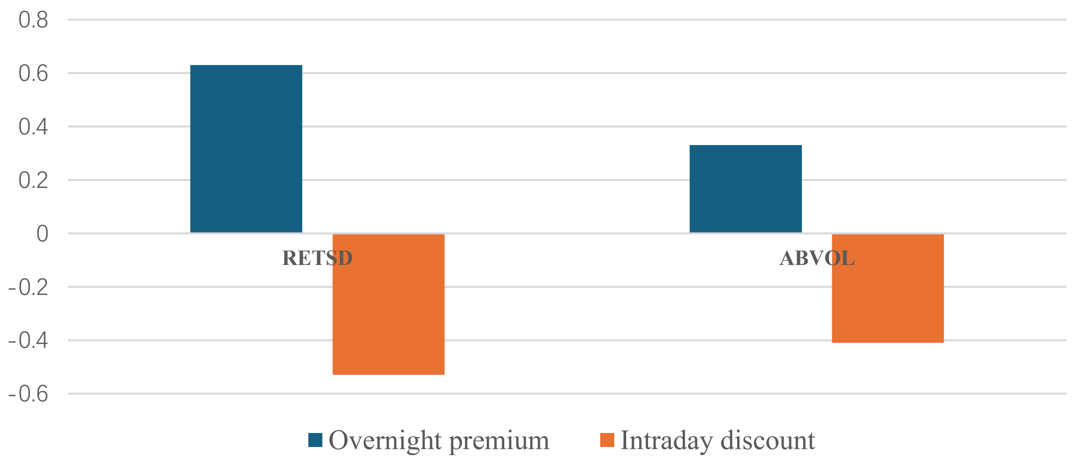
However, while Barber and Odean (2008) demonstrate the influence of attention on retail investors through trading volume, their study does not explore the impact of attention on overnight and intraday returns. On the other hand, Cosemans and Frehen (2021) highlight the impact of salience values on intraday and overnight returns but do not provide a comparison of attention-grabbing measures.

Thus, this study incorporates investor attention by examining extreme returns, salience deviation, and investor heterogeneity. It documents the predictive power of salience deviation as an attention metric on returns generated by intraday trades and overnight trades and focuses on examining how attention-grabbing stocks affect returns during these distinct trading periods to observe the response patterns of participants across different trading intervals.

Empirically, I provide evidence supporting the aforementioned hypothesis. First, a univariate portfolio sort based on salience deviation reveals that the overnight returns of high-salience deviation stocks are significantly higher than those of the low-decile stocks. Moreover, risk-adjusted alpha returns, derived from a multifactor model, originate mainly from high salience deviation stocks, thereby explaining the presence of the overnight premium. In contrast, during intraday trading, the returns of high salience deviation stocks are significantly negative, reflecting the intraday traders, as "rational traders," attempt to correct the overvaluation caused by elevated salience deviation.

Consequently, as figure 1, a salience deviation high-minus-low value-weighted portfolio strategy generates an overnight premium of 0.63% per month (t-statistic = 6.29) but incurs an intraday discount of -0.53% per month (t-statistic = -2.73). These findings are consistent with the earlier hypothesis and explanation, suggesting that overnight investors are especially vulnerable to the effects of salience deviation. Their focus is drawn toward high-salience stocks with returns that markedly diverge from the market average, resulting in the sustained overpricing of these stocks. Further, I replaced salience deviation with abnormal trading volume as an alternative attention-grabbing proxy (Barber and Odean, 2008) and found that overnight and intraday returns exhibited a pattern consistent with the salience deviation portfolio. Notably, when salience deviation is used as an attention-grabbing measure, the portfolio's excess return exhibits larger economic magnitude.

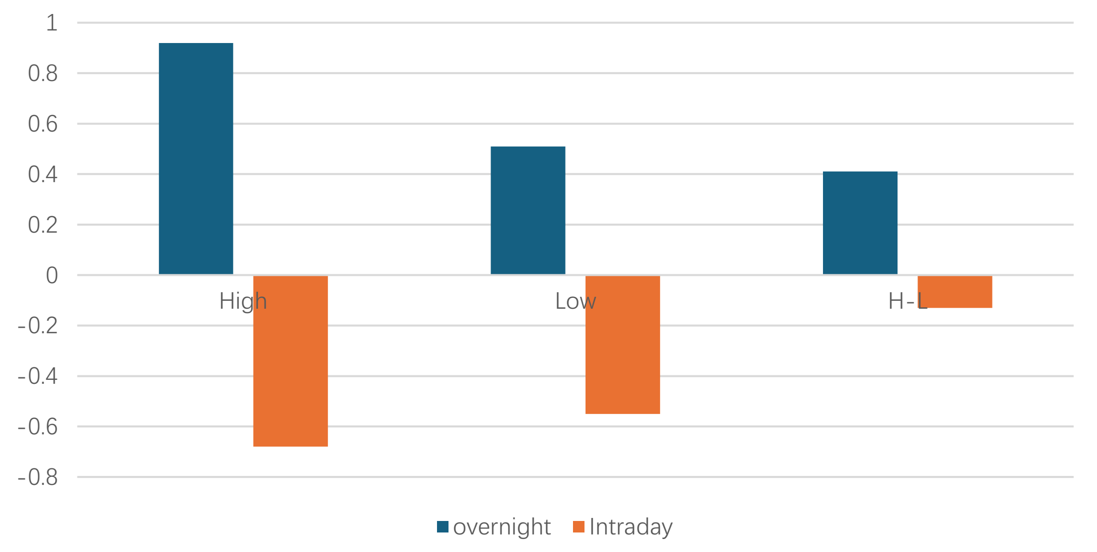
Figure 1. Overnight Premium and Intraday Discount in the Salience Deviation Portfolio: A High-Minus-Low Strategy Analysis



Moreover, the behavioural biases of overnight traders, driven by attention distortion, vary significantly across different market conditions. Up-market states (Antoniou, Doukas and Subrahmanyam, 2012) and high market uncertainty (Birru and Young, 2022) are associated with significantly larger positive differences compared to down-market state and low-uncertainty conditions. Consistently, I find that overnight investors' attention distortion due to high salience deviation varies significantly with market conditions, while intraday investors remain largely unaffected (statistically insignificant).

Figure 2. Difference between Up and down market states for intraday and overnight excess return

Figure 3. Difference between High and Low Market Uncertainty for Intraday and Overnight Excess Return



To the best of my knowledge, this is the first study to propose using salience deviation to examine the reactions of intraday and overnight investors, based on the phenomenon that investor attention is drawn to stocks with extreme returns relative to the market average return. This study demonstrates that when stock returns deviate significantly from market returns, overnight investors are attracted by such deviations and engage in heavy buying, leading to overvaluation and a persistent overnight premium. In contrast, intraday investors counteract this overvaluation by employing arbitrage strategies, selling these overvalued stocks and thereby creating an intraday discount.

2. Literature review

Limited attention is a widespread phenomenon in the stock market. It is caused by the scarcity of cognitive resources (Kahneman, 1973), which makes it difficult for investors to process all available market information. Stimuli attract disproportionate attention, may misdirect focus and distort judgment. Salience, defined as the prominence or contrast of a stimulus, influences judgments and can lead to selective information processing. Consequently, investors may fail to respond effectively and promptly to all relevant market information, deviating from the assumptions of standard asset-pricing models (Hirshleifer and Teoh, 2003).

Investor attention significantly influences the stock market, affecting price and volume information through various mechanisms. These distortions can lead to observable mispricing patterns that alter return performance. For instance, Dellavigna and Pollet (2009) illustrate that investor attention fluctuates on weekdays, leading to underreaction to announcements on Fridays, characterized by a 15% lower immediate response, 70% higher delayed response, and 8% lower trading volume. Li and Yu (2012) suggest that the combined effects of anchoring and limited investor attention influence future market returns, providing evidence that the 52-week high positively predicts future aggregate market returns, while proximity to the historical high negatively predicts future returns. Chen et al. (2021) construct an aggregate market investor attention index based on 12 investor attention proxies and find that periods of high market-wide investor attention are followed by significantly negative returns.

Due to the limited attention, retail traders often fail to adjust stock prices promptly for the securities they pursue and trade. In contrast, institutional investors respond significantly faster. For instance, Ben-Rephael, Da, and Israelsen (2017) propose a proxy for measuring institutional investor attention, abnormal institutional investor attention (AIA), and demonstrate that institutional investors respond more rapidly to news on Bloomberg terminal compared to retail traders who searching on Google. Thus, by inevitability of limited attention, coupled with associated behavioural biases, restricts retail traders from reacting only to a subset of assets that capture their attention, causing these investors to tend to prioritize market- and sector-wide information (Peng and Xiong, 2005).

Past research has shown that retail investors are subject to limited attention leading to mispricing and distorted trading behaviour. Barber and Odean (2008) provide evidence that retail traders exhibit distinctive attention patterns toward stocks experiencing extreme increases or decreases in returns compared to their past performance. Regardless of whether the extreme returns are positive or negative, retail traders tend to buy these stocks, creating price pressure. Whether driven by a "bottom-fishing" or "increasing-position" motive, this behaviour results in significantly high trading volumes accompanied by a buy-sell imbalance for stocks with extreme positive or negative returns. Da, Engelberg, and Gao (2011) use the Google Search Volume Index to capture the attention of retail traders and demonstrate that retail trader attention significantly predicts price movements of Russell 3000 stocks. Lou (2014) demonstrates that managers of publicly listed companies increase advertising spending to attract the attention of retail traders, leading to a short-term rise in retail buying and abnormal returns, followed by lower future returns.

In the discussion of the impact of investor attention on stock pricing, Barber, Odean, and Zhu (2009) suggest that the systematic trading patterns of retail investors stem from 'shared psychological biases' rather than passive reactions to institutional trading, as well as empirical evidence further supports the notion that individual investors exhibit a stronger preference for purchasing attention-grabbing stocks in the market. Barber, Odean, and Zhu (2008) argue that retail investors act as persistent buyers, sustaining the short-term price pressures they create, and leading to short-term positive autocorrelation in stock prices. Furthermore, Barber, Lin, and Odean (2021) reveal that attention-grabbing trading in the short term fuels irrational stock price increases driven by retail trade orders. This phenomenon is closely linked to attention-based trading, where stocks dominated by retail traders exhibit heightened imbalance, increased trading volume, and subsequent price surges, often accompanied by poor return performance. Meanwhile, investors who are “less wealthy, less experienced, and less sophisticated” are more tend to engage in small trades centred on attention-grabbing stocks, and exhibit significantly different performance characteristics compared to large trades.

Moreover, in certain scenarios, mispricing driven by investor attention can become more pronounced. For instance, Barber et al. (2022) argue that the gamified operational model of the fintech platform Robinhood attracts inexperienced retail investors, increasing their susceptibility to attention-driven trading compared to non-Robinhood retail investors. Additionally, Robinhood users are more likely to be drawn to events characterized by extreme gains or losses, consistent with the findings of Barber and Odean (2008), who highlight retail investors’ stronger inclination to hold stocks with absolute extreme returns.

Intuitively, the above discussions point to an analysis of investor attention grounded in investor heterogeneity, emphasizing the differing dynamics of attention-driven mispricing in trading environments dominated by various types of investors. A behaviour-based explanation for attention-induced stock mispricing is likely to yield differentiated patterns in empirical results across such contexts. Overnight trading and intraday trading provide a comparable framework, illustrating how trading environments dominated by different investor types can distinctively influence stock returns.

Using overnight returns to represent the outcomes of retail trader activities and intraday returns to reflect the outcomes of institutional trader activities has been validated for its economic significance in recent studies. Lou et al. (2019) evidence the "tug-of-war effect," driven by investor heterogeneity primarily between overnight traders (noise traders and retail traders) and intraday traders (arbitrageurs and institutional traders). On the other hand, Barardehi, Bogousslavsky and Muravyev (2023) argue that overnight returns are driven by news but not pure noise. Akbas et al. (2022) argue that the noise-trading nature of overnight traders serves as a long-term reference for the price pressure arbitrage conducted by intraday traders. However, the neglect of overnight news leads to a persistent underestimation of intraday returns.

This discussion on the driving forces behind stock price movements in overnight and intraday trading environments prompts further inquiry into how different types of investors respond to attention-driven trading across varying trading contexts. For instance, Barardehi, Bogousslavsky and Muravyev (2023) and Akbas et al. (2022) both highlight the influence of news on overnight trading prices, while emphasizing that intraday trading is primarily driven by trading information, with limited sensitivity to news effects. This suggests the impact of overnight investors' attention on stock returns may vary significantly in response to certain market conditions , whereas such variations are much weaker in the attention-driven returns of intraday traders.

In summary, this paper aims to investigate the relationship between stock returns in overnight and intraday trading and an attention proxy derived from a salience deviation function measure. By distinguishing between overnight and intraday returns, I examine how investor heterogeneity in different trading environments influences stock performance under attention-grabbing trading. Furthermore, I explore how this relationship adjusts to changing market conditions. Building on Barber and Odean's (2008) discussion of the impact of extreme stock returns on investor behaviour, I consider the tendency of retail investors to be drawn to events characterized by extreme returns—whether positive or negative. Based on this insight, I construct a measure of the "deviation of individual stock returns from the market average return" as a proxy to capture the attention-grabbing trading characteristics of individual stocks.

The construction of this proxy is inspired by the methodologies of Chen, Wang, and Yu (2023) and Cosemans and Frehen (2021). Chen, Wang, and Yu (2023) refine the construction of the salience function by replacing the market average return with the peer group average return, based on stocks covered by the same analyst. This adjustment represents "the return divergence between individual stocks and their peers" and demonstrates that the predictability of future returns based on past performance largely depends on their constructed peer salience deviation. Notably, the concept of salience deviation, as proposed by Bordalo, Gennaioli, and Shleifer (2012, 2021), argues that the attention of a decision-maker is drawn to salient payoffs. They propose that certain prominent attributes of an option attract more attention, while nonsalient attributes tend to be overlooked. Cosemans and Frehen (2021) adopt Bordalo, Gennaioli, and Shleifer's (2012) salience function to measure the extent to which individual asset returns deviate from the overall returns of their environment, using it to rank stocks by their level of salience.

Additionally, compared to intraday arbitragers, overnight traders are noise or retail traders and are likely to be more strongly influenced by market conditions. I aim to further examine how changes in market conditions influence attention-grabbing trading behaviours among different types of investors. For instance, market up and down state (Antoniou, Doukas and Subrahmanyam, 2012) and VIX as market uncertainty (Birru and Young, 2022).

This paper is likely the first to explore the extent to which a stock's deviation from the market average return can serve as a measure of investor attention and to use this measure to examine how investor heterogeneity is influenced by attention-grabbing stocks in distorting pricing. The testing results related to changes in market conditions may lack direct comparisons with findings from prior literature. However, both intuition and empirical evidence presented in this paper demonstrate that overnight traders, when drawn to attention-grabbing events involving extreme stock returns, generate significant return differentials under varying market conditions. In contrast, intraday arbitragers exhibit a generally weaker or insignificant pattern.

3. Data and Methodology

3.1 Data sample

I obtain monthly and daily stock return, price data, trading volume, and market equity value from the Center for Research in Security Prices (CRSP), and annual and quarterly accounting data from Compustat. The preliminary sample includes all common stocks listed on the NYSE, AMEX and Nasdaq, identified by a CRSP exchange code (EXCHCD) of 1, 2, or 3, and a share code (SHRCD) of 10 or 11. To mitigate market microstructure effects, I exclude stocks with a closing price below $1 per share at the end of the previous month. I also exclude firms with zero or negative book equity and financial firms (SIC codes 6000–6999). The main sample period runs from June 1992 to December 2023 to ensure complete data for intraday and overnight returns derived from close-to-close prices in CRSP.

3.2 Attention Measure from Investor Attention Driven by Extreme Return

Inspired by Barber and Odean's (2008) findings that retail investors are attracted to extreme stock returns, leading to imbalanced abnormal trading volumes, I utilize the salience deviation function initially proposed by Bordalo, Gennaioli, and Shleifer (2012, 2013) as part of their theoretical framework, while Cosemans and Frehen (2021) incorporate this concept as a step in their empirical process for ranking stocks. This approach enables an analysis of how attention-grabbing stocks influence the trading behaviours of investors during overnight and intraday.

Intuitively, overnight traders are more likely to be affected by attention-grabbing because overnight trading is mostly led by retail traders, leading to noise trading. I assume that highly stimulating stocks in overnight trading will attract significant attention and buying activity from overnight traders, leading to an imbalance in buying. This reflects the judgment distortion caused by such stimuli.

If overnight traders are drawn to stocks that deviate significantly from the market average, the resulting price distortion is not determined by whether the deviation is positive or negative. Instead, it follows the "prominence of stimulus" principle—where the greater the deviation from the market average, regardless of its sign, the more likely investors are to exert price pressure and create a buy-side imbalance, driving asset prices higher in the short term. To capture this characteristic, I measure it using salience deviation.

Hence, salience deviation function in equation (1) becomes:

$$\sigma_{(r_{i.s}, r_{m.s})} = \frac{|r_{i.s} - r_{m.s}|}{|r_{i.s}| + |r_{m.s}| + \theta} \qquad \text{e.q.(1)}$$

where $r_{i,s}$ is the stock *i*'s return on month s, and $r_{m,s}$ is the market return of the equally weighted CRSP index on month s, and θ equal to 0.1 following Cosemans and Frehen (2021) and Guo et al. (2023).

3.3 Intraday and Overnight Return

Following Lou, Polk, and Skouras (2019), I decompose daily stock returns into intraday and overnight components. For each firm *i* on day *s*, I define the intraday return (*RETOTC*) as the relative price change during the daytime, calculated as the price change from the market open to close on day *s*.

$$r^i_{intraday,s} = \frac{P^i_{close,s}}{P^i_{open,s}} - 1 \qquad \text{e.q. (2)}$$

Then I calculate the overnight return (*RETCTO*), which is from the previous day (*s-1*) closing to the next available open price as equation (3).

$$r^i_{overnight,s} = \frac{1 + r^i_{close-to-close,s}}{1 + r^i_{intraday,s}} - 1 \qquad \text{e.q. (3)}$$

If the opening price on day s for a particular stock is missing, I hold the overnight position from the closing price of day s-1 to the next available opening price. After calculating all daily decomposed returns, I compute the monthly cumulative intraday and overnight returns.

I calculate the cumulative intraday and overnight returns across days within each month to derive the monthly intraday and overnight return components for individual stocks:

$$r\_intraday_{i.t} = \prod_{s=1}^{N_t}(1 + r_{i,intraday,t,s}) - 1 \quad \text{e.q.(4)}$$

$$r\_overnight_{i.t} = \prod_{s=1}^{N_t}(1 + r_{i,overnight,t,s}) - 1 \quad \text{e.q.(5)}$$

where $r_{i,intraday,t,s}$ and $r_{i,overnight,t,s}$ denote the open-to-close and close-to-open return of stock i on day s in month t, and N_t denotes the number of available trading days in month t.

Equations (4) and (5) represent the cumulative return that could be achieved by an investor who always held the individual stock during the intraday and overnight periods within the month, respectively.

3.4 Market Conditions

To further examine the differences in attention-based trading behaviour between overnight and intraday investors within their respective trading environments, I construct market condition contexts, the market CRSP index as an market state proxy (Antoniou, Doukas and Subrahmanyam, 2012), and the VIX as uncertainty proxy (Birru and Young, 2022). In subsequent tests, I analyze whether traders participating in overnight trading exhibit response patterns to stimuli from attention that are significantly different from, or comparable to, those of intraday investors.

3.4.1 Market States

Based on the evidence provided by Barber and Odean (2008), retail traders tend to buy stocks regardless of whether they exhibit abnormally high or low returns, although their motivations may differ. Specifically, they engage in "chasing high-return stocks" while also "acquiring low-return stocks at a lower cost." Antoniou, Doukas, and Subrahmanyam (2012) suggest that the widespread presence of cognitive dissonance (Festinger, 1957) among investors may cause a delayed reaction to negative news in an up-market state. Additionally, retail investors tend to be drawn to analysts' extreme positive opinions, making them more likely to buy stocks rather than short-sell. Inspired by these findings, I use the CRSP index as a proxy for market state, where high CRSP index values indicate up market state and low CRSP index values correspond to down market state. I classify high and low uncertainty based on whether the mean of the 1-month CRSP index is above or below the sample median.

Moreover, Antoniou, Doukas, and Subrahmanyam (2012) construct their market state measure using the past six-month CRSP value-weighted market return as the basis for classification:

$$Market\ State = \sum_{-6}^{-1} w_t R_t \qquad \text{e.q. (6)}$$

where R_t represents the monthly market return over the past six months**, while** w_t which typically decay over time to give greater importance to more recent market performance. For example, the weight for the most recent month is 6, while the weight for the furthest month is Thus, I tested the 6-month weighted CRSP index, and overall, its conclusions remain consistent with those derived from the 1-month CRSP index.

3.4.2 Uncertainty

Birru and Young (2022) find that increases in aggregate uncertainty in the stock market are closely linked to the enhanced predictive power of sentiment on market returns. When the market is in a state of high uncertainty, sentiment-sensitive assets exhibit a highly predictable cross-section of returns. VIX, the Chicago Board of Exchange (CBOE) measure of risk-neutral expected stock market volatility over the next 30 days for the S&P 500, serves as their first uncertainty measure. Meanwhile, Aboody et al. (2018) suggest that overnight returns reflect temporary sentiment-driven mispricing and can be used to measure firm-specific investor sentiment. Inspired by these findings, I use the VIX as a proxy for market uncertainty, where high VIX values indicate high uncertainty and low VIX values correspond to low uncertainty. I classify high and low uncertainty based on whether the mean of the 1-month VIX is above or below the sample median.

3.5 Robustness check

In this section, to confirm the robustness of the main results, I examine the impact of adjusting the value of θ in Equation (1) from 0.1 to 0.001 and modifying the minimum last-month price requirement from $1 to $5.

3.6 Summary Statistics

Table 1 presents summary statistics for overnight and intraday returns, as well as for salience deviation (RETSD). In Panel 1, the monthly compounded overnight returns exhibit higher volatility compared to monthly compounded intraday returns, with volatilities of 0.215 and 0.162, respectively. Meanwhile, the volatility of RETSD is 0.212. It is important to note that RETSD measures the magnitude of a stock's deviation from the market average return, and, by definition, all its values are positive.

Panel 2 reports the correlation coefficients. The correlation coefficients between RETSD and monthly compounded overnight returns and intraday returns are 0.047 and 0.034, respectively, indicating a low correlation between RETSD and both intraday and overnight returns. In contrast, the correlation between overnight returns and intraday returns is -0.289, reflecting a relatively strong negative relationship. This aligns with the "tug-of-war effect" described by Lou et al. (2019).

[Insert Table 1 about here.]

4. Empirical Results

4.1 Univariate portfolio sort by salience deviation for overnight and intraday return

I begin the empirical analysis with univariate portfolio sorts. At the end of each month *t*, I sort stocks into quintile portfolios based on value of salience deviation and calculate the equal-weighted (EW) and value-weighted (VW) portfolio returns over the next month t+1. Table 2 reports for each portfolio the time-series average of the one-month-ahead excess portfolio return (*Excess Ret*), the five-factor alpha (*FF5 alpha*) obtained from Fama and French's (2015) five factor model, the six-factor alpha (*FF6 alpha*) obtain from Fama and French (2018) model that extends the Fama and French (2015) five-factor model with a momentum factor, the Hou-Xue-Zhang Q-factor alpha (*HXZ_Q alpha*) obtain from Hou, Xue and Zhang (2015), Hou-Xue-Zhang Q5 alpha (*HXZ_Q5 alpha*) obtain from Hou, Xue and Zhang (2020). Moreover, five factors with a liquidity factor alpha (*FF5_li alpha*) were obtained from Fama and French's (2015) five-factor model with a liquidity factor from Pastor and Stambaugh (2003) and the six-factor with a liquidity factor alpha (*FF6_li alpha*) from Fama and French (2018) six-factor model with a liquidity factor from Pastor and Stambaugh (2003). Portfolio sorting is based on NYSE breakpoints. Test statistics are adjusted for heteroscedasticity and autocorrelation using the Newey and West (1987) correction method with five lags.

In Table 2, I primarily report the results from the value-weighted (VW) portfolio and the results from equally weighted (EW) portfolio exhibit similar patterns. These findings strongly support the prediction and hypothesis that attention-grabbing stocks—measured by salience deviation to capture the extent of their deviation from the market average—stimulate distortions in overnight investors' behaviour, resulting in a significant overnight premium. In contrast, the excess return and multi-factor alphas of attention-grabbing portfolios are mostly negative during the intraday period. Moreover, there is a monotonically increasing pattern in the excess return and multi-factor alphas of attention-grabbing-based quintile portfolios during overnight trading, and a monotonically decreasing pattern in the excess return and multi-factor alphas of attention-grabbing-based quintile portfolios during intraday trading. Differences in the performance of high- and low- attention-grabbing stocks are not only statistically significant but also large in economic magnitudes.

Panel A reports excess return and multiple factor alphas during the overnight period, which are mostly positive. Panel A.1 shows that the high-minus-low portfolio delivers a sizable positive excess return of 0.63% per month, with a Newey and West (1987) t-statistic of 6.29. This return difference is not explained by Fama and French's (2015, 2018) multi-factor model, which includes market (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA), and momentum (UMD), yielding a six-factor alpha of 0.61% per month (t-statistic = 5.47). Similarly, it is not accounted for by Hou, Xue, and Zhang's (2015, 2020) five-factor model, which incorporates market (MKT), size (SMB), profitability (ROE), investment (I/A), and expected growth (EG), with a five-factor alpha of 0.53% per month and a Newey and West (1987) t-statistic of 4.78. Moreover, the results remain robust even when incorporating Fama and French's (2015, 2018) multi-factor models and Pastor and Stambaugh's (2003) liquidity factor; ie. See FF5_li and FF6_li alpha.

Notably, the positive premium from portfolio excess returns and multiple-factor alphas during overnight trading is primarily driven by the high-side portfolio (quintile 5). This aligns with the hypothesis that high attention-grabbing stocks attract investors in overnight trading, leading to mispricing. In Panel A.1, I observe that the overnight excess return for quintile 1 is 0.61% per month, with a t-statistic of 4.16. However, its risk-adjusted return remains statistically insignificant in partial multi-factor models. In contrast, portfolio quintile 5 exhibits a substantial excess return of 1.25% per month, with a t-statistic of 6.65, regardless of the multi-factor model used to compute the alpha, results hold robustly across all multi-factor models. This stark contrast explains the robustness and economic magnitude of the high-minus-low return, indicating that the overnight premium is driven by high attention-grabbing stocks.

Furthermore, Panel A.2 reveals that the high-minus-low portfolio for intraday return generates a significantly negative excess return of -0.53% per month, with a Newey and West (1987) t-statistic of -2.73. This result remains robust across all multi-factor alpha models. For high attention-grabbing stocks in quintile 5, both the excess return and multi-factor alpha are significantly negative.

[Insert Table 2 about here.]

4.2 Firm-level Fama-Macbeth regression

The portfolio analysis strongly supports the relationship between salience deviation, which reflects the extent of a stock's price deviation from the market average, and overnight and intraday returns. However, portfolio analysis does not rely on a specific functional form and, therefore, cannot control for various firm characteristics known to be correlated with returns. Thus, I account for a comprehensive set of characteristics that are known to explain the cross-sectional variation in returns.

Lou et al. (2019) show that the previous month's intraday and overnight return persistent impact on the future intraday and overnight return with a back-and-forth tug-of-war between overnight and intraday traders. Thus, I control the previous overnight return (*RETCTO*) and intraday return (*RETOTC*). Given that the characteristics of "extreme returns" may be influenced by a stock's past highest and lowest return levels, I control for the stock's maximum daily return (*MAX*) and minimum daily return (*MIN*) within a month, following the approach of Bali et al. (2011). For size and the B/M ratio, I use the logarithm of their values (*LNSIZE*, *LNBM*) in the Fama-MacBeth regression. Consistent with Fama and French (1992, 1993, 2008, 2015), I impose a six-month lag between annual accounting data and subsequent returns to avoid look-ahead bias. For instance, if a firm's fiscal year ends in December of calendar year t-1, I assume these data are publicly available by the end of June in calendar year t. The book-to-market ratio is computed at the end of June in year t as the ratio of the book value of equity at the end of fiscal year t-1 to the market value of equity at the end of December in calendar year t-1. Book value is defined as shareholder's equity plus deferred taxes minus preferred stock. Market value of equity is calculated as the stock price per share multiplied by the number of shares outstanding at the end of June in year t. Turnover (*Tnovm1*) is calculated by dividing the total volume of trades by the number of shares outstanding to obtain share turnover, as described by Lo and Wang (2000) and Avramov, Chordia, and Goyal (2006). To ensure comparability with NYSE and AMEX stocks, the trading volume of NASDAQ stocks before 2004 is adjusted by Gao and Ritter (2010). 12-month momentum (*MOM_12m*) is measured as a stock's cumulative return which skips formation month and over 11 months ending two months prior to the current month. Short-term reversal is measured as a stock's previous one-month return (*Ret_1_0*). Amihud's (2002) illiquidity (*ILLIQ*), idiosyncratic volatility (*IVOL*) following Ang et al. (2006), market beta (*Beta*) following Fama and MacBeth (1973), and idiosyncratic skewness (*SKEW*) from the Fama-French 3-factor model following Bali, Engle, and Murray (2016) are obtained from the characteristics database provided by Jensen, Kelly, and Pedersen (2023). All independent variables are winsorized at the 1st and 99th percentile and and cross-sectionally standardized with a mean of zero and a standard deviation of one.

I run the Fama and MacBeth (1973) cross-sectional regressions in the following form overnight and intraday trading separately:

$$r_{DN,i,t} = \alpha + \varphi_1 RETST_{i,t-1} + \varphi_1 ControlVar_{i,t-1} + \epsilon \quad \text{(e.q. 6)}$$

where $r_{DN,i,t}$ is current intraday or overnight return as the dependent variable, $RETST_{i,t-1}$ represents the salience deviation in the previous month as the main variable. In the most general specification, $ControlVar_{i,t-1}$ represents control variables includes previous month overnight return (*RETCTO*) and intraday return (*RETOTC*), previous month's max daily return (*MAX*) and min daily return (*MIN*), size (*LNSIZE*), book-to-market (*LNBM*), illiquidity (*ILLIQ*), idiosyncratic volatility (*IVOL*), turnover (*TNOVM1*), market beta(*BETA*), momentum

(*MOM*) and idiosyncratic skewness (*SKEW*). All independent variables are winsorized at the 1% and 99% levels and cross-sectionally standardized with a mean of zero and a standard deviation of one, and t-statistics are calculated based on Newey-West (1987) standard errors with five lags.

Table 3 presents the results, demonstrating the robust explanatory power of salience deviation for both intraday and overnight returns. The first row specifies the dependent variables: CTOY represents the future overnight (close-to-open) return, and OTCY represents the future intraday (open-to-close) return. The primary independent variable is salience deviation (RETSD). Consistent with the hypothesis, salience deviation serves as a proxy for attention-grabbing stocks, where high salience deviation stocks drive an overnight premium by capturing the limited attention of overnight traders. This suggests that overnight traders are more likely to be attracted to stocks with returns that deviate significantly from market averages.

Consistent with the portfolio analysis result, I find a significantly positive relation between RETSD and CTOY. In panel A for overnight return (*CTOY*), I can see that the coefficient of *RETSD* is statistically positive. The coefficient on RETSD in the univariate regression in column (1) is statistically significant at a 1% level (t-statistic = 14.99), a one deviation increase in *RETSD* predicts an increase in the next month's overnight return of more than 0.040 bps. Column 2 shows the inclusion of consideration from the previous month's tug-of-war effect from intraday and overnight trading, but it hardly changes the coefficient estimate on *RETSD*. Controlling for *MAX* and *MIN* reduces the magnitude of the *RETSD* slope magnitude nearly half (0.0218 with a t-statistic is 11.56). After accounting for all control variables in column (4), a one deviation increase in *RETSD* predicts an increase in the next month's overnight return of 0.0166 bps and keeps a statistically significant at 1% level (t-statistic = 8.6).

For comparison, in panel B for intraday return, the coefficient of RETSD in the univariate regression in column (1) is statistically significant at a 1% level (t-statistic = -5.33), a one deviation increasing in *RETSD* predicts a decrease in next month's intraday return of -0.0165 bps. Controlling for the previous month's intraday and overnight returns, as well as the maximum and minimum daily returns, has a minor impact on the coefficients and slope magnitudes. However, these adjustments do not alter the economic significance or statistical significance of the results(i.e. see columns (2) and (3) in intraday). After accounting for all control variables in column (4), a one deviation increase in *RETSD* predicts an increase in the next month's overnight return of -0.0061 bps and keeps a statistically significant at 1% level (t-statistic = -4.23).

[Insert Table 3 about here.]

5. Inspecting the mechanisms

I first provide several pieces of evidence on overnight trading behaviour, including the effects of abnormal trading volume, direct evidence of retail trading from a large broker house, the size effect and the limits to arbitrage. Furthermore, I examine how market conditions, which are market state and market uncertainty, affect the overnight and intraday trading behaviour.

5.1 Direct evidence of retail trading from a large brokerhouse

Retail investors are typically characterized as noise traders who are less sophisticated than institutional investors and are more prone to the effects of their limited attention, often leading to irrational trading behaviour. Meanwhile, a series of studies have demonstrated that behaviour-based activities in overnight trading are predominantly driven by the significant influence of retail trades (Lou et al., 2019; Akbas et al., 2021; Chhaochharia et al., 2023; Barardehi, Bogousslavsky, and Muravyev, 2023; Fan and He, 2024). Barber and Odean (2008) find that when individual stocks exhibit extreme returns—whether positive or negative—they attract substantial buying activity from retail traders, resulting in a pronounced buy-sell imbalance and creating price pressure.

Inspired by prior studies, I provide direct evidence of monthly trading activities based on daily frequency data at the account level, using data from a large U.S. discount brokerage house (Barber and Odean, 2000). I examine whether individual investors aggressively buy stocks with high salience deviation, which reflects significant deviations of individual stock returns from the market average, thereby inducing strong buy-side price pressure. To test this conjecture, inspired by Boehmer et al. (2021), I use both dollar volume and the number of shares in accounts as alternative proxies. This approach facilitates a cross-check between the measures to ensure robustness, the $BSI_{i,j,t}$ is buy-sell imbalance:

$$BSI = \frac{Monthly\ Buying - |Monthly\ Selling|}{Monthly\ Buying + |Monthly\ Selling|} \quad \text{(e.q 7)}$$

Then I estimate the following regression:

$$BSI_{j,t} = \varphi_1 RETST_{j,t} + \varphi_1 ControlVar_{j,t-1} + \omega_i + \theta_t + \epsilon \quad \text{(e.q. 8)}$$

where $RETST_{j,t}$ is the salience deviation of stock *j* in month *t*. $ControlVar_{j,t-1}$ are the control variables as aforementioned in month *t-1*. The regression includes firm (ω_i) and month (θ_t) fixed two-way effects. The sample period is from 1992 to 1996 since the main data sample started in 1992.

I hypothesize that retail investors are attracted to stocks with high salience deviation. During periods characterized by retail-dominated trading activity, stocks with high salience deviation are heavily purchased, resulting in significant buy-sell imbalances.

Table 4 presents the results. Panel A and Panel B use the buy-sell imbalance (BSI) as the dependent variable, constructed based on dollar volume and the number of shares reported in panels A and B, respectively. Both panels yield consistent conclusions. Column (1) shows that the coefficient of *RETSD* is significantly positive, suggesting that investors trade in the direction of *RETSD*. This provides strong support to the intuition that salience deviation impacts on the trading behaviour of retail traders. In column (2), I included all control variables as previously described. The significance level and magnitude of the coefficient remain comparable to the results for RETSD in column (1). This finding suggests that the intensity of buying behaviour increases as the deviation of stock returns from the market average becomes more pronounced.

[Insert table 4 about here]

Moreover, I also tested the relationship between salience deviation over the past month and future buying behaviour, as measured by the buy-sell imbalance (BSI). The regression results are as follows:

$$BSI_{i,j,t} = \varphi_1 RETST_{j,t-1} + \varphi_1 ControlVar_{j,t-1} + \omega_i + \theta_t + \epsilon \quad \text{(e.q. 9)}$$

where $RETST_{j,t-1}$ is the salience deviation of stock j in month *t-1*. $ControlVar_{j,t-1}$ are the control variables as aforementioned in month *t-1*. The regression includes firm (ω_i) and month (θ_t) fixed two-way effects.

Similar to the results in Table 4, Table 5 shows that *RETSD* consistently exhibits significantly positive results, regardless of whether control variables are included. This finding indicates that the greater the deviation of a firm's past returns from the market average, the stronger its appeal to retail traders in the following month, leading to competitive buying behaviour and, consequently, a buy-sell imbalance.

[Insert table 5 about here.]

5.2 Alternative proxy of attention-grabbing in overnight and intraday trading

As Tables 4 and 5 confirm the explanatory power of salience deviation for buy-sell imbalances, I aim to further demonstrate that other relevant attention-grabbing proxies, as alternative measures, can similarly reveal how overnight traders' behaviour is influenced by attention distortion. Additionally, I contrast these findings with the trading outcomes of intraday investors to provide a comprehensive comparison.

Barber and Odean (2008) propose abnormal trading volume (*ABVOL*) as a proxy for retail traders' attention, showing that stocks with high abnormal trading volume experience the strongest buy-sell imbalance driven by retail orders, creating significant purchase pressure from retail traders. Intuitively, investors' limited attention, influenced by investor heterogeneity, may affect behaviour differently in overnight and intraday trading. Therefore, a portfolio single sort based on *ABVOL* should exhibit a pattern similar to that observed for RETSD in Table 2. Specifically, stocks that distort overnight investors' attention due to abnormal trading activity in the past month are expected to generate a notable overnight premium, primarily driven by the highest quintile portfolio. In contrast, the intraday discount is expected to display a significant opposite sign as a comparison.

Building on this framework, I calculate the monthly abnormal trading volume (ABVOL) for each stock, the $ABVOL_{i,t}$ to be

$$ABVOL_{i,t} = \frac{Vol_{i,t}}{\overline{Vol}_{it}} \qquad \text{(e.q. 10)}$$

where $Vol_{i,t}$ is the dollar volume from stock *i* traded on month t as reported in the Center for Research in Security Prices (CRSP) monthly stock return files for New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ stocks and

$$\overline{Vol}_{i,t} = \sum_{m=t-12}^{t-1} \frac{Vol_{i,m}}{12} \qquad \text{(e.q.11)}$$

where the $\overline{Vol}_{i,t}$ is the average trading volume in the previous 12 months.

Table 6 reports the results from the equally weighted (EW) portfolio (Panel A), while the results from the value-weighted (VW) portfolio (Panel B) exhibit similar patterns. These findings strongly support intuition and are consistent with the initial hypothesis that attention-grabbing stocks—measured by the abnormal trading volume as an alternative attention-grabbing proxy—stimulate distortions in overnight investors' behaviour, resulting in a significant overnight premium. In contrast, the excess return and multi-factor alphas of attention-grabbing portfolios are mostly negative during the intraday period. Meanwhile, I can observe the monotonically increasing (decreasing) pattern in the excess return and multi-factor in overnight (intraday) trading in panel A.1 (panel A.2) , and an approximately monotonicity in value-weighted portfolio in panel B.

[Insert table 6 about here.]

5.3 Size effect and the attention-grabbing trading in overnight and intraday

Investor heterogeneity between overnight and intraday traders may lead to distinct behavioural patterns when influenced by attention-grabbing factors. Cosemans and Frehen (2021) and Guo et al. (2023) find that small-cap stocks exhibit a stronger salience effect, with evidence suggesting that the salience effect is predominantly driven by these stocks. Barber and

Odean (2008) demonstrate that attention grabbing induces buy-sell imbalances that are prevalent among both large-cap and small-cap stocks, suggesting that both categories may attract retail traders' attention based on similar psychological biases. However, these studies appear to have overlooked the simultaneous consideration of attention-grabbing, size effects, and investor heterogeneity, which serves as the primary motivation for this segment of the analysis.

Hence, I hypothesize that microcap stocks may generate differing return patterns in overnight and intraday trading. Intuitively, the size effect from microcap stocks is likely to result in stronger economic significance and larger magnitudes during overnight trading.

Table 7 shows the performance of size-conditional standard deviation strategies. I use 5*5 independent double sort on *SIZE* and *RETSD* for intraday and overnight returns, respectively. The breakpoints are the 20^{th},40^{th},60^{th} and 80^{th} percentiles for NYSE stocks. Portfolios are EW and VW and rebalanced at the end of each month. For brevity, I will only show the salience deviation high-minus-low portfolio returns with different sizes condition.

Table 7 reports for each portfolio the time-series average of the one-month-ahead excess portfolio return, the six-factor alpha (*FF6 alpha*) obtain from Fama and French (2018) model that extends the Fama and French (2015) five-factor model with a momentum factor, and Hou-Xue-Zhang Q5 alpha (*HXZ_Q5 alpha*) obtain from Hou, Xue and Zhang (2020). Test statistics are adjusted for heteroscedasticity and autocorrelation using the Newey and West (1987) correction method with five lags. A comparison of the return performance of RETSD portfolios across different size quintiles in overnight trading (Panel A) and intraday trading (Panel B) reveals that the size effect is primarily concentrated in overnight trading.

In Panel A, the high-minus-low size portfolio delivers a sizable negative excess return of -1.2% per month and is statistically significant at the 1% level, with a Newey and West (1987) t-statistic of -7.77. The inclusion of *FF6 alpha* and *HXZ-Q5 alpha* does not substantially alter the coefficients, and the results are consistent across both value-weighted (VW) and equal-weighted (EW) portfolios.

In panel B, the high-minus-low size portfolio delivers a weak positive excess return of 0.42% per month and is statistically significant at the 10% level, with a Newey and West (1987) t-statistic of 1.83. Notably, once risk adjustment is applied, the significance of the excess returns disappears.

By and large, stocks with high (low) salience deviation exhibit significantly higher positive (negative) premiums in overnight (intraday) trading compared to those with low (high) salience deviation. Moreover, the size effect has a markedly stronger impact on overnight traders than on intraday traders. This result further underscores the differentiated impact of attention-grabbing stocks on overnight and intraday traders, emphasizing the importance of categorizing investors to better capture their distinctive trading behaviours across different trading periods.

[Insert Table 7 about here.]

5.4 Limits to arbitrage and the attention-grabbing trading in overnight and intraday

In salience-related studies, cognitive abilities among different investors determine variations in their salient thinking (Cosemans and Frehen, 2021). Stronger limits to arbitrage exacerbate short-selling constraints, preventing arbitrageurs from promptly correcting mispricing (Guo et al., 2023). Meanwhile, retail traders are attracted to stocks with extreme abnormal returns, leading to substantial buying activity, whereas institutional arbitrageurs are more likely to short-sell stocks with high positive premiums (Barber and Odean, 2008). Accordingly, I aim to examine how limits to arbitrage influence attention-grabbing-driven mispricing in intraday and overnight trading, and expect that attention-grabbing pattern is most pronounced among stocks with greater arbitrage cost in overnight trading. I examine the expectation with three proxies for limits to arbitrage: firm size, illiquidity, and idiosyncratic volatility.

Table 8 reports the results of Fama-MacBeth regressions that include interaction terms between salience deviation and each of the proxies of arbitrage cost (size, idiosyncratic volatility and Amihud's illiquidity). Investor attention distorted by extreme return proxied by salience deviation is most pronounced among stocks with greater limits to arbitrage during overnight trading. However, this effect becomes limited in intraday trading.

In Panel A, the interaction terms between salience deviation and high IVOL, high ILLIQ, and low Size yield statistically significant coefficients. This suggests that overnight traders' attention, distorted by extreme phenomena, drives continued price increases for these stocks due to the inability to promptly arbitrage their mispricing. On the other hand, in Panel B, attention-grabbing stocks during the intraday trading phase show only a marginally positive interaction coefficient driven by liquidity issues. However, no statistically significant interaction patterns are observed for SIZE and IVOL.

[Insert table 8 about here.]

6. Market conditions and attention-grabbing in overnight and intraday trading

The previous tests primarily examined how extreme return events, as reflected by a stock's deviation from the market average, capture investor attention and influence the formation of mispricing in overnight trading, and were largely focused on the cross-sectional characteristics of stocks.

In this section, I investigate how intraday and overnight traders respond to attention-grabbing stocks under different market conditions, aiming to explore the characteristics of their trading behaviours.

I follow Antoniou, Doukas and Subrahmanyam (2012) to classify high and low states by whether the mean of the market condition proxies is above or below the sample median. Then I report the monthly average percentage of excess return and Fama-French 6 factor alphas for VW portfolios sorted on salience deviation during up different conditions, respectively.

These empirical findings validate and extend the earlier results, confirming that overnight investors' attention, distorted by extreme stock returns, varies significantly with shifts in market conditions. In contrast, intraday investors remain unaffected by these changes.

6.1 Market State

Antoniou, Doukas, and Subrahmanyam (2012) emphasize that when the market is in an up state, investors, influenced by cognitive dissonance, tend to over-optimistically believe that favorable market conditions will persist. Intuitively, if overnight traders become convinced that the bullish trend will continue, then in an up-market environment, stocks with high RETSD are likely to trigger momentum-chasing or contrarian trading behaviors (Barber and Odean, 2008), leading to a significant divergence between up- and down-market dynamics.

Building on this, I hypothesize that this mechanism may further amplify the behavioral biases induced by attention-grabbing effects on overnight traders. In contrast, I extend the assumption regarding intraday traders, who are predominantly institutional or sophisticated investors. Given their trading strategies, the changes in market state may not be sufficient to generate significant differences in intraday returns.

In table 9, I report the monthly average percentage of FF6 factor alphas for portfolios sorted on salience deviation (RETSD) during up and down market states, respectively.

[Insert table 9 about here.]

Consistent with the expectation, the results exhibit a much stronger attention-grabbing overnight premium in the up-state market compared with the lows-state market. Overnight premium is 0.87% in the up-state market and 0.54% in the down market, and the difference for the up state minus down state is 0.33% with statistically significant at 10% significance level. In contrast, intraday excess return without a statistically significant difference between up- and down- state conditions.

Meanwhile, I can also observe the different responses of overnight and intraday traders to high attention-grabbing stocks. Under up-state market conditions, the overnight return for high RETSD stocks is 1.09, while under down-state market conditions, it is 0.51, resulting in a difference of 0.57 (t-value = 2.06). In contrast, I do not observe a statistically significant or similar pattern in intraday trading returns.

Additionally, I further test the market state measured by the six-month weighted CRSP index. As shown in Table 10, the RETSD high-minus-low strategy return in intraday trading still does not exhibit a statistically significant difference pattern. However, it is worth noting that the overnight premium demonstrates a stronger economic magnitude. While the underlying cause of this phenomenon is beyond the scope of this paper, it could be an interesting avenue for future research.

[Insert table 10 about here.]

6.2 Market Uncertainty

Birru and Young (2022) find that market uncertainty increases investors' susceptibility to emotional influences, thereby enhancing the predictive power of investor sentiment on market returns and improving the predictability of cross-sectional returns for sentiment-sensitive assets. Moreover, Aboody et al. (2018) evidence that overnight returns can be used to measure firm-specific investor sentiment. Intuitively, if salience deviation influences investor behaviour in overnight trading, heightened market uncertainty is likely to affect overnight traders, prompting them to persist in their prior buying behaviour toward attention-grabbing stocks. Hence, I assume that heightened market uncertainty further drives overnight traders to push up the prices of stocks that attract their attention.

Hence, following Birru and Young (2022), I use the VIX as a proxy for market uncertainty, where high VIX values indicate high uncertainty and low VIX values correspond to low uncertainty. I classify high and low uncertainty based on whether the mean of the 1-month VIX is above or below the sample median. In Table 10, I find that the salience deviation high-minus-low portfolio strategy generates statistically significant differences in excess returns and FF6 alpha as market uncertainty changes.

[Insert table 11 about here.]

The results exhibit much stronger attention-grabbing overnight premium in the high uncertainty market compared with the low uncertainty market. Overnight premium is 0.92% in the high uncertainty market and 0.51% in the low uncertainty market, and the difference for the High uncertainty minus low uncertainty is 0.41% with statistically significant at 10% significance level. On the other hand, condition difference of intraday excess return is -0.13 with t-statistics is -0.37 which is statistically insignificant.

Meanwhile, I can also observe the different responses of overnight and intraday traders to high attention-grabbing stocks. Under up-state market conditions, the overnight return for high RETSD stocks is 1.05 while under down-state market conditions, it is 0.56, resulting in a difference of 0.49 (t-value = 1.66). In contrast, a statistically significant or similar pattern can in intraday trading returns.

7. Robustness test

In this section, I primarily report the robustness of the portfolio sort and Fama-MacBeth (1973) regression results after replacing θ (0.1 in Equation 1) with 0.001 and adjusting the last-month price filter from a minimum of $1 to $5. Tables 12 and 13 show that these changes do not affect the pattern or its significance, confirming the overall consistency of the results.

[Insert table 12 about here.]

[Insert table 13 about here.]

8. Conclusion

In this study, I integrate previous approaches and findings while innovatively proposing the use of salience deviation—measuring the extent to which stock returns deviate from market average returns—as a proxy for investor attention to extreme return events. This measure is applied to analyze attention-driven investment behaviour stemming from the heterogeneity between intraday and overnight traders, offering a new perspective on the influence of investor attention on trading behaviour.

These findings suggest that overnight traders, with limited attention, tend to be drawn to stocks with returns that deviate significantly from the market average, leading to a buy-sell imbalance and generating positive price pressure, thereby forming an overnight premium (Barber and Odean, 2008). This effect is consistently pronounced when abnormal trading volume is used as a alternative proxy, further supporting the attention-driven nature of overnight trading. In contrast, intraday traders engage in contrarian arbitrage, which offsets some of the price distortions created overnight, leading to an intraday discount.

Notably, while market conditions, such as an up-market state and heightened market uncertainty, significantly influence overnight traders' trading behavior driven by attention-grabbing stocks, they appear to have no statistically significant impact on intraday traders' arbitrage activity. This distinction highlights the differential role of attention-driven trading versus arbitrage trading across trading sessions, offering insights into how investor behavior varies based on market conditions and trading horizons.

A potential direction for future research is to explore whether the attention-grabbing patterns observed in overnight trading are driven solely by retail traders, or alternatively, whether all participants in overnight trading—regardless of whether they are individual investors—are inherently more prone to having their stock price judgments distorted by attention-grabbing stocks.

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Appendix

Table 1. Summary Statistics

This table reports statistics for main characteristics (Panel A) and correlation coefficients (Panel B). Main characteristics are the previous month's standard deviation (RETSD), current month's intraday and overnight return. For brevity, the previous month's intraday (RETOTC) and overnight (RETCTO) returns, as monthly characteristics, are not included in the table, as they can effectively be considered lagged data for the current month's intraday and overnight returns. The sample includes NYSE/Amex/Nasdaq common stocks with a price of at least $1 per share at the end of last month, and non-negative book equity. The sample period is from June 1992 to December 2023.

Panel 1. Statistic summary

	Mean	StdDev	P1st	P5th	Median	P95th	P99th
RETSD	0.350	0.212	0.007	0.034	0.338	0.712	0.815
Intraday return	0.010	0.162	-0.356	-0.182	0.003	0.213	0.505
Overnight return	0.011	0.215	-0.449	-0.257	0.003	0.288	0.616

Panel 2. Correlation Coefficient

	RETSD	Intraday return	Overnight return
RETSD	1		
Intraday return	0.034	1	
Overnight return	0.047	-0.289	1

Table 2. Single sort by Salience Deviation for Overnight and Intraday return

This table reports the monthly average intraday and overnight returns (in percentage) for portfolios sorted on the salience deviation (RETSD). Panel A.1 (A.2) show equally-weighted portfolio is held for one month in month t and sort by RETSD for overnight (intraday) return , panel B.1 and B.2 show value-weighted portfolio is held for one month in month t and sort by RETSD for overnight (intraday) return. All panels show the average monthly excess returns and alphas with respect to Fama and French (1993) -factor with Carhart (1997) 4-factor (FF4), Fama and French (2015) 5-factor (FF5), FF5 with with Carhart (1997) 6–factor (FF6), Hou, Xue and Zhang (2015) Q-facto (HXZ_Q), Hou, Xue and Zhang (2020) Q5-facto (HXZ_Q5), and FF5 and FF6 with Pastor and Stambaugh (2003) liquidity factors (FF5_li, FF6_li). H-L refers to the high minus low RETSD portfolios. The sample includes NYSE/Amex/Nasdaq common stocks with a price of at least $1 per share in the end of last month and non-negative book equity. The sample period is from June 1992 to December 2023. All t-statistics (in parentheses) are calculated using Newey-West (1987) standard errors and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A.1. Value-weighted Sort by Salience Deviation for Future Overnight return

Overnight Return	Excess Ret	FF4	FF5	FF6	HXZ_Q	HXZ_Q5	FF5_li	FF6_li
Low(Quintile 1)	0.61	0.13	0.16	0.14	0.16	0.26	0.24	0.21
	(4.16)	(1.00)	(1.20)	(1.03)	(1.15)	(2.02)	(1.92)	(1.73)
Quintile 2	0.62	0.11	0.12	0.10	0.12	0.18	0.22	0.19
	(4.10)	(0.88)	(0.90)	(0.74)	(0.86)	(1.31)	(1.71)	(1.55)
Quintile 3	0.66	0.14	0.17	0.14	0.16	0.22	0.26	0.22
	(4.29)	(0.98)	(1.10)	(0.88)	(0.97)	(1.52)	(1.82)	(1.56)
Quintile 4	0.82	0.30	0.36	0.33	0.37	0.38	0.42	0.38
	(4.95)	(2.09)	(2.34)	(2.17)	(2.26)	(2.41)	(2.80)	(2.60)
High(Quintile 5)	1.25	0.74	0.78	0.75	0.81	0.79	0.87	0.83
	(6.65)	(4.62)	(4.61)	(4.42)	(4.47)	(4.53)	(4.66)	(4.40)
H-L	0.63***	0.62***	0.62***	0.61***	0.65***	0.53***	0.63***	0.62***
	(6.29)	(5.88)	(5.47)	(5.21)	(5.75)	(4.78)	(4.64)	(4.37)

Panel A.2. Value-weighted Sort by Salience Deviation for Future Intraday return

Intraday Return	Excess Ret	FF4	FF5	FF6	HXZ_Q	HXZ_Q5	FF5_li	FF6_li
Low(Quintile 1)	0.38	-0.17	-0.23	-0.19	-0.24	-0.28	-0.36	-0.31
	(2.24)	(-1.14)	(-1.48)	(-1.19)	(-1.46)	(-1.96)	(-2.41)	(-2.06)
Quintile 2	0.43	-0.15	-0.21	-0.19	-0.23	-0.27	-0.33	-0.30
	(2.62)	(-1.01)	(-1.40)	(-1.22)	(-1.45)	(-1.88)	(-2.29)	(-2.13)
Quintile 3	0.32	-0.24	-0.35	-0.28	-0.31	-0.38	-0.43	-0.36
	(1.76)	(-1.57)	(-2.10)	(-1.75)	(-1.75)	(-2.32)	(-2.70)	(-2.29)
Quintile 4	0.23	-0.34	-0.45	-0.39	-0.43	-0.44	-0.52	-0.46
	(1.30)	(-2.57)	(-3.08)	(-2.78)	(-2.83)	(-2.93)	(-3.64)	(-3.23)
High(Quintile 5)	-0.14	-0.79	-0.89	-0.81	-0.85	-0.91	-0.91	-0.83
	(-0.63)	(-4.34)	(-4.90)	(-4.51)	(-4.51)	(-4.99)	(-5.25)	(-4.70)
H-L	-0.53***	-0.61***	-0.65***	-0.62***	-0.61***	-0.64***	-0.56***	-0.52***
	(-2.73)	(-3.17)	(-3.63)	(-3.36)	(-3.34)	(-3.74)	(-3.34)	(-2.95)

Panel B.1. Equal-weighted Sort by Salience Deviation for Future Overnight return

Overnight Return	Excess Ret	FF4	FF5	FF6	HXZ_Q	HXZ_Q5	FF5_li	FF6_li
Low(Quintile 1)	**0.33**	**-0.13**	**-0.14**	**-0.14**	**-0.10**	**-0.00**	**-0.09**	**-0.09**
	(1.76)	**(-0.79)**	**(-0.82)**	**(-0.84)**	**(-0.59)**	**(-0.02)**	**(-0.53)**	**(-0.54)**
Quintile 2	0.36	-0.10	-0.11	-0.11	-0.07	0.02	-0.07	-0.07
	(1.88)	(-0.57)	(-0.66)	(-0.65)	(-0.42)	(0.11)	(-0.44)	(-0.42)
Quintile 3	0.58	0.12	0.10	0.11	0.14	0.23	0.14	0.14
	(2.91)	(0.70)	(0.59)	(0.62)	(0.79)	(1.20)	(0.79)	(0.83)
Quintile 4	1.03	0.62	0.56	0.58	0.63	0.66	0.48	0.51
	(4.70)	(2.70)	(2.43)	(2.56)	(2.67)	(2.90)	(2.31)	(2.46)

High(Quintile 5)	**2.19**	**1.75**	**1.72**	**1.74**	**1.81**	**1.80**	**1.74**	**1.77**
	(7.81)	**(7.01)**	**(6.65)**	**(6.76)**	**(7.04)**	**(7.42)**	**(6.46)**	**(6.62)**
H-L	**1.86*** **	**1.88*** **	**1.86*** **	**1.88*** **	**1.91*** **	**1.80*** **	**1.82*** **	**1.85*** **
	(11.59)	**(11.52)**	**(11.38)**	**(11.50)**	**(11.42)**	**(11.90)**	**(10.89)**	**(11.12)**

Panel B.2. Equal-weighted Sort by Salience Deviation for Future Intraday return

Intraday Return	Excess Ret	FF4	FF5	FF6	HXZ_Q	HXZ_Q5	FF5_li	FF6_li
Low(Quintile 1)	**1.38**	**0.75**	**0.68**	**0.75**	**0.72**	**0.66**	**0.58**	**0.67**
	(5.66)	**(4.21)**	**(3.90)**	**(4.32)**	**(3.82)**	**(3.49)**	**(3.40)**	**(3.81)**
Quintile 2	1.33	0.69	0.65	0.73	0.68	0.65	0.54	0.63
	(5.36)	(3.78)	(3.44)	(3.87)	(3.27)	(3.13)	(2.93)	(3.35)
Quintile 3	1.20	0.57	0.52	0.61	0.58	0.56	0.37	0.48
	(4.72)	(2.98)	(2.66)	(3.15)	(2.68)	(2.65)	(1.98)	(2.50)
Quintile 4	1.00	0.32	0.30	0.39	0.36	0.34	0.24	0.34
	(3.35)	(1.54)	(1.40)	(1.86)	(1.51)	(1.50)	(1.11)	(1.61)
High(Quintile 5)	**0.37**	**-0.32**	**-0.34**	**-0.23**	**-0.24**	**-0.26**	**-0.37**	**-0.24**
	(1.05)	**(-1.21)**	**(-1.25)**	**(-0.88)**	**(-0.87)**	**(-0.96)**	**(-1.38)**	**(-0.91)**
H-L	**-1.00*** **	**-1.06*** **	**-1.01*** **	**-0.98*** **	**-0.96*** **	**-0.91*** **	**-0.95*** **	**-0.90*** **
	(-6.14)	**(-7.00)**	**(-6.67)**	**(-6.57)**	**(-6.42)**	**(-6.54)**	**(-6.80)**	**(-6.65)**

Table 3. Fama-Macbeth cross-section regression

This table reports the results of the Fama-MacBeth (1973) regression of monthly returns on lagged variables. The independent variables include the attention-grabbing measure (RETSD), tug-of-war effect (Lou et al., 2019) measure represented by previous month's overnight and intraday and overnight return (RETCTO, RETOTC), max daily return (Bali, Cakici and Whitelaw, 2011) and corresponding minimum daily return (MAX and MIN),log of market value (LNSIZE), and log of book-to-market equity (LNBM). Amihud's (2002) illiquidity (ILLIQ), idiosyncratic volatility (IVOL), turnover (TNOVM1), market beta (BETA), idiosyncratic skew (Skew), 12-month momentum (skip one month before formation month) and short-term reversal effect (Mom_12m and Ret_1_0). The sample includes NYSE/Amex/Nasdaq common stocks with a price of at least $1 per share in the end of last month and non-negative book equity. Independent variables are winsorized at the 1% and the 99% levels and cross-sectionally standardized with a mean of zero and a standard deviation of one. . The regression coefficients are reported in percentages. The sample is from June 1992 to December 2023. All t-statistics (in parentheses) are calculated using Newey-West (1987) standard errors and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A. Overnight return

	(1)	(2)	(3)	(4)
retsd	**0.0090*****	**0.0098*****	**0.0054*****	**0.0042*****
.	**(14.65)**	**(16.27)**	**(12.01)**	**(7.39)**
retcto		0.0201***	0.0199***	0.0230***
.		(14.59)	(16.59)	(15.74)
retotc		-0.0094***	-0.0095***	-0.0028***
.		(-9.76)	(-10.41)	(-3.68)
max			0.0013**	-0.0038***
.			(2.57)	(-5.43)
min			-0.0122***	-0.0027***
.			(-12.57)	(-5.55)
lnsize				-0.0014*
.				(-1.80)
lnbm				-0.0023***

Panel B. Intraday return

	(1)	(2)	(3)	(4)
retsd	**-0.0046*****	**-0.0064*****	**-0.0052*****	**0.0042*****
.	**(-6.65)**	**(-9.19)**	**(-9.75)**	**(7.39)**
retcto		-0.0194***	-0.0199***	0.0230***
.		(-16.74)	(-19.27)	(15.74)
retotc		0.0137***	0.0130***	-0.0028***
.		(8.74)	(8.03)	(-3.68)
max			-0.0010	-0.0038***
.			(-1.29)	(-5.43)
min			0.0024*	-0.0027***
.			(1.87)	(-5.55)
lnsize				-0.0014*
.				(-1.80)
lnbm				-0.0023***

.	(-6.72)
illiq	-0.0019***
.	(-3.52)
ivol	0.0099***
.	(8.10)
tnovm1	0.0045***
.	(7.05)
beta	-0.0024***
.	(-8.06)
mom_12m	-0.0009**
.	(-2.02)
ret_1_0	-0.0122***
.	(-9.08)
skew	0.0016***
.	(8.55)

.	(-6.72)
illiq	-0.0019***
.	(-3.52)
ivol	0.0099***
.	(8.10)
tnovm1	0.0045***
.	(7.05)
beta	-0.0024***
.	(-8.06)
mom_12m	-0.0009**
.	(-2.02)
ret_1_0	-0.0122***
.	(-9.08)
skew	0.0016***
.	(8.55)

Table 4. Buy-sell imbalance (Current Salience Deviation)

This table reports the results of regressions of buy-sell imbalance on current month's attention-grabbing measure (CUR_RETSD) and previous month's control variables. The estimated coefficient and t-statistics are reported. In panel A (B), the dependent variable BSI is the buy-sell imbalance (BSI) is calculated as the total monthly dollar volume (number of shares) of buy orders minus the absolute value of sell orders, divided by the sum of the two. The main independent variable is current attention-grabbing measure (CUR_RETSD). The control variables include the tug-of-war effect (Lou et al., 2019) measure represented by previous month's overnight and intraday and overnight return (RETCTO, RETOTC), max daily return (Bali, Cakici and Whitelaw, 2011) and corresponding minimum daily return (MAX and MIN),log of market value (LNSIZE), and log of book-to-market equity (LNBM). Amihud's (2002) illiquidity (ILLIQ), idiosyncratic volatility (IVOL), turnover (TNOVM1), market beta (BETA), idiosyncratic skew (Skew), 12-month momentum (skip one month before formation month) and short-term reversal effect (Mom_12m and Ret_1_0). The sample includes NYSE/Amex/Nasdaq common stocks with a price of at least $1 per share in the end of last month and non-negative book equity. The sample period is from 1992 to 1996. t-statistics are in parentheses and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A. Buy-sell imbalance (dollar-volume)		
	(1)	(2)
cur_retsd_stdr	0.0269***	0.0257***
	(9.59)	(9.21)
max_stdr		0.00231
		(0.31)
min_stdr		-0.00824
		(-1.29)
retcto_stdr		0.0142
		(1.62)
retotc_stdr		0.00228
		(0.20)
lnsize_stdr		0.0930***
		(6.20)
lnbm_stdr		0.00188

Panel B. Buy-sell imbalance (number of shares)		
	(1)	(2)
cur_retsd_stdr	0.0275***	0.0263***
	(9.82)	(9.45)
max_stdr		0.00638
		(0.86)
min_stdr		-0.00783
		(-1.23)
retcto_stdr		0.0141
		(1.62)
retotc_stdr		0.00157
		(0.14)
lnsize_stdr		0.0947***
		(6.33)
lnbm_stdr		0.00125

		(0.29)
illiq_stdr		0.0350***
		(4.71)
ivol_stdr		0.00440
		(0.46)
tnovm1_stdr		0.0121**
		(2.96)
beta_stdr		-0.00503
		(-1.01)
skew_stdr		-0.0125**
		(-3.28)
mom_12m_stdr		-0.00831*
		(-2.51)
ret_1_0_stdr		-0.0525***
		(-5.18)
Firm FE	YES	YES
Month FE	YES	YES

		(0.19)
illiq_stdr		0.0333***
		(4.50)
ivol_stdr		0.00205
		(0.22)
tnovm1_stdr		0.0120**
		(2.93)
beta_stdr		-0.00521
		(-1.05)
skew_stdr		-0.0134***
		(-3.54)
mom_12m_stdr		-0.00856**
		(-2.59)
ret_1_0_stdr		-0.0531***
		(-5.25)
Firm FE	YES	YES
Month FE	YES	YES

Table 5. Buy-sell imbalance (Previous Salience Deviation))

This table reports the results of regressions of buy-sell imbalance on previous month's attention-grabbing measure (RETSD) and control variables. The estimated coefficient and t-statistics are reported. In panel A (B), the dependent variable BSI is the buy-sell imbalance (BSI) is calculated as the total monthly dollar volume (number of shares) of buy orders minus the absolute value of sell orders, divided by the sum of the two. The main independent variable is previous month's attention-grabbing measure (RETSD). The control variables include the tug-of-war effect (Lou et al., 2019) measure represented by previous month's overnight and intraday and overnight return (RETCTO, RETOTC), max daily return (Bali, Cakici and Whitelaw, 2011) and corresponding minimum daily return (MAX and MIN),log of market value (LNSIZE), and log of book-to-market equity (LNBM). Amihud's (2002) illiquidity (ILLIQ), idiosyncratic volatility (IVOL), turnover (TNOVM1), market beta (BETA), idiosyncratic skew (Skew), 12-month momentum (skip one month before formation month) and short-term reversal effect (Mom_12m and Ret_1_0). The sample includes NYSE/Amex/Nasdaq common stocks with a price of at least $1 per share in the end of last month and non-negative book equity. The sample period is from 1992 to 1996. t-statistics are in parentheses and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A. Buy-sell imbalance (dollar-volume)		
	(3)	(4)
retsd_stdr	0.0152***	0.0143***
	(5.45)	(4.84)
max_stdr		0.00308
		(0.41)
min_stdr		-0.00512
		(-0.80)
retcto_stdr		0.0175*
		(1.99)
retotc_stdr		0.00637
		(0.56)
lnsize_stdr		0.0921***
		(6.13)
lnbm_stdr		0.00149

Panel B. Buy-sell imbalance (number of shares)		
	(3)	(4)
retsd_stdr	0.0152***	0.0129***
	(5.48)	(4.37)
max_stdr		0.00475
		(0.64)
min_stdr		-0.00909
		(-1.43)
retcto_stdr		-0.0248**
		(-3.18)
retotc_stdr		-0.0519***
		(-5.27)
lnsize_stdr		0.0988***
		(6.56)
lnbm_stdr		0.00249

		(0.23)
illiq_stdr		0.0370***
		(4.99)
ivol_stdr		0.00224
		(0.24)
tnovm1_stdr		0.00861*
		(2.08)
beta_stdr		-0.00460
		(-0.92)
skew_stdr		-0.0124**
		(-3.25)
mom_12m_stdr		-0.00809*
		(-2.44)
ret_1_0_stdr		-0.0584***
		(-5.73)
Firm FE	YES	YES
Month FE	YES	YES

		(0.39)
illiq_stdr		0.0363***
		(4.87)
ivol_stdr		-0.00165
		(-0.17)
tnovm1_stdr		0.00811*
		(1.96)
beta_stdr		-0.00530
		(-1.06)
skew_stdr		-0.0130***
		(-3.43)
mom_12m_stdr		-0.0140***
		(-3.45)
ret_1_0_stdr		-0.0255
		(-0.44)
Firm FE	YES	YES
Month FE	YES	YES

Table 6. Single sort by Abnormal Trading Volume for Overnight and Intraday return

This table reports the monthly average intraday and overnight returns (in percentage) for portfolios sorted on the abnormal trading volume (ABVOL). Panel A.1 (A.2) show equally-weighted portfolio is held for one month in month t and sort by ABVOL for overnight (intraday) return , panel B.1 and B.2 show value-weighted portfolio is held for one month in month t and sort by ABVOL for overnight (intraday) return. All panels show the average monthly excess returns and alphas with respect to Fama and French (1993) -factor with Carhart (1997) 4-factor (FF4), Fama and French (2015) 5-factor (FF5), FF5 with with Carhart (1997) 6–factor (FF6), Hou, Xue and Zhang (2015) Q-facto (HXZ_Q), Hou, Xue and Zhang (20220) Q5-facto (HXZ_Q5), and FF5 and FF6 with Pastor and Stambaugh (2003) liquidity factors (FF5_li, FF6_li). H-L refers to the high minus low RETSD portfolios. The sample includes NYSE/Amex/Nasdaq common stocks with a price of at least $1 per share in the end of last month and non-negative book equity. The sample period is from June 1992 to December 2023. All t-statistics (in parentheses) are calculated using Newey-West (1987) standard errors and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A.1. Equal-weighted Sort by Abnormal Trading Volume for Future Overnight return

Overnight Return	Excess Ret	FF4	FF5	FF6	HXZ_Q	HXZ_Q5	FF5_li	FF6_li
Low(Quintile 1)	0.34	-0.12	-0.12	-0.12	-0.08	0.02	-0.07	-0.07
	(1.82)	(-0.71)	(-0.74)	(-0.73)	(-0.49)	(0.10)	(-0.46)	(-0.46)
Quintile 2	0.63	0.18	0.19	0.20	0.23	0.33	0.19	0.21
	(2.91)	(0.93)	(0.91)	(0.95)	(1.07)	(1.56)	(0.97)	(1.05)
Quintile 3	1.16	0.69	0.66	0.66	0.70	0.74	0.63	0.63
	(5.60)	(3.62)	(3.41)	(3.42)	(3.44)	(3.71)	(3.35)	(3.33)
Quintile 4	1.19	0.78	0.72	0.75	0.78	0.84	0.68	0.71
	(5.40)	(3.41)	(3.17)	(3.29)	(3.32)	(3.64)	(3.26)	(3.39)
High(Quintile 5)	1.34	0.89	0.84	0.85	0.93	0.92	0.97	0.99
	(5.17)	(3.89)	(3.81)	(3.78)	(4.20)	(4.20)	(4.10)	(4.10)
H-L	1.00***	1.00***	0.96***	0.97***	1.02***	0.90***	1.05***	1.06***
	(8.26)	(7.81)	(7.95)	(7.76)	(8.04)	(7.87)	(8.27)	(8.27)

Panel A.2. Equal-weighted Sort by Abnormal Trading Volume for Future Intraday return

Intraday Return	Excess Ret	FF4	FF5	FF6	HXZ_Q	HXZ_Q5	FF5_li	FF6_li

Low(Quintile 1)	1.35	0.72	0.65	0.73	0.70	0.64	0.55	0.63
	(5.55)	(4.06)	(3.72)	(4.12)	(3.58)	(3.21)	(3.18)	(3.56)
Quintile 2	1.20	0.57	0.55	0.64	0.60	0.58	0.41	0.51
	(4.55)	(2.85)	(2.68)	(3.11)	(2.67)	(2.44)	(2.04)	(2.48)
Quintile 3	0.80	0.15	0.11	0.21	0.17	0.16	-0.01	0.12
	(2.83)	(0.72)	(0.50)	(1.04)	(0.72)	(0.73)	(-0.04)	(0.58)
Quintile 4	0.88	0.18	0.10	0.19	0.15	0.09	0.08	0.18
	(2.92)	(0.89)	(0.50)	(0.92)	(0.67)	(0.45)	(0.37)	(0.83)
High(Quintile 5)	0.94	0.26	0.21	0.29	0.27	0.26	0.18	0.27
	(2.82)	(0.99)	(0.81)	(1.10)	(1.01)	(1.01)	(0.70)	(1.05)
H-L	-0.42***	-0.47***	-0.44***	-0.44***	-0.43***	-0.39**	-0.36**	-0.37**
	(-2.82)	(-2.99)	(-2.89)	(-2.79)	(-2.75)	(-2.28)	(-2.48)	(-2.41)

Panel B.1. Value-weighted Sort by Abnormal Trading Volume for Future Overnight return

Overnight Return	Excess Ret	FF4	FF5	FF6	HXZ_Q	HXZ_Q5	FF5_li	FF6_li
Low(Quintile 1)	0.60	0.10	0.13	0.11	0.13	0.22	0.22	0.19
	(3.99)	(0.80)	(0.97)	(0.82)	(0.91)	(1.70)	(1.74)	(1.57)
Quintile 2	0.75	0.24	0.28	0.25	0.27	0.33	0.36	0.33
	(4.58)	(1.80)	(1.85)	(1.74)	(1.72)	(2.21)	(2.54)	(2.42)
Quintile 3	0.87	0.33	0.33	0.30	0.33	0.42	0.35	0.31
	(5.38)	(2.17)	(2.08)	(1.88)	(1.96)	(2.60)	(2.29)	(2.05)
Quintile 4	0.73	0.24	0.31	0.28	0.30	0.31	0.40	0.36
	(4.81)	(1.84)	(2.20)	(2.02)	(2.03)	(2.24)	(2.88)	(2.67)
High(Quintile 5)	0.93	0.43	0.45	0.42	0.49	0.46	0.60	0.57
	(5.41)	(2.90)	(3.08)	(2.80)	(3.03)	(2.86)	(4.05)	(3.68)
H-L	0.33***	0.33***	0.32***	0.31***	0.36***	0.24**	0.39***	0.38***

	(3.76)	(3.48)	(3.41)	(3.16)	(3.68)	(2.41)	(3.84)	(3.55)

Panel B.2. Value-weighted Sort by Abnormal Trading Volume for Future Intraday return

Intraday Return	Excess Ret	FF4	FF5	FF6	HXZ_Q	HXZ_Q5	FF5_li	FF6_li
Low(Quintile 1)	0.44	-0.10	-0.16	-0.10	-0.15	-0.19	-0.30	-0.24
	(2.72)	(-0.69)	(-1.04)	(-0.69)	(-0.97)	(-1.31)	(-2.10)	(-1.67)
Quintile 2	0.40	-0.18	-0.22	-0.18	-0.22	-0.27	-0.33	-0.28
	(2.19)	(-1.10)	(-1.31)	(-1.06)	(-1.22)	(-1.61)	(-2.01)	(-1.74)
Quintile 3	0.07	-0.52	-0.59	-0.53	-0.59	-0.62	-0.62	-0.56
	(0.37)	(-3.17)	(-3.45)	(-3.03)	(-3.19)	(-3.42)	(-3.83)	(-3.35)
Quintile 4	0.30	-0.32	-0.46	-0.42	-0.44	-0.48	-0.53	-0.49
	(1.67)	(-2.42)	(-3.42)	(-3.12)	(-3.11)	(-3.38)	(-3.66)	(-3.29)
High(Quintile 5)	0.03	-0.60	-0.69	-0.66	-0.72	-0.77	-0.74	-0.71
	(0.13)	(-3.21)	(-3.90)	(-3.68)	(-3.86)	(-4.50)	(-4.55)	(-4.23)
H-L	-0.41**	-0.50***	-0.53***	-0.56***	-0.57***	-0.59***	-0.44***	-0.47***
	(-2.34)	(-2.89)	(-3.25)	(-3.29)	(-3.49)	(-3.64)	(-2.77)	(-2.83)

Table 7. Size effect and the attention-grabbing trading in overnight and intraday

This table reports the monthly average returns (in percentage) for portfolios double sorted independently on size (SIZE) and salience deviation (RETSD). Portfolios are sorted into quintiles based on SIZE and RETSD in month $t-1$. The table presents the excess returns and alphas of RETSD quintiles within SIZE quintiles. Results are reported for both equally weighted and value-weighted portfolios, held for one month.Panels A and B display the average monthly excess overnight and intraday returns, along with alphas calculated using the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor (FF6) and the Hou, Xue, and Zhang (2020) Q5-factor model (HXZ_Q5). The results include the RETSD High-minus-Low (H-L) portfolios across SIZE quintiles. The sample includes NYSE, Amex, and Nasdaq common stocks with a price of at least $1 per share at the end of the previous month and non-negative book equity. The sample period spans from June 1992 to December 2023. All t-statistics (in parentheses) are calculated using Newey-West (1987) standard errors. Significance levels are indicated by asterisks: *** (1%), ** (5%), and * (10%).

Panel A. Overnight retrun

	Equal weighted			Value weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
	Excess Return	FF6 alpha	HXZ Q5	Excess Return	FF6 alpha	HXZ Q5
Microcap (L)	1.64***	1.61***	1.56***	1.29***	1.27***	1.26***
	(10.92)	(10.79)	(11.29)	(9.25)	(8.34)	(7.22)
2	1.01***	0.96***	0.94***	0.73***	0.72***	0.68***
	(7.35)	(7.31)	(7.07)	(6.46)	(6.64)	(6.59)
3	0.64***	0.60***	0.54***	0.51***	0.51***	0.41***
	(5.47)	(5.19)	(4.63)	(4.31)	(4.19)	(3.72)
4	0.50***	0.48***	0.41***	0.39***	0.36***	0.28***
	(4.74)	(4.32)	(3.80)	(4.09)	(3.48)	(2.86)
Megacap(H)	0.44***	0.47***	0.36***	0.33***	0.29**	0.18
	(4.43)	(4.29)	(3.82)	(3.04)	(2.34)	(1.54)
Size H-L	-1.20***	-1.14***	-1.20***	-0.96***	-0.98***	-1.07***
	(-7.77)	(-7.58)	(-7.78)	(-6.77)	(-6.24)	(-6.07)

Panel B. Intraday retrun

	Equal weighted			Value weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
	Excess Return	FF6 alpha	HXZ Q5	Excess Return	FF6 alpha	HXZ Q5
Microcap (L)	-0.96***	-0.97***	-0.93***	-0.95***	-1.00***	-1.05***
	(-5.78)	(-5.59)	(-5.30)	(-5.87)	(-5.46)	(-5.00)
2	-0.72***	-0.71***	-0.68***	-0.50***	-0.53***	-0.50***
	(-5.22)	(-4.90)	(-3.88)	(-4.10)	(-3.62)	(-2.72)
3	-0.73***	-0.76***	-0.77***	-0.66***	-0.75***	-0.75***
	(-4.48)	(-4.57)	(-3.65)	(-4.67)	(-4.57)	(-3.78)
4	-0.52***	-0.52***	-0.54***	-0.44***	-0.49***	-0.51***
	(-3.20)	(-3.13)	(-3.06)	(-2.92)	(-2.98)	(-3.04)
Megacap(H)	-0.53***	-0.58***	-0.59***	-0.47**	-0.56**	-0.58***
	(-2.93)	(-3.22)	(-3.42)	(-2.02)	(-2.55)	(-2.77)
Size H-L	0.42*	0.39	0.33	0.49*	0.43	0.47
	-1.83	(1.62)	(1.43)	(1.73)	(1.43)	(1.53)

Table 8. Fama-MacBeth regressions: limits to arbitrage

This table reports the results of the Fama-MacBeth (1973) regression of limits to arbitrage on the relation between a stock's attention-grabbing proxy (RETSD) and future overnight and intraday return. The main independent variables include the attention-grabbing measure (RETSD) and the interaction terms between three proxies of limits to arbitrage, and control variables are tug-of-war effect (Lou et al., 2019) measure represented by previous month's overnight and intraday and overnight return (RETCTO, RETOTC), max daily return (Bali, Cakici and Whitelaw, 2011) and corresponding minimum daily return (MAX and MIN),log of market value (LNSIZE), and log of book-to-market equity (LNBM). Amihud's (2002) illiquidity (ILLIQ), idiosyncratic volatility (IVOL), turnover (TNOVM1), market beta (BETA), idiosyncratic skew (Skew), 12-month momentum (skip one month before formation month) and short-term reversal effect (Mom_12m and Ret_1_0). The sample includes NYSE/Amex/Nasdaq common stocks with a price of at least $1 per share in the end of last month and non-negative book equity. Independent variables are winsorized at the 1% and the 99% levels and cross-sectionally standardized with a mean of zero and a standard deviation of one. The regression coefficients are reported in percentages. The sample is from June 1992 to December 2023. All t-statistics (in parentheses) are calculated using Newey-West (1987) standard errors and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A: Overnight return with standarized independent variables				Panel B: Intraday return with standarized independent variables			
	IVOL	**LNSIZE**	**Illiq**		**IVOL**	**LNSIZE**	**Illiq**
RETSD	**0.0026*** **	**0.0023*** **	**0.0022*** **	**RETSD**	**-0.0008*** **	**-0.0008*** **	**-0.0008*** **
.	**(7.22)**	**(6.59)**	**(6.50)**	**.**	**(-2.76)**	**(-2.84)**	**(-2.89)**
RETSD_ivol	**0.0020*** **			**RETSD_ivol**	**-0.0000**		
.	**(6.90)**			**.**	**(-0.01)**		
RETSD_SIZE		**-0.0017*** **		**RETSD_SIZE**		**0.0000**	
.		**(-7.47)**		**.**		**(0.19)**	
RETSD_illiq			**0.0009** **	**RETSD_illiq**			**0.0009* **
.			**(2.25)**	**.**			**(1.94)**
retotc	-0.0112***	-0.0114***	-0.0115***	retotc	0.0393***	0.0392***	0.0392***
.	(-7.08)	(-7.19)	(-7.23)	.	(8.41)	(8.39)	(8.35)
retcto	0.0159***	0.0158***	0.0158***	retcto	0.0054***	0.0054***	0.0053**
.	(14.06)	(13.80)	(13.76)	.	(2.64)	(2.63)	(2.59)
lnsize	-0.0012	-0.0011	-0.0010	lnsize	-0.0032***	-0.0033***	-0.0033***

.	(-1.64)	(-1.51)	(-1.31)
illiq	-0.0036***	-0.0036***	-0.0039***
.	(-6.89)	(-7.03)	(-7.94)
ivol	0.0103***	0.0109***	0.0112***
.	(7.86)	(8.29)	(8.52)
min	-0.0019***	-0.0019***	-0.0019***
.	(-3.86)	(-3.85)	(-3.87)
max	-0.0034***	-0.0034***	-0.0034***
.	(-5.17)	(-5.16)	(-5.22)
lnbm	-0.0028***	-0.0028***	-0.0028***
.	(-7.91)	(-7.74)	(-7.72)
tnovm1	0.0037***	0.0038***	0.0037***
.	(6.06)	(6.20)	(6.10)
mom_12m	-0.0005	-0.0005	-0.0005
.	(-1.12)	(-1.16)	(-1.17)
ret_1_0	-0.0030**	-0.0027**	-0.0027**
.	(-2.27)	(-2.04)	(-2.02)
skew	0.0005***	0.0004**	0.0004**
.	(2.62)	(2.12)	(2.11)

.	(-3.48)	(-3.50)	(-3.55)
illiq	0.0095***	0.0095***	0.0095***
.	(13.69)	(13.82)	(14.42)
ivol	-0.0027*	-0.0027*	-0.0027*
.	(-1.76)	(-1.82)	(-1.86)
min	0.0018*	0.0019*	0.0019*
.	(1.71)	(1.83)	(1.86)
max	0.0005	0.0006	0.0006
.	(0.51)	(0.58)	(0.57)
lnbm	0.0040***	0.0040***	0.0040***
.	(5.52)	(5.53)	(5.52)
tnovm1	-0.0064***	-0.0064***	-0.0064***
.	(-9.74)	(-9.69)	(-9.66)
mom_12m	-0.0002	-0.0002	-0.0001
.	(-0.21)	(-0.21)	(-0.19)
ret_1_0	-0.0266***	-0.0266***	-0.0265***
.	(-7.89)	(-7.85)	(-7.82)
skew	0.0004	0.0004	0.0003
.	(1.27)	(1.25)	(1.15)

Table 9. Salience Deviation in Overnight and Intraday trading with Market state (one-month CRSP index return)

This table reports the monthly average of excess return and Fama and French (2015) 5-factor with Carhart(1997) momentum factor alphas (FF6, in percentage) during up and down market states. Up and down market states is as classified as the mean of CRSP value-weighted index (Guo et al., 2023) above (blow) the sample median, respectively. I sort stocks into quintiles based on RETSD in month t−1. The portfolio is held for one month in month t and is value-weighted. H-L refers to the high minus low RETSD portfolios. The sample includes NYSE/Amex/Nasdaq common stocks with a price of at least $1 per share at the end of last month and non-negative book equity. The sample period is from June 1992 to December 2023. All t-statistics (in parentheses) are calculated using Newey-West (1987) standard errors and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%). For brevity, I only report asterisks for the hedged portfolios.

Panel A.Overnight return			
retsdport	Up Market	Down Market	Up-Down
Low	0.21	-0.03	0.24
	(1.27)	(-0.17)	(1.18)
2	0.10	0.07	0.03
	(0.61)	(0.40)	(0.17)
3	0.16	0.10	0.05
	(0.93)	(0.51)	(0.24)
4	0.41	0.21	0.20
	(2.55)	(1.01)	(0.91)
High	1.09	0.51	**0.57**
	(4.92)	(2.26)	**(2.06)**
H-L	0.87***	0.54***	**0.33***
	(5.34)	(3.78)	**(1.69)**

Panel B. Intraday return			
	Up Market	Down Market	Up-Down
Low	-0.32	-0.02	0.30
	(-1.94)	(-0.09)	(1.37)
2	-0.37	-0.06	0.31
	(-2.15)	(-0.30)	(1.37)
3	-0.23	-0.19	0.03
	(-1.34)	(-0.84)	(0.14)
4	-0.45	-0.38	0.06
	(-2.72)	(-1.87)	(0.25)
High	-0.84	-0.73	0.12
	(-3.68)	(-2.78)	(0.35)
H-L	-0.52**	-0.71***	**-0.18**
	(-2.47)	(-2.62)	**(-0.57)**

Table 10. Salience Deviation in Overnight and Intraday trading with Market state (six-month weighted CRSP index return)

This table reports the monthly average of excess return and Fama and French (2015) 5-factor with Carhart(1997) momentum factor alphas (FF6, in percentage) during up and down market states. Up and down market states is as classified as the mean of CRSP value-weighted index (Guo et al., 2023) above (blow) the sample median, respectively. I sort stocks into quintiles based on RETSD in month t−1. The portfolio is held for one month in month t and is value-weighted. H-L refers to the high minus low RETSD portfolios. The sample includes NYSE/Amex/Nasdaq common stocks with a price of at least $1 per share at the end of last month and non-negative book equity. The sample period is from June 1992 to December 2023. All t-statistics (in parentheses) are calculated using Newey-West (1987) standard errors and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%). For brevity, I only report asterisks for the hedged portfolios.

Panel A.Overnight return

RETSDport	Up Market	Down Market	Up-Down
Low	0.35	-0.17	0.52
	(1.93)	(-1.07)	(2.45)
2	0.30	-0.13	0.43
	(1.70)	(-0.82)	(2.04)
3	0.29	-0.03	0.32
	(1.59)	(-0.17)	(1.46)
4	0.66	-0.06	0.72
	(3.70)	(-0.31)	(3.24)
High	1.30	0.28	**1.02**
	(5.45)	(1.52)	**(3.84)**
H-L	0.96***	0.45***	**0.50****
	(5.80)	(3.30)	**(2.59)**

Panel B. Intraday return

	Up Market	Down Market	Up-Down
Low	-0.46	0.13	-0.60
	(-2.88)	(0.61)	(-2.60)
2	-0.51	0.09	-0.60
	(-2.99)	(0.40)	(-2.51)
3	-0.35	-0.07	-0.28
	(-1.83)	(-0.30)	(-1.12)
4	-0.69	-0.13	-0.56
	(-4.25)	(-0.67)	(-2.40)
High	-1.12	-0.43	-0.69
	(-4.64)	(-1.87)	(-2.26)
H-L	-0.66***	-0.57*	**-0.09**
	(-3.51)	(-1.91)	**(-0.28)**

Table 11. Salience Deviation in Overnight and Intraday trading with Market Uncertainty Conditions

This table reports the monthly average of excess return and Fama and French (2015) 5-factor with Carhart (1997) momentum factor alphas (FF6, in percentage) during high and low market uncertaity. High and low market uncertainty condition states is as classified as the mean of VIX above (blow) the sample median, respectively. I sort stocks into quintiles based on RETSD in month t−1. The portfolio is held for one month in month t and is value-weighted. H-L refers to the high minus low RETSD portfolios. The sample includes NYSE/Amex/Nasdaq common stocks with a price of at least $1 per share at the end of last month and non-negative book equity. The sample period is from June 1992 to December 2023. All t-statistics (in parentheses) are calculated using Newey-West (1987) standard errors and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%). For brevity, I only report asterisks for the hedged portfolios.

Panel A.Overnight return			
retsdport	High VIX	Low VIX	High-Low
Low	0.13	0.05	0.08
	(0.66)	(0.39)	(0.38)
2	0.20	-0.03	0.23
	(0.96)	(-0.21)	(1.00)
3	0.21	0.05	0.16
	(0.89)	(0.37)	(0.66)
4	0.35	0.27	0.09
	(1.51)	(1.85)	(0.36)
High	1.05	0.56	**0.49**
	(3.56)	(3.97)	**(1.66)**
H-L	0.92***	0.51***	**0.41***
	(4.35)	(5.19)	**(1.84)**

Panel B. Intraday return			
retsdport	High VIX	Low VIX	High-Low
Low	-0.25	-0.09	-0.16
	(-1.02)	(-0.60)	(-0.63)
2	-0.30	-0.15	-0.15
	(-1.13)	(-1.01)	(-0.54)
3	-0.34	-0.09	-0.25
	(-1.30)	(-0.57)	(-0.94)
4	-0.40	-0.43	0.03
	(-1.76)	(-3.26)	(0.12)
High	-0.93	-0.64	**-0.29**
	(-3.32)	(-3.67)	**(-1.00)**
H-L	-0.68**	-0.55***	**-0.13**
	(-2.07)	(-3.95)	**(-0.37)**

Table 12. Robustness test for single sort by Salience Deviation for Overnight and Intraday return

This table reports the monthly average intraday and overnight returns (in percentage) for portfolios sorted on the salience deviation (RETSD). Panel A.1 (A.2) show equally-weighted portfolio is held for one month in month t and sort by RETSD for overnight (intraday) return , panel B.1 and B.2 show value-weighted portfolio is held for one month in month t and sort by RETSD for overnight (intraday) return. All panels show the average monthly excess returns and alphas with respect to Fama and French (1993) -factor with Carhart (1997) 4-factor (FF4), Fama and French (2015) 5-factor (FF5), FF5 with with Carhart (1997) 6–factor (FF6), Hou, Xue and Zhang (2015) Q-facto (HXZ_Q), Hou, Xue and Zhang (2020) Q5-facto (HXZ_Q5), and FF5 and FF6 with Pastor and Stambaugh (2003) liquidity factors (FF5_li, FF6_li). H-L refers to the high minus low RETSD portfolios. The sample includes NYSE/Amex/Nasdaq common stocks with a price of at least $5 per share in the end of last month and non-negative book equity. The sample period is from June 1992 to December 2023. All t-statistics (in parentheses) are calculated using Newey-West (1987) standard errors and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A.1. Value-weighted Sort by Salience Deviation for Future Overnight return

Overnight Return	Excess Ret	FF4	FF5	FF6	HXZ_Q	HXZ_Q5	FF5_li	FF6_li
Low(Quintile 1)	0.54	0.05	0.08	0.16	0.06	0.14	0.08	0.17
	(3.62)	(0.41)	(0.60)	(1.31)	(0.43)	(1.11)	(0.57)	(1.30)
Quintile 2	0.73	0.21	0.25	0.33	0.23	0.30	0.24	0.30
	(4.31)	(1.58)	(1.68)	(2.35)	(1.57)	(2.23)	(1.54)	(1.96)
Quintile 3	0.83	0.29	0.28	0.29	0.24	0.24	0.28	0.36
	(5.05)	(1.96)	(1.80)	(1.93)	(1.57)	(1.65)	(1.73)	(2.29)
Quintile 4	0.72	0.23	0.30	0.39	0.27	0.35	0.29	0.30
	(4.47)	(1.72)	(2.03)	(2.60)	(1.84)	(2.38)	(1.87)	(2.00)
High(Quintile 5)	0.87	0.36	0.39	0.55	0.36	0.50	0.42	0.41
	(4.87)	(2.36)	(2.63)	(3.65)	(2.32)	(3.24)	(2.54)	(2.44)
H-L	0.33***	0.31***	0.31***	0.38***	0.30***	0.37***	0.34***	0.24**
	(3.53)	(3.23)	(3.34)	(3.77)	(3.05)	(3.43)	(3.45)	(2.30)

Panel A.2. Value-weighted Sort by Salience Deviation for Future Intraday return

Intraday Return	Excess Ret	FF4	FF5	FF6	HXZ_Q	HXZ_Q5	FF5_li	FF6_li
Low(Quintile 1)	0.48	-0.04	-0.13	-0.26	-0.08	-0.20	-0.09	-0.14
	(2.98)	(-0.25)	(-0.88)	(-1.79)	(-0.51)	(-1.35)	(-0.54)	(-0.96)
Quintile 2	0.38	-0.18	-0.26	-0.35	-0.23	-0.31	-0.23	-0.28
	(2.03)	(-1.15)	(-1.49)	(-2.02)	(-1.32)	(-1.84)	(-1.22)	(-1.55)
Quintile 3	0.14	-0.44	-0.52	-0.56	-0.46	-0.50	-0.49	-0.52
	(0.74)	(-2.88)	(-3.15)	(-3.45)	(-2.77)	(-3.03)	(-2.73)	(-2.92)
Quintile 4	0.36	-0.26	-0.42	-0.48	-0.39	-0.44	-0.36	-0.38
	(2.02)	(-1.85)	(-2.98)	(-3.13)	(-2.77)	(-2.87)	(-2.44)	(-2.62)
High(Quintile 5)	0.07	-0.51	-0.63	-0.68	-0.60	-0.65	-0.62	-0.67
	(0.36)	(-2.61)	(-3.48)	(-4.03)	(-3.24)	(-3.68)	(-3.08)	(-3.67)
H-L	-0.41**	-0.47**	-0.50***	-0.42**	-0.52***	-0.45**	-0.53***	-0.53***
	(-2.25)	(-2.56)	(-2.87)	(-2.45)	(-2.89)	(-2.50)	(-3.03)	(-3.15)

Panel B.1. Equal-weighted Sort by Salience Deviation for Future Overnight return

Overnight Return	Excess Ret	FF4	FF5	FF6	HXZ_Q	HXZ_Q5	FF5_li	FF6_li
Low(Quintile 1)	0.29	-0.19	-0.19	-0.12	-0.20	-0.14	-0.17	-0.04
	(1.77)	(-1.29)	(-1.32)	(-0.89)	(-1.39)	(-0.99)	(-1.10)	(-0.29)
Quintile 2	0.51	0.01	0.03	0.09	0.01	0.08	0.02	0.14
	(2.71)	(0.03)	(0.16)	(0.58)	(0.06)	(0.47)	(0.12)	(0.86)
Quintile 3	0.73	0.22	0.21	0.21	0.19	0.19	0.22	0.30
	(4.22)	(1.48)	(1.38)	(1.48)	(1.25)	(1.30)	(1.33)	(1.88)
Quintile 4	0.69	0.21	0.19	0.24	0.18	0.23	0.20	0.30
	(3.94)	(1.41)	(1.28)	(1.60)	(1.16)	(1.48)	(1.28)	(1.87)

High(Quintile 5)	0.79	0.30	0.30	0.43	0.28	0.41	0.34	0.37
	(3.94)	(1.73)	(1.84)	(2.49)	(1.68)	(2.31)	(1.92)	(2.10)
H-L	0.50***	0.48***	0.49***	0.55***	0.49***	0.55***	0.51***	0.42***
	(6.27)	(5.80)	(6.10)	(6.30)	(5.93)	(6.15)	(6.11)	(5.57)

Panel B.2. Equal-weighted Sort by Salience Deviation for Future Intraday return

Intraday Return	Excess Ret	FF4	FF5	FF6	HXZ_Q	HXZ_Q5	FF5_li	FF6_li
Low(Quintile 1)	1.13	0.50	0.39	0.32	0.47	0.40	0.45	0.38
	(5.20)	(3.20)	(2.58)	(2.12)	(3.03)	(2.59)	(2.55)	(2.10)
Quintile 2	0.89	0.22	0.19	0.06	0.25	0.13	0.24	0.21
	(3.82)	(1.34)	(1.12)	(0.34)	(1.46)	(0.71)	(1.26)	(1.04)
Quintile 3	0.68	-0.00	-0.06	-0.12	0.02	-0.04	-0.01	-0.04
	(2.83)	(-0.00)	(-0.34)	(-0.73)	(0.10)	(-0.22)	(-0.07)	(-0.19)
Quintile 4	0.79	0.10	-0.02	-0.04	0.06	0.05	0.05	-0.02
	(3.06)	(0.57)	(-0.11)	(-0.20)	(0.32)	(0.27)	(0.23)	(-0.08)
High(Quintile 5)	0.70	0.01	-0.06	-0.04	-0.01	0.03	-0.01	-0.04
	(2.60)	(0.06)	(-0.30)	(-0.20)	(-0.04)	(0.13)	(-0.04)	(-0.21)
H-L	-0.43***	-0.49***	-0.45***	-0.36***	-0.47***	-0.38***	-0.46***	-0.42***
	(-4.17)	(-4.45)	(-3.99)	(-3.08)	(-3.93)	(-3.07)	(-3.89)	(-3.11)

Table 13. Robustness test for Fama-Macbeth cross-section regression

This table reports the results of the Fama-MacBeth (1973) regression of monthly returns on lagged variables. The independent variables include the attention-grabbing measure (RETSD), tug-of-war effect (Lou et al., 2019) measure represented by previous month's overnight and intraday and overnight return (RETCTO, RETOTC), max daily return (Bali, Cakici and Whitelaw, 2011) and corresponding minimum daily return (MAX and MIN),log of market value (LNSIZE), and log of book-to-market equity (LNBM). Amihud's (2002) illiquidity (ILLIQ), idiosyncratic volatility (IVOL), turnover (TNOVM1), market beta (BETA), idiosyncratic skew (Skew), 12-month momentum (skip one month before formation month) and short-term reversal effect (Mom_12m and Ret_1_0). The sample includes NYSE/Amex/Nasdaq common stocks with a price of at least $5 per share in the end of last month and non-negative book equity. Independent variables are winsorized at the 1% and the 99% levels and cross-sectionally standardized with a mean of zero and a standard deviation of one. . The regression coefficients are reported in percentages. The sample is from June 1992 to December 2023. All t-statistics (in parentheses) are calculated using Newey-West (1987) standard errors and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A. Overnight return

	(1)	(2)	(3)	(4)
RETSD	0.0058***	0.0077***	0.0046***	0.0047***
.	(5.98)	(9.19)	(6.69)	(5.85)
retcto		0.1378***	0.1471***	0.1510***
.		(19.40)	(22.22)	(22.00)
retotc		-0.0666***	-0.0625***	-0.0269***
.		(-9.92)	(-9.29)	(-4.33)
max			-0.0178**	-0.0552***
.			(-2.51)	(-5.76)
min			-0.1918***	-0.0770***
.			(-13.57)	(-5.75)
lnsize				0.0001
.				(0.30)
lnbm				-0.0014***

Panel B. Intraday return

	(1)	(2)	(3)	(4)
RETSD	-0.0057***	-0.0079***	-0.0053***	-0.0043***
.	(-4.06)	(-5.65)	(-4.21)	(-3.68)
retcto		-0.1430***	-0.1540***	-0.1344***
.		(-19.19)	(-21.67)	(-18.22)
retotc		0.0727***	0.0693***	0.0617***
.		(6.70)	(6.17)	(4.84)
max			0.0065	0.0364**
.			(0.54)	(2.48)
min			0.1543***	0.1317***
.			(7.53)	(8.97)
lnsize				-0.0012***
.				(-2.86)
lnbm				0.0023***

.	(-4.28)
illiq	-0.0042***
.	(-5.68)
ivol	0.2144***
.	(4.69)
tnovm1	0.0052***
.	(8.07)
beta	-0.0023***
.	(-8.07)
skew	0.0018***
.	(6.20)
mom_12m	0.0049***
.	(8.05)
ret_1_0	-0.0379***
	(-7.51)

.	(3.07)
illiq	0.0085***
.	(5.16)
ivol	-0.1142*
.	(-1.94)
tnovm1	-0.0059***
.	(-8.16)
beta	0.0031***
.	(5.66)
skew	-0.0007*
.	(-1.71)
mom_12m	-0.0018
.	(-1.04)
ret_1_0	-0.0061
	(-0.77)