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Investor attention and the salience effect in the Chinese stock market: Insights from the COVID-19 pandemic

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A B S T R A C T

We investigate the relationship between investor attention and the salience effect (i.e. a negative relation between salience measures and subsequent returns (Cosemans & Frehen, 2021)) in the Chinese stock market using the COVID-19 pandemic as an exogenous shock to attention. We find that COVID-19 significantly distracted individual investors' attention from stock market activities, leading to a weaker salience effect. However, institutional investors increased their attention during COVID-19 by attending more investor-firm interactive activities. Furthermore, we show that the reduction in retail attention during the COVID period is stronger for negative salient returns than for positive salient returns. As a result, the reduced salience effect during the pandemic is more pronounced for stocks with salient downsides than for stocks with salient upsides. These results indicate that investor attention causes the salience effect.

1. Introduction

Investors face bounded rationality and limited attention (Miller, 1956; Simon, 1955), resulting in selective processing of information (DellaVigna and Pollet, 2009; Gabaix, 2014; Odean, 1999). Salience makes certain cues prominent and directs what is noticed and encoded (Taylor & Thompson, 1982), while attention enables deeper processing (Parr & Friston, 2019). In stock markets, the relationship between attention and salience may be endogenous. Salient returns attract investors' attention and allow them to focus their analysis on price moves (Ramos et al., 2020). However, attention can also boost excess demand, generating salient price moves.

This endogeneity complicates causal inference because both salience bias and attention lead to subsequent price reversals. Specifically, overweighting of salient return signals produces mispricing (Bordalo et al., 2012, 2013), and the subsequent correction produces a negative relation between salience measures and subsequent returns, known as the "salience effect" (Cosemans & Frehen, 2021).[1] Alternatively, attention to attention-grabbing stocks induces excess buying and a temporary increase in prices, which may gradually decline over time, because investors can more easily buy new stocks rather than sell those not in their holdings (Barber & Odean, 2008; Da et al., 2011). As both mechanisms produce similar price patterns, isolating salience-driven from attention-driven reversals is empirically challenging. Cosemans and Frehen (2021) use double sorts on salience and attention to separate price

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[1] Specifically, investors influenced by salience bias (often referred to as "salient thinkers") are likely to overprice stocks with salient upsides and underprice those with salient downsides. This salience-induced mispricing is typically followed by a price reversal when stock prices revert to their fundamental values, resulting in a negative relation between the variable that captures such salience bias (i.e., ST value) and the future stock return.

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patterns, but salient returns typically coincide with heightened attention, leaving this endogeneity unresolved.

We use COVID-19, an unforeseen, widespread, and life-altering global event, as an exogenous distraction of investor attention to identify its role in driving the salience effect. After the WHO declared COVID-19 a Public Health Emergency of International Concern on January 30, 2020, China's strict zero-COVID measures absorbed public cognitive bandwidth and diverted attention from markets, creating a "poverty of attention" effect (Da et al., 2011). Consistent with the scarcity of attention during COVID-19, Wang and Xing (2020) find that when attending corporate earnings calls, investors focus more on COVID-19 news than on credible firm signals. This exogenous distraction thus serves as a natural experiment to identify the causal relationship between investor attention and the salience effect. Fig. 1 summarizes the framework: Distinctive cues make information salient, which captures scarce investor attention and shapes how signals are encoded and weighted, forming trading intent. COVID reduces effective market attention without altering the inherent salience of return signals. Consequently, the link between salience and attention is weakened by the shock, reducing the salience-driven trading.

Although COVID-19 was a global event, China is particularly well-suited for this analysis for three reasons. First, the salience effect in China is substantial (Sun et al., 2023), the third largest out of 49 markets (Cakici & Zaremba, 2022). Second, although the severity of the pandemic in terms of confirmed cases and deaths was relatively low in China compared to many other countries, this was largely due to strong government control. The Chinese government adopted a zero-COVID strategy that involved frequent mass testing, contact tracing, school closures, and strict lockdowns. Such strong government measures to control the spread of the virus were likely to create a pervasive and plausibly exogenous diversion of public attention from markets compared to other countries. Third, China offers investor-type separation that sharpens identification: rich retail attention data (e.g., forum activity) and institutional interaction disclosures allow us to separate retail attention from institutional channels. These features make China a particularly informative laboratory for isolating how exogenous attention scarcity shapes the salience effect.

In this study, we first hypothesize that COVID-19 disrupted investor attention to stock markets. We further conjecture that only individual investors would be distracted, while institutional attention may have even increased due to the heightened uncertainty brought by the pandemic. In support of this hypothesis, we find that retail attention (measured by Guba[2] posts/reads) to individual stocks declined during COVID, especially for highly salient returns, whereas institutional attention (measured by institutions attending investor-firm interaction events) increased. To the extent that the salience effect is likely to be driven by retail investors' attention (Cakici & Zaremba, 2022; Cosemans & Frehen, 2021), we predict and find that the salience effect should be weakened during COVID, with a stronger attenuation where the pandemic was more severe. Our finding also implies that investor attention is a prerequisite for salience bias to influence asset prices. Moreover, we show that retail attention declined more for negative than positive salient returns, yielding a larger reduction in the downside salience effect.

This study makes two contributions. First, from a theoretical perspective, the salience effect arises because investors focus their attention on the most unusual-or salient-attributes (e.g. past extreme returns). Although prior studies document the salience effect across different countries and markets (e.g. Cosemans & Frehen, 2021; Goh et al., 2026 for U.S.; Liu et al., 2023; Sun et al., 2023 for China; Lee et al., 2024 for Australia; Cai & Zhao, 2024; Chen et al., 2022 in the cryptocurrency market), to the best of our knowledge, it has not been established whether investor attention is the underlying driver. Exploiting COVID-19 as an exogenous attention shock, we show that weakening retail attention attenuates the salience effect, providing causal evidence that attention is a prerequisite for salience bias. Second, from an empirical perspective, we show that there is heterogeneous investor attention during COVID-19. While retail investors attenuate their attention to the stock market, institutional investors increase their attention by engaging in more investor-firm interactive activities. Our evidence thus contributes to the strand of literature showing that institutional investors may play a price discovery role at periods of great uncertainty by acquiring more fundamental information (e.g. Gompers & Metrick, 2001; Liu et al., 2023; Yan & Zhang, 2009).

Although our study focuses on China, the empirical results may be generalized to other countries. For instance, as retail investors remain dominant participants in most emerging markets, our findings suggest that variation in retail investors' attention can influence the salience effect, thereby contributing to market inefficiency. To the extent that institutional investors are less affected by salience, our results imply that regulatory authorities in emerging economies could enhance market efficiency by encouraging greater participation from institutional investors. In addition, given that the COVID-19 pandemic was a global health crisis, our results highlight that its effects extend beyond health outcomes to include potential impacts on the allocation of human cognitive resources and decision-making processes under uncertainty. Taken together, our results and their implications are likely to extend beyond the Chinese context.

The remainder proceeds as follows: Section 2 reviews related literatures. Section 3 states hypotheses. Section 4 describes data and variables. Section 5 presents empirical results. Section 6 reports robustness. Section 7 concludes.

2. Literature review

Classic studies in psychology and behavioral finance posit that attention is a scarce cognitive resource that must be allocated selectively among competing stimuli (Gabaix et al., 2003; Miller, 1956; Simon, 1955). This scarcity limits investors' capacity to process information in parallel and pushes them toward cues that capture attention (Gabaix, 2014; Hirshleifer & Teoh, 2003; Odean, 1999; Shefrin & Statman, 1985).

[2] Guba is a leading public stock discussion forum in China where retail investors share and consume stock-specific posts and replies. Following prior work, we use Guba's daily counts of posts and reads to construct our retail-attention proxy.

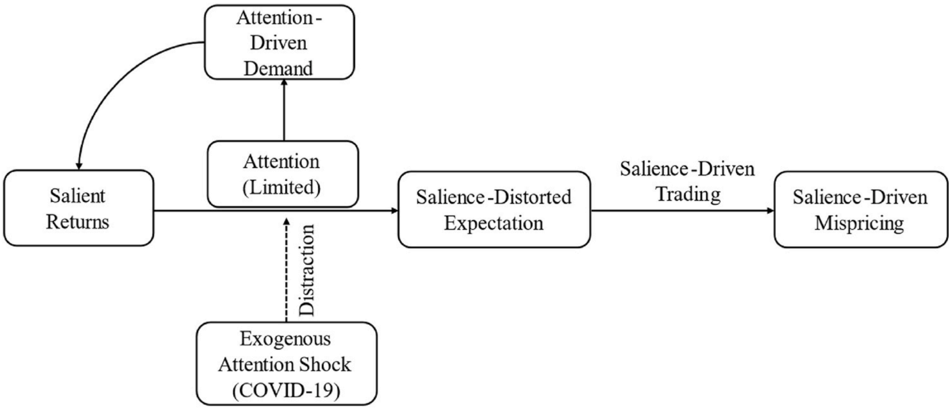

Fig. 1. Attention-salience relationship with COVID-19 shock.

Salience theory provides a formal framework for understanding how certain information becomes attention-grabbing. Salience is the perceptual distinctiveness of an outcome relative to its context, which causes that information to receive disproportionate decision weight (Bordalo et al., 2012; Fiske & Taylor, 1991; Taylor & Thompson, 1982). In financial markets, returns that stand out as unusually high or low attract attention. When investors overweight recent salient returns, the resulting bias generates overreaction and subsequent reversals, a phenomenon often labelled the salience effect (Bordalo et al., 2013; Cosemans & Frehen, 2021).

Although attention and salience are frequently linked together, prior research largely treats the role of attention in salience-based evaluation as an assumption rather than a tested mechanism. Early behavioral models formalize how attention filters and weights attribute differences. For instance, Tversky (1969) shows that decision makers often disregard small differences on important attributes while disproportionately reacting to large differences, implying a non-linear "noticeability" threshold that effectively reweights attributes as a function of contrast. Later, Kőszegi and Szeidl (2013) advance a focusing model in which people allocate more attention to attributes exhibiting greater dispersion across available options; differences magnify focus, and focus magnifies weight. Both models make a precise central mechanism: differential attention is the channel through which salience translates into overweighting.

Empirically, Bali et al. (2021) document that social interactions propagate focus on salient payoff features (e.g., lottery-like tails), thereby increasing retail demand and overpricing for such stocks. Their interpretation is explicit: when attention is limited and belief formation leans on observation and communication, social networks steer attention toward the most striking features, amplifying preference- and salience-based effects. Retail investors are particularly susceptible, consistent with their higher exposure to social media cues and lower baseline monitoring intensity. Relatedly, Barber et al. (2019) note that salience shapes how attention is distributed across presented choices, whereas coverage and its placement determine which choices are seen at all. Taken together, these streams converge on a common premise: salient attributes must first be noticed before they can distort valuation and trading, yet this premise remains largely untested.

The empirical challenge is that attention and salience frequently coincide and produce similar short-horizon anomalies. Stocks that draw attention because of news or large price moves exhibit abnormal contemporaneous demand and later reversals (Barber & Odean, 2008; Da et al., 2011). Disentangling the two mechanisms is difficult because salience can attract attention and attention can amplify salience. As a result, prior work rarely tests the relation between attention and salience. Establishing this link is essential for explaining when and why salience-driven mispricing emerges or recedes.

Motivated by this gap, we exploit COVID-19 as an exogenous distraction that reduces investor attention to stock-specific salient signals without diminishing the underlying salience of returns. This design enables a cleaner test of whether attention scarcity attenuates salience-driven pricing, thereby moving from an assumed linkage to a tested mechanism and clarifying the conditions under which salience translates into pricing outcomes.

3. Hypotheses

According to limited attention theory (Gabaix et al., 2003; Simon, 1955), attention is a scarce cognitive resource allocated selectively among stimuli. Following major shocks such as terrorist attacks or natural disasters, investor attention can be diverted from the financial markets (Hirshleifer et al., 2009), resulting in less stock trading and slow information processing (Levy & Galili, 2006; Wang et al., 2024). COVID-19 is an unexpected global event that can shift cognition toward health risks and daily-life uncertainties (Xu et al., 2021), evidenced by surges in coronavirus-related searches and information demand (Gong et al., 2020; Shear et al., 2020; Smales, 2021). Therefore, the continuous stream of pandemic news (case counts, lockdowns, travel bans, vaccine rollouts) plausibly diluted market-focused attention without directly altering the return-generation process, serving as a natural experiment to identify the causal relationship between investor attention and the salience effect.

We argue that the strength of this relationship could be dependent on investor groups. Individual investors, bounded by limited cognitive capacity (Odean, 1999; Simon, 1955) and facing competing life concerns during COVID-19 (Forsythe et al., 2020), are more easily distracted from markets (Smales, 2021) and from salient return signals. By contrast, institutional investors, who work under professional mandates with analytical infrastructure, face fewer cognitive constraints and can increase their attention when uncertainty rises (Barber & Odean, 2008; Liu et al., 2023). In addition, agency theory (Eisenhardt, 1988) predicts stronger institutional monitoring when information asymmetry increases (Chung & Wang, 2014; Eisenhardt, 1988; Kang, 2006). Furthermore, heightened market volatility during the pandemic increased the need for portfolio rebalancing and active risk monitoring, which in turn required institutional investors to gather more timely information (Döttling & Kim, 2024; Giglio, Maggiori, Stroebel, & Utkus, 2021; Wang et al., 2024). Empirically, mutual funds actively adjusted positions (i.e., engaged in investment-style shifts) and sustained performance during the COVID-19 shock, indicating intensified institutional engagement rather than distraction (Sha & Wu, 2024). Based on this discussion, we propose the following hypothesis:

H1. Individual investors' attention to the stock market and salient stock returns decreased during the COVID period, whereas institutional investors' attention remained stable or even increased during this period.

Previous studies suggest that salience bias primarily stems from the cognitive limitations of individual investors, who often prioritize unusual attributes of investment options due to their limited attention and processing capacities (e.g. Bordalo et al., 2012). Cosemans and Frehen (2021) find that salience effects are concentrated in intraday returns, which are typically dominated by institutional trading. They interpret this as evidence that institutional investors help correct mispricing caused by salience-driven retail trades from the previous month. Consistent with this, Cakici and Zaremba (2022) describe the salience anomaly as "beyond the scope of typical institutional investors," noting that the salience effect mostly appears in microcap stocks—an asset class typically avoided by institutional investors. In addition to this, Hu et al. (2023) provide direct evidence from mutual fund flows in China, showing that retail investors exhibit salience-consistent allocation behavior by channeling flows into funds with previously salient payoffs while institutional investors do not. Their findings suggest that salience-driven distortions in capital allocation are largely attributable to retail behavior. To the extent that exogenous shocks like the COVID-19 pandemic tend to divert the attention of individual investors away from stock market activities, we expect the salience effect to be weakened during the COVID period.

Therefore, we propose the following hypothesis:

H2. The salience effect is weakened during the COVID period.

Building on H1 and H2, we further propose an asymmetric weakening of the salience effect during COVID, with a stronger attenuation for salient downside returns. The mechanism combines attentional and emotional responses under crisis conditions. First, salience theory holds that attention is drawn to what is distinctive in context (Bordalo et al., 2012). During the pandemic, most salient news was negative, so negative salient returns became less distinctive, whereas positive salient returns stood out more. Because greater salience attracts more attention, positive salient returns should be less affected by the overall reduction in retail attention. Second, the ostrich effect implies avoidance of negative information (Galai & Sade, 2006; Hou et al., 2009). Recent evidence shows attention drops when personal finances turn negative (Olafsson & Pagel, 2025). With pandemic stress and heightened uncertainty, investors were even more reluctant to face negative stock news, further reducing attention to negative salient returns. Moreover, rational inattention model formalizes that attention is costly and allocated only when expected benefits exceed costs (Sims, 2003). Under pandemic uncertainty, the emotional and cognitive cost of attending to salient downsides is higher, whereas attending to salient upsides may carry an affective reward. Consistent with this, prior empirical evidence documents that investor attention falls after market declines and rises after gains, reflecting selective monitoring (Sicherman et al., 2016). Complementing these patterns, the theory of information aversion (Andries & Haddad, 2020) predicts reduced information acquisition when volatility rises—precisely the conditions prevailing during COVID. Similarly, Klemola et al. (2016) also show that after market declines investors shift attention to positive signals (e.g., increased searches for "market rally"), indicating optimism-seeking in downturns.

Taken together, retail attention is likely reduced more for negative than for positive salience, implying a sharper decline in the downside salience effect. Our third hypothesis is proposed accordingly as:

H3. Retail attention diversion induced by COVID-19 produced a greater attenuation of the downside than the upside salience effect.

4. Data and sample

4.1. Sample selection

Our sample of stocks includes A-shares listed on the main boards of the Shenzhen Stock Exchange (SZSE) and the Shanghai Stock Exchange (SSE), covering the period from 2011 to 2023. We also include stocks from the Growth Enterprise Market (GEM) board, a marketplace for innovative, R&D intensive, high-growth small and medium-sized firms to list their shares, similar to U.S. firms listed on the NASDAQ, for the period from 2011 to August 23, 2020.[3] To mitigate the impact of initial public offerings (IPOs), we exclude observations from the first six months following an IPO to avoid the typical volatility and heightened attention associated with newly listed stocks. Moreover, we exclude data from the trading day and the subsequent trading day of any stock's capital change (e.g., stock split) to avoid artificial price changes caused by such events.

[3] In August 2020, the price limit rule on the GEM board was increased from 10 % to 20 %, while the main boards maintained a 10 % price limit rule. We exclude GEM board stocks after August 2020 to eliminate potential influences from this rule change on the measurement of salience.

4.2. Data sources

We measure attention along retail and institutional channels using two independent sources. Retail attention comes from the open investor message board on Guba Forum (http://guba.eastmoney.com), accessed via the China Research Data Service (CNRDS) database. CNRDS provides firm-level BBS data since 2008: the number of posts and total counts of readings and comments for each firm is available on a daily basis. We aggregate these records to our working frequency to construct our primary retail-attention indicator (GBATT). Institutional attention is drawn from China Stock Market and Accounting Research (CSMAR). CSMAR provides daily records of investor–firm research interactions (e.g., on-site visits, roadshows, and conference calls) since 2011. All return-based variables are obtained from CSMAR at the daily frequency. For the exogenous shock, CSMAR also provides daily COVID-19 series since January 2020. CSMAR offers officially reported, highly detailed case data, including but not limited to active (existing) cases, cumulative totals, and new daily counts for confirmed, severe, critical, suspected, deaths, and recoveries.

4.3. Attention measure

In China, the Guba forum has emerged as a leading platform for stock information exchange, known for its broad investor reach, extended user engagement, and frequent daily visits (Zhang et al., 2023). On Guba, individual investors share news, opinions, and experiences through stock posts, which constitute the primary form of content on the platform. By engaging in activities such as posting, reading, and replying, users effectively disseminate news and investment insights about both the broader market and specific stocks. Nearly all users on Guba are individual investors seeking or sharing stock-related information, making the platform highly relevant for stock market analysis (Huang et al., 2016).

Following the literature that measures retail attention from Guba activity, we construct a stock-day attention measure using Guba's message-board data. For example, Jiang et al. (2022) use the number of posts in each stock's subforum to build a comprehensive stock-level attention measure for all A-shares in the Chinese market, documenting that higher attention predicts stronger anomaly returns. Operationally, they employ daily post counts by stock and align them at the stock-day level. We extend their approach to capture both active (posting) and passive (reading) engagement, constructing our primary individual attention measure (*GBATT*) as the number of posts and reads for each stock at each day in our sample. To derive monthly *GBATT*, we compute the average of daily *GBATT* values for individual stocks over each calendar month. Additionally, in our regression analyses, the *GBATT* is its natural logarithm version, calculated as $ln(1 + \textit{number of posts and reads})$, to ensure an appropriate scaling of the data.[4]

In our study, we utilize institutional investor-firm interactions as a measure of institutional investor attention. Such interactions, including site visits, conference calls, roadshows, and office meetings (Solomon & Soltes, 2015), are predominantly available to professional entities such as securities analysts and fund managers (Brown et al., 2015; Dong et al., 2021; Roberts et al., 2006; Xu et al., 2024). In contrast, retail investors generally lack direct access to these channels (Kirk & Piao, 2024; Wong et al., 2024). Previous research highlights that these interactions serve as crucial avenues for institutional investors and analysts to gather firm-specific information, particularly in China, where the information environment tends to be opaque (Cheng et al., 2019; Liu et al., 2017; Morck et al., 2000). In this context, institutional investors allocate considerable effort to engaging with public firms to obtain timely information and receive assistance in processing complex corporate events (Kirk & Piao, 2024).

Our data on institutional investor-firm interactions comes from the detailed records of engagements between institutional investors and listed companies. Unlike in the United States, where information about in-house meetings and non-deal roadshows is often limited (Zhang, 2023), interactions between Chinese public companies and their investors are closely monitored by regulatory authorities (Yu & Shao, 2024). In our sample, the data on institutional attention covers most firms listed on the Shenzhen Stock Exchange (SZSE) main board (97 %) and the Growth Enterprise Market (GEM) board (94 %), as well as about half of the firms listed on the Shanghai Stock Exchange (SSE) main board. The lower coverage of SSE firms is likely due to the fact that the disclosure of investment engagement activities is not mandatory for SSE-listed firms, and such information is typically disclosed voluntarily (Guo et al., 2023; Yu & Shao, 2024).

Specifically, the institutional investor attention (*INSATT*) in this study is defined as the total number of institutional investors participating in various forms of company research activities for each listed firm during each month. In a similar manner to the individual investor attention measure, in regression analyses, we use the natural logarithmic version of the *INSATT*.

4.4. Salience theory measure (*ST*)

The salience effect is primarily assessed by examining the relationship between a stock's salience theory measure (denoted as *ST*) each month and its return in subsequent month. We strictly follow the methodology developed by Cosemans and Frehen (2021) when calculating the salience theory measure (*ST*).

Specifically, we first calculate the degree of salience for each stock's daily return, denoted as *Sigma*:

[4] There are caveats about the Baidu Index search volumes. As Baidu searches can also be used for searching for products of relevant companies, using the searches for the stock's name can be a noisy measure for attention. However, using only the searches for the stock code may underestimate the extent of attention from investors. Therefore, this study employs Guba forum posts and reads as a more precise measure of individual investor attention. As a robustness check, we report the Baidu Index-based result in the Appendix Table A1-A2. Our conclusions remain if we use Baidu search index as an alternative proxy for retail attention. The detailed discussion is provided in Section 6–Robustness Test.

$$\sigma(r_{i,s}, \bar{r}_s) = \frac{|r_{i,s} - \bar{r}_s|}{|r_{i,s}| + |\bar{r}_s| + \theta}, \tag{1}$$

Following Cosemans and Frehen (2021), θ is set to 0.1 to avoid the case that zero-returns always get the maximum salience, and $\bar{r}_s$ represents the average return across all stocks at day s, calculated as $\bar{r}_s = \sum_i^N r_{i,s}/N$, with N denoting the number of individual stocks in existence at this day. *Sigma* captures the degree of salience for each stock return, and salient returns will cause investors who suffer from the salience bias to assign greater weight to these returns, leading to overvaluation or undervaluation of stocks.

Then we estimate the decision weight $\omega_{i,s,t}$ for each stock's daily return within a month t:

$$\omega_{i,s,t} = \frac{\delta^{k_{i,s,t}}}{\sum_{s'} \delta^{k_{i,s',t}} \cdot \pi_{i,s',t}}, \tag{2}$$

In Eq. (2), $k_{i,s}$ is the salience ranking of return $r_{i,s}$, ranging from 1 (most salient) to S (least salient), within month t. In addition, δ captures the degree to which salience distorts decision weights and it proxies for the investors' cognitive ability. Following previous studies, we set it to 0.7 to match the experimental evidence from Bordalo et al. (2012). Overall, the decision weight $\omega_{i,s,t}$ aims to capture the weight assigned to return $r_{i,s}$ by investors, reflecting its perceived salience or how attention-grabbing it is.

Finally, the salience theory measure, $ST_{i,t}$, is determined by the difference between the salience-weighted and equal-weighted daily returns over month t:

$$ST_{i,t} = \sum_s^{S_t} \pi_{s,t}\omega_{i,s,t} r_{i,s,t} - \sum_s^{S_t} \pi_{s,t} r_{i,s,t} \tag{3}$$

where $\pi_{s,t}$ represents the objective probability of each return within month t. In particular, $\pi_{s,t} = 1/S$, and S is equal to the number of trading days in this month. The assumption behind the calculation of the salience theory value is that, investors form their expectations of future returns by extrapolating the salience-weighted daily returns, rather than the objective probability weighted return, over the past month. This salience theory value (ST) thus quantifies the distortion in return expectations driven by salient thinking. When the highest (or lowest) past returns of a stock are salient, salient thinking investors tend to overemphasize the upside (downside) potential of stocks, resulting in the overvaluation (undervaluation) of the prices. Therefore, stocks with salient upsides (positive ST) tend to be overpriced while stocks with salient downside (negative ST) tend to be underpriced. Such mispricing will reverse in the future, causing the negative relation between ST and future return.

4.5. Abnormal stock return

In our analysis, we employ two metrics to assess stock performance in the subsequent month: raw returns and DGTW-adjusted abnormal returns. Raw monthly returns are calculated by compounding the daily returns over a calendar month. Additionally, we also utilize the Daniel et al.'s (1997) method to adjust returns to measure the abnormal performance of a stock. The DGTW model adjusts raw stock returns by benchmarking them against returns from portfolios composed of similar stocks. We first group stocks into the benchmark portfolios based on their size, book-to-market ratios, and prior performance. We then calculate the daily DGTW-adjusted return by subtracting daily stock return from the returns from the benchmark portfolios to which a particular stock belongs. We then compound these daily abnormal returns over the calendar month to obtain the monthly abnormal return.

4.6. Control variables

To isolate the attention–salience mechanism from known return predictors, we follow Cosemans and Frehen (2021) and include the standard cross-sectional controls including size, book-to-market, momentum, liquidity, beta, short-term reversals as well as lottery demand and tail risk proxies such as idiosyncratic volatility, MAX/MIN, skewness, coskewness, idiosyncratic skewness. Specifically, according to variable definition in Cosemans and Frehen's study, ME represents the natural logarithm of a firm's market capitalization (in CNY). BM denotes the book-to-market ratio. Momentum (MOM) is defined as a stock's cumulative return (in percentage) over the 11-month period ending two months prior to the current month. ILLIQ refers to the Amihud (2002) illiquidity measure, calculated as the average of daily illiquidity over all trading days in a given month. BETA represents the market beta, estimated through a regression of daily excess stock returns on daily excess market returns over a one-month window. IVOL is the idiosyncratic volatility (in percentage) obtained from this regression. REV indicates the stock return over the previous month (in percentage). MAX (MIN) represents the maximum (minimum) daily return of a stock within a month (in percentage), calculated following Bali et al. (2011). SKEW measures the skewness of daily stock returns, calculated over a one-year window. COSKEW represents the coskewness of daily stock returns with daily market returns over a one-year period, calculated following the methodology of Harvey and Siddique (2000). ISKEW refers to the skewness of the residuals obtained from a Fama and French (1993) three-factor model regression, estimated over a one-year window of daily returns, as in Boyer et al. (2010). DBETA is the downside beta, estimated by regressing daily excess stock returns on daily excess market returns over a one-year window, using only the days when the market return was below the average daily market return during that year, as outlined by Ang et al. (2006).

In addition to the standard characteristics included by Cosemans and Frehen (2021), we incorporate a sentiment measure to account for the potential confounding effects of COVID-19 on market sentiment and investor behavior. The sentiment measure in our study is derived from data obtained from the Guba Forum. Following the method of previous studies (e.g., Antweiler & Frank, 2004; Yin & Nan, 2024; Yin & Wang, 2024), we construct a monthly investor sentiment measure based on the number of optimistic and pessimistic posts for each stock in each month. For each stock i, the monthly sentiment is calculated using the following formula:

$$Sentiment_{i,t} = ln\frac{(1 + positive\ posts_{i,t})}{\left(1 + negative\ posts_{i,t}\right)} \tag{4}$$

To summarize this section, the definitions of all the variables mentioned above are included in Table 1.

4.7. Statistical description

Table 2 provides the descriptive statistics for the main variables, all of which are measured at a monthly frequency for use in the regression analysis conducted in the empirical analysis. In Table 3, we report the correlation coefficients among these variables, and we observe that the abnormal return of stocks is negatively correlated with the salience theory value ST. This is consistent with the salience effect.

In Table 4, we present the summary statistics for the daily measure of retail attention and institutional attention, as well as the ST value, separately for the COVID and non-COVID periods. We observe that the mean retail attention during the COVID period is lower than that during the non-COVID period, while the opposite is true for institutional attention. When comparing the two periods, the salience theory value ST is actually higher during the COVID period; hence, the decline in retail attention during this period cannot be attributed to a decrease in salience itself.

5. Research design and empirical results

5.1. Defining the COVID period

Consensus in the literature identifies the initial outbreak of the coronavirus in Wuhan, China, in December 2019. Following China's decision to isolate Wuhan on January 23, 2020, and the subsequent declaration of the COVID-19 epidemic as a Public Health Emergency of International Concern (PHEIC) by the World Health Organization on January 30, 2020, we define the start of the COVID-19 period as January 2020 in our study.

Defining the end of the pandemic period poses a challenge due to the varying stages of the pandemic's development and the absence of consensus in the literature. Most studies on COVID-19 were published while the pandemic was ongoing and did not provide a definitive end date. Further complicating the definition of an end date are the diverse policies enacted globally to mitigate the virus's impact. Countries implemented measures ranging from stringent lockdowns to more relaxed coexistence strategies, depending on their public health capabilities and the compliance levels of their populations. However, China strictly maintained a zero-COVID policy well into May 2022 (Zhou et al., 2024).

During this period, government policies profoundly influenced daily life and investor behavior within China. Specifically, local governments were mandated to publicly report daily new cases, with strict penalties for officials who failed to detect new cases early. This led to frequent mass testing campaigns aimed at uncovering asymptomatic cases. Additionally, aggressive localized lockdowns were frequently enforced in response to new outbreaks. The widespread media coverage of pandemic-related updates, routine community health checks, and mandatory health codes for accessing public spaces made the pandemic a constant presence in people's lives, significantly diverting their attention from other activities, including stock market investments. Notably, this window includes major enforcement episodes (e.g., the Shanghai lockdown, March 28–May 31, 2022).

Based on the above discussion, we define the end of the COVID-19 period as May 2022 in our study. Accordingly, the non-COVID period in our study is defined as the period spanning 2011 to December 2019 and June 2022 to December 2023. As a robustness check, we re-estimate all analyses by extending the COVID window to December 2022 (the formal policy shift), and the results remain qualitatively unchanged (Appendix Tables A13–A17).

5.2. The impact of COVID on investor attention

To test Hypothesis 1, we first employ regression analysis to investigate the impact of COVID-19 on the level of retail and institutional attention in individual stocks. The regression models we test are:

$$GBATT_{i,t}\ or\ INSATT_{i,t} = \beta_0 + \beta_1 COVID_t + \sum \gamma_j CONTROL_{i,j,t} + \mu_i + \tau_t + \varepsilon_{i,t} \tag{5}$$

$$GBATT_{i,t}\ or\ INSATT_{i,t} = \beta_0 + \beta_1 CASES_t + \sum \gamma_j CONTROL_{i,j,t} + \mu_i + \tau_t + \varepsilon_{i,t} \tag{6}$$

In the above models, $GBATT_{i,t}$ and $INSATT_{i,t}$ represent the natural logarithm version of individual investor attention and institutional investor attention for stock i in month t, respectively. $COVID_t$ is a dummy variable indicating the COVID-19 period and *CASE* is the natural logarithm of one plus the total number of newly confirmed COVID-19 cases and related deaths in China in month t. *CONTROL* represents a vector of control variables as described in the variable construction section. The model also incorporates firm fixed effects (μ_i) and month fixed effects (τ_t).

Table 1
Variable description.

Variable	Definition
RET	Monthly compound return (in %) in a month
AR	DGTW-adjusted abnormal return compound over a month (in %)
ST	Salience theory measure computed according to Cosemans and Frehen (2021)
GBATT	Guba-based individual investor attention, computed as the monthly average of the daily total number of posts and reads for individual stock on Guba forum
INSATT	Institutional investor attention, computed as the monthly total number of institutional investors participating in research activities for individual firms
COVID	Time dummy coded 1 for periods during the zero-Covid policy in China, and 0 otherwise
CASES	The total number of newly-confirmed COVID-19 cases and deaths in a month
ME	Size measure, computed as the log of a firm's market capitalization (in CNY)
BM	Book-to-market ratio
MOM	Stock's cumulative return (in %) over the 11-month period ending two months prior to a month
ILLIQ	Amihud (2002) illiquidity measure, averaged over all trading days in a month
BETA	The market beta, estimated from a regression of daily excess stock returns on the daily excess market return over a one-month window
IVOL	The idiosyncratic volatility (in %) obtained from above regression
REV	The stock return over the previous month (in %)
MAX	A stock's maximum daily return within a month (in %), as in Bali et al. (2011)
MIN	A stock's minimum daily return within a month (in %), as in Bali et al. (2011)
SKEW	The skewness of daily stock returns, calculated over a one-year window
COSKEW	The coskewness of daily stock returns with daily market returns over a one-year window, calculated following Harvey and Siddique (2000)
ISKEW	Skewness of the residuals from F-F three-factor model (1993) regression estimated over a one-year window of daily returns, as in Boyer et al. (2010)
DBETA	Downside beta, estimated from a regression of daily excess stock returns on the daily excess market return over a one-year window, using only days on which the market return was below the average daily market return during that year, as in Ang et al. (2006)
SENTIMENT	Sentiment measure based on Guba forum posts, calculated as ln[(1+positive posts)/(1+negative posts)] on monthly basis

Table 2
Summary statistics of main variables.

	Mean	S.D.	Max	Median	Min	N
AR	−0.084	9.334	42.197	−0.915	−24.817	404,994
ST	0.007	0.017	0.056	0.005	−0.036	404,994
ME	22.360	1.148	26.417	22.218	19.881	404,994
BM	0.506	0.396	2.694	0.406	−0.019	402,178
MOM	8.996	40.583	167.683	3.548	−78.905	404,977
ILLQ	0.048	0.068	0.562	0.027	0.001	404,994
BETA	0.975	0.527	2.855	0.979	−0.829	404,929
IVOL	2.001	1.069	6.039	1.750	0.446	404,669
REV	0.817	12.821	56.159	−0.377	−33.687	404,994
MAX	5.266	2.800	10.112	4.546	0.923	401,146
MIN	−4.960	2.510	−0.889	−4.380	−10.053	401,146
SKEW	0.195	0.575	3.855	0.171	−1.462	404,993
COSKEW	0.000	0.003	0.009	0.000	−0.007	404,991
ISKEW	0.897	0.685	2.947	0.891	−1.630	404,994
DBETA	0.989	0.350	2.063	1.009	−0.168	404,993
SENTIMENT	0.277	0.485	2.091	0.226	−1.065	404,982
GBATT	26664	42032	317280	11637	662	404,994
INSATT	4.262	25.480	545.000	0.000	0.000	287,100

The regression model in Eq. (5) offers a comparison of the investor attention between the COVID period and the non-COVID period, with various stock characteristics controlled for. In the regression model of Eq. (6), we also quantify the influence of the pandemic's severity on investor attention.

In Table 5, we report the regression results for Eq. (5) and Eq. (6). Two patterns emerge. First, COVID reallocates attention across investor types. With controls, retail attention is markedly lower during the COVID period (COVID = −0.577, t=*−33.77*), while institutional attention is higher (COVID = 0.333, t=*10.81*). Because the outcomes are log-scaled, these coefficients translate into large economic effects: retail attention is about 44 % lower,[5] whereas institutional attention is about 40 % higher during the COVID, relative to non-COVID months. Even without controls, the direction is the same (−21 % vs. +93 %). The contrast is not only economically meaningful and statistically significant, suggesting that a system-wide attention-absorbing shock did not uniformly depress attention but reallocated it from retail investors toward institutions.

[5] When the dependent variable is log-scaled (GBATT or INSATT) and the regressor is an indicator (COVID), the coefficient b gives a multiplicative effect on the original level: $\%\Delta = 100 \times (e^{b}-1)$. Thus, for Table 5, $b = -0.577$ implies $e^{-0.577}-1 = -0.438$ (≈44 % lower retail attention) and $b = 0.333$ implies $e^{0.333}-1 = 0.395$ (≈40 % higher institutional attention).

Table 3
Correlation matrix.

	AR	ST	ME	BM	MOM	ILLIQ	BETA	IVOL	REV	MAX	MIN	SKEW	COSK~	ISK~	DBETA	SENT~	GB~	INS~
AR	1																	
ST	−0.073	1																
ME	−0.027	0.001	1															
BM	0.024	−0.097	0.128	1														
MOM	−0.051	0.044	0.181	−0.279	1													
ILLIQ	0.034	−0.038	−0.476	−0.010	−0.189	1												
BETA	0.023	0.038	−0.144	−0.116	0.075	−0.015	1											
IVOL	−0.091	0.458	0.019	−0.254	0.332	−0.030	0.103	1										
REV	−0.086	0.531	−0.001	−0.113	−0.009	−0.057	−0.034	0.288	1									
MAX	−0.065	0.625	−0.014	−0.236	0.245	−0.044	0.236	0.597	0.395	1								
MIN	0.010	0.012	0.070	0.189	−0.249	−0.045	−0.318	−0.572	0.224	−0.434	1							
SKEW	−0.031	0.139	0.046	−0.024	0.140	−0.077	0.013	0.144	0.096	0.147	0.073	1						
COSKEW	−0.010	−0.021	0.164	−0.100	0.072	−0.132	0.054	0.046	0.015	0.057	0.001	0.218	1					
ISKEW	0.003	0.089	−0.143	0.069	−0.088	0.047	0.050	−0.089	0.001	0.017	0.045	0.180	−0.078	1				
DBETA	0.001	0.054	−0.317	−0.106	0.022	0.072	0.354	0.107	0.005	0.143	−0.208	−0.059	−0.260	0.126	1			
SENTIMENT	0.000	0.110	0.042	0.007	−0.031	0.008	−0.057	−0.078	0.207	−0.013	0.166	−0.011	−0.009	−0.040	−0.068	1		
GBATT	−0.053	0.118	0.301	−0.125	0.287	−0.148	0.033	0.335	0.085	0.278	−0.289	−0.009	0.062	0.008	−0.012	−0.067	1	
INSATT	−0.010	0.020	0.156	−0.050	0.055	−0.069	0.002	0.063	0.018	0.044	−0.020	0.028	0.041	−0.064	−0.043	0.040	0.023	1

Table 4
Descriptive Statistics for Salience and Attention during COVID and non-COVID Period.

Panel A: Non-COVID period						
	Mean	S.D.	Max	Median	Min	N
ST	0.006	0.016	0.056	0.005	−0.036	317,717
GBATT	29,694	44,718	317,280	13,404	662	317,717
INSATT	3.773	21.996	545	0	0	222,566
Panel B: COVID period						
	Mean	S.D.	Max	Median	Min	N
ST	0.008	0.018	0.056	0.006	−0.036	87,277
GBATT	15,634	27,631	317,280	7582	662	87,277
INSATT	5.951	34.870	545	0	0	64,534

Table 5
The impact of COVID on individual and institutional investor attention.

	GBATT				INSATT			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
COVID	−0.235***	−0.577***			0.657***	0.333***		
	(-10.77)	(-33.77)			(21.90)	(10.81)		
CASES			−0.088***	−0.127***			0.096***	−0.008
			(-12.49)	(-22.76)			(9.85)	(-0.79)
ME		0.306***		0.306***		0.222***		0.222***
		(132.67)		(132.67)		(49.32)		(49.32)
BM		0.014***		0.014***		−0.018***		−0.018***
		(8.14)		(8.14)		(-5.06)		(-5.06)
MOM		−0.015***		−0.015***		0.030***		0.030***
		(-12.37)		(-12.37)		(12.98)		(12.98)
ILLIQ		−0.109***		−0.109***		0.002		0.002
		(-90.22)		(-90.22)		(0.92)		(0.92)
BETA		0.032***		0.032***		0.013***		0.013***
		(28.71)		(28.71)		(6.14)		(6.14)
IVOL		0.403***		0.403***		0.051***		0.051***
		(197.86)		(197.86)		(13.67)		(13.67)
REV		−0.007***		−0.007***		0.034***		0.034***
		(-4.70)		(-4.70)		(13.04)		(13.04)
MAX		−0.033***		−0.033***		−0.007**		−0.007**
		(-18.99)		(-18.99)		(-2.09)		(-2.09)
MIN		−0.056***		−0.056***		−0.007**		−0.007**
		(-32.13)		(-32.13)		(-2.18)		(-2.18)
SKEW		0.022***		0.022***		0.005**		0.005**
		(20.18)		(20.18)		(2.23)		(2.23)
COSKEW		0.028***		0.028***		−0.004**		−0.004**
		(27.20)		(27.20)		(-2.22)		(-2.22)
ISEW		0.008***		0.008***		−0.017***		−0.017***
		(7.42)		(7.42)		(-8.42)		(-8.42)
DBETA		0.062***		0.062***		−0.008***		−0.008***
		(52.49)		(52.49)		(-3.73)		(-3.73)
SENTIMENT		−0.160***		−0.160***		0.042***		0.042***
		(-135.77)		(-135.77)		(18.81)		(18.81)
Constant	10.450***	9.959***	10.398***	9.884***	0.368***	−0.039	0.424***	−0.044
	(174.42)	(214.78)	(175.83)	(215.66)	(4.75)	(-0.51)	(5.56)	(-0.58)
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES
# of obs.	404,994	398,070	404,994	398,070	287,100	282,658	287,100	282,658
Adj. R^2	0.666	0.803	0.666	0.803	0.222	0.241	0.222	0.241

Notes: This table presents the regression results analyzing the relationship between the individual investor attention (GBATT)/institutional investor attention (INSATT) and the COVID dummy/the confirming cases (CASES). The independent variables and dependent variables are measured in the same month. All continuous variables are winsorized at the top and bottom 0.5 %. All independent variables have been standardized. Test statistics and significance levels are computed using standard errors clustered by firm and month. Significance levels are indicated as follows: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. t-statistics are reported in parentheses.

Second, the severity of the pandemic further depresses retail attention but does not systematically lift institutional attention. Columns (3)–(4) replace the COVID dummy with CASES (log new cases and deaths). The coefficients on CASES for retail attention are negative and highly significant (−0.127, $t = -22.76$ with controls), indicating that months with more severe outbreaks crowd out retail monitoring even more. By contrast, columns (7)–(8) show that the estimates of CASES are economically small and statistically indistinguishable from zero once controls are included. These patterns indicate that while institutional attention is higher in COVID months on average, it is not monotonically increasing with monthly severity. Together, our observations suggest that institutional investors raised their baseline monitoring during the pandemic, but their marginal response to month-to-month fluctuations in severity was limited—consistent with higher capacity and more stable processes on the institutional side, and sharper bandwidth constraints on the retail side.

In order to examine whether the change in investor attention during the COVID period is associated with the degree of salience in stock returns, we also conduct a portfolio analysis, comparing investor attention in the portfolio with the most salient returns to that in the portfolio with non-salient returns. Specifically, on each trading day, we divide our sample of stocks into quintile portfolios based on the salience degree measure (i.e., *Simga*). We then calculate the average investor attention for each of the five portfolios on the following day to gauge how much attention these portfolios attract. We repeat this analysis separately for observations within the COVID period and the non-COVID period, then compare the results between the two periods.

In Table 6, which reports the results of the portfolio analysis, we observe a divergence in attention responses to the COVID-19 pandemic between individual investors and institutional investors. On the retail side, attention (*GBATT*) is uniformly lower during COVID across all salience levels, and the absolute contraction is largest exactly where retail investors normally concentrate their focus—the highest salient quintile. Specifically, the reduction in the pandemic period is 26,604 for quintile 5 and it is 20,527 for quintile 1. More importantly, the High–Low spread in *GBATT* narrows from 27,487 pre-COVID to 21,410 during COVID (DIFF $= -6077$, $t = -6.65$). This flattening of the salience gradient indicates that when the pandemic consumed public attention, retail monitoring becomes thinner and less selective: they scale back broadly and especially reduce the incremental attention they would otherwise devote to highly salient stocks.

Institutional behavior is the mirror image. Attention of institutional investor (*INSATT*) rises in every quintile during COVID, but the increase is disproportionately concentrated in the most salient group. Particularly, the increase during the COVID period is 1.07 for the most salient returns (quintile 5), whereas it is only 0.1 for non-salient returns (quintile 1). Consequently, the institutional High–Low spread steepens from 0.13 pre-COVID to 1.10 in COVID (DIFF $= 0.97$, $t = 2.79$). This shift toward salience is consistent with capacity and mandate: institutions appear to redeploy attention toward stocks where information frictions and pricing risk are likely higher when aggregate uncertainty is elevated.

Table 6 therefore demonstrates that, consistent with Hypothesis 1, individual investors' attention to salient returns was significantly reduced due to the distractions of the pandemic. By contrast, salient returns attracted increased attention from institutional investors during this period, supporting the argument that institutional investors heightened their focus on stock market activities due to the increased uncertainty brought by the pandemic. In a highly uncertain environment, salient returns in relevant stocks likely became more alert for institutional investors. Overall, the results presented in Table 6 align with Hypothesis 1.

In Figs. 1 and 2, we plot the dynamic change in the attention gap between the top quintile of stocks with salient returns and the bottom quintile with non-salient returns during our sample period. In Fig. 1, we observe that the attention gap for retail investors tends to fluctuate in close alignment with changes in stock prices, as indicated by its volatile pattern that coincides with stock market performance. This suggests that salient returns are effective in capturing the attention from retail investors in general. By contrast, such a pattern is not evident in the attention gap for institutional investors, indicating that their attention, in general, responds less immediately to short-term returns.[6]

Despite this difference, both retail investors and institutional investors experienced a clear structural break in the attention gap between salient and non-salient returns from January to March 2020. For retail investors, there was a structural shift to a lower attention gap after March 2020, while institutional investors saw a structural shift to a higher attention gap after January 2020. The evidence presented in Figs. 2 and 3 is consistent with the results reported in Table 6 and it also directly pinpoints the timing of the structural change as the beginning of the COVID-19 period. This observation validates the use of the COVID-19 pandemic as an external event that distracted attention, enabling this study of the relationship between investor attention and the salience effect (see Fig. 3).

5.3. The Salience Effect during the COVID and non-COVID period

To test Hypothesis 2, which posits that the salience effect is weakened during the COVID-19 period, we examine the strength of the salience effect in the COVID and non-COVID periods. First, at each month within each sub-period, we divide our sample into decile portfolios based on the salience theory value (*ST*), and we calculate the raw and abnormal return (i.e., the DGTW-adjusted return) for each portfolio in the following month. According to Cosemans and Frehen (2021), stocks with salient upsides are likely to attract excess demand, leading to overvaluation in the current month and consequently lower returns in the following month. Conversely, stocks with salient downsides tend to be undervalued and yield higher subsequent returns. Therefore, a significant negative relation between the *ST* value and future return indicates the presence of a salience effect. Within the framework of portfolio analysis, the magnitude of the salience effect is measured by the differential returns between the highest and lowest decile (i.e., High-Low).

Secondly, to evaluate the variation of the salience effect between the normal and COVID-19 periods, the differential returns between the top and bottom decile (i.e., High-Low) are compared across the two periods. A diminished salience effect during the

[6] The differential pattern between retail attention and institutional attention may also be attributed to the different ways in which attention is measured.

Table 6
Retail and Institutional Attention in Sigma-sorted portfolios during COVID and non-COVID Periods.

Quintile	GBATT			INSATT		
	Non-COVID	COVID	DIFF	Non-COVID	COVID	DIFF
Low Sigma	35027***	14500***	−20527***	0.14***	0.24***	0.10***
	(404.73)	*(257.41)*	*(-115.51)*	*(33.06)*	*(18.10)*	*(7.86)*
2	35718***	14920***	−20798***	0.15***	0.23***	0.08***
	(219.38)	*(259.76)*	*(-62.99)*	*(38.03)*	*(17.91)*	*(6.78)*
3	37477***	16321***	−21156***	0.17***	0.28***	0.11***
	(349.74)	*(254.84)*	*(-96.21)*	*(24.56)*	*(18.06)*	*(6.07)*
4	40964***	19477***	−21487***	0.19***	0.37***	0.18***
	(424.04)	*(222.48)*	*(-105.57)*	*(42.33)*	*(19.97)*	*(12.20)*
High Sigma	62514***	35910***	−26604***	0.27***	1.34*	1.07***
	(375.76)	*(247.54)*	*(-75.20)*	*(45.16)*	*(1.94)*	*(2.90)*
High-Low	27487***	21410***	−6077***	0.13***	1.10	0.97***
	(151.06)	*(138.31)*	*(-6.65)*	*(18.05)*	*(1.55)*	*(2.79)*

Notes: This table reports the attention level across quintile portfolios sorted on the daily level of salience in stock returns (Sigma) for both the COVID and non-COVID periods. GBATT represents the attention for individual investors and INSATT represents institutional attention. Sigma captures how the individual stock return departures the sample average on a specific day. The High-Low row quantifies the difference in investor attention between the most salient and the least salient quintiles. The differential column (DIFF) further elucidates the changes in the attention allocation between COVID and non-COVID period. To avoid the endogeneity issue, Sigma is measured on day t while the attention variables are measured on day t+1. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

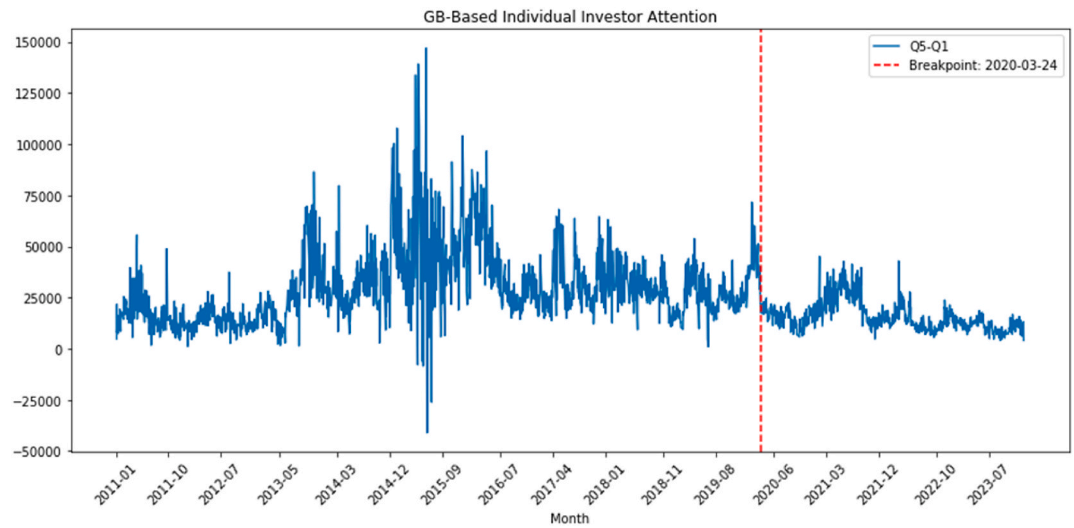

Fig. 2. The differential retail attention between salient and non-salient stock returns over time.

pandemic period supports Hypothesis 2, underscoring the impact of external attention shocks to individual investors on the salience effect.

In Table 7, we report the performance of the decile portfolios sorted on the salience theory value, *ST*. For robustness checks, we report the results for both the raw returns and the abnormal returns, and for both equally-weighted method and value-weighted method. The final row of Table 7 reports the performance of High-Low (i.e., the indicator of the salience effect). The non-COVID pattern is clear and consistent with salience theory: high-ST deciles (salient upsides likely overvalued) earn lower subsequent returns than low-ST deciles, yielding large negative High–Low spreads. For example, the High–Low spread is −1.94 ($t = -7.76$) over non-COVID period with equally weighted raw returns and is −2.29 ($t = -11.58$) with DGTW-adjusted returns. Using value-weighted returns gives a similar picture (RET: −1.31, t=−*3.36*; AR: −1.86, t=−*6.96*). During COVID, these spreads compress materially and often lose significance: the equally weighted raw return spread shrinks to −0.73 (t=−*0.96*), and the equally weighted AR spread eases to −1.42 (t=−*2.47*). In value-weighted terms, the salience effect nearly disappears (RET: 0.54, t=*0.51*; AR: −0.62, t=−*0.77*). Consistent with hypothesis 2, the differential High-Low between the non-COVID and the COVID is statistically significantly different from zero, indicating a meaningful attenuation of the salience effect in the pandemic period.

In addition, we employ a regression methodology to confirm the results from the aforementioned portfolio analysis. The regression analysis allows us to control a wider range of return-influencing factors than those that cannot be captured by the DGTW-adjusted abnormal return. The regression model is specified as follows:

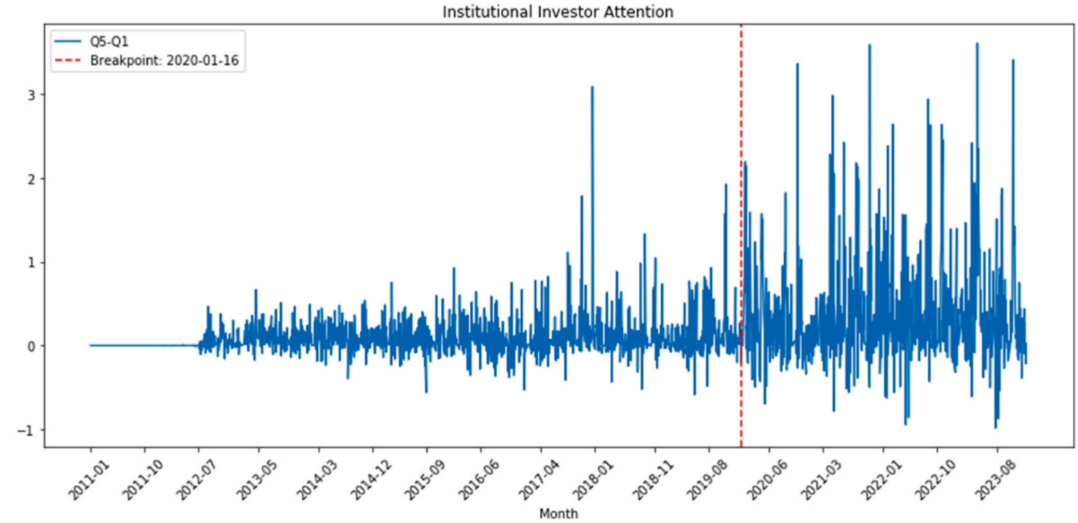

Fig. 3. The differential institutional attention between salient and non-salient stock returns over time.

$$AR_{i,t+1} = \beta_0 + \beta_1 ST_{i,t} + \beta_2 COVID_t + \beta_3 (ST_{i,t} \times COVID_t) + \sum \gamma_j CONTROL_{i,j,t} + \mu_i + \tau_t + \varepsilon_{i,t}, \quad (7)$$

where $AR_{i,t+1}$ represents the DGTW-adjusted abnormal return over the next month. $ST_{i,t}$ denotes the salience theory measure, and $COVID_t$ is a dummy variable indicating the occurrence of the COVID-19 pandemic during month t. The interaction term ($ST_{i,t} \times COVID_t$) is the key variable assessing how the pandemic context alters the typical salience effect. $CONTROL_{i,t}$ represents the vector of control variables. The model also incorporates firm fixed effects (μ_i) and month fixed effects (τ_t).

In Table 8, we report the results for the regression model of Eq. (7). Across specifications, ST is strongly negative in normal times: −0.796 (*t*=*−45.95*) without controls in column 1, and −0.136 (*t*=*−5.09*) to −0.138 (*t*=*−4.33*) with controls in columns 2–3, confirming a robust salience effect in the non-COVID period, whereby stocks with more salient upsides tend to be overpriced and thus earn lower subsequent abnormal returns. Crucially, the interaction $ST_{i,t} \times COVID_t$ is positive and highly significant in all COVID-dummy specifications, i.e., 0.211 (*t*=*6.11*), 0.336 (*t*=*9.71*), and 0.317 (*t*=*7.79*) in columns (1)–(3), respectively. Quantitatively, the net slope with respect to ST during COVID is much less negative and is slightly positive in the fully controlled model (−0.138 + 0.317≈0.179 in col. 3), showing that the salience effect is largely neutralized and sometimes modestly reversed during the pandemic period.

Furthermore, replacing the dummy with monthly severity yields the same message. The significantly positive coefficients on the interaction term $ST_{i,t} \times CASES_t$ in columns (5) and (6) indicate that the severe the pandemic, the weaker the salience effect. This result is not only consistent with Hypothesis 2, but also in line with the evidence in Table 5, which shows that the severity of the pandemic is negatively associated with the level of retail attention in individual stocks.

5.4. The asymmetric impact of COVID on retail attention and Salience Effect

We support Hypothesis 3 with similar types of analyses that test Hypothesis 1 and Hypothesis 2, but by separating the positive salient returns and salient upsides (i.e., positive values of ST) from the negative salient returns and salient downsides (i.e., negative values of ST). Specifically, we calculate the differential retail attention between the positive salient returns and non-salient returns, and compare this value between the COVID and the non-COVID period. We also conduct the same analysis for the negative salient returns.

As shown in Table 9, retail attention (*GBATT*) falls in COVID for all bins, but the reduction is relatively larger for negative salient returns than for positive ones (−26,850 vs. −26,423). Consistently, the retail High–Low spread (Q5−Q1) declined more on the downside than on the upside. Specifically, for the positive salient return, the retail attention declined by 6324 during the pandemic, representing a 20 % reduction in its value during the non-COVID period. For the negative salient return, the reduction in this value is around 25 %. The greater reduction in retail attention for stocks with salient downsides is consistent with Hypothesis 3. As a comparison, in Table 9, we also report the change in institutional attention (*INSATT*) for the positive salient returns and negative salient returns in the COVID period. Again, we observe a very distinct behavior for the institutional investors. The increase in *INSATT* is heavily skewed toward positive salience: institutional High–Low spread amplifies sharply by 2.06 (*t*=*2.51*) on the upside, while is much smaller on the downside (0.09, *t*=*3.67*). In other words, during the pandemic institutions concentrated additional monitoring on salient winners much more than on salient losers.

Furthermore, Table 10 tests the difference in attenuation of the salience effect between return directions, we extend the regression analysis of Eq. (5) by splitting the *ST* measure into positive and negative components: ST^+ for salient upsides and ST^- for salient downsides. In particular, ST^+ takes the value of *ST* when it is positive, and zero otherwise, while ST^- takes the value of *ST* when it is negative, and zero otherwise. In Table 10, we report the results for such analysis. The coefficients on ST^+ and ST^- indicate the salience

Table 7
Salience Effect during COVID and non-COVID period.

Decile	Equally-Weighted Returns						Value-Weighted Returns					
	RET			AR			RET			AR		
	Non-COVID	COVID	DIFF	Non-COVID	COVID	DIFF	Non-COVID	COVID	DIFF	Non-COVID	COVID	DIFF
Low ST	1.31*	0.84	0.47	0.90***	0.10	0.80**	0.81	0.18	0.63	0.61***	−0.41	1.02***
	(1.66)	(0.75)	(0.27)	(6.23)	(0.36)	(2.40)	(1.17)	(0.17)	(0.41)	(3.57)	(-1.32)	(2.64)
2	1.32*	1.46	−0.14	0.91***	0.80***	0.11	0.69	0.84	−0.15	0.47***	0.50*	−0.03
	(1.79)	(1.38)	(-0.09)	(7.66)	(3.18)	(0.41)	(1.19)	(0.87)	(-0.11)	(3.96)	(1.79)	(-0.10)
3	1.22*	1.33	−0.11	0.79***	0.76***	0.03	0.51	0.55	−0.04	0.23**	0.32	−0.09
	(1.71)	(1.29)	(-0.06)	(7.62)	(3.15)	(0.12)	(0.94)	(0.70)	(-0.03)	(2.51)	(1.28)	(-0.40)
4	1.16*	1.29	−0.13	0.76***	0.79***	−0.03	0.37	0.53	−0.16	0.25**	0.33	−0.08
	(1.66)	(1.21)	(-0.08)	(8.51)	(3.73)	(-0.14)	(0.71)	(0.65)	(-0.15)	(2.16)	(1.61)	(-0.30)
5	0.98	1.38	−0.40	0.57***	0.73***	−0.16	0.39	0.54	−0.15	0.11	0.24	−0.13
	(1.41)	(1.29)	(-0.26)	(6.76)	(3.25)	(-0.77)	(0.71)	(0.60)	(-0.12)	(1.25)	(0.75)	(-0.52)
6	0.88	1.40	−0.52	0.45***	0.64***	−0.19	0.27	0.83	−0.56	0.08	0.10	−0.02
	(1.27)	(1.28)	(-0.33)	(6.22)	(3.29)	(-1.11)	(0.49)	(0.88)	(-0.47)	(0.90)	(0.42)	(-0.08)
7	0.69	1.46	−0.77	0.21***	0.58**	−0.37**	0.05	1.22	−1.17	−0.10	0.08	−0.18
	(0.99)	(1.37)	(-0.50)	(2.97)	(2.53)	(-2.02)	(0.09)	(1.31)	(-0.92)	(-0.94)	(0.31)	(-0.70)
8	0.47	1.07	−0.60	−0.07	0.05	−0.12	−0.15	0.96	−1.11	−0.43***	−0.29	−0.14
	(0.67)	(0.97)	(-0.38)	(-0.94)	(0.25)	(-0.66)	(-0.24)	(0.95)	(-0.81)	(-3.77)	(-1.02)	(-0.50)
9	0.32	1.50	−1.18	−0.31***	0.28	−0.59**	0.03	1.23	−1.20	−0.47***	−0.06	−0.41
	(0.45)	(1.26)	(-0.74)	(-3.13)	(1.21)	(-2.53)	(0.05)	(1.15)	(-0.86)	(-3.31)	(-0.21)	(-1.27)
High ST	−0.63	0.11	−0.74	−1.39***	−1.32***	−0.07	−0.50	0.72	−1.22	−1.25***	−1.03*	−0.22
	(-0.81)	(0.07)	(-0.42)	(-9.36)	(-2.79)	(-0.18)	(-0.67)	(0.52)	(-0.73)	(-6.06)	(-1.72)	(-0.42)
High-Low	−1.94***	−0.73	−1.21**	−2.29***	−1.42**	−0.87**	−1.31***	0.54	−1.85**	−1.86***	−0.62	−1.24**
	(-7.76)	(-0.96)	(-1.90)	(-11.58)	(-2.47)	(-1.74)	(-3.36)	(0.51)	(-1.93)	(-6.96)	(-0.77)	(-1.83)

Notes: This table presents the comparative analysis of the salience effect during the normal period and the COVID period. This table divide the sample into deciles based on the salience measure (ST), and analyzes both raw and DGTW-adjusted returns. The High-Low row quantifies the difference in returns between top and bottom ST deciles. The column DIFF further elucidates the changes in the salience effect between normal period and COVID period. In this test, the null hypothesis posits that the salience effect is weakened during the COVID period. Thus, the t-statistics for DIFF test in comparing the high-low differences between normal and COVID periods is reported for the hypothesized one-tailed test. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 8
The impact of COVID on salient effect.

	AR					
	(1)	(2)	(3)	(4)	(5)	(6)
ST	−0.796***	−0.136***	−0.138***	−0.744***	−0.058**	−0.063**
	(-45.95)	(-5.09)	(-4.33)	(-49.42)	(-2.29)	(-2.09)
COVID	−0.998***	0.519*	2.897***			
	(-3.52)	(1.79)	(8.72)			
ST×COVID	0.211***	0.336***	0.317***			
	(6.11)	(9.71)	(7.79)			
CASES				−0.066	0.453***	1.064***
				(-0.72)	(4.81)	(9.75)
ST×CASES				0.012	0.065***	0.058***
				(0.81)	(4.46)	(3.42)
ME		−1.138***	−1.150***		−1.138***	−1.149***
		(-29.16)	(-23.21)		(-29.17)	(-23.19)
BM		0.353***	0.433***		0.351***	0.433***
		(11.92)	(11.39)		(11.86)	(11.37)
MOM		−0.463***	−0.455***		−0.462***	−0.454***
		(-22.03)	(-18.12)		(-21.98)	(-18.08)
ILLIQ		0.270***	0.237***		0.268***	0.234***
		(13.17)	(9.31)		(13.08)	(9.21)
BETA		0.176***	0.157***		0.175***	0.156***
		(9.35)	(7.04)		(9.29)	(6.99)
IVOL		−1.095***	−0.881***		−1.096***	−0.880***
		(-31.80)	(-20.61)		(-31.80)	(-20.60)
REV		−0.842***	−0.867***		−0.836***	−0.861***
		(-32.34)	(-28.05)		(-32.11)	(-27.86)
MAX		0.461***	0.469***		0.458***	0.467***
		(14.04)	(12.03)		(13.94)	(11.97)
MIN		−0.283***	−0.296***		−0.285***	−0.298***
		(-9.19)	(-8.06)		(-9.27)	(-8.11)
SKEW		−0.154***	−0.125***		−0.154***	−0.125***
		(-8.37)	(-5.33)		(-8.34)	(-5.33)
COSKEW		−0.044**	−0.035*		−0.043**	−0.034
		(-2.50)	(-1.66)		(-2.46)	(-1.61)
ISKEW		−0.048***	−0.099***		−0.050***	−0.100***
		(-2.71)	(-4.49)		(-2.80)	(-4.56)
DBETA		−0.101***	−0.091***		−0.098***	−0.088***
		(-5.10)	(-3.81)		(-4.96)	(-3.70)
SENTIMENT		0.181***	0.092***		0.182***	0.092***
		(9.11)	(3.72)		(9.14)	(3.74)
GBATT			−0.639***			−0.643***
			(-15.50)			(-15.58)
INSATT			0.034*			0.034*
			(1.68)			(1.67)
Constant	−0.417	1.750**	0.003	−0.446	2.030***	0.662
	(-0.53)	(2.23)	(0.00)	(-0.58)	(2.62)	(0.80)
Firm FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
# of obs.	398,070	398,070	398,070	398,070	398,070	398,070
Adj. R^2	0.003	0.023	0.024	0.003	0.023	0.024

Notes: This table presents the regression results analyzing the impact of COVID on the salience effect. COVID is a time dummy which equals to 1 for COVID period and 0 otherwise. CASES represents the newly-confirmed COVID cases and deaths in the month. All continuous independent variables have been standardized. Test statistics and significance levels are computed using standard errors clustered by firm and month. Significance levels are indicated as follows: ***p < 0.01, **p < 0.05, *p < 0.10. t-statistics are reported in parentheses.

effect during the non-COVID period. The significantly negative coefficients on ST^{+} in all columns of Table 10 suggest that the salience effect is quite robust for stocks with salient upsides in the non-COVID period. However, for stocks with salient downsides, the magnitude of the salience effect is much smaller and even statistically insignificant in columns (5) and (6). This is consistent with our expectation. Given the short-sale constraints in China, the salience bias is likely to cause less undervaluation of the stocks with salient downsides.

The interaction terms reveal how this asymmetry evolves during COVID. For $ST^{-} \times COVID$, the corresponding coefficients are 0.562 ($t=8.29$), 0.417 ($t=6.14$), and 0.336 ($t=4.18$) across columns 1 to 3, all highly significant. For $ST^{+} \times COVID$, the coefficients are 0.012 ($t=0.21$), 0.283 ($t=5.09$), and 0.307 ($t=4.66$), indicating effects that are smaller in magnitude and not uniformly significant. The difference between these two interaction effects indicates that the pandemic weakened the salience effect much more for downside salience than for upside salience.

A similar pattern appears when substituting the COVID dummy with monthly severity (CASES). The coefficient on $ST^{-} \times CASES$

Table 9
Retail and Institutional Attention in Positive and Negative Salient Returns during COVID and non-COVID Periods.

		GBATT			INSATT		
		Non-COVID	COVID	DIFF	Non-COVID	COVID	DIFF
Sigma_Q1 (non salient returns)		35025***	14499***	−20526***	0.14***	0.24***	0.10***
		(404.95)	(257.58)	(-115.59)	(33.05)	(18.21)	(8.02)
Sigma_Q5 (salient returns)	Positive	64482***	38059***	−26423***	0.28***	2.44	2.16***
		(275.78)	(180.50)	(-54.49)	(35.03)	(1.62)	(2.67)
	Negative	60379***	33529***	−26850***	0.25***	0.44***	0.19***
		(256.20)	(170.90)	(-52.10)	(28.81)	(16.37)	(6.72)
Q5-Q1	Positive	29457***	23560***	−5897***	0.14***	2.20*	2.06**
		(150.25)	(137.37)	(-5.51)	(17.07)	(1.91)	(2.51)
	Negative	25354***	19030***	−6324***	0.11***	0.20***	0.09***
		(122.17)	(121.27)	(-5.14)	(14.27)	(7.72)	(3.67)

Notes: This table presents the comparative analysis of the individual (GBATT) and institutional (INSATT) investor attention level during the COVID and non-COVID period for stocks with non-salient returns, positive salient returns and negative salient returns. The sample is segmented into quintiles based on the daily return salience of stocks (Sigma). The highest Sigma quintile is further divided into positive and negative groups. The Q5-Q1 row quantifies the difference in investor attention between the most salient and the least salient quintiles. The differential column (DIFF) further elucidates the changes in the attention allocation between normal and COVID periods. In this test, Sigma is measured on day t, while the attention variables are measured on day t+1. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

remains strongly positive and significant across columns (5)–(6), whereas $ST^{+} \times CASES$ is insignificant. This observation suggests that the stronger the intensity of pandemic, the greater the erosion of the downside salience effect, whereas the upside salience–return relation remains relatively stable. Together, these findings provide direct regression evidence for Hypothesis 3: COVID-19 attenuated the salience effect asymmetrically, erasing it primarily on the downside where retail attention was most diminished. In other words, when attention became a scarce resource, the behavioral component of downside salience largely disappeared, while upside salience persisted, mirroring the asymmetric shifts in attention observed earlier in Table 9.

6. Robustness Tests

We have conducted a range of additional tests to confirm the robustness of our conclusions. Firstly, we also used the Baidu search frequency as an alternative measure of the retail attention in our empirical testing of Hypothesis 1. We find that retail investors' search activities on Baidu.com for company information were significantly less frequent during the COVID period. Further, such reduction in Baidu search frequency is more pronounced for salient stock returns than non-salient returns. The results for this robustness check are reported in Appendix Tables A1 to A2.

Secondly, the sample period for our study covers a significant market crash, characterized by the heightened investor attention as well as stock price bubbles that eventually burst. We examine whether our conclusions, especially Hypothesis 1, are influenced by this market crash. Following Chen and Gong (2019), we define this abnormal period of the market as spanning from June 2015 to September 2016, and we find that all of our conclusions hold when we exclude data during this period from our analysis. The results for this robustness check are reported in Appendix Tables A3 to A7.

Thirdly, in Fig. 1, we can see that, the behavioral change in retail attention persisted after the COVID period. The retail attention has still not recovered to its pre-COVID level in 2023. This could be caused by several possibilities: 1) the pandemic may have caused people to reassess their personal priorities, with greater focus on health and safety issues than on investment activities. This may have led to less attention to the stock market even as life returns to normal; 2) The world post pandemic is still filled with events that could distract investors from investment activities. The geopolitical tensions between nations (e.g., Russia-Ukraine war), the shortage in energy and spikes in energy prices, the ever more frequent natural disasters, and the breakthrough in AI technologies could all contribute to the prolonged weakening of attention to the stock market. We conducted further analysis by merging the post-COVID period with the COVID period, and comparing the salience effect between pre-pandemic and post-pandemic periods. We find that all three hypotheses hold. This suggests that our analysis and conclusions do not depend on the nature of the events that distracted investors' attention, i.e., whether they are related to COVID or not. The results for this robustness check are reported in Appendix Tables A8 to A12.

Fourthly, to address the concern that China formally exited zero-COVID in December 2022, we re-estimate main tests by extending the COVID window through December 2022 (instead of our baseline cutoff in May 2022, which aligns with the period of strictly enforced zero-COVID and mandated high-frequency case disclosures). Results are qualitatively unchanged. Retail attention (*GBATT*) remains significantly lower and institutional attention (*INSATT*) remains higher in the COVID period (Appendix A13–A14). The salience effect continues to attenuate during COVID in regression analyses, with $ST \times CASES$ positive and significant (Appendix A15). Moreover, the drop in retail attention is relatively larger for negative salient returns (Appendix A16), and the attenuation in salience effect is stronger on the downside (i.e., $ST^{-} \times COVID > ST^{+} \times COVID$ as in Appendix A17).

Table 10
The impact of COVID on salient effect in stocks with salient upsides and downsides.

	AR					
	(1)	(2)	(3)	(4)	(5)	(6)
ST^+	−1.254***	−0.202***	−0.183***	−1.239***	−0.130***	−0.102**
	(-44.46)	(-5.18)	(-3.95)	(-50.46)	(-3.56)	(-2.37)
ST^-	−0.242***	−0.084**	−0.099**	−0.116***	0.010	−0.023
	(-7.56)	(-2.25)	(-2.20)	(-4.10)	(0.30)	(-0.56)
COVID	−0.738**	0.564*	2.900***			
	(-2.58)	(1.93)	(8.64)			
ST^+ ×COVID	0.012	0.283***	0.307***			
	(0.21)	(5.09)	(4.66)			
ST^- ×COVID	0.562***	0.417***	0.336***			
	(8.29)	(6.14)	(4.18)			
CASES				0.010	0.497***	1.112***
				(0.11)	(5.22)	(10.09)
ST^+ ×CASES				−0.101***	0.006	−0.007
				(-4.44)	(0.24)	(-0.26)
ST^- ×CASES				0.223***	0.153***	0.154***
				(7.73)	(5.31)	(4.51)
ME		−1.136***	−1.149***		−1.134***	−1.145***
		(-29.09)	(-23.19)		(-29.06)	(-23.11)
BM		0.353***	0.433***		0.349***	0.430***
		(11.90)	(11.39)		(11.78)	(11.30)
MOM		−0.463***	−0.455***		−0.461***	−0.453***
		(-22.04)	(18.13)		(-21.96)	(-18.05)
ILLIQ		0.270***	0.237***		0.269***	0.235***
		(13.20)	(9.33)		(13.12)	(9.24)
BETA		0.181***	0.161***		0.180***	0.159***
		(9.60)	(7.16)		(9.52)	(7.09)
IVOL		−1.072***	−0.867***		−1.071***	−0.866***
		(-30.34)	(-19.89)		(-30.32)	(-19.86)
REV		−0.835***	−0.863***		−0.829***	−0.857***
		(-31.97)	(-27.82)		(-31.76)	(-27.63)
MAX		0.460***	0.468***		0.455***	0.464***
		(14.00)	(12.01)		(13.86)	(11.89)
MIN		−0.290***	−0.300***		−0.292***	−0.303***
		(-9.39)	(-8.15)		(-9.46)	(-8.21)
SKEW		−0.153***	−0.124***		−0.153***	−0.124***
		(-8.29)	(-5.30)		(-8.28)	(-5.31)
COSKEW		−0.044**	−0.035*		−0.043**	−0.033
		(-2.52)	(-1.67)		(-2.45)	(-1.59)
ISKEW		−0.048***	−0.099***		−0.049***	−0.100***
		(-2.69)	(-4.48)		(-2.77)	(-4.53)
DBETA		−0.101***	−0.091***		−0.098***	−0.088***
		(-5.09)	(-3.81)		(-4.96)	(-3.71)
SENTIMENT		0.178***	0.090***		0.178***	0.090***
		(8.95)	(3.65)		(8.96)	(3.64)
GBATT			−0.637***			−0.640***
			(-15.44)			(-15.50)
INSATT			0.035*			0.034*
			(1.69)			(1.68)
Constant	−0.14	1.792**	0.038	−0.147	2.076***	0.68
	(-0.18)	(2.29)	(0.05)	(-0.19)	(2.68)	(0.82)
Firm FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
# of obs.	398,070	398,070	398,070	398,070	398,070	398,070
Adj. R^2	0.005	0.023	0.024	0.005	0.023	0.240

Notes: This table presents the regression results exploring the differential impact of COVID-19 on the salience effect for stocks associated with salient upwards and salient downwards. The independent variables are measured in the current month, while the dependent variable is observed in the subsequent month. COVID is a time dummy which equals to 1 for COVID-19 period and 0 otherwise. CASES is the number of newly-confirmed COVID-19 cases and deaths at each month. The classification of ST^+ and ST^- depends on signs of salience measure (ST). All continuous independent variables have been standardized. Test statistics and significance levels are computed using robust standard errors that are clustered by firm and month. Significance levels are indicated as follows: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. t-statistics are reported in parentheses.

7. Conclusions

This study leverages COVID-19 as a plausibly exogenous shock to investor attention to identify how attention affects the salience effect. Our central findings are threefold. First, we find that retail investor attention to stock-specific salient returns declined markedly during COVID-19, with the attenuation particularly pronounced for negative salient returns. By contrast, institutional investors increased their attention, possibly due to the elevated uncertainty in economic conditions during this period. The more salient the returns are, the higher the institutional attention during the pandemic. Second, the aggregate salience effect weakened in the pandemic period, indicating that diminished retail attention curtails the translation of return salience into salience-distorted prices. Third, this attenuation exhibits an asymmetric pattern: the weakening effect is stronger on the downside than the upside because a depressed backdrop makes negative signals unsurprising, less prominent, and thus attracts even less attention. Taken together, these results indicate investor attention plays a key role in driving the salience effect.

Our study advances salience theory by shifting an assumed linkage to a tested mechanism. We show that the impact of salience on prices is conditional on the attention available to market participant. We provide the causal link between attention and salience. We also clarify investor heterogeneity in driving and dampening salience. The drop in retail attention coincides with a weaker salience effect, implying that retail investors are likely to be salient thinkers who drive the mispricing of relevant stocks. In contrast, the rise in institutional attention during the pandemic is associated with mitigation of salience-driven distortions, particularly where downside signals would otherwise persist. This evidence highlights the role of institutional investors in stabilizing the financial markets when the market faces great uncertainties. Thus, one of implications of our study is that regulatory bodies from emerging markets can improve market efficiency by encouraging institutional investors to hold and trade stocks.

As emerging financial markets may share some characteristics with Chin including high retail participation, tighter short-sale frictions, and stringent COVID controls, the implication of our study can go beyond the context of China. For example, exogenous attention scarcity weakens salience-driven mispricing, especially on the downside, where signals lack novelty and trading is more constrained. We therefore expect that other emerging financial markets may learn from our China case.

From the theoretical point of view, our study suggests that COVID-19 is not only a world health crisis but also an unexpected event that can influence the allocation of cognitive resources and therefore the decision-making process. In this sense, our study is consistent with prior studies, which show that terrorist attacks or natural disasters can divert investor attention away from financial markets, leading to reduced trading activity and a slow speed of information processing (Levy & Galili, 2006; Wang et al., 2024).

Overall, our analyses have largely improved our understanding of the complex relationship between investor attention and the salience effect. By establishing attention as the conditioning resource, the study helps explain variation in salience effects and offers a framework for anticipating when, and for whom, salient signals will move markets. It also highlights the significant impact of external shocks on investors' behavior, and how individual and institutional investors may behave differently.

Author statement

We appreciate your consideration of this article for publication in the International Review of Economics & Finance. We confirm that this manuscript is original, has not been previously published, and is not currently under consideration for publication elsewhere. All authors have reviewed and approved the manuscript, and we have no conflicts of interest to disclose.

Appendix A

Appendix Table A1
The Impact of COVID on Baidu Index-based Individual Investor Attention

	BIATT	
	(1)	(2)
COVID	−0.413***	
	(-25.91)	
CASES		−0.080***
		(-14.88)
ME	0.272***	0.272***
	(115.07)	(115.07)
BM	0.020***	0.020***
	(11.14)	(11.14)
MOM	0.001	0.001
	(0.45)	(0.45)
ILLIQ	−0.038***	−0.038***
	(-31.68)	(-31.68)
BETA	0.016***	0.016***
	(14.53)	(14.53)

(continued on next page)

Appendix Table A1 (*continued*)

	BIATT	
	(1)	(2)
IVOL	0.141***	0.141***
	(69.14)	(69.14)
REV	0.012***	0.012***
	(8.86)	(8.86)
MAX	−0.001	−0.001
	(-0.72)	(-0.72)
MIN	−0.018***	−0.018***
	(-10.27)	(-10.27)
SKEW	−0.003**	−0.003**
	(-2.47)	(-2.47)
COSKEW	0.024***	0.024***
	(23.63)	(23.63)
ISEW	0.016***	0.016***
	(14.56)	(14.56)
DBETA	0.042***	0.042***
	(35.26)	(35.26)
SENTIMENT	−0.052***	−0.052***
	(-43.52)	(-43.52)
Constant	8.398***	8.349***
	(181.92)	(182.61)
Firm FE	YES	YES
Month FE	YES	YES
# of obs.	368,237	368,237
Adj. R^2	0.881	0.881

Notes: This table presents the regression results analyzing the relationship between the Baidu Index-based individual investor attention (BIATT) and the COVID dummy/the confirming cases (CASES). The independent variables and dependent variables are measured in the same month. All continuous variables are winsorized at the top and bottom 0.5 %. All independent variables have been standardized. Test statistics and significance levels are computed using standard errors clustered by firm and month. Significance levels are indicated as follows: ***p $<$ 0.01, **p $<$ 0.05, *p $<$ 0.10. t-statistics are reported in parentheses.

Appendix Table A2
Baidu Index-based Retail Attention in Sigma-sorted portfolios during COVID and non-COVID Periods

Quintile	BIATT		
	Non-COVID	COVID	DIFF
Low Sigma	526***	288***	−238***
	(802.87)	(511.62)	(-165.76)
2	529***	290***	−239***
	(797.82)	(509.81)	(-164.61)
3	540***	301***	−239***
	(830.64)	(516.60)	(-167.72)
4	567***	323***	−244***
	(803.58)	(492.44)	(-156.47)
High Sigma	699***	407***	−292***
	(687.56)	(517.38)	(-131.23)
High-Low	173***	119***	−54***
	(146.83)	(123.73)	(-8.40)

Notes: This table reports the attention level across quintile portfolios sorted on the daily level of salience in stock returns (Sigma) for both the COVID and non-COVID periods. BIATT represents the attention for individual investors based on Baidu Index. Sigma captures how the individual stock return departures the sample average on a specific day. The High-Low row quantifies the difference in investor attention between the most salient and the least salient quintiles. The differential column (DIFF) further elucidates the changes in the attention allocation between COVID and non-COVID period. To avoid the endogeneity issue, Sigma is measured on day t while the attention variables are measured on day t+1. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Appendix Table A3
The Impact of COVID on Individual and Institutional Investor Attention (Excluding Market Crash Period)

	GBATT		INSATT	
	(1)	(2)	(3)	(4)
COVID	−0.601***		0.332***	
	(-35.01)		(10.76)	
CASES		−0.143***		−0.009
		(-24.80)		(-0.83)
ME	0.311***	0.311***	0.222***	0.222***
	(126.07)	(126.07)	(46.32)	(46.32)
BM	0.019***	0.019***	−0.018***	−0.018***
	(10.06)	(10.06)	(-4.87)	(-4.87)
MOM	−0.021***	−0.021***	0.031***	0.031***
	(-16.17)	(-16.17)	(12.95)	(12.95)
ILLIQ	−0.127***	−0.127***	0.001	0.001
	(-95.52)	(-95.52)	(0.47)	(0.47)
BETA	0.041***	0.041***	0.013***	0.013***
	(34.37)	(34.37)	(5.92)	(5.92)
IVOL	0.449***	0.449***	0.049***	0.049***
	(197.12)	(197.12)	(11.59)	(11.59)
REV	−0.008***	−0.008***	0.032***	0.032***
	(-5.68)	(-5.68)	(11.94)	(11.94)
MAX	−0.062***	−0.062***	−0.007**	−0.007**
	(-33.24)	(-33.24)	(-2.12)	(-2.12)
MIN	−0.030***	−0.030***	−0.008**	−0.008**
	(-16.38)	(-16.38)	(-2.47)	(-2.47)
SKEW	0.016***	0.016***	0.005**	0.005**
	(14.13)	(14.13)	(2.29)	(2.29)
COSKEW	0.027***	0.027***	−0.007***	−0.007***
	(24.03)	(24.03)	(-3.15)	(-3.15)
ISEW	0.014***	0.014***	−0.018***	−0.018***
	(12.56)	(12.56)	(-8.26)	(-8.26)
DBETA	0.062***	0.062***	−0.008***	−0.008***
	(50.06)	(50.06)	(-3.31)	(-3.31)
SENTIMENT	−0.157***	−0.157***	0.041***	0.041***
	(-130.52)	(-130.52)	(18.25)	(18.25)
Constant	9.983***	9.893***	−0.053	−0.059
	(204.04)	(204.49)	(-0.65)	(-0.73)
Firm FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
# of obs.	360072	360072	253750	253750
Adj. R^2	0.774	0.774	0.245	0.245

Notes: This table presents the regression results analyzing the relationship between the individual investor attention (GBATT)/ institutional investor attention (INSATT) and the COVID dummy/the confirming cases (CASES), with the analysis excluding the market crash period (defined as June 2015 to September 2016, according to Chen & Gong, 2019). The independent variables and dependent variables are measured in the same month. All continuous variables are winsorized at the top and bottom 0.5 %. All independent variables have been standardized. Test statistics and significance levels are computed using standard errors clustered by firm and month. Significance levels are indicated as follows: ***p < 0.01, **p < 0.05, *p < 0.10. t-statistics are reported in parentheses.

Appendix Table A4
Retail and Institutional Attention in Sigma-sorted portfolios during COVID and non-COVID Periods (Excluding Market Crash Period)

Quintile	GBATT			INSATT		
	Non-COVID	COVID	DIFF	Non-COVID	COVID	DIFF
Low Sigma	23886***	12891***	−10995***	0.13***	0.18***	0.05***
	(390.19)	(292.14)	(-90.81)	(23.27)	(19.61)	(3.48)
2	24790***	13509***	−11281***	0.13***	0.80	0.67**
	(302.84)	(296.39)	(-70.44)	(37.74)	(1.42)	(2.11)
3	26671***	15254***	−11417***	0.14***	0.24***	0.10***
	(411.02)	(248.79)	(-87.08)	(37.15)	(18.99)	(8.57)
4	31469***	19176***	−12293***	0.17***	0.33***	0.16***
	(86.23)	(306.92)	(-17.20)	(38.29)	(11.90)	(8.19)

(*continued on next page*)

Appendix Table A4 (*continued*)

Quintile	GBATT			INSATT		
	Non-COVID	COVID	DIFF	Non-COVID	COVID	DIFF
High Sigma	56986***	39673***	−17313***	0.29***	0.63***	0.34***
	(380.37)	(289.85)	(-56.78)	(42.86)	(28.43)	(17.04)
High-Low	33100***	26782***	−6318***	0.16***	0.45***	0.29***
	(208.09)	(186.56)	(-6.82)	(18.45)	(18.39)	(10.82)

Notes: This table reports the attention level across quintile portfolios sorted on the daily level of salience in stock returns (Sigma) for both the COVID and non-COVID periods, with the analysis excluding the market crash period (defined as June 2015 to September 2016, according to Chen & Gong, 2019). GBATT represents the attention for individual investors and INSATT represents institutional attention. Sigma captures how the individual stock return departures the sample average on a specific day. The High-Low row quantifies the difference in investor attention between the most salient and the least salient quintiles. The differential column (DIFF) further elucidates the changes in the attention allocation between COVID and non-COVID period. To avoid the endogeneity issue, Sigma is measured on day t while the attention variables are measured on day t+1. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Appendix Table A5
The Impact of COVID on Salient Effect (Excluding Market Crash Period)

	AR			
	(1)	(2)	(3)	(4)
ST	−0.157***	−0.156***	−0.071***	−0.076**
	(-5.35)	(-4.46)	(-2.58)	(-2.30)
COVID	0.433	2.854***		
	(1.51)	(8.65)		
ST×COVID	0.318***	0.290***		
	(9.20)	(7.13)		
CASES			0.446***	1.090***
			(4.63)	(9.73)
ST×CASES			0.057***	0.046***
			(3.80)	(2.61)
ME	−1.167***	−1.181***	−1.167***	−1.179***
	(-28.42)	(-22.52)	(-28.43)	(-22.49)
BM	0.337***	0.432***	0.335***	0.432***
	(10.90)	(10.80)	(10.86)	(10.79)
MOM	−0.529***	−0.529***	−0.528***	−0.528***
	(-24.91)	(-20.73)	(-24.86)	(-20.69)
ILLIQ	0.278***	0.225***	0.277***	0.222***
	(12.59)	(8.02)	(12.53)	(7.93)
BETA	0.189***	0.171***	0.188***	0.170***
	(9.63)	(7.33)	(9.58)	(7.29)
IVOL	−1.030***	−0.794***	−1.029***	−0.791***
	(-27.11)	(-16.65)	(-27.07)	(-16.60)
REV	−0.737***	−0.757***	−0.731***	−0.750***
	(-27.48)	(-23.62)	(-27.25)	(-23.43)
MAX	0.397***	0.392***	0.389***	0.385***
	(11.33)	(9.38)	(11.09)	(9.19)
MIN	−0.262***	−0.274***	−0.267***	−0.278***
	(-8.29)	(-7.22)	(-8.43)	(-7.34)
SKEW	−0.131***	−0.094***	−0.131***	−0.095***
	(-6.88)	(-3.85)	(-6.90)	(-3.89)
COSKEW	−0.022	−0.005	−0.021	−0.004
	(-1.18)	(-0.25)	(-1.12)	(-0.18)
ISKEW	−0.040**	−0.093***	−0.042**	−0.095***
	(-2.15)	(-4.03)	(-2.23)	(-4.09)
DBETA	−0.073***	−0.061**	−0.070***	−0.059**
	(-3.52)	(-2.46)	(-3.39)	(-2.36)
SENTIMENT	0.166***	0.082***	0.166***	0.082***
	(8.29)	(3.31)	(8.31)	(3.30)
GBATT		−0.620***		−0.624***
		(-15.39)		(-15.51)
INSATT		0.037*		0.037*
		(1.74)		(1.72)
Constant	2.236***	0.532	2.528***	1.257
	(2.75)	(0.61)	(3.14)	(1.46)

(*continued on next page*)

Appendix Table A5 (*continued*)

	AR			
	(1)	(2)	(3)	(4)
Firm FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
# of obs.	360,072	253,750	360,072	253,750
Adj. R^2	0.023	0.024	0.022	0.023

Notes: This table presents the regression results analyzing the impact of COVID on the salience effect, with the analysis excluding the market crash period (defined as June 2015 to September 2016, according to Chen & Gong, 2019). COVID is a time dummy which equals to 1 for COVID period and 0 otherwise. CASES represents the newly-confirmed COVID cases and deaths in the month. All continuous independent variables have been standardized. Test statistics and significance levels are computed using standard errors clustered by firm and month. Significance levels are indicated as follows: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. t-statistics are reported in parentheses.

Appendix Table A6

Retail and Institutional Attention in Positive and Negative Salient Returns during COVID and non-COVID Periods (Excluding Market Crash Period)

		GBATT			INSATT		
		Non-COVID	COVID	DIFF	Non-COVID	COVID	DIFF
Sigma_Q1 (non salient returns)		26311***	14499***	−11812***	0.14***	0.24***	0.10***
		(335.93)	(257.58)	(-76.21)	(30.12)	(18.21)	(7.56)
Sigma_Q5 (salient returns)	Positive	53223***	38059***	−15164***	0.29***	2.44	2.15**
		(226.47)	(180.50)	(-31.96)	(32.16)	(1.62)	(2.49)
	Negative	48908***	33529***	−15379***	0.26***	0.44***	0.18***
		(229.79)	(170.90)	(-34.41)	(26.93)	(16.37)	(6.07)
Q5-Q1	Positive	26912***	23560***	−3352***	0.15***	2.20*	2.05**
		(137.66)	(137.37)	(-3.44)	(16.01)	(1.91)	(2.34)
	Negative	22597***	19030***	−3567***	0.12***	0.20***	0.08***
		(123.06)	(121.27)	(-3.26)	(13.66)	(7.72)	(3.22)

Notes: This table presents the comparative analysis of the individual (GBATT) and institutional (INSATT) investor attention level during the COVID and non-COVID period for stocks with non-salient returns, positive salient returns and negative salient returns. The analysis excludes the market crash period (defined as June 2015 to September 2016, according to Chen & Gong, 2019). The sample is segmented into quintiles based on the daily return salience of stocks (Sigma). The highest Sigma quintile is further divided into positive and negative groups. The Q5-Q1 row quantifies the difference in investor attention between the most salient and the least salient quintiles. The differential column (DIFF) further elucidates the changes in the attention allocation between normal and COVID periods. In this test, Sigma is measured on day t, while the attention variables are measured on day t+1. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Appendix Table A7

The Impact of COVID on Salient Effect in Stocks with Salient Upsides and Downsides (Excluding Market Crash Period)

	AR			
	(1)	(2)	(3)	(4)
ST^+	−0.224***	−0.210***	−0.140***	−0.117**
	(-5.25)	(-4.11)	(-3.56)	(-2.48)
ST^-	−0.107***	−0.113**	−0.005	−0.032
	(-2.68)	(-2.33)	(-0.12)	(-0.74)
COVID	0.477*	2.857***		
	(1.65)	(8.56)		
ST^+ ×COVID	0.265***	0.280***		
	(4.77)	(4.25)		
ST^- ×COVID	0.402***	0.313***		
	(5.87)	(3.86)		
CASES			0.493***	1.142***
			(5.07)	(10.08)
ST^+ ×CASES			−0.005	−0.024
			(-0.22)	(-0.84)
ST^- ×CASES			0.153***	0.151***
			(5.07)	(4.21)
ME	−1.165***	−1.180***	−1.163***	−1.174***
	(-28.35)	(-22.50)	(-28.31)	(-22.39)
BM	0.337***	0.432***	0.333***	0.430***
	(10.90)	(10.80)	(10.79)	(10.73)
MOM	−0.529***	−0.530***	−0.527***	−0.527***
	(-24.92)	(-20.74)	(-24.82)	(-20.63)
ILLIQ	0.279***	0.225***	0.278***	0.223***
	(12.61)	(8.02)	(12.57)	(7.98)

(continued on next page)

Appendix Table A7 (*continued*)

	AR			
	(1)	(2)	(3)	(4)
BETA	0.195***	0.175***	0.194***	0.174***
	(9.87)	(7.46)	(9.81)	(7.42)
IVOL	−1.005***	−0.777***	−1.002***	−0.773***
	(-25.82)	(-16.01)	(-25.75)	(-15.92)
REV	−0.730***	−0.751***	−0.724***	−0.746***
	(-27.08)	(-23.35)	(-26.89)	(-23.19)
MAX	0.396***	0.392***	0.385***	0.380***
	(11.30)	(9.37)	(10.98)	(9.08)
MIN	−0.267***	−0.278***	−0.270***	−0.281***
	(-8.43)	(-7.31)	(-8.53)	(-7.38)
SKEW	−0.130***	−0.093***	−0.130***	−0.094***
	(-6.80)	(-3.81)	(-6.85)	(-3.88)
COSKEW	−0.022	−0.006	−0.020	−0.004
	(-1.19)	(-0.26)	(-1.10)	(-0.16)
ISKEW	−0.040**	−0.093***	−0.041**	−0.094***
	(-2.14)	(-4.02)	(-2.20)	(-4.05)
DBETA	−0.073***	−0.061**	−0.070***	−0.059**
	(-3.51)	(-2.46)	(-3.40)	(-2.37)
SENTIMENT	0.163***	0.081***	0.163***	0.080***
	(8.13)	(3.23)	(8.13)	(3.20)
GBATT		−0.617***		−0.623***
		(-15.32)		(-15.46)
INSATT		0.037*		0.037*
		(1.75)		(1.74)
Constant	2.276***	0.570	2.568***	1.271
	(2.80)	(0.65)	(3.19)	(1.47)
Firm FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
# of obs.	360,072	253,750	360,072	253,750
Adj. R^2	0.023	0.024	0.022	0.023

Notes: This table presents the regression results exploring the differential impact of COVID-19 on the salience effect for stocks associated with salient upwards and salient downwards, with the analysis excluding the market crash period (defined as June 2015 to September 2016, according to Chen & Gong, 2019). The independent variables are measured in the current month, while the dependent variable is observed in the subsequent month. COVID is a time dummy which equals to 1 for COVID-19 period and 0 otherwise. CASES is the number of newly-confirmed COVID-19 cases and deaths at each month. The classification of ST^{+} and ST^{-} depends on signs of salience measure (ST). All continuous independent variables have been standardized. Test statistics and significance levels are computed using robust standard errors that are clustered by firm and month. Significance levels are indicated as follows: ***p < 0.01, **p < 0.05, *p < 0.10. t-statistics are reported in parentheses.

Appendix Table A8
The Impact of COVID on Individual and Institutional Investor Attention: Comparison between Pre-COVID and Post-COVID Periods

	GBATT	INSATT
	(1)	(2)
POST-COVID	−0.481***	0.482***
	(-23.89)	(13.03)
ME	0.306***	0.222***
	(132.67)	(49.32)
BM	0.014***	−0.018***
	(8.14)	(-5.06)
MOM	−0.015***	0.030***
	(-12.37)	(12.98)
ILLIQ	−0.109***	0.002
	(-90.22)	(0.92)
BETA	0.032***	0.013***
	(28.71)	(6.14)
IVOL	0.403***	0.051***
	(197.86)	(13.67)
REV	−0.007***	0.034***
	(-4.70)	(13.04)
MAX	−0.033***	−0.007**
	(-18.99)	(-2.09)
MIN	−0.056***	−0.007**
	(-32.13)	(-2.18)
SKEW	0.022***	0.005**

(*continued on next page*)

Appendix Table A8 (*continued*)

	GBATT	INSATT
	(1)	(2)
	(20.18)	(2.23)
COSKEW	0.028***	−0.004**
	(27.20)	(-2.22)
ISEW	0.008***	−0.017***
	(7.42)	(-8.42)
DBETA	0.062***	−0.008***
	(52.49)	(-3.73)
SENTIMENT	−0.160***	0.042***
	(-135.77)	(18.81)
Constant	9.959***	−0.039
	(214.78)	(-0.51)
Firm FE	YES	YES
Month FE	YES	YES
# of obs.	398,070	282,658
Adj. R^2	0.803	0.241

Notes: This table presents the regression results analyzing the relationship between individual investor attention (GBATT)/institutional investor attention (INSATT) and the post-COVID dummy. For observations from 2020 onwards, the post-COVID dummy is coded as 1, while data before 2020 is coded as 0. The independent variables and dependent variables are measured in the same month. All continuous variables are winsorized at the top and bottom 0.5 %. All independent variables have been standardized. Test statistics and significance levels are computed using standard errors clustered by firm and month. Significance levels are indicated as follows: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. t-statistics are reported in parentheses.

Appendix Table A9
Retail and Institutional Attention in Sigma-sorted portfolios during Pre-COVID and Post-COVID Periods

Quintile	GBATT			INSATT		
	Pre-COVID	Post-COVID	DIFF	Pre-COVID	Post-COVID	DIFF
Low Sigma	39911***	11718***	−28193***	0.10***	0.28***	0.18***
	(393.87)	(307.18)	(-196.85)	(28.93)	(25.92)	(18.52)
2	40687***	12056***	−28631***	0.10***	0.30***	0.20***
	(211.30)	(311.88)	(-106.63)	(34.42)	(27.97)	(21.58)
3	42666***	13103***	−29563***	0.11***	0.36***	0.25***
	(338.66)	(309.32)	(-166.67)	(35.22)	(19.81)	(16.99)
4	46559***	15479***	−31080***	0.13***	0.41***	0.28***
	(411.96)	(272.42)	(-190.69)	(36.23)	(30.75)	(24.44)
High Sigma	70211***	29220***	−40991***	0.18***	1.09***	0.91***
	(389.43)	(175.95)	(-145.63)	(38.20)	(2.75)	(3.02)
High-Low	30300***	17502***	−12798***	0.08***	0.81**	0.73**
	(150.58)	(103.17)	(-17.52)	(14.25)	(1.98)	(2.49)

Notes: This table reports the attention level across quintile portfolios sorted on the daily level of salience in stock returns (Sigma) for both the Pre-COVID and Post-COVID periods. The Pre-COVID period covers data before 2020, and the Post-COVID period includes data from 2020 onwards. GBATT represents the attention for individual investors and INSATT represents institutional attention. Sigma captures how the individual stock return departures the sample average on a specific day. The High-Low row quantifies the difference in investor attention between the most salient and the least salient quintiles. The differential column (DIFF) further elucidates the changes in the attention allocation between Post-COVID and Pre-COVID period. To avoid the endogeneity issue, Sigma is measured on day t while the attention variables are measured on day t+1. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Appendix Table A10
The Impact of COVID on Salient Effect: Comparison between Pre-COVID and Post-COVID Periods

	AR	
	(1)	(2)
ST	−0.148***	−0.150***
	(-5.36)	(-4.58)
POST-COVID	1.240***	3.019***
	(3.65)	(7.56)
ST×POST-COVID	0.278***	0.266***
	(8.83)	(7.19)

(*continued on next page*)

Appendix Table A10 (*continued*)

	AR	
	(1)	(2)
ME	−1.140***	−1.150***
	(-29.23)	(-23.23)
BM	0.356***	0.437***
	(12.02)	(11.48)
MOM	−0.461***	−0.453***
	(-21.95)	(-18.06)
ILLIQ	0.269***	0.236***
	(13.12)	(9.27)
BETA	0.173***	0.155***
	(9.22)	(6.96)
IVOL	−1.095***	−0.879***
	(-31.77)	(-20.56)
REV	−0.839***	−0.865***
	(-32.24)	(-27.98)
MAX	0.453***	0.462***
	(13.82)	(11.84)
MIN	−0.287***	−0.300***
	(-9.32)	(-8.15)
SKEW	−0.158***	−0.129***
	(-8.56)	(-5.50)
COSKEW	−0.043**	−0.034
	(-2.48)	(-1.63)
ISKEW	−0.049***	−0.099***
	(-2.73)	(-4.51)
DBETA	−0.101***	−0.091***
	(-5.11)	(-3.82)
SENTIMENT	0.180***	0.090***
	(9.07)	(3.66)
GBATT		−0.643***
		(-15.59)
INSATT		0.034*
		(1.68)
Constant	1.754**	0.005
	(2.24)	(0.01)
Firm FE	YES	YES
Month FE	YES	YES
# of obs.	398,070	282,658
Adj. R^2	0.023	0.024

Notes: This table presents the regression results analyzing the impact of COVID on the salience effect. Post-COVID is a time dummy which equals to 1 for observations from 2020 onwards and 0 otherwise. All continuous independent variables have been standardized. Test statistics and significance levels are computed using standard errors clustered by firm and month. Significance levels are indicated as follows: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. t-statistics are reported in parentheses.

Appendix Table A11

Retail and Institutional Attention in Positive and Negative Salient Returns during Pre-COVID and Post-COVID Periods

		GBATT			INSATT		
		Pre-COVID	Post-COVID	DIFF	Pre-COVID	Post-COVID	DIFF
Sigma_Q1 (non-salient returns)		39910***	11716***	−28194***	0.10***	0.28***	0.18***
		(394.09)	(307.41)	(-196.99)	(28.91)	(26.00)	(18.63)
Sigma_Q5 (salient returns)	Positive	72143***	31397***	−40746***	0.19***	1.75**	1.56**
		(304.63)	(107.68)	(-102.03)	(32.32)	(2.05)	(2.44)
	Negative	68112***	26928***	−41184***	0.17***	0.53***	0.36***
		(245.10)	(207.35)	(-104.59)	(22.42)	(24.62)	(17.75)

(*continued on next page*)

Appendix Table A11 (*continued*)

		GBATT			INSATT		
		Pre-COVID	Post-COVID	DIFF	Pre-COVID	Post-COVID	DIFF
Q5-Q1	Positive	32233***	19681***	−12552***	0.09***	1.47**	1.38**
		(152.31)	(91.09)	(-14.40)	(14.22)	(2.26)	(2.02)
	Negative	28202***	15212***	−12990***	0.07***	0.25***	0.18***
		(116.94)	(143.25)	(-12.68)	(10.57)	(12.06)	(8.82)

Notes: This table presents the comparative analysis of the individual (GBATT) and institutional (INSATT) investor attention level during the Pre-COVID and Post-COVID period for stocks with non-salient returns, positive salient returns and negative salient returns. The Pre-COVID period covers data before 2020, and the Post-COVID period includes data from 2020 onwards. The sample is segmented into quintiles based on the daily return salience of stocks (Sigma). The highest Sigma quintile is further divided into positive and negative groups. The Q5-Q1 row quantifies the difference in investor attention between the most salient and the least salient quintiles. The differential column (DIFF) further elucidates the changes in the attention allocation between Post-COVID and Pre-COVID periods. In this test, Sigma is measured on day t, while the attention variables are measured on day t+1. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Appendix Table A12
The Impact of COVID on Salient Effect in Stocks with Salient Upsides and Downsides: Comparison between Pre-COVID and Post-COVID Periods

	AR	
	(1)	(2)
ST^{+}	−0.202***	−0.181***
	(-4.98)	(-3.75)
ST^{-}	−0.108***	−0.128***
	(-2.76)	(-2.71)
POST-COVID	1.293***	3.055***
	(3.79)	(7.61)
ST^{+} ×POST-COVID	0.210***	0.219***
	(4.18)	(3.67)
ST^{-} ×POST-COVID	0.372***	0.332***
	(6.17)	(4.63)
ME	−1.137***	−1.149***
	(-29.13)	(-23.18)
BM	0.355***	0.436***
	(11.98)	(11.45)
MOM	−0.461***	−0.453***
	(-21.95)	(-18.06)
ILLIQ	0.270***	0.236***
	(13.16)	(9.29)
BETA	0.179***	0.158***
	(9.45)	(7.07)
IVOL	−1.071***	−0.865***
	(-30.31)	(-19.84)
REV	−0.832***	−0.860***
	(-31.88)	(-27.75)
MAX	0.452***	0.461***
	(13.78)	(11.81)
MIN	−0.294***	−0.304***
	(-9.54)	(-8.25)
SKEW	−0.157***	−0.128***
	(-8.50)	(-5.47)
COSKEW	−0.043**	−0.034
	(-2.49)	(-1.63)
ISKEW	−0.048***	−0.099***
	(-2.70)	(-4.50)
DBETA	−0.101***	−0.091***
	(-5.09)	(-3.81)
SENTIMENT	0.177***	0.088***
	(8.90)	(3.58)
GBATT		−0.641***
		(-15.52)
INSATT		0.035*
		(1.70)
Constant	1.788**	0.025

(*continued on next page*)

Appendix Table A12 (*continued*)

	AR	
	(1)	(2)
	(2.28)	(0.03)
Firm FE	YES	YES
Month FE	YES	YES
# of obs.	398,070	282,658
Adj. R^2	0.023	0.024

Notes: This table presents the regression results exploring the differential impact of COVID-19 on the salience effect for stocks associated with salient upwards and salient downwards. The independent variables are measured in the current month, while the dependent variable is observed in the subsequent month. Post-COVID is a time dummy which equals to 1 for observations from 2020 onwards and 0 otherwise. The classification of ST^+ and ST^- depends on signs of salience measure (ST). All continuous independent variables have been standardized. Test statistics and significance levels are computed using robust standard errors that are clustered by firm and month. Significance levels are indicated as follows: ***p < 0.01, **p < 0.05, *p < 0.10. t-statistics are reported in parentheses.

Appendix Table A13
The Impact of COVID on Individual and Institutional Investor Attention

	GBATT		INSATT	
	(1)	(2)	(5)	(6)
COVID	−0.204***	−0.539***	0.337***	0.054*
	(-9.34)	*(-31.44)*	*(11.24)*	*(1.75)*
CASES				
ME		0.306***		0.222***
		(132.67)		*(49.32)*
BM		0.014***		−0.018***
		(8.14)		*(-5.06)*
MOM		−0.015***		0.030***
		(-12.37)		*(12.98)*
ILLIQ		−0.109***		0.002
		(-90.22)		*(0.92)*
BETA		0.032***		0.013***
		(28.71)		*(6.14)*
IVOL		0.403***		0.051***
		(197.86)		*(13.67)*
REV		−0.007***		0.034***
		(-4.70)		*(13.04)*
MAX		−0.033***		−0.007**
		(-18.99)		*(-2.09)*
MIN		−0.056***		−0.007**
		(-32.13)		*(-2.18)*
SKEW		0.022***		0.005**
		(20.18)		*(2.23)*
COSKEW		0.028***		−0.004**
		(27.20)		*(-2.22)*
ISEW		0.008***		−0.017***
		(7.42)		*(-8.42)*
DBETA		0.062***		−0.008***
		(52.49)		*(-3.73)*
SENTIMENT		−0.160***		0.042***
		(-135.77)		*(18.81)*
Constant	10.450***	9.959***	0.368***	−0.039
	(174.42)	*(214.78)*	*(4.75)*	*(-0.51)*
Firm FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
# of obs.	404994	398070	287100	282658
Adj. R^2	0.666	0.803	0.222	0.241

Notes: This table presents the regression results analyzing the relationship between the individual investor attention (GBATT)/ institutional investor attention (INSATT) and the COVID dummy. The COVID time dummy equals to 1 for observations from year 2000–2022 and 0 otherwise. The independent variables and dependent variables are measured in the same month. All continuous variables are winsorized at the top and bottom 0.5 %. All independent variables have been standardized. Test statistics and significance levels are computed using standard errors clustered by firm and month. Significance levels are indicated as follows: ***p < 0.01, **p < 0.05, *p < 0.10. t-statistics are reported in parentheses.

Appendix Table A14
Retail and Institutional Attention in Sigma-sorted portfolios during COVID and non-COVID Periods

Quintile	GBATT			INSATT		
	Non-COVID	COVID	DIFF	Non-COVID	COVID	DIFF
Low Sigma	33507***	11664***	−21843***	0.11***	0.22***	0.11***
	(461.57)	*(320.42)*	*(-171.89)*	*(38.68)*	*(13.90)*	*(9.03)*
2	34487***	12238***	−22249***	0.12***	0.70	0.58**
	(389.95)	*(323.33)*	*(-144.53)*	*(40.23)*	*(1.58)*	*(2.16)*
3	36938***	13778***	−23160***	0.13***	0.26***	0.13***
	(266.40)	*(274.28)*	*(-96.12)*	*(38.75)*	*(23.16)*	*(14.09)*
4	42550***	17284***	−25266***	0.15***	0.36***	0.21***
	(120.67)	*(332.89)*	*(-41.34)*	*(43.18)*	*(14.97)*	*(12.33)*
High Sigma	71792***	36021***	−35771***	0.24***	0.67***	0.43***
	(438.08)	*(314.52)*	*(-121.61)*	*(42.34)*	*(33.69)*	*(25.23)*
High-Low	38285***	24357***	−13928***	0.13***	0.45***	0.32***
	(218.26)	*(203.01)*	*(-14.87)*	*(20.48)*	*(17.70)*	*(14.07)*

Notes: This table reports the attention level across quintile portfolios sorted on the daily level of salience in stock returns (Sigma) for both the COVID (2020–2022) and non-COVID periods. GBATT represents the attention for individual investors and INSATT represents institutional attention. Sigma captures how the individual stock return departures the sample average on a specific day. The High-Low row quantifies the difference in investor attention between the most salient and the least salient quintiles. The differential column (DIFF) further elucidates the changes in the attention allocation between COVID and non-COVID period. To avoid the endogeneity issue, Sigma is measured on day t while the attention variables are measured on day t+1. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Appendix Table A15
The Impact of COVID on Salient Effect

	AR		
	(1)	(2)	(3)
ST	−0.775***	−0.122***	−0.125***
	(-43.23)	*(-4.50)*	*(-3.88)*
COVID	−0.140	0.643**	2.887***
	(-0.49)	*(2.22)*	*(8.60)*
ST×COVID	0.108***	0.231***	0.221***
	(3.32)	*(7.07)*	*(5.75)*
ME		−1.138***	−1.148***
		(-29.16)	*(-23.18)*
BM		0.353***	0.434***
		(11.93)	*(11.41)*
MOM		−0.462***	−0.454***
		(-22.00)	*(-18.10)*
ILLIQ		0.269***	0.235***
		(13.11)	*(9.25)*
BETA		0.175***	0.156***
		(9.30)	*(7.00)*
IVOL		−1.095***	−0.880***
		(-31.79)	*(-20.59)*
REV		−0.839***	−0.864***
		(-32.22)	*(-27.96)*
MAX		0.458***	0.467***
		(13.96)	*(11.97)*
MIN		−0.284***	−0.297***
		(-9.23)	*(-8.08)*
SKEW		−0.154***	−0.124***
		(-8.33)	*(-5.31)*
COSKEW		−0.044**	−0.034
		(-2.49)	*(-1.65)*
ISKEW		−0.049***	−0.099***
		(-2.75)	*(-4.52)*
DBETA		−0.099***	−0.089***
		(-5.01)	*(-3.73)*
SENTIMENT		0.182***	0.092***
		(9.13)	*(3.72)*
GBATT			−0.642***
			(-15.57)
INSATT			0.034*
			(1.68)
Constant	−0.412	1.755**	0.014
	(-0.53)	*(2.24)*	*(0.02)*
Firm FE	YES	YES	YES

(*continued on next page*)

Appendix Table A15 (*continued*)

	AR		
	(1)	(2)	(3)
Month FE	YES	YES	YES
# of obs.	404994	398070	398070
Adj. R^2	0.003	0.023	0.024

Notes: This table presents the regression results analyzing the impact of COVID on the salience effect. COVID is a time dummy which equals to 1 for observations from 2020 to 2022 and 0 otherwise. All continuous independent variables have been standardized. Test statistics and significance levels are computed using standard errors clustered by firm and month. Significance levels are indicated as follows: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. t-statistics are reported in parentheses.

Appendix Table A16
Retail and Institutional Attention in Positive and Negative Salient Returns during COVID and non-COVID Periods

		GBATT			INSATT		
		Non-COVID	COVID	DIFF	Non-COVID	COVID	DIFF
Sigma_Q1 (non salient returns)		36681***	13116***	−23565***	0.13***	0.25***	0.12***
		(400.39)	*(281.26)*	*(-146.81)*	*(31.08)*	*(21.39)*	*(11.12)*
Sigma_Q5 (salient returns)	Positive	67082***	34726***	−32356***	0.25***	2.11*	1.86**
		(270.82)	*(196.88)*	*(-73.66)*	*(33.55)*	*(1.79)*	*(2.55)*
	Negative	62985***	30282***	−32703***	0.22***	0.49***	0.27***
		(252.01)	*(184.22)*	*(-71.78)*	*(26.47)*	*(19.90)*	*(11.10)*
Q5-Q1	Positive	30401***	21610***	−8791***	0.12***	1.86**	1.74**
		(146.08)	*(151.15)*	*(-9.00)*	*(15.16)*	*(2.05)*	*(2.31)*
	Negative	26304***	17166***	−9138***	0.09***	0.24***	0.15***
		(119.57)	*(130.45)*	*(-8.05)*	*(12.52)*	*(10.09)*	*(6.18)*

Notes: This table presents the comparative analysis of the individual (GBATT) and institutional (INSATT) investor attention level during the COVID (2020–2022) and non-COVID period for stocks with non-salient returns, positive salient returns and negative salient returns. The sample is segmented into quintiles based on the daily return salience of stocks (Sigma). The highest Sigma quintile is further divided into positive and negative groups. The Q5-Q1 row quantifies the difference in investor attention between the most salient and the least salient quintiles. The differential column (DIFF) further elucidates the changes in the attention allocation between normal and COVID periods. In this test, Sigma is measured on day t, while the attention variables are measured on day t+1. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Appendix Table A17
he Impact of COVID on Salient Effect in Stocks with Salient Upsides and Downsides

	AR		
	(1)	(2)	(3)
ST^+	−1.227***	−0.190***	−0.165***
	(-41.83)	*(-4.76)*	*(-3.49)*
ST^-	−0.238***	−0.069*	−0.092**
	(-7.22)	*(-1.79)*	*(-2.02)*
COVID	0.005	0.673**	2.904***
	(0.02)	*(2.31)*	*(8.59)*
ST^+×COVID	−0.073	0.194***	0.197***
	(-1.40)	*(3.72)*	*(3.18)*
ST^-×COVID	0.454***	0.291***	0.261***
	(7.12)	*(4.55)*	*(3.44)*
ME		−1.136***	−1.147***
		(-29.09)	*(-23.16)*
BM		0.353***	0.434***
		(11.92)	*(11.40)*
MOM		−0.463***	−0.454***
		(-22.02)	*(18.11)*
ILLIQ		0.269***	0.236***
		(13.14)	*(9.27)*
BETA		0.180***	0.160***
		(9.54)	*(7.12)*
IVOL		−1.072***	−0.866***
		(-30.34)	*(-19.87)*
REV		−0.832***	−0.860***
		(-31.87)	*(-27.74)*
MAX		0.457***	0.466***
		(13.93)	*(11.95)*
MIN		−0.291***	−0.301***
		(-9.43)	*(-8.17)*

(*continued on next page*)

Appendix Table A17 (*continued*)

	AR		
	(1)	(2)	(3)
SKEW		−0.152***	−0.123***
		(-8.25)	*(-5.27)*
COSKEW		−0.044**	−0.035*
		(-2.51)	*(-1.66)*
ISKEW		−0.049***	−0.099***
		(-2.73)	*(-4.51)*
DBETA		−0.099***	−0.089***
		(-5.00)	*(-3.74)*
SENTIMENT		0.179***	0.090***
		(8.98)	*(3.65)*
GBATT			−0.640***
			(-15.50)
INSATT			0.035*
			(1.69)
Constant	−0.141	1.798**	0.044
	(-0.18)	*(2.30)*	*(0.05)*
Firm FE	YES	YES	YES
Month FE	YES	YES	YES
# of obs.	404994	398070	398070
Adj. R^2	0.005	0.023	0.024

Notes: This table presents the regression results exploring the differential impact of COVID-19 on the salience effect for stocks associated with salient upwards and salient downwards. The independent variables are measured in the current month, while the dependent variable is observed in the subsequent month. COVID is a time dummy which equals to 1 for observations from 2020 to 2022 and 0 otherwise. The classification of ST_UP and ST_DOWN depends on signs of salience measure (ST). All continuous independent variables have been standardized. Test statistics and significance levels are computed using robust standard errors that are clustered by firm and month. Significance levels are indicated as follows: ***p < 0.01, **p < 0.05, *p < 0.10. t-statistics are reported in parentheses.

Data availability

The authors do not have permission to share data.

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