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Attention allocation: An empirical analysis of the asymmetric market responses to information shocks in China

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Abstract

Attention allocation—investors allocate their attention disproportionately within a day—has implications on how the market responds to information. Using high-frequency jumps detected in China, we show that the market underreacts to overnight information shocks, and the underreaction stems mainly from the short-leg stocks with highly negative overnight jumps. In comparison, the market overreacts to intraday information shocks, and the overreaction stems mainly from the long-leg stocks with highly positive intraday jumps. Moreover, the underreaction pattern strengthens while the overreaction pattern attenuates during market crashes, as investors pay limited attention when market performance is poor. Overall, these patterns are consistent with the interplay between attention allocation and investor sophistication in reshaping the asymmetric market reactions to information.

KEYWORDS
asymmetric reactions, attention allocation, overnight, information shocks, intraday

JEL CLASSIFICATION
G11, G12, G14, G17

1 INTRODUCTION

Traditional asset pricing models assume that information is instantaneously incorporated into the price, implying that new information draws immediate attention and is "digested" seamlessly by market participants. This, however, goes counter to the reality that investors (whether institutions or individuals) do not always stay attentive because attention is a scarce cognitive resource (Gargano & Rossi, 2018).

Limited investor attention (i.e., limits to the central cognitive processing capacity of the human brain) is well established as a prominent form of cognitive bias in the psychological literature (see Pashler & Johnston, 1998), and it is associated with several financial anomalies. For example, investors are easily distracted and less capable of processing value-relevant information when there is unusually high information density (DellaVigna & Pollet, 2009; Jiang et al., 2021).

This paper takes a novel perspective by examining how attention allocation leads the aggregate market to respond differently to the lagged information shocks occurring within a day. We argue that limited attention indicates that investors have a capacity constraint (i.e., the total volume of cognitive resources that can be allocated) and a time constraint (i.e., the total amount of time that can be devoted) in processing the information flows. In particular, the time constraint makes investors allocate attention disproportionally within a day, offering a plausible explanation for the aggregated market to display an asymmetric pattern of information shocks between day and night.[1]

We first conjecture that the aggregate market allocates more attention during the intraday period than during the overnight period in China.[2] This specific day-and-night attention allocation pattern is mainly driven by small individual investors, who are subject to time constraints and can only devote limited time within a day to financial markets. In comparison, large institutions are less subject to time constraints because they have more economic resources and can schedule staff to cover more timespan and allocate attention more evenly across the whole day. Empirically, we find corroborating evidence that the increase of small individual investors' trades is negatively correlated with the overnight trading ratio (the proportion of overnight trading volume to total trading volume), while the increase of large institutional investors' trades is positively correlated. Since trading requires attention, this confirmative evidence supports our conjecture (See the motivating evidence in Section 3.1).

In light of the specific day-and-night attention allocation, we postulate that the aggregated market responds asymmetrically to information shocks occurring during the day and over the night:

On the one hand, the aggregated market tends to underreact to value-relevant informational flows during the overnight period because a significant fraction of investors, mainly small individual investors, do not stay attentive to the market. Inattention or lack of market participation is associated with slow information diffusion (i.e., underreaction), a prominent symptom in financial markets. The lack of market participation by small and uninformed retail investors also has microstructure implications (i.e., transaction costs): It negatively impacts market liquidity and magnifies the adverse selection risk for liquidity providers in the overnight period. Consequently, attentive institutional investors cannot fully adjust their positions in response to new information due to the high implicit trading cost (i.e.,

[1] A growing body of literature reveals that the market behaves differently during the day and at night. For example, Hendershott et al. (2020) find that the beta-return relation differs between day and night. Muravyev and Ni (2020) reveal that volatility is substantially higher during the day than at night. Bogousslavsky (2021) finds that the mispricing factor earns positive returns throughout the day but performs poorly at the end. Lou et al. (2019) and Akbas et al. (2022) find that institutions tend to initiate trades throughout the intraday period while individuals tend to trade near the market open (i.e., overnight) in the US. Gao et al. (2021) and Liu et al.(2023) also find that the market behaves differently between intraday and overnight in China. However, none of the papers directly test whether the market responds differently to the information arriving at different times of the day.

[2] There has been a growing interest in understanding the Chinese stock market, the world's second-largest market in terms of total market capitalization. The Chinese stock market features a heavy presence of small retail investors: Above 99% of the trading accounts are held directly by individuals, and 82.01% of the trading volumes are contributed by retail investors (according to the 2018 Shanghai Stock Exchange Statistical Yearbook). Individual investors in China tend to actively invest in the market, which contrasts those in the US, who prefer to make passive and indirect investments via mutual funds. Studies exploring these unique features offer an interesting setting to deepen our understanding of asset pricing theory (Chui et al., 2022; Pan et al., 2021; Wan et al., 2024).

price impact). In short, this transaction cost mechanism deters information dissemination over the night.[3] Moreover, slow information diffusion is more pronounced among stocks with negative information, as bad news travels slowly (Hong et al., 2000), which indicates that the underreaction over the night stems mainly from stocks with lagged negative information shocks.

On the other hand, the aggregated market tends to overreact to value-relevant informational flows during the intraday period for several reasons. First, less sophisticated individual investors focus their attention during the day (Seaholes & Wu, 2007), and they tend to overreact to new information by engaging in attention-induced trading. It is well known in the literature that attention-induced trading is associated with negative abnormal returns in subsequent periods (Barber & Odean, 2008; Pedersen, 2022). Second, overreaction to information arrival during the day should stem mainly from the stocks with lagged positive information shocks because small individual investors have a stronger tendency to engage in attention-grabbing buying rather than selling. Various market frictions (such as short-selling constraints and costs) and behavioral biases (such as confirmatory bias and overconfidence) also render less sophisticated individual investors to cluster in attention-grabbing purchases rather than sells.

Based on the above arguments, we formulate testable hypotheses as follows:

Hypothesis 1: During the overnight period, when a significant fraction of investors (mainly small individual investors) do not stay attentive, the aggregate market tends to underreact to new information. Moreover, the underreaction stems mainly from stocks with negative information shocks because negative information travels more slowly due to short-selling constraints.

Hypothesis 2: During the intraday period, when investors (in particular, small individual investors) focus their attention on trading, the aggregate market tends to overreact to new information, as it increases the potential for attention-induced trading. Moreover, the overreaction stems mainly from stocks with positive information shocks because small individual investors tend to engage in attention-grabbing buying.

To better understand the possible market reactions to the information arrivals over different times of the day, we employ jumps detected from 5-min data from 1996 to 2018 to capture the identified information shocks during the intraday and overnight. The empirical analysis proceeds as follows:

Firstly, we document a strongly *asymmetric* pattern in the market reactions to lagged information shocks from the intraday and overnight periods, consistent with Hypotheses 1 and 2. Specifically, the market underreacts (overreacts) to lagged overnight (intraday) information shocks: A long-short strategy that buys stocks with the highest overnight (intraday) jumps and sells those with the lowest overnight (intraday) jumps generates a highly positive (negative) return spread over the next 1–10-day horizons. The return differential remains large in magnitude and statistically significant at the 1% level after we adjust the risk exposures with Fama-French three- or five-factor models. Moreover, the positive (negative) return spread mainly stems from the short-leg (long-leg) stocks with the lowest overnight (highest intraday) jumps. This pattern remains strong at the firm level when we control for several well-known return predictors in the cross-sectional regression. In particular, the negative returns following lagged intraday jumps are not simply inventory-based reversals as modeled in Jegadeesh and Titman (1995) and Nagel (2012), given that we control for return reversals with lagged stock returns. Instead, it is more in line with the attention-induced trading mechanism (i.e., overreaction), as investors (in particular, small individual investors) focus their attention during the intraday period.

Second, our documented asymmetric market reactions to overnight and intraday information shocks are not a pure manifestation of the well-known asymmetry that investors tend to pay more attention to positive information than

[3] We are highly indebted to an anonymous referee for pointing out this complementary microstructure perspective, which contributes (partially) to the observed underreaction pattern on overnight information shocks. Subsection 5.2 provides a more detailed discussion of the influence of liquidity and transaction costs.

to negative one (see Chan, 2003; Frank & Sanati, 2018; Ivkovic ´& Jegadeesh, 2004; Jiang & Zhu, 2017; Kothari et al., 2009; Park et al., 2014). In principle, inattention-induced underreaction to lagged overnight information should be less sensitive to the types of information (positive or negative), as investors do not pay attention or effort to learn the new information in the first place. In comparison, attention-induced overreaction to lagged intraday information could vary between positive and negative information content. It is more likely to happen for buying than selling due to various market frictions (such as short-selling constraints and costs) and behavioral biases. Consistent with our projection, we find that irrespective of positive or negative information shocks in the overnight period, the market *uniformly* underreacts in subsequent days (i.e., price drifts), implying a pattern of slow information diffusion. This uniform pattern, however, does not hold for intraday jumps. A significant negative risk-adjusted return exists when we sort on lagged positive jumps in the intraday period, while a significant positive risk-adjusted return emerges when we sort on lagged negative intraday jumps. The fact that overreaction to intraday jumps only exists in those cases with positive shocks is a telling story, as it supports the attention-induced trading mechanism by small retail investors who pay more attention to buying (on good news) than selling (on bad news) due to various market frictions and behavioral biases. Overall, these new sets of "high-resolution" evidence complement the prior work (Frank & Sanati, 2018; Jiang & Zhu, 2017; Park et al., 2014) and suggest that the nature of information (positive or negative) would only matter when the market pay attention during the intraday trading periods.

Third, we assess the market responses to lagged jumps associated with public news. Note that our detected jumps are a comprehensive measure of information shocks, encompassing public (i.e., news announcements) and private information. The portfolio results confirm that the asymmetric market reactions are robust across the news-related and no-news subsamples, which reinforces our adoption of jumps as a valid measure of information shocks (Jiang & Zhu, 2017; Savor, 2012). More importantly, we document that the market exhibits a stronger asymmetric pattern for the jumps associated with public news: A more prominent overreaction to news-related intraday jumps, manifested by large alphas (in absolute terms) of the long-short portfolio, is consistent with the notion that public news should grab immediate attention, induce attention-induced trading and more persistent return reversals in subsequent days (see Barber & Odean, 2008; Da et al., 2011). Similarly, a stronger underreaction to news-related overnight jumps is also in line with our attention allocation mechanism because inattentive or lack of attention to the salient news released at night (by a significant fraction of investors) deters information dissemination and causes more substantial and more persistent underreaction in subsequent days.

We perform several tests to shed light on the attention allocation-based mechanism in explaining the *asymmetric* market responses to overnight and intraday jumps:

The first test explores the interplay between attention allocation and information density in reshaping *asymmetric market* responses. Specifically, we focus on the subsample with a higher-than-average number of jumps (i.e., days with an above-average number of overnight/intraday jumps in the cross-section) to replicate the univariate portfolio analysis. Strikingly, the market exhibits stronger subsequent price drifts (i.e., underreactions) after these high information density days with relatively more jumps across stocks, indicating slow information diffusion at an even lower pace. This reinforces the (adverse) consequence of inattention by the market despite massive (lagged) informational flows at night. In comparison, we document that after days with relatively high intraday jump density, the market exhibits more substantial price reversals (i.e., overreactions). One possible explanation is that massive informational shocks during the intraday periods are likely to amplify the contemporaneous attention-induced trading and lead to more persistent subsequent return reversal because the market, primarily small and inexperienced individual investors, pay close attention. Overall, high information density amplifies the asymmetric market responses.

The second test explores how the attention allocation-related *asymmetric* market responses behave during the adverse market states. Prior literature suggests that investors allocate less attention to their stocks when the overall market return is low (Huang et al., 2019; Peng & Xiong, 2006), implying that slow information diffusion (i.e., underreaction) is likely to strengthen, while the return reversal related to attention-induced trading might be dampened during these "difficult times" as investors devote less attention when the overall market has extreme performances.

We confirm the above notion by focusing on the two historical episodes featuring extreme market states in China (i.e., the period ranging from January 1, 2006 to November 11, 2008 and from July 18, 2014 to March 1, 2016). That is, we find that the market strongly and persistently underreacts to lagged overnight jumps, while the overreaction pattern to lagged intraday jumps is dampened during the two well-known episodes.

The third test investigates individual investors' search behavior to validate our attention allocation-based mechanism. We perform a panel regression to regress the daily abnormal search volume (constructed similarly as in Da et al., 2011) on the overnight and intraday jumps (in absolute terms) while controlling for other factors. Consistent with our projection that the market (mainly individual investors) is inattentive to overnight information, we document that overnight jumps do not induce much search volume in subsequent days. In contrast, intraday jumps motivate assertive searching behavior by individual investors in contemporaneous and subsequent days, which is in line with our projection that the market (mainly individual investors) pays close attention to (lagged) intraday information. These search volume patterns support that the market as a whole allocates disproportionally more attention during the day.

Finally, we also perform a battery of robustness checks. Firstly, we show that other well-known firm characteristics do not explain away the cross-sectional solid return predictability. The positive (negative) alpha of the long-short portfolios sorted on overnight (intraday) jumps remains strong after controlling for one specific firm characteristic. Secondly, the asymmetric market reaction patterns are robust to alternative definitions of open price and overnight jumps, indicating microstructure noises do not drive our key results. Thirdly, the asymmetric market reactions are not purely driven by return autocorrelation, as we exclude samples with consecutive jumps during the portfolio formation periods and/or subsequent jumps in the holding periods. Fourthly, the asymmetric market responses to information are not purely driven by size and illiquidity, as excluding small and micro-cap stocks does not alter our findings. Lastly, we show that the solid cross-sectional return predictability of overnight jumps survives transaction cost concerns, which is not valid for intraday jumps.

In summary, this paper makes three contributions to understanding how financial markets react to new information. First, it contributes to the growing literature on the market implications of limited attention (Barber & Odean, 2008; Gargano & Rossi, 2018). We highlight the time constraint (the total amount of time within a day that can be devoted) faced by investors and how this relates to the market (mis-)reactions to informational shocks. Slow information diffusion (i.e., underreaction) is associated with limited attention paid to overnight information, while price reversal (i.e., overreaction) is associated with disproportionate allocation with high attention-driven trading. Consistent with the predictions of the attention allocation-based mechanism, we find that a long-short strategy that buys stocks with the highest overnight (intraday) jumps and sells those with the lowest overnight (intraday) jumps generates a highly positive (negative) return spread over the next 1–10-day horizons. Second, it highlights the interplay between attention allocation and investor sophistication in reshaping the asymmetric market reactions to information: The fact that the solid negative return spread of the long-short portfolio mainly stems from long-leg stocks with the highest intraday jumps is consistent with small individual investors pay close attention during the intraday period, and engage in massive attention-driven buying. Moreover, the underreaction strengthens while the overreaction attenuates during extreme market states, which is consistent with small individual investors who tend to pay little or no attention when the market performance is poor. Finally, our paper contributes to the evolving literature on the cross-sectional return patterns over the overnight and intraday periods (Akbas et al., 2022; Hendershott et al., 2020; Lou et al., 2019), reveals that lagged overnight (intraday) informational shocks are a positive (negative) return predictor in the cross-section, and find the positive underreaction-related return spread is large in magnitude and survives transaction cost concerns.

The remainder is organized as follows. Section 2 documents the data source, jump detection method, and summary statistics. Section 3 presents the motivating evidence and reveals asymmetric market reactions to overnight and intraday jumps. Section 4 uncovers the link between investor attention allocation and asymmetric market reactions. Section 5 performs robustness checks. Section 6 concludes the paper.

2 | DATA AND JUMP DETECTION

2.1 | Data sources and return definition

We retrieve a high-frequency dataset of Chinese A-share stocks from the Thomson Reuters Tick History (TRTH) database, with the sample period from January 1996 to May 2018. The high-frequency data include the stock price and trading volume at 5-min intervals. We adopt the following filtering rules to clean the data: First, we remove all special-treatment stocks. Second, we retain stocks with active trading over the prior year to avoid stock suspension or delisting. We then match the high-frequency dataset with the "low-frequency" dataset, such as the daily trading data, firm characteristics, and market-wide variables sourced from the China Stock Market and Accounting Research (CSMAR) database. We obtain data on public news and search volume index from the Chinese Research Data Services Platform (CNRDS) database.

Following Jiang and Zhu (2017) and Lou et al. (2019), we calculate returns in different periods as follows:

The daily return is calculated based on the close prices on day t and day $t-1$:

$$R_{\text{daily}} = (\text{close}_t - \text{close}_{t-1})/\text{close}_{t-1}. \tag{1}$$

The intraday return is calculated based on the open price and close price on day t:

$$R_{\text{intraday}} = (\text{close}_t - \text{open}_t)/\text{open}_t. \tag{2}$$

The overnight return is calculated based on the daily return and intraday return:

$$R_{\text{overnight}} = \frac{1 + R_{\text{daily}}}{1 + R_{\text{intraday}}} - 1. \tag{3}$$

Both the daily return and overnight return are adjusted for cash dividends.[4]

The 5-min return on day t is calculated based on the close prices at times m and $m-5$ (m begins at 9:35 a.m. and ends at 3:00 p.m.):

$$R_{t,m} = (\text{close}_{t,m} - \text{close}_{t,m-5})/\text{close}_{t,m-5}. \tag{4}$$

2.2 | Jump detection method

To detect jumps, we follow the approach of Andersen et al. (2012) and Jiang and Zhu (2017) by including the overnight return as one of the intraday return observations in jump detection. The jump tests are performed daily. An overnight or intraday jump is identified based on the recursive jump detection procedure, conditional on it is a jump day. We know that treating the overnight return as one of the equally-spaced intraday returns violates the assumptions of a jump-diffusion process, but this empirical compromise preserves the information content of the overnight jump. Moreover, as we show in robustness checks (Section 5.3), our key empirical patterns do not hinge on how we define overnight jumps. For brevity, we leave the technical details on our jump detection methods in the online appendix for reference.

Throughout the paper, we refer to an intraday jump as the 5-min intraday return (rather than the squared intraday return) identified by the above recursive procedure. Similarly, an overnight jump refers to the overnight return (rather

[4] The daily return encompasses all corporate events, such as dividend adjustments. Moreover, we follow the convention in the literature by assuming that all corporate events, such as dividend adjustments, accrue over the night (Lou et al., 2019). That is, the overnight return includes dividend reinvestments.

TABLE 1 Summary statistics of returns and detected jumps.

Panel A		*N*	5%	25%	Median	Mean	75%	95%	SD
Intraday	Return	7,872,970	−4.317	−1.290	0.136	0.165	1.570	4.795	2.774
	Jump	873,960	−2.487	−0.671	1.149	0.881	2.013	3.996	2.072
	P_jump	617,339	0.546	1.066	1.597	1.930	2.428	4.461	1.303
	N_jump	256,621	−4.082	−2.044	−1.307	−1.640	−0.858	−0.317	1.240
Overnight	Return	7,872,970	−1.869	−0.530	0.000	−0.115	0.260	1.463	1.367
	Jump	755,336	−4.428	−2.006	−0.940	−0.277	1.581	4.327	2.869
	P_jump	323,647	0.694	1.193	1.811	2.389	2.886	6.399	1.842
	N_jump	431,689	−5.417	−2.792	−1.822	−2.276	−1.226	−0.720	1.591

Panel B	Same sign with daily return		Contribution to daily return	
	Intraday period	Overnight period	Intraday period	Overnight period
Whole sample	90.85%	59.33%	89.62%	10.38%
without jump	90.66%	57.80%	88.85%	8.00%
With jump	92.35%	73.80%	95.70%	32.59%
With P_jump	92.41%	74.00%	98.38%	43.83%
With N _jump	92.20%	73.64%	89.30%	24.19%

The table reports the descriptive statistics of stock returns and jumps detected from the overnight and intraday periods. Summary statistics in Panel A include the sample size (*N*), mean values, standard deviation (SD), the 5%, 25%, 50%, 75%, and 95% quantile values of returns, jumps (Jump), positive jumps (P_jump), and negative jumps (N_jump). Except for the sample size (*N*), data in Panel A are in percentages, with the omitted %. Panel B reports the same sign ratio and contribution ratio of intraday and overnight returns, including results from the whole sample and samples without jumps, with jumps, with positive jumps, and with negative jumps in its period. The same sign ratio measures the percentage of intraday/overnight returns having the same sign as daily returns, and the contribution ratio is the proportion of intraday/overnight returns to daily returns. The sample period is from 1996 to 2018.

than the squared overnight return) detected by the recursive procedure. Moreover, a positive (negative) jump means that the identified intraday or overnight jump return is positive (negative).

2.3 | Descriptive statistics

Panel A of Table 1 presents the summary statistics of the stock returns and jumps during the intraday and overnight periods. After comparing the sample statistics of returns, jumps (Jump), positive jumps (P_ jump), and negative jumps (N_ jump) over the two periods, it reveals that there exists vastly different return dynamics between day and night. Specifically, we document a significant positive average intraday return of 0.165% and a sizeable negative average overnight return of −0.115% daily. The standard deviation of intraday returns (2.774%) is much larger than that of overnight returns (1.367%). The negative average overnight return is consistent with the overnight puzzle in China documented in the prior literature (see Gao et al., 2021; Qiao & Dam, 2020).

Jumps also exhibit distinct features between day and night: First, intraday jump frequency—the ratio of days with intraday jumps—amounts to 11.10% and is higher than overnight jump frequency, which amounts to 9.59%. Second, intraday jumps are overwhelmingly positive, as 70.64% are above zero. In comparison, most overnight jumps tend to be negative, as 57.15% are below zero.[5] As a result, both the mean and median of intraday (overnight) jumps are positive

[5] Days with both overnight and intraday jumps are not included in our sample.

(negative), which amounts to 0.881% and 1.149% (−0.940% and −0.277%), respectively. Finally, the standard deviations of intraday jumps are smaller than those of overnight jumps, whether one compares all jumps, positive jumps, or negative jumps. These findings reveal more cross-sectional variations in jumps during the overnight period than during the intraday period.

Panel B of Table 1 reveals the information-related features of jumps by comparing the same sign ratio and the contribution ratio over the subsamples without and with various jumps (i.e., the subsample days without jumps, with jumps, with only positive jumps, and with only negative jumps). The same sign ratio of intraday (overnight) return measures the proportion of sample days when the intraday (overnight) return has the same sign as the daily return. Following Jiang and Zhu (2017), the contribution ratio of intraday (overnight) return measures the proportion of daily return that is contributed by the intraday (overnight) return component.[6] Several salient features emerge from the table: First, on the subsample days with no jumps (i.e., the benchmark case), intraday returns play a relatively important role, as its same sign and contribution ratio amounts to 90.66% and 88.85%, respectively. In comparison, these two ratios for the overnight returns amount to 57.80% and 8.00%, respectively. The fact that intraday returns contribute more to daily (total) returns than overnight returns is reasonable because most trades occur during the day rather than at night. Second, intraday (overnight) jumps increase the intraday (overnight) return contribution to the daily total return as a valid proxy of informational shocks. For example, compared to days without jumps, when jumps exist during intraday, the same sign ratio and contribution ratio increase from 90.66% to 92.35% and from 88.85% to 95.70%, respectively. More strikingly, when we examine the performance of the overnight jump subsamples, the information-based features also exist and are more pronounced: compared to days without jumps, when there are jumps during the overnight period, the same sign ratio and contribution ratio increase from 57.80% to 73.80% and from 8.00% to 32.59%, respectively. Besides, the more substantial improvement during the overnight period is consistent with that most firm-specific news in China is released after the market closes.[7] Overall, the stark contrasts in the same sign ratio and the contribution ratio between subsample days with and without jumps are consistent with the fact that intraday and overnight jumps are valid measures of informational shocks.

3 EMPIRICAL RESULTS

3.1 Motivating evidence

In this section, we provide preliminary evidence on investor attention allocation in China to motivate our empirical analyses in later sections. We focus on the overnight period, as investors, whether individuals or institutions, tend to pay close attention during the intraday trading sessions. Our empirical predictions on the asymmetric market reactions hinge on the interplay between limited attention and investor sophistication: Less sophisticated individual investors, who are subject more to the time and capacity constraints, allocate little, or perhaps no, attention at night while large institutional investors could allocate their attention more evenly within 24 h.[8] This generates the specific day-and-night attention allocation of the aggregate market.

[6] The contribution ratios are computed as $(ln\,(1+R_{\text{overnight}})/ln\,(1+R_{\text{daily}})$ and $ln\,(1+R_{\text{intraday}})/ln\,(1+R_{\text{daily}})$ for the two returns. Each day, the contribution ratios of overnight and intraday returns sum up to 1.

[7] There is a discrepancy in the types of information that is released between day and night: By regulation, material information such as quarterly earnings announcements and mergers and acquisitions (M&As) is mandatory to be released "off the market", while non-material information is released throughout the day. Our data confirm this: Approximately 69.78% of public news in our sample is released during the night, and the overnight jumps might be more informational. In addition, Liu et al. (2023) document a striking overnight-intraday disparity in terms of the reaction to earnings news, indicating that informed institutional investors tend to trade and react to earnings news in the pre-open auction, while individuals only respond after the market opens during the day. Similarly, Boudoukh et al. (2019) also find different information features during the two periods of the US stock market: firm-specific information accounts for 49.6% overnight idiosyncratic volatility, while the ratio during the intraday period is only 12.4%. Overall, their findings are primarily in line with our attention allocation mechanism.

[8] We remain agnostic about the economic forces explaining why small individual investors allocate their attention disproportionately within a day. Besides limited attention, other factors such as preference, habits, and the specific market design, such as the 9:15–9:25 a.m. pre-open call auction, could (jointly)

Based on the premise that trading requires attention, we investigate the trading tendency of large institutional and small retail investors during the overnight period (i.e., the pre-open call auction). Our analysis is straightforward but subject to one caveat: we do not have account-level data to pin down the identity of institutional investors versus retail investors. Instead, we use the (daily) super-large and small trades as valid proxies. To figure out which investor clientele prefer to trade in the pre-open call auction (i.e., overnight period), we perform the following correlation analysis: First, we compute the daily super-large (small) trade ratio that quantifies the trading volume contributed by the institutional (retail) investors. The super-large (small) trade ratio is the ratio of super-large (small) trades to total trades.[9] Next, we calculate the overnight trading ratio, which is the proportion of the daily trading volume that occurs during the overnight period. These ratios are computed for each stock daily. We then calculate the daily cross-sectional correlation between the overnight trading ratio and the super-large (small) trade ratio among the sample stocks. Finally, we report the time series mean to reveal the average tendency of large institutional (small retail) investors to bet overnight.

Table A2 in the online appendix reveals a strong positive (negative) correlation between the overnight trading ratio and the super-large (small) trade ratio across various stocks, indicating that large institutional investors (small retail investors) tend to trade during the overnight (intraday) period. Moreover, the positive (negative) association between the overnight trading ratio and the super-large (small) trade ratio is stronger (weaker) among stocks with above-average size, price, analyst coverage, institutional ownership, or below-average liquidity and idiosyncratic volatility, which is consistent with the fact that institutional (retail) investors like (dis-like) large, liquid, and safe stocks.

Overall, the correlation analysis indicates that large institutional investors tend to trade overnight, while small retail investors tend to bet during the intraday period in China, which differs markedly from the US stock market. Based on the premise that trading requires attention, these patterns support the interplay between attention allocation and investor sophistication: Under limited attention, individual investors allocate little or no attention overnight, while institutional investors stay attentive.

3.2 | Portfolio analysis

In this section, we investigate the *subsequent market* reactions to jumps detected in the intraday and overnight periods. We employ a univariate portfolio analysis to address the issue. Specifically, we sort stocks (in ascending order) into decile portfolios based on the detected jumps. Next, we construct the long-short portfolio that buys the highest decile (D10) and sells the lowest decile (D1). Note that the long leg (D10) contains stocks with the largest positive jumps, while the short leg (D1) contains stocks with negative jumps of the largest magnitude. We then compute the value-weighted average daily return spread (D10–D1) over the next 1–10-day horizons. Our choice of limiting the holding period to up to 10 days is motivated by the empirical observation that the jump frequency is 11.10% and 9.59% for the intraday and overnight periods, respectively. Therefore, holding the portfolios for no more than 10 days would minimize the possible interference of subsequent jumps over the holding periods. Moreover, the returns of the decile portfolios are averaged based on Jegadeesh and Titman (1993) by utilizing the active portfolios that overlap in the holding period.

Table 2 presents the portfolio spreads between the highest and lowest deciles (D10–D1) and alphas adjusted by the Fama-French three-factor (FF3) and Fama-French five-factor (FF5) models in this part. The reported

contribute to the observed attention allocation pattern. However, our data do not allow us to determine whether they are the primary drivers. Instead, our paper focuses on the aftermath of attention allocation-based mechanisms (i.e., market implications).

[9] The daily firm-level trade data are retrieved from the CSMAR database, covering the sample period from 2003 to 2018 due to data availability. Super-large trades are those with a transaction amount equal to or greater than 1 million Chinese yuan (CNY), while small trades are those with less than 50,000 CNY. We focus narrowly on super-large and small trades because they are almost certainly initiated by large institutions and small individuals, respectively. We ignore large and medium-sized trades because either institutions or individuals could initiate them. For example, large institutions may split their super-large trades into large and medium trades to minimize the price impact.

TABLE 2 Univariate portfolio sort.

Panel A: Sorted on overnight jumps						
	1 day	2 days	3 days	4 days	5 days	10 days
D1	−0.311***	−0.221***	−0.176***	−0.149***	−0.117***	−0.066
	(−6.99)	(−5.17)	(−4.20)	(−3.59)	(−2.84)	(−1.63)
D10	0.155***	0.061	0.025	0.002	−0.023	−0.014
	(3.15)	(1.34)	(0.57)	(0.05)	(−0.57)	(−0.35)
D10–D1	0.467***	0.283***	0.201***	0.151***	0.094***	0.052***
	(12.26)	(9.42)	(8.13)	(7.31)	(5.23)	(4.41)
FF3 alpha	0.464***	0.281***	0.200***	0.150***	0.093***	0.051***
	(12.18)	(9.40)	(8.17)	(7.40)	(5.32)	(4.45)
FF5 alpha	0.468***	0.283***	0.202***	0.152***	0.094***	0.052***
	(12.12)	(9.36)	(8.17)	(7.36)	(5.32)	(4.54)
Panel B: Sorted on intraday jumps						
	1 day	2 days	3 days	4 days	5 days	10 days
D1	−0.047	−0.012	−0.012	−0.007	0.003	0.005
	(−1.37)	(−0.34)	(−0.35)	(−0.22)	(0.10)	(0.16)
D10	−0.115***	−0.118***	−0.101***	−0.086***	−0.091***	−0.050
	(−3.69)	(−3.80)	(−3.18)	(−2.71)	(−2.87)	(−1.57)
D10–D1	−0.067***	−0.106***	−0.089***	−0.079***	−0.094***	−0.056***
	(−4.62)	(−9.24)	(−9.33)	(−9.80)	(−12.63)	(−10.61)
FF3 alpha	−0.067***	−0.106***	−0.089***	−0.079***	−0.095***	−0.058***
	(−4.63)	(−9.25)	(−9.21)	(−9.67)	(−12.33)	(−10.72)
FF5 alpha	−0.067***	−0.105***	−0.088***	−0.078***	−0.094***	−0.057***
	(−4.65)	(−9.21)	(−9.22)	(−9.62)	(−12.41)	(−10.81)

The table reports the market reactions to intraday and overnight jumps. Specifically, we sort stocks into decile portfolios by detected jumps (in ascending order). The hedge portfolio (D10–D1) is constructed by going long the top decile (D10) and short the bottom decile (D1). Portfolios are value-weighted, and the average daily portfolio returns in the next 1–10-day horizons are computed by averaging across active portfolios with overlapping holding periods under the Jegadeesh and Titman (1993) method. We report the portfolio excess returns for the D1, D10, and the hedge portfolio (D10–D1). For the hedge portfolio, we also report the risk-adjusted returns (alphas) using the Fama-French three-factor (FF3) and Fama-French five-factor (FF5) models. All returns are expressed in percent, and Newey and West (1987) adjusted *t*-statistics are reported in parenthesis. Statistical significance at the 1%, 5%, and 10% levels is denoted as ***, **, and *, respectively. The sample period is from 1996 to 2018.

t-statistics are based on Newey and West (1987) standard errors that adjust for heteroskedasticity and serial correlation.

The results in Table 2 show the significantly different market reactions following the two periods. Specifically, the return differences between the highest and lowest deciles are significantly positive (negative) when sorted on the overnight (intraday) jumps. For example, when we rank stocks based on the overnight jumps, the portfolio spreads are 0.467%, 0.283%, 0.201%, 0.151%, 0.094%, and 0.052% over the next 1–10-day horizons, respectively. Fama-French three- and five-factor alphas are of similar magnitudes and significant at the 1% level.[10] However, when we sort stocks

[10] The FF3 alpha amounts to 0.464% per day, which is relatively large. It is at least two times larger than the US stock market (i.e., roughly 19 bps per day in Jiang and Zhu, 2017). As expected, the sizeable economic magnitude comes mainly from the short leg because there are short-selling constraints in practice.

based on intraday jumps, the return spreads are small in magnitude, which amounts to –0.067%, –0.106%, –0.089%, –0.079%, –0.094%, and –0.056% over the next 1–10-day horizons, respectively.

Furthermore, the results also show the critical side that drives the spreads between the highest and lowest deciles. Specifically, the average abnormal returns of the lowest decile (D1) from the overnight jump studies have a larger magnitude than those of the highest decile (D10). The positive spreads (and thus, underreactions) are mainly from the overnight negative jumps, and the influence of positive jumps is only significant in the next 1-day horizon. In comparison, the average abnormal returns of D10 from the intraday jump studies have a larger magnitude than those of D1, the negative spreads (and thus, overreactions) are mainly from the intraday positive jumps in decile D1, and the influences of negative jumps detected in this period are insignificant for all horizons. These results hold whether based on the values of returns or the t-values.

In summary, one salient feature of this table is that the long-short portfolios sorted on overnight (intraday) jumps generate significantly positive (negative) return spreads over the holding period. These empirical patterns indicate strong underreaction (overreaction) to lagged overnight (intraday) information shocks over the subsequent trading days, which are consistent with our empirical predictions (Hypotheses 1 and 2).

3.3 | Firm-level analysis

In this subsection, we examine whether the (lagged) jumps detected in the overnight or intraday periods are strong return predictors at the firm level. The empirical literature has identified many well-known firms' attributes with strong predictive power for stock returns, including the firm size, book-to-market ratio, past stock returns, etc. Therefore, we employ the Fama and Macbeth (1973) cross-sectional regression that regresses the average of the *h*-day stock return on jumps while controlling for a wide range of return predictors. The model specification is as follows:

$$Ret_{i,t+1\_t+h} = \alpha + \beta_1 Jump_{i,t}^{OVNT} + \beta_2 Jump_{i,t}^{INTD} + \sum_{i=1}^{K} \gamma_{i,t} \times Z_{i,t} + \varepsilon_{i,t} \tag{5}$$

where $Ret_{i,t+1\_t+h}$ is the average daily return of stock *i* over the next 1–10-day horizons (*h* takes the value of 1, 2, 3, 4, 5, and 10, respectively), $Jump_{i,t}^{OVNT}$ and $Jump_{i,t}^{INTD}$ are the lagged overnight and intraday jump of stock *i* at day *t*, respectively. Following Jiang and Zhu (2017), we control several cross-sectional return determinants (denoted as $Z_{i,t}$), which includes the lagged non-jump return ($non\_Jump_{i,t}$), defined as the remaining part of the daily returns excluding the jump components, if any. Other cross-sectional determinants include the lagged returns in the past 5 and 10 days ($ret_{i,t-5\_t-1}$ and $ret_{i,t-10\_t-6}$), daily turnover (*Turn*), market capitalization (*SIZE*), book-to-market ratio (*BM*), Amihud illiquidity ratio (*ILLIQ*), idiosyncratic volatility (*IVOL*), leverage ratio (*LEV*), idiosyncratic skewness (*ISKEW*), and idiosyncratic kurtosis (*IKURT*).[11] For brevity, technical details on how to construct the control variables are documented in Table A1 in the online appendix. We drop financial firms from the sample as their leverage ratios differ. However, our key results on the effect of jumps remain robust with financial firms included. The reported t-statistics are based on Newey and West (1987) standard errors.[12]

Panel A of Table 3 reports the estimation results for lagged jumps and non-jump returns without other control variables. The results are consistent with portfolio-level evidence that overnight (intraday) jump is a positive (negative) return predictor for subsequent stock returns, indicating a strong underreaction (overreaction) to the informational

Short-selling stocks with negative news is more costly than buying stocks with positive news. Moreover, due to the disposition effect or other behavioral biases, investors (in particular, individual investors) are reluctant to sell their stocks in a losing position, even if there are negative news releases on the underlying stock.

[11] Using past returns over different horizons is following Grinblatt and Moskowitz (2004) and Jiang and Zhu (2017).

[12] We also do regressions based only on intraday jumps or overnight jumps, and the results are similar to Table 3, considering that there exists only one kind of jump for each day in our study.

TABLE 3 Fama–Macbeth regression.

Panel A:	1 day	2 days	3 days	4 days	5 days	10 days
$Jump^{OVNT}$	0.073***	0.032***	0.022***	0.015***	0.004**	0.001
	(16.36)	(10.10)	(8.74)	(7.04)	(2.34)	(0.93)
$Jump^{INTD}$	−0.006*	−0.021***	−0.017***	−0.015***	−0.020***	−0.011***
	(−1.69)	(−8.50)	(−8.60)	(−8.62)	(−13.02)	(−10.69)
non_Jump	0.052***	0.017***	0.013***	0.010***	0.002*	0.002***
	(18.69)	(8.47)	(7.78)	(7.22)	(1.70)	(3.28)
Cons	0.039	0.035	0.030	0.035	0.040	0.052**
	(1.40)	(1.27)	(1.11)	(1.31)	(1.51)	(2.11)
Obs	7,092,654	7,031,487	6,970,131	6,909,621	6,849,935	6,556,848
R^2	0.027	0.023	0.022	0.021	0.020	0.018
Panel B: with control variables						
$Jump^{OVNT}$	0.062***	0.024***	0.016***	0.011***	0.004**	0.004***
	(13.25)	(7.45)	(6.99)	(5.19)	(2.39)	(3.96)
$Jump^{INTD}$	−0.006*	−0.022***	−0.018***	−0.014***	−0.018***	−0.008***
	(−1.74)	(−8.54)	(−9.36)	(−8.17)	(−11.93)	(−8.25)
non_Jump	0.030***	0.003	0.001	0.002	−0.004***	0.001
	(11.33)	(1.50)	(1.03)	(1.46)	(−4.17)	(1.34)
ret_{t-5_t-1}	−0.017***	−0.013***	−0.011***	−0.009***	−0.007***	−0.002***
	(−19.52)	(−17.19)	(−16.28)	(−14.91)	(−11.81)	(−3.51)
ret_{t-10_t-6}	0.002***	0.002***	0.002***	0.002***	0.002***	0.000
	(3.40)	(3.69)	(3.66)	(3.38)	(3.43)	(0.86)
TURN	−3.989***	−3.727***	−3.744***	−3.922***	−3.980***	−3.697***
	(−16.82)	(−18.40)	(−20.56)	(−23.56)	(−25.18)	(−27.94)
SIZE	−0.072***	−0.068***	−0.066***	−0.066***	−0.066***	−0.064***
	(−11.27)	(−10.71)	(−10.71)	(−11.14)	(−11.31)	(−12.14)
BM	0.006	0.006	0.004	0.007	0.010	0.025**
	(0.40)	(0.45)	(0.31)	(0.56)	(0.78)	(2.18)
ILLIQ	0.106***	0.113***	0.120***	0.128***	0.135***	0.164***
	(15.57)	(16.08)	(16.89)	(17.65)	(18.32)	(21.49)
IVOL	−1.498***	−1.472***	−1.459***	−1.475***	−1.487***	−1.447***
	(−12.83)	(−13.02)	(−13.18)	(−13.46)	(−13.61)	(−14.15)
LEV	0.011***	0.009***	0.009***	0.009***	0.009***	0.007***
	(5.85)	(5.29)	(5.50)	(5.41)	(5.44)	(4.97)
SIKEW	0.090***	0.089***	0.085***	0.081***	0.078***	0.062***
	(14.19)	(14.39)	(14.30)	(14.20)	(14.06)	(12.94)
IKURT	−0.010***	−0.010***	−0.009***	−0.009***	−0.008***	−0.005***
	(−6.81)	(−6.96)	(−6.95)	(−6.60)	(−6.38)	(−4.56)

(Continues)

TABLE 3 (Continued)

Panel B: with control variables						
Cons	1.654***	1.536***	1.467***	1.471***	1.457***	1.361***
	(10.88)	(10.25)	(10.11)	(10.48)	(10.59)	(11.14)
Obs	5,602,803	5,558,483	5,514,323	5,470,905	5,428,114	5,219,401
R^2	0.111	0.118	0.125	0.132	0.140	0.178

The table presents the results of the Fama and Macbeth (1973) cross-sectional regression. The dependent variables are the average daily returns in the next 1–10-day horizons, and the main explanatory variables are the overnight and intraday jumps ($Jump^{OVNT}$ and $Jump^{INTD}$). *non_Jump* is the residual return that excludes the overnight and intraday jumps (i.e., it equals daily return if there is no detected jump). We include lagged returns in days t-1 till t-5 (ret_{t-5_t-1}), and in days t-6 till day t-10 (ret_{t-10_t-6}) to control for return autocorrelation. Other control variables include the daily turnover ratio (*Turn*), market capitalization (*SIZE*), book-to-market ratio (*BM*), Amihud illiquidity ratio (*ILLIQ*), idiosyncratic volatility (*IVOL*), leverage ratio (*LEV*), and idiosyncratic skewness (kurtosis) *ISKEW* (*IKURT*). Newey & West (1987) adjusted t-statistics are reported in parenthesis. Statistical significance at the 1%, 5%, and 10% levels is denoted as ***, **, and *, respectively. The sample period is from 1996 to 2018.

shocks from overnight (intraday) periods. Specifically, the influences of overnight jumps are significantly positive in the next 1–5-day horizons, with the magnitude of the coefficients decreasing over time. The impacts of intraday jumps are significantly negative in the next 1–10-day horizons, and the magnitude of the coefficients shows a slightly decaying pattern. In comparison, the impacts of non-jump returns are much smaller based on their coefficients and associated t-values, indicating the dominant role of jumps on future return performances.

Panel B of Table 3 reports the estimation results with control variables included. The differential market reactions to overnight and intraday jumps remain unchanged. The coefficients on lagged overnight jumps amount to 0.062, 0.024, 0.016, 0.011, 0.004, and 0.004 over the 1–10-day horizons, respectively. These coefficients are statistically significant at the 1% level, indicating strong return drifts following overnight informational shocks. In comparison, the coefficients on intraday jumps amount to –0.006, –0.022, –0.018, –0.014, –0.018, and –0.008, respectively. Again, all of these coefficients, except for the 1-day horizon, are significant at the 1% level, indicating strong return reversals following intraday informational shocks.

Most coefficients of non-jump returns are smaller than the jump components, and the influences of past returns are significant, indicating the strong return autocorrelation (i.e., negatively related to past 5-day returns and positively related to past 10-day returns). The coefficients of firm-specific variables are broadly consistent with previous findings (see also Ang et al., 2006; Fama & French, 2012; Gao et al., 2021; Liu et al., 2019): future stock returns are negatively related to the turnover ratio (*TURN*), market capitalization (*SIZE*) and idiosyncratic volatility (*IVOL*), but positively related to the book-to-market ratio (*BM*), illiquidity proxy (*ILLIQ*), and leverage ratio (*LEV*).

Overall, our findings from the Fama-Macbeth cross-sectional regression further support that the timing of information arrivals matters in China. The market tends to underreact (overreact) to lagged informational shocks from the overnight (intraday) period, and the subsequent price drift (reversal) over the next 1–10 days is robust after controlling for a set of well-known return determinants.

3.4 | Market reactions to positive and negative jumps

It is well established in the literature that investors tend to pay more attention to positive information than to negative information (see Chan, 2003; Frank & Sanati, 2018; Ivkovic ́& Jegadeesh, 2004; Jiang & Zhu, 2017; Kothari et al., 2009; Park et al., 2014). Moreover, descriptive statistics in Section 2.3 indicate that overnight jumps tend to be negative, while intraday jumps tend to be positive (see Table 1). Therefore, the asymmetric market reactions to overnight and intraday informational shocks might be simply driven by the fact that intraday jumps are overwhelmingly positive, which triggers investors' overreaction, while overnight jumps are overwhelmingly negative, to which investors pay little or no attention.

In this section, we demonstrate that our documented asymmetric market reactions to overnight and intraday informational shocks (Table 2) are not a pure manifestation of the above well-known biased behavior that investors tend to pay more attention to positive information than to negative information (see Frank & Sanati, 2018; Jiang & Zhu, 2017; Park et al., 2014). We project that inattention-induced underreaction to lagged overnight information should be insensitive to the types of information, as investors do not pay attention or effort to learn the new information in the first place. In comparison, attention-induced overreaction to lagged intraday information could vary between positive and negative information content, given that attention-induced overreaction is more likely to happen for buying than selling due to various market frictions (such as short-selling constraints and costs) and behavioral biases.

We separately study the market reactions to negative or positive jumps occurring in intraday and overnight periods to validate our projections. Our approach proceeds as follows: In the first step, we separate the overnight (intraday) jumps into positive and negative subsamples. We have four subsamples (i.e., positive overnight, negative overnight, positive intraday, and negative intraday jumps). Next, we perform the univariate portfolio analysis for each subsample by sorting stocks based on the value of jumps. Due to the smaller sample size of the subsample, we sort stocks (in ascending order) into quintile groups rather than decile groups. The long-short portfolio buys the top quintile (Q5) and sells the bottom quintile (Q1). The value-weighted average daily return spread is calculated over the next 1–10-day horizons. Table 4 presents the portfolio spreads between the highest and lowest deciles (Q5–Q1) and alphas adjusted by the Fama-French three-factor (FF3) and Fama-French five-factor (FF5) models.

Consistent with our projection, we find that irrespective of whether they are positive or negative overnight jumps, there exists a significant positive return spread for the long-short portfolio before and after adjusting the risk exposures. The market does not distinguish between positive or negative overnight informational shocks and uniformly underreacts in subsequent days (i.e., price drifts), implying a pattern of slow information diffusion. In particular, underreaction (to overnight information) stems mainly from the stocks with the most salient informational shocks. That is, the long-leg stock portfolio with the largest positive jumps generates a sizeable positive alpha, while the short-leg stock portfolio with the smallest positive jumps has an indistinguishable alpha from zero (in Panel A). Similarly, the short-leg stock portfolio with the largest negative jumps in magnitude possesses a significantly negative alpha, while the alpha of the long-leg stock portfolio with the smallest negative jumps in magnitude is insignificant (in Panel B). In principle, one should react more promptly to the salient jumps because these are the most visible given their large economic magnitude (i.e., containing more value-relevant information). Therefore, the sizable positive (negative) alpha of the Q5 (Q1) portfolio in Panel A (B) reinforces our underreaction story, as it suggests that investors, in particular individual investors, do not pay sufficient attention to these "high-stake" informational events.

This uniform pattern, however, does not hold when we sort on intraday positive and negative jumps because the empirical results are mixed. First, the long-short portfolio sorted by lagged positive intraday jumps generates a significantly negative risk-adjusted return in subsequent days, suggesting that investors overreact to the positive information released during the day (in Panel C). As expected, the long-leg stock portfolio with the most salient positive informational shocks (i.e., the largest intraday positive jumps) delivers a sizeable negative alpha, confirming that investors overreact to the most favorable information released during the day. However, we do not find corroborating evidence for the short-leg stock portfolio with the smallest positive intraday jumps, as it has a positive alpha (rather than a negative one). Second, investors underreact to intraday negative information, as a significant positive risk-adjusted return emerges for the long-short portfolio sorted on lagged negative intraday jumps. In particular, the short-leg stock portfolio with the most salient negative informational shocks (i.e., the largest intraday negative jumps in magnitude) generates a highly negative alpha, implying that investors underreact to the most unfavorable information released during the day (in Panel D). Taken together, overreaction to intraday jumps only exists in those cases with positive shocks is a telling story, as it supports the attention-induced trading mechanism by small retail investors who pay more attention to buying (on good news) than selling (on bad news) due to various market frictions (such as short-selling constraints and costs) and behavioral biases.

TABLE 4 Market reactions to positive and negative overnight or intraday jumps.

	1 day	2 days	3 days	4 days	5 days	10 days
Panel A: Positive overnight jumps						
Q1	0.044	0.038	0.031	0.033	0.035	0.041
	(1.14)	(1.00)	(0.82)	(0.90)	(0.96)	(1.13)
Q5	0.525***	0.304***	0.209***	0.142***	0.088**	0.052
	(9.45)	(6.30)	(4.69)	(3.30)	(2.10)	(1.32)
Q5-Q1	0.481***	0.266***	0.178***	0.108***	0.052***	0.012
	(11.94)	(8.38)	(6.87)	(4.72)	(2.58)	(0.83)
FF3 alpha	0.474***	0.254***	0.166***	0.096***	0.039**	−0.001
	(11.97)	(8.28)	(6.59)	(4.33)	(2.03)	(−0.10)
FF5 alpha	0.476***	0.254***	0.166***	0.095***	0.038**	−0.002
	(11.95)	(8.18)	(6.49)	(4.26)	(1.97)	(−0.14)
Panel B: Negative overnight jumps						
Q1	−0.431***	−0.327***	−0.270***	−0.224***	−0.180***	−0.109**
	(−8.89)	(−7.02)	(−5.87)	(−5.00)	(−4.05)	(−2.55)
Q5	0.045	0.055	0.049	0.047	0.053	0.049
	(1.12)	(1.39)	(1.24)	(1.20)	(1.40)	(1.31)
Q5-Q1	0.476***	0.382***	0.318***	0.271***	0.234***	0.158***
	(17.43)	(15.71)	(14.91)	(14.48)	(12.94)	(11.51)
FF3 alpha	0.486***	0.391***	0.327***	0.279***	0.242***	0.168***
	(17.83)	(16.11)	(15.70)	(15.66)	(14.33)	(12.67)
FF5 alpha	0.474***	0.381***	0.319***	0.274***	0.237***	0.165***
	(17.53)	(16.14)	(15.96)	(15.65)	(14.26)	(12.50)
Panel C: Positive intraday jumps						
Q1	0.099***	0.074**	0.074**	0.074**	0.071**	0.070**
	(3.03)	(2.29)	(2.29)	(2.30)	(2.19)	(2.16)
Q5	−0.135***	−0.134***	−0.095***	−0.080**	−0.088**	−0.028
	(−3.75)	(−3.79)	(−2.70)	(−2.26)	(−2.49)	(−0.79)
Q5-Q1	−0.234***	−0.208***	−0.169***	−0.154***	−0.159***	−0.098***
	(−14.24)	(−14.62)	(−13.49)	(−13.89)	(−15.25)	(−11.34)
FF3 alpha	−0.242***	−0.218***	−0.182***	−0.167***	−0.173***	−0.112***
	(−14.75)	(−15.31)	(−14.42)	(−15.02)	(−16.56)	(−13.72)
FF5 alpha	−0.238***	−0.215***	−0.179***	−0.164***	−0.170***	−0.109***
	(−14.50)	(−15.13)	(−14.21)	(−14.73)	(−16.17)	(−13.33)
Panel D: Negative intraday jumps						
Q1	−0.273***	−0.195***	−0.174***	−0.163***	−0.129***	−0.101**
	(−6.06)	(−4.44)	(−4.02)	(−3.83)	(−3.06)	(−2.51)
Q5	−0.019	−0.020	−0.028	−0.032	−0.025	−0.027
	(−0.47)	(−0.52)	(−0.72)	(−0.83)	(−0.66)	(−0.73)

(Continues)

TABLE 4 (Continued)

Panel D: Negative intraday jumps						
Q5-Q1	0.254***	0.175***	0.146***	0.132***	0.104***	0.075***
	(11.21)	(9.16)	(8.25)	(8.22)	(6.89)	(5.99)
FF3 alpha	0.254***	0.175***	0.147***	0.132***	0.105***	0.075***
	(11.44)	(9.40)	(8.70)	(8.76)	(7.52)	(6.65)
FF5 alpha	0.253***	0.175***	0.147***	0.133***	0.106***	0.076***
	(10.97)	(9.10)	(8.48)	(8.59)	(7.42)	(6.65)

The table reports the differential market reactions to positive and negative overnight (intraday) jumps in Panels A and B (C and D), respectively. Specifically, we sort stocks into quintile portfolios by jumps (in ascending order). The hedge portfolio (Q5–Q1) is constructed by going long the top quintile (Q5) and short the bottom quintile (Q1). Portfolios are value-weighted, and the average daily portfolio returns in the next 1–10-day horizons are computed by averaging across active portfolios with overlapping holding periods under the Jegadeesh and Titman (1993) method. We report the portfolio excess returns for the Q1, Q5, and the hedge portfolios (Q5--Q1). For the hedge portfolio, we also report the risk-adjusted returns (alphas) using the Fama-French three-factor (FF3) and Fama-French five-factor (FF5) models. All returns are expressed in percent, and Newey and West (1987) adjusted t-statistics are reported in parenthesis. Statistical significance at the 1%, 5%, and 10% levels is denoted as ***, **, and *, respectively. The sample period is from 1996 to 2018.

Overall, these new sets of "high-resolution" evidence complement the prior work (see Frank & Sanati, 2018; Jiang & Zhu, 2017; Park et al., 2014) and suggest that the nature of information (positive or negative) only matters when the market pays close attention during the intraday trading periods.

3.5 | Market reactions to news-related and non-news jumps

This subsection investigates the market responses to jumps associated with and without public news. Our detected jumps are a comprehensive measure of informational shocks, encompassing both public and private information.[13] In theory, news announcements are public information events that attract investor attention (see Barber & Odean, 2008; Da et al., 2011). Moreover, public news is one of the legitimate drivers of the detected jumps, as investors trade on the new information acquired from the announcements. Therefore, we perform univariate portfolios on the jump subsamples associated with news announcements versus those without—to compare their respective market responses.

Our news dataset is constructed from the Financial News Database of Chinese Listed Companies (CFND) sourced via the CNRDS database. The CFND news database contains financial news reports from more than 400 online financial media and more than 600 print newspapers in China, from which we build a comprehensive panel dataset on the date and time of news reports covering individual listed firms. We then match the news dataset with the jumps based on the stock identity and release time. If at least one public news report covers a specific stock during the detected jump period (the overnight or intraday period), we classify it as jumps associated with public news; otherwise, it is defined as jumps without news. That is, the news subsample refers to the intraday (overnight) jumps that are associated with at least one public news event during the intraday (overnight) period, while the no-news subsample is the remaining intraday (overnight) jumps that have no news during the intraday (overnight) period.

[13] Jumps are a reliable measure of firm-level informational shocks. Lee and Mykland (2008) reveal that misclassification of jumps is negligible when using high-frequency data, and the detected jumps are related to firm-level information arrivals. Lee (2012) documents that jumps are related to firm-level information events, such as earnings releases and analyst recommendations. Some studies explain market reactions following price shocks by distinguishing whether they are news-based. Savor (2012) finds that non-information-based shocks experience reversals, whereas information-based shocks exhibit momentum. Piccotti (2018) and Xiao et al. (2020) find that price shocks related to public news have a more persistent influence. We follow the procedure of Jiang and Zhu (2017) by filtering out jumps less than twice the tick size to ensure that the identified jumps are not spurious due to bid-ask bounces. Therefore, jumps detected in this paper can be a good proxy for information arrivals, measuring public and unobservable private information (see Savor, 2012; Jiang and Zhu, 2017).

Panel A of Table 5 reports the portfolio performance for the no-news subsample. The empirical patterns are similar to our baseline analysis in Table 2, albeit weaker in magnitude. Specifically, the return spread and alphas of the long-short portfolios sorted on lagged overnight (intraday) jumps are significantly positive (negative), and the return drifts (reversals) stem mainly from D1 (D10), indicating an underreaction (overreaction) to the informational shocks, proxied by no-news jumps.

In comparison, the portfolio performance for the news-related subsample exhibits similar but stronger patterns (see Panel B of Table 5). Specifically, the market underreactions (overreactions) to overnight (intraday) jumps associated with public news are more prominent with larger return spreads and alphas in magnitude. These stronger patterns in the news-related subsample than those in the no-news subsample are consistent with attention allocation between day and night. During the intraday period, when individuals allocate more attention, public news attracts their immediate attention and induces more substantial overreactions—larger price reversal in subsequent days. During the overnight period, when individuals allocate less or no attention (due to cognitive constraints), value-relevant information contained in the public news is disseminated slower, leading to stronger return continuation.

Overall, the robust asymmetric market reactions across the news-related and no-news subsamples implies two things. First, it supports the role of attention allocation in reconciling underreaction to lagged overnight jumps and overreaction to lagged intraday jumps. Second, it reinforces our adoption of jumps as a comprehensive measure of informational shocks, given that not all jumps are triggered by public news but also stem from private information (Jiang & Zhu, 2017; Savor, 2012).[14]

4 | FURTHER ANALYSES ON THE ASYMMETRIC MARKET REACTIONS

4.1 | The interplay between attention allocation and information density

This section explores the interplay between attention allocation and information density in reshaping the *asymmetric market* responses to overnight and intraday jumps. To be specific, we follow Jiang et al. (2021) by focusing on the subsample with higher-than-average jump density—days with above 85 (121) jumps during the overnight (intraday) period. Then, we repeat the univariate portfolio sorts on the subsample.

Table 6 presents the portfolio results. Strikingly, the market exhibits much stronger subsequent price drifts (i.e., underreactions) after these high information density days with relatively more jumps across stocks. As expected, the positive alphas of the long-short portfolio are contributed by both the long leg (D10) and the short leg (D1), indicating a slower-than-usual information diffusion for both positive and negative overnight informational shocks. This reinforces the (adverse) consequence of inattention by the market despite massive (lagged) informational flows during the night.

In comparison, we also document that after days with relatively high intraday jump density, the market exhibits more substantial price reversals (i.e., overreactions). One possible explanation is that massive informational shocks during the intraday trading periods are likely to amplify the contemporaneous attention-induced trading and lead to more persistent subsequent return reversal because the market, primarily small and inexperienced individual investors, pay close attention. Consistent with the fact that individual investors are more likely to engage in attention-driven buying than selling, we find that the negative alphas of the long-short portfolio are mainly contributed by the long leg (D10), which are stocks with the most positive information and mainly likely to be associated with attention-induced buying.

Collectively, we find that high information density amplifies the asymmetric market responses to overnight and intraday informational shocks.

[14] Sentiment- or fake news-driven jumps are unlikely to be the underlying mechanism of our findings. A central prediction of sentiment (or fake news) is a reversal, as an overreaction to sentiment (or mis-reaction to fake news) leads to a subsequent price reversal. For example, Savor (2012) finds that non-information-based shocks experience reversals, whereas information-based shocks exhibit momentum. If jumps are indeed driven by sentiment or fake news, we should only observe price reversal, whether it is during the overnight or intraday period because there are no reasons to believe that sentiment or fake news only occurs during the day but not at night. This, however, does not correspond to our documented pattern of strong underreaction to lagged overnight jumps.

TABLE 5 Market reactions to jumps with or without news.

	1 day	2 days	3 days	4 days	5 days	10 days
Panel A: Overnight jumps without news						
Q1	−0.296***	−0.216***	−0.174***	−0.148***	−0.120***	−0.070*
	(−6.61)	(−5.01)	(−4.11)	(−3.56)	(−2.88)	(−1.74)
Q5	0.049	−0.003	−0.018	−0.029	−0.046	−0.025
	(1.04)	(−0.06)	(−0.41)	(−0.69)	(−1.13)	(−0.64)
Q5-Q1	0.345***	0.214***	0.156***	0.120***	0.073***	0.045***
	(10.05)	(7.73)	(6.77)	(6.16)	(4.24)	(3.89)
FF3 alpha	0.343***	0.212***	0.155***	0.119***	0.073***	0.045***
	(9.97)	(7.70)	(6.82)	(6.23)	(4.31)	(3.91)
FF5 alpha	0.346***	0.214***	0.156***	0.119***	0.073***	0.046***
	(9.97)	(7.70)	(6.86)	(6.22)	(4.33)	(4.00)
Panel B: Overnight jumps with news						
Q1	−0.497***	−0.431***	−0.377***	−0.339***	−0.321***	−0.259***
	(−4.60)	(−4.34)	(−4.24)	(−3.80)	(−3.68)	(−3.02)
Q5	0.458***	0.338***	0.245***	0.188**	0.146*	0.024
	(4.81)	(3.74)	(2.80)	(2.26)	(1.84)	(0.32)
Q5-Q1	0.955***	0.769***	0.623***	0.526***	0.467***	0.283***
	(7.90)	(7.43)	(8.31)	(7.36)	(6.99)	(5.05)
FF3 alpha	0.935***	0.761***	0.619***	0.523***	0.462***	0.276***
	(7.65)	(7.23)	(8.03)	(7.11)	(6.72)	(4.86)
FF5 alpha	0.950***	0.787***	0.647***	0.546***	0.480***	0.284***
	(8.38)	(8.15)	(8.86)	(7.71)	(7.19)	(4.92)
Panel C: Intraday jumps without news						
Q1	−0.044	−0.008	−0.009	−0.005	0.007	0.007
	(−1.27)	(−0.22)	(−0.25)	(−0.14)	(0.20)	(0.23)
Q5	−0.123***	−0.122***	−0.105***	−0.089***	−0.092***	−0.051
	(−3.91)	(−3.88)	(−3.25)	(−2.72)	(−2.85)	(−1.56)
Q5-Q1	−0.079***	−0.115***	−0.096***	−0.084***	−0.099***	−0.058***
	(−5.49)	(−10.11)	(−10.10)	(−10.52)	(−13.12)	(−10.76)
FF3 alpha	−0.079***	−0.115***	−0.097***	−0.085***	−0.100***	−0.061***
	(−5.58)	(−10.16)	(−10.00)	(−10.39)	(−12.84)	(−10.91)
FF5 alpha	−0.079***	−0.113***	−0.096***	−0.084***	−0.099***	−0.060***
	(−5.59)	(−10.14)	(−10.08)	(−10.37)	(−12.95)	(−11.06)
Panel D: Intraday jumps with news						
Q1	−0.197**	−0.169**	−0.159*	−0.160*	−0.142*	−0.149*
	(−2.26)	(−2.01)	(−1.89)	(−1.90)	(−1.70)	(−1.86)
Q5	−0.349***	−0.335***	−0.307***	−0.311***	−0.311***	−0.254***
	(−4.33)	(−4.19)	(−3.89)	(−3.85)	(−3.84)	(−3.10)

(Continues)

TABLE 5 (Continued)

Panel D: Intraday jumps with news						
Q5-Q1	−0.152***	−0.166***	−0.149***	−0.151***	−0.169***	−0.104***
	(−3.72)	(−4.83)	(−4.75)	(−5.25)	(−6.39)	(−4.91)
FF3 alpha	−0.170***	−0.181***	−0.162***	−0.159***	−0.174***	−0.102***
	(−4.30)	(−5.30)	(−5.30)	(−5.58)	(−6.71)	(−4.80)
FF5 alpha	−0.173***	−0.179***	−0.159***	−0.159***	−0.173***	−0.105***
	(−4.38)	(−5.16)	(−5.06)	(−5.37)	(−6.56)	(−5.15)

The table reports the market reactions to overnight (intraday) jumps without and with public news in Panels A and B (C and D), respectively. News data are retrieved from the CNRDS database and are matched with overnight and intraday jumps based on the release time. The hedge portfolio (D10–D1) is constructed by going long the top decile (D10) and short the bottom decile (D1). Portfolios are value-weighted, and the average daily portfolio returns in the next 1–10-day horizons are computed by averaging across active portfolios with overlapping holding periods under the Jegadeesh and Titman (1993) method. We report the portfolio excess returns for the D1, D10, and the hedge portfolio (D10–D1). For the hedge portfolio, we report the risk-adjusted returns (alphas) using the Fama-French three-factor (FF3) and Fama-French five-factor (FF5) models. All returns are expressed in percent, and Newey and West (1987) adjusted t-statistics are reported in parenthesis. Statistical significance at the 1%, 5%, and 10% levels is denoted as ***, **, and *, respectively.

4.2 | Slower information diffusion in adverse market conditions

In this section, we shed light on how attention allocation-related *asymmetric* market responses behave during adverse market states. Prior literature suggests that investors allocate less attention to their stocks when the overall market return is low (Peng & Xiong, 2006; Huang et al., 2019). This implies that slow information diffusion (i.e., underreaction) is likely to strengthen, while the return reversal related to attention-induced trading might be dampened during these "difficult times" as investors devote less attention when the overall market has extreme performances.

To validate the above conjecture, we explore two historical episodes featuring extreme market states in China (i.e., from January 1, 2006 to November 11, 2008 and July 18, 2014 to March 1, 2016). Again, we perform univariate portfolio sorts on intraday and overnight jumps over these episodes. The portfolio results are in Table 7.

Consistent with our intuition, we document that the market strongly and persistently underreacts to lagged overnight jumps. Specifically, the price drift is highly prominent, with a large and positive alpha that underreacts to lag overnight in the long-short portfolio, indicating a more persistent slow information diffusion during the market downturns. Moreover, the positive alphas are contributed by both the long leg (D10) and the short leg (D1), which is consistent with our expectation that investors allocate less attention to their stocks when the overall market return is low (Huang et al., 2019; Peng & Xiong, 2006). In comparison, we find that the overreaction to lagged intraday jumps is weakened (compared to our baseline case in Table 2) during the two well-known episodes with depressive market performance. Again, this is consistent with our conjecture that the return reversal related to attention-induced trading should be dampened during these "difficult times" as investors devote little (or no) attention when the overall market has poor performances.

4.3 | Investors searching behavior

This section uses the investor search data sourced from the CNRDS database to validate our attention allocation-based mechanism. The CNRDS database collects and compiles the daily search volume of stock by individual investors' search with keywords (such as the stock code, ticker, company abbreviation, and full names) via the leading Chinese web search engines. Following the convention (Da et al., 2011), we compute the daily abnormal search volume (*ASVI*)

TABLE 6 Subsample analysis over the days with high jump density.

Panel A: Sorted on overnight jumps						
	1 day	2 days	3 days	4 days	5 days	10 days
D1	−0.302***	−0.206***	−0.161***	−0.127***	−0.092*	−0.042
	(−5.81)	(−4.17)	(−3.29)	(−2.62)	(−1.92)	(−0.91)
D10	0.289***	0.175***	0.121**	0.086*	0.055	0.046
	(5.23)	(3.38)	(2.48)	(1.82)	(1.19)	(1.03)
D10–D1	0.591***	0.381***	0.282***	0.213***	0.147***	0.088***
	(14.13)	(11.47)	(10.35)	(9.60)	(7.59)	(6.98)
FF3 alpha	0.592***	0.381***	0.282***	0.213***	0.147***	0.088***
	(14.11)	(11.57)	(10.67)	(10.02)	(8.03)	(7.25)
FF5 alpha	0.599***	0.386***	0.285***	0.216***	0.149***	0.090***
	(14.11)	(11.59)	(10.75)	(10.08)	(8.15)	(7.41)
Panel B: Sorted on intraday jumps						
	1 day	2 days	3 days	4 days	5 days	10 days
D1	−0.038	−0.003	0.001	0.007	0.021	0.022
	(−0.83)	(−0.07)	(0.03)	(0.16)	(0.49)	(0.52)
D10	−0.150***	−0.140***	−0.111***	−0.093**	−0.101**	−0.051
	(−3.63)	(−3.38)	(−2.64)	(−2.19)	(−2.37)	(−1.19)
D10–D1	−0.113***	−0.137***	−0.113***	−0.100***	−0.122***	−0.073***
	(−6.25)	(−9.73)	(−9.61)	(−9.52)	(−13.07)	(−11.34)
FF3 alpha	−0.111***	−0.136***	−0.113***	−0.101***	−0.124***	−0.077***
	(−6.27)	(−9.75)	(−9.51)	(−9.38)	(−12.81)	(−11.72)
FF5 alpha	−0.113***	−0.135***	−0.111***	−0.100***	−0.123***	−0.077***
	(−6.28)	(−9.62)	(−9.32)	(−9.15)	(−12.60)	(−11.71)

The table reports the market reactions to intraday and overnight jumps over the days with high jump density. Days with high jump density are defined as the jump days with the total number of overnight (intraday) jumps summed over all stocks that exceeds the full-sample median value of 85 (121). Again, we adopt the univariate portfolio analysis. Specifically, we sort stocks into decile portfolios by detected jumps (in ascending order). The hedge portfolio (D10–D1) is constructed by going long the top decile (D10) and short the bottom decile (D1). Portfolios are value-weighted, and the average daily portfolio returns in the next 1–10-day horizons are computed by averaging across active portfolios with overlapping holding periods under the Jegadeesh and Titman (1993) method. We report the portfolio excess returns for the D1, D10, and the hedge portfolio (D10–D1). For the hedge portfolio, we also report the risk-adjusted returns (alphas) using the Fama-French three-factor (FF3) and Fama-French five-factor (FF5) models. All returns are expressed in percent, and Newey and West (1987) adjusted t-statistics are reported in parenthesis. Statistical significance at the 1%, 5%, and 10% levels is denoted as ***, **, and *, respectively.

of a particular stock as follows:

$$ASVI_{i,t} = log\left(SVI_{i,t}\right) - log\left(Mean\left(SVI_{i,t-1}, SVI_{i,t-10}\right)\right), \tag{5}$$

where $SVI_{i,t}$ is the daily search volume index of stock i at day t. Following the literature, we first take the natural log of the SVI. Next, to account for the possible time trend over time, *ASVI* is computed by subtracting the log of the mean of *SVI* averaged over the past 10 days from the log of *SVI*. Note that the sample period is confined from 2011 to 2018 due to the availability of *SVI* data.

TABLE 7 Subsample analysis over the period with extreme market fluctuations.

Panel A: Sorted on overnight jumps						
	1 day	2 days	3 days	4 days	5 days	10 days
D1	−0.398***	−0.284**	−0.209	−0.165	−0.123	−0.028
	(−2.79)	(−2.03)	(−1.52)	(−1.20)	(−0.90)	(−0.21)
D10	0.484***	0.331**	0.252*	0.197	0.141	0.104
	(3.27)	(2.41)	(1.92)	(1.54)	(1.12)	(0.85)
D10–D1	0.881***	0.615***	0.461***	0.361***	0.264***	0.132***
	(8.30)	(7.30)	(6.33)	(5.98)	(5.09)	(4.20)
FF3 alpha	0.885***	0.617***	0.462***	0.361***	0.262***	0.131***
	(8.31)	(7.50)	(6.59)	(6.39)	(5.49)	(4.38)
FF5 alpha	0.895***	0.623***	0.467***	0.365***	0.265***	0.134***
	(8.32)	(7.48)	(6.62)	(6.44)	(5.59)	(4.55)
Panel B: Sorted on intraday jumps						
	1 day	2 days	3 days	4 days	5 days	10 days
D1	−0.060	0.002	0.004	0.017	0.043	0.058
	(−0.49)	(0.02)	(0.03)	(0.15)	(0.36)	(0.50)
D10	0.014	−0.044	−0.053	−0.043	−0.058	−0.015
	(0.13)	(−0.40)	(−0.46)	(−0.38)	(−0.50)	(−0.13)
D10–D1	0.074*	−0.046	−0.057**	−0.061***	−0.101***	−0.073***
	(1.85)	(−1.37)	(−2.20)	(−2.83)	(−5.16)	(−5.08)
FF3 alpha	0.081**	−0.041	−0.053**	−0.059***	−0.100***	−0.075***
	(2.11)	(−1.29)	(−2.10)	(−2.74)	(−5.02)	(−5.21)
FF5 alpha	0.074*	−0.043	−0.053**	−0.058***	−0.099***	−0.075***
	(1.84)	(−1.31)	(−2.03)	(−2.68)	(−4.97)	(−5.46)

The table reports the market reactions to intraday and overnight jumps over the subsample period with notable, extreme market fluctuations (i.e., from 1st January 2006 to 11th November 2008 and 18th July 2014 to 1st March 2016). Again, we adopt the univariate portfolio analysis. Specifically, we sort stocks into decile portfolios by detected jumps (in ascending order). The hedge portfolio (D10–D1) is constructed by going long the top decile (D10) and short the bottom decile (D1). Portfolios are value-weighted, and the average daily portfolio returns in the next 1–10-day horizons are computed by averaging across active portfolios with overlapping holding periods under the Jegadeesh and Titman (1993) method. We report the portfolio excess returns for the D1, D10, and the hedge portfolio (D10–D1). For the hedge portfolio, we also report the risk-adjusted returns (alphas) using the Fama-French three-factor (FF3) and Fama-French five-factor (FF5) models. All returns are expressed in percent, and Newey and West (1987) adjusted t-statistics are reported in parenthesis. Statistical significance at the 1%, 5%, and 10% levels is denoted as ***, **, and *, respectively.

Next, we perform a panel regression to study the influence of jumps on individual investors' search behavior. The model specification is as follows:

$$ASV\,I_{i,t(t+h)} = \alpha + \beta_1 Jump^{OVNT}_{i,t} + \beta_2 Jump^{INTD}_{i,t} + \sum_{k=1}^{K} \gamma_{k,t} \times Z_{k,t} + \sigma_i + \mu_i + \varepsilon_{i,t}, \tag{6}$$

where the dependent variable, $ASVI_{i,t(t+h)}$, is the abnormal search volume index on jump day t and the subsequent days (h equals 0, 1, 2, 3, 5, and 10). The key explanatory variables, $Jump^{OVNT}_{i,t}$ and $Jump^{INTD}_{i,t}$, are the absolute values of the overnight and intraday jumps. This is because both large positive and negative jumps are likely to trigger investor attention (i.e., it is the salience and magnitude, rather than the sign, of the information shocks (jumps) that grab investor attention). $Z_{k,t}$ denotes the k-th control variables in the regression model. We account for a wide range of control variables, which includes the non-jump returns (*non_Jump*), lagged stock returns over the past 1–5 days and over the past 6–10 days ($ret_{i,t-5\_t-1}$ and $ret_{i,t-10\_t-6}$), turnover ratio (*Turn*), the log value of market capitalization (*SIZE*), book-to-market ratio (*BM*), close price (*PRICE*), idiosyncratic volatility (*IVOL*), Amihud illiquidity (*ILLIQ*), institutional ownership (*IO*), analyst coverage (*COVER*), and market beta (*BETA*). We also control for the firm and year-fixed effects. We report the two-way clustered standard errors (i.e., clustered by firm and year).

Table 8 reports the estimation results for the panel regression. Consistent with our projection that individual investors pay close attention during the intraday trading periods, we find that intraday jumps motivate strong searching behavior by individual investors in contemporaneous and subsequent days. The influence of intraday jump on individual investors' searching behavior is highly significant till the next 3 days, with the coefficients of 0.024, 0.024, 0.021, and 0.021, and the corresponding t-values of 10.97, 10.91, 6.93, and 3.75, respectively. In other words, more salient and prominent intraday information shocks (in absolute terms) are associated with stronger searching behavior over contemporaneous and subsequent days. In contrast, overnight jumps do not induce much search volume in subsequent days, which aligns with our projection that individual investors are inattentive to overnight informational shocks.

Overall, the results reveal different individual investors searching behaviors following intraday and overnight jumps. These search volume patterns provide supportive evidence that individual investors, constrained by limited attention, allocate their attention disproportionally more during the day than at night.

5 | ROBUSTNESS CHECKS

5.1 | Controlling stock characteristics

In this section, we assess whether the positive (negative) return predictability of lagged overnight (intraday) jumps is simply a manifestation of other well-known cross-sectional return predictors, such as size and value. It is well known that individual investors prefer speculative stocks (i.e., those small and volatile stocks with low analyst coverage), while institutional investors tend to hold large stocks with more analyst coverage (Da et al., 2021; Gargano & Rossi, 2018; Jang & Kang, 2019; Jiang et al., 2021). We re-assess the performance of the characteristic controlled portfolios to ensure this preference difference does not simply drive our findings.

Specifically, the characteristic-controlled portfolios are constructed as follows: First, we sort all stocks into five groups based on one specific (ex-ante) firm characteristic. Second, we further sort stocks into decile portfolios based on overnight or intraday jumps within each characteristic group. This sequential sorting process generates the return series of 50 double-sorted portfolios. Next, the returns of the characteristic-controlled jump-sorted decile portfolios are computed by averaging the portfolio returns (of the same jump decile) across different characteristic quintile groups. The long-short portfolio is defined similarly by going long the D10 and short the D1 portfolios. We control for a wide range of firm characteristics, which include market beta (BETA), market capitalization (SIZE), book-to-market ratio (BM), turnover ratio (TURN), stock price (PRICE), Amihud ratio (ILLIQ), analyst coverage (COVER), idiosyncratic volatility (IVOL), and institutional ownership (IO).

Table 9 presents the portfolio performance for these characteristic-controlled portfolios. For brevity, we only report the Fama-French five-factor alphas. However, our results are robust under alternative factor models. The positive (negative) alpha of the long-short portfolios sorted on overnight (intraday) jumps remains strong after we control for the firm characteristics. Overall, this indicates that the solid cross-sectional return predictability of overnight and intraday jumps is driven by attention allocation-based mechanisms rather than explained away by other well-known firm characteristics.

TABLE 8 The influence of jumps on investors' searching.

	Day 0	Day 1	Day 2	Day 3	Day 5	Day 10
$Jump^{OVNT}$	0.020***	0.013*	0.009	0.011*	−0.022***	0.002
	(4.27)	(2.06)	(1.31)	(1.91)	(−5.21)	(1.02)
$Jump^{INTD}$	0.024***	0.024***	0.021***	0.011***	−0.012***	−0.000
	(10.97)	(10.91)	(6.93)	(3.75)	(−4.00)	(−0.19)
non_Jump	0.013***	0.015***	0.017***	0.011***	−0.000	0.000
	(9.46)	(7.67)	(6.08)	(4.94)	(−0.05)	(0.19)
TURN	2.704***	1.562***	0.393*	−0.444**	−0.435**	−1.661***
	(23.55)	(11.89)	(2.36)	(−2.42)	(−2.71)	(−5.77)
ret_{t-5_t-1}	0.006***	0.004***	0.003***	0.002**	−0.000	0.001
	(6.30)	(7.43)	(6.76)	(3.50)	(−0.34)	(0.93)
ret_{t-10_t-6}	−0.002***	−0.001	−0.001	−0.000	−0.001	−0.000
	(−4.16)	(−1.86)	(−0.90)	(−0.00)	(−1.30)	(−0.34)
SIZE	0.030***	0.013***	−0.006*	−0.005*	0.004	−0.013**
	(4.64)	(4.20)	(−2.17)	(−2.35)	(1.75)	(−3.48)
BM	−0.021**	−0.004	0.012**	0.012	0.003	0.024***
	(−3.19)	(−1.04)	(2.54)	(1.88)	(0.53)	(3.68)
IVOL	−0.009**	−0.006*	−0.002	0.003	0.009**	0.017***
	(−2.87)	(−2.27)	(−0.44)	(0.92)	(2.63)	(3.94)
ILLIQ	−0.022	0.009	0.045	−0.025	−0.077	−0.132***
	(−0.83)	(0.40)	(1.48)	(−0.68)	(−1.27)	(−3.64)
PRICE	−0.031**	−0.006	0.017**	0.017***	0.013**	0.026***
	(−3.50)	(−0.81)	(3.11)	(3.57)	(2.43)	(5.50)
IO	−0.036**	−0.020	−0.006	0.007	0.021**	0.016
	(−2.93)	(−1.72)	(−0.58)	(0.96)	(2.67)	(1.40)
COVER	−0.004	−0.005	−0.006**	−0.004	−0.017***	−0.002
	(−1.15)	(−1.86)	(−2.41)	(−1.70)	(−8.06)	(−0.99)
BETA	0.002**	0.001	−0.001	−0.001	−0.001	−0.002
	(2.45)	(1.31)	(−0.63)	(−1.05)	(−0.47)	(−0.89)
Firm& Year	Yes	Yes	Yes	Yes	Yes	Yes
Cons	−0.387**	−0.243***	−0.038	−0.055	−0.168***	0.111
	(−2.83)	(−3.89)	(−0.59)	(−1.18)	(−3.86)	(1.29)
Obs	1,322,734	1,317,282	1,313,749	1,312,996	1,313,674	1,309,613
R^2	0.225	0.026	0.015	0.007	0.004	0.007

The table presents the results of the panel regression. The dependent variables are the abnormal search volume index data (*ASVI*) on the jump day and the subsequent ten days (Day 0–Day 10). The main independent variables are the **absolute values** of overnight and intraday jumps ($Jump^{OVNT}$ and $Jump^{INTD}$). *non_Jump* is the residual return that excludes the overnight and intraday jumps, which controls for the influence of non-jump returns. We also control for other well-known firm characteristics, including lagged returns in days *t*-1 till *t*-5 (ret_{t-5_t-1}), and in days *t*-6 till day *t*-10 (ret_{t-10_t-6}), the daily turnover ratio (*TURN*), the log value of market capitalization (*SIZE*), book-to-market ratio (*BM*), close price (*PRICE*), idiosyncratic volatility (*IVOL*), Amihud illiquidity (*ILLIQ*), institutional ownership (*IO*), analyst coverage (*COVER*), and market beta (*BETA*). The t-statistics clustered by firm and year are reported in the parenthesis. Statistical significance at the 1%, 5%, and 10% levels is denoted as ***, **, and *, respectively. The sample period is from 2011 to 2018.

TABLE 9 Portfolio sorts controlling for other firm characteristics.

Controlling for	Panel A: Overnight jumps						Panel B: Intraday jumps					
	1 day	2 days	3 days	4 days	5 days	10 days	1 day	2 days	3 days	4 days	5 days	10 days
BETA	0.437***	0.267***	0.196***	0.153***	0.099***	0.064***	−0.059***	−0.106***	−0.095***	−0.078***	−0.099***	−0.052***
	(9.81)	(7.38)	(6.80)	(6.36)	(4.93)	(5.21)	(−2.62)	(−6.04)	(−6.36)	(−5.67)	(−7.55)	(−5.52)
SIZE	0.502***	0.294***	0.205***	0.162***	0.104***	0.061***	−0.059***	−0.091***	−0.067***	−0.059***	−0.076***	−0.046***
	(10.09)	(7.63)	(7.07)	(6.74)	(5.20)	(5.05)	(−3.31)	(−6.26)	(−5.54)	(−5.51)	(−7.34)	(−5.91)
BM	0.469***	0.264***	0.193***	0.150***	0.095***	0.050***	−0.050***	−0.087***	−0.077***	−0.065***	−0.084***	−0.050***
	(10.40)	(7.68)	(7.27)	(6.84)	(5.01)	(4.50)	(−2.58)	(−5.94)	(−6.49)	(−6.49)	(−9.03)	(−7.28)
TURN	0.485***	0.273***	0.200***	0.155***	0.094***	0.055***	−0.038**	−0.079***	−0.069***	−0.056***	−0.072***	−0.039***
	(10.41)	(7.95)	(7.58)	(7.21)	(5.25)	(4.94)	(−1.98)	(−5.20)	(−5.86)	(−5.46)	(−7.50)	(−5.39)
PRICE	0.482***	0.278***	0.196***	0.149***	0.094***	0.052***	−0.061***	−0.104***	−0.089***	−0.076***	−0.090***	−0.049***
	(10.66)	(8.19)	(7.32)	(6.80)	(5.17)	(4.62)	(−3.37)	(−7.11)	(−7.04)	(−7.35)	(−9.38)	(−6.70)
ILLIQ	0.475***	0.266***	0.200***	0.150***	0.092***	0.048***	−0.055***	−0.093***	−0.074***	−0.063***	−0.079***	−0.050***
	(10.75)	(8.45)	(8.11)	(7.36)	(5.16)	(4.48)	(−3.05)	(−7.12)	(−6.53)	(−6.44)	(−8.59)	(−7.50)
IVOL	0.443***	0.244***	0.176***	0.131***	0.074***	0.040***	−0.036*	−0.070***	−0.065***	−0.058***	−0.078***	−0.042***
	(9.95)	(7.49)	(6.94)	(6.50)	(4.35)	(3.83)	(−1.94)	(−4.97)	(−5.61)	(−5.54)	(−8.17)	(−5.83)
IO	0.553***	0.327***	0.238***	0.187***	0.121***	0.068***	−0.042**	−0.105***	−0.086***	−0.079***	−0.100***	−0.055***
	(11.40)	(8.85)	(8.16)	(7.83)	(6.14)	(6.36)	(−2.11)	(−6.84)	(−6.88)	(−7.37)	(−10.62)	(−9.33)

Panel A (B) of the table reports the Fama-French five-factor alphas of the characteristic-controlled decile portfolios that sorted on overnight (intraday) jumps. Specifically, we first sort stocks into five quintiles based on one firm characteristic (such as beta). Within each quintile, we further sort stocks into decile portfolios based on overnight (intraday) jumps. Next, we average across the firm-characteristic quintiles to get the returns of the characteristic-controlled decile portfolios. The firm characteristics include market beta (*BETA*), market capitalization (*SIZE*), book-to-market ratio (*BM*), turnover ratio (*TURN*), stock price (*PRICE*), Amihud ratio (*ILLIQ*), analyst coverage (*COVER*), idiosyncratic volatility (*IVOL*), and institutional ownership (*IO*). All returns are in percent, and the Newey–West adjusted *t*-statistics are in parenthesis. Statistical significance at the 1%, 5%, and 10% levels is denoted as ***, **, and *, respectively.

TABLE 10 Considering transaction costs.

Panel A: Sorted on overnight jumps						
	1 day	2 days	3 days	4 days	5 days	10 days
D1	−0.260***	−0.169***	−0.124***	−0.097**	−0.065	−0.013
	(−5.82)	(−3.96)	(−2.96)	(−2.33)	(−1.58)	(−0.33)
D10	0.108**	0.014	−0.023	−0.046	−0.072*	−0.062
	(2.18)	(0.30)	(−0.54)	(−1.11)	(−1.75)	(−1.59)
D10–D1	0.367***	0.183***	0.101***	0.051**	−0.006	−0.049***
	(9.57)	(6.05)	(4.03)	(2.42)	(−0.35)	(−4.00)
FF3 alpha	0.365***	0.182***	0.100***	0.050**	−0.007	−0.049***
	(9.50)	(6.03)	(4.05)	(2.43)	(−0.38)	(−4.06)
FF5 alpha	0.369***	0.184***	0.102***	0.052**	−0.006	−0.048***
	(9.49)	(6.04)	(4.09)	(2.47)	(−0.33)	(−3.98)
Panel B: Sorted on intraday jumps						
	1 day	2 days	3 days	4 days	5 days	10 days
D1	−0.096***	−0.060*	−0.061*	−0.056*	−0.045	−0.044
	(−2.79)	(−1.78)	(−1.80)	(−1.69)	(−1.38)	(−1.37)
D10	−0.057*	−0.061*	−0.043	−0.029	−0.034	0.007
	(−1.84)	(−1.95)	(−1.37)	(−0.90)	(−1.06)	(0.21)
D1-D10	−0.039**	0.000	−0.017*	−0.027***	−0.012	−0.051***
	(−2.52)	(0.04)	(−1.74)	(−3.26)	(−1.49)	(−8.68)
FF3 alpha	−0.039**	0.000	−0.017*	−0.027***	−0.011	−0.048***
	(−2.57)	(0.01)	(−1.69)	(−3.11)	(−1.32)	(−7.98)
FF5 alpha	−0.039***	−0.001	−0.018*	−0.028***	−0.012	−0.049***
	(−2.59)	(−0.09)	(−1.81)	(−3.27)	(−1.46)	(−8.29)

The table reports the portfolio performance net of transaction costs. The transaction cost is measured by the Corwin and Schultz (2012) implied bid-ask spread. Specifically, we sort stocks into decile portfolios by detected jumps in ascending order. The hedge portfolio is constructed by going long (short) the top (bottom) decile and short the bottom (top) decile for the overnight (intraday) jumps in Panel A (B). Portfolios are value-weighted, and the average daily portfolio returns in the next 1–10-day horizons are computed by averaging across active portfolios with overlapping holding periods under the Jegadeesh and Titman (1993) method. We report the excess returns and the risk-adjusted returns (alphas) using the Fama-French three-factor (FF3) and Fama-French five-factor (FF5) models. All returns are expressed in percent, and Newey and West (1987) adjusted t-statistics are reported in parenthesis. Statistical significance at the 1%, 5%, and 10% levels is denoted as ***, **, and *.

5.2 | Transaction cost analysis

This section examines whether the return spreads of long-short portfolios based on intraday and overnight jumps remain sizeable after considering transaction costs. To capture the cost, we adopt the implied bid-ask spread proposed by Corwin and Schultz (2012). Table 10 presents the portfolio performance net of transaction costs.

Panel A of the table presents the after-transaction-cost performance for the long-short strategies based on overnight jumps. The net returns are still significantly positive until the next 1–4-day horizon, indicating that the long-short strategy based on overnight jumps is profitable, even considering the transaction costs.

Panel B of the table presents the after-transaction-cost performance for the long-short strategies based on intraday jumps. For ease of interpretation, we construct a long-short portfolio that buys the bottom decile of the smallest intraday jumps and sells the top decile of the largest intraday jumps, which generates an unconditional positive return spread (i.e., capturing the overreaction pattern). The results indicate that the portfolio strategy becomes unprofitable once transaction costs are considered. This is expected as the long-short portfolio spreads are much smaller (in magnitude) for intraday jumps than those for overnight jumps (see Table 2).

The above findings should be interpreted with caution. In theory, explicit transaction costs, such as brokerage and commission fees, are the same whether an investor executes his trades in the pre-open auction or the continuous trading period. Therefore, the long-short strategies based on overnight jumps remain profitable for a small-sized (round-trip) transaction after accounting for transaction costs. This, however, does not hold for large-sized transactions, because the overnight session only accounts for 0.59% of the total trading volume within a day. The feature of illiquidity and thin trades of the pre-open auction (i.e., the overnight session) suggests that institutions cannot trade on the information fully (i.e., in large quantities) due to the absence of uninformed retail investors in the overnight period. Moreover, liquidity providers are less likely to supply liquidity over the night, because they also fear being picked up by informed institutions in the absence of noise traders (i.e., greater adverse selection risk). In short, the positive net return of the long-short strategies based on overnight jumps does not necessarily imply it is cost-effective to trade on information during the overnight period, given the low participation by retail investors (and liquidity providers).

5.3 | Other robustness checks

5.3.1 | Alternative definition of open price

This section examines whether our key findings are sensitive to the definition of open price. One legitimate concern is that the inefficient open price might drive our documented strong underreaction to lagged overnight jumps due to the specific market design. Our baseline analysis uses the open price at 9:30 (i.e., the auction price determined by the pre-open auction) to compute the overnight return. On the one hand, using the auction price avoids contamination by price movements in the early trading hours unrelated to overnight information. This increases the accuracy in measuring the overnight returns and detecting the overnight jumps. On the other hand, market participation (i.e., liquidity) might be low at the pre-open auction, leading to the concern of inefficient price at the market open (at 9:30). Therefore, similar to prior studies (Lou et al., 2019), we adopt the alternative definition of open price by using the market price at 9:35 to re-calculate the overnight and intraday returns for jump identification.[15]

Table A3 in the online appendix presents the portfolio sorting results based on jumps detected based on the alternative open price. The table shows a similar underreaction (overreaction) pattern following the overnight (intraday) jumps as the baseline results in Table 2. Overall, our key findings are insensitive to adopting alternative open prices.

5.3.2 | Alternative definition of overnight jumps

This section examines whether our key findings are sensitive to the definition of overnight jumps. In our baseline analysis, we follow the approach of Jiang and Zhu (2017) and Andersen et al. (2012) by including the overnight return as one of the intraday return observations in the jump detection. An overnight (or intraday) jump is identified based on the recursive jump detection procedure (see Section 2), conditional on a jump day. We know that treating the overnight return as one of the equally-spaced intraday returns violates the assumptions of a jump-diffusion process, but this

[15] Market-wide liquidity is relatively low during the overnight, as the average (median) overnight trading volume accounts for only 0.59% (0.27%) of the entire day's trading volume. In principle, the overnight period (i.e., the pre-open auction) provides investors the "first" opportunity to respond to the material information released since the prior-day market close. The low market liquidity over the night strengthens our attention-based story that individual investors pay little attention over the night and do not participate actively in trading during the pre-open auction. In comparison, market liquidity is relatively high during the intraday period.

empirical comprise preserves the information content of the overnight return. Moreover, as we show later, our key empirical patterns do not hinge on how we define overnight jumps.

Andersen et al. (2012) and Todorova and Soucek (2014) indicate that overnight returns may naturally be labeled as deterministic jumps, as they contain all information flows after the market closure on the prior day. Following these leads, we adopt the alternative definition of overnight jumps by treating all overnight returns as (deterministic) jumps and repeating the univariate portfolio sorts on overnight jumps.

Results in Table A4 in the online appendix confirm that the market underreacts to overnight jumps in the subsequent 1–10 days, consistent with our baseline results in Table 2. The minor difference might be that the long-short return spreads are smaller under the alternative definition of overnight jumps. For example, the portfolio spreads are 0.227%, 0.191%, 0.146%, 0.113%, 0.080%, and 0.047% over the next 1–10-day horizons, respectively. Overall, our key empirical findings are robust to the alternative definition of overnight jumps.

5.3.3 | Addressing the concern of jump autocorrelation

One legitimate concern is jump autocorrelation—the occurrence of subsequent jumps right after the initial jump. To ensure that our documented asymmetric market reactions are not unduly interfered with or confounded by these rare cases of autocorrelated jumps, we perform two sets of tests.

First, we exclude these observations when there is an overnight jump on a subsequent day (i.e., day 1 in the portfolio holding period) right after an intraday jump on the jump day (i.e., day 1 in the portfolio holding period). These observations account for approximately 2.82% of our full sample. After excluding these days with successive jumps, we re-evaluate the jump effects with the univariate portfolio sort on overnight or intraday jumps. The results in Table A5 in the online appendix indicate that the key empirical pattern remains virtually intact, as the market underreacts (overreacts) to overnight (intraday) jumps in the subsequent 1–10 days, consistent with Table 2.

Second, we perform a more restricted test by filtering all observations when there are any subsequent jumps following the initial jump day within the holding period. Specifically, we set the (daily) returns with subsequent jumps in the holding period as missing and re-evaluate the jump effects with the univariate portfolio sort on overnight or intraday jumps. The results in Table A6 in the online appendix show that excluding the days with subsequent jumps in the holding periods does not change our main findings: The positive (negative) portfolio return spreads following overnight (intraday) jumps remain sizeable and highly significant. They also exhibit magnitudes similar to those in Table 2. Overall, jump persistence has a limited impact on our key findings.

5.3.4 | Analyzing large, salient jumps

Our full sample features a relatively high jump frequency compared to the US stock market (see Jiang & Zhu, 2017; Xiao et al., 2020), which is reasonable given the high return volatility in China. However, it is crucial to understand whether the asymmetric market responses remain stable with more salient informational shocks—relatively large jumps. For simplicity, we define salient informational shocks as those jumps with above-median magnitude. Specifically, we focus on jumps with absolute values above their respective median (1.816% for overnight jumps and 1.509% for intraday jumps) and replicate the univariate portfolio sorts based on the salient jumps.

Findings on the salient jumps are reported in Table A7 in the online appendix, consistent with our baseline results in Table 2. The long-short return spreads (alphas) based on the portfolio sort on overnight jumps are highly positive in the subsequent 1–10-day horizons, and the spreads mainly stem from the short leg, negative jumps (i.e., the D1 portfolio). In comparison, the return spreads (alphas) of the long-short portfolio sorted on intraday jumps are highly negative in the subsequent 1–10-day horizons, and the spreads mainly stem from the long leg, positive jumps (i.e., the D10 portfolio). Overall, we document similar underreaction (overreaction) patterns following the overnight (intraday) jumps as the full sample by focusing on the salient informational shocks and excluding jumps with smaller magnitudes.

5.3.5 | Addressing the size and illiquidity concern

To avoid the concern that our results might be unduly driven by the proportion of small and illiquid stocks, we evaluate the large-cap, liquid stocks and the small-cap, illiquid stocks separately. The large and liquid stock subsample includes 1738 stocks on the main board, while the small and illiquid stock subsample includes 1486 stocks on the SME and ChiNext boards. We perform the univariate portfolio sort on the two subsamples, respectively. The portfolio results are documented in Tables A8 and A9 in the online appendix. Again, we find strong underreaction (overreaction) patterns following the overnight (intraday) jump in the large and liquid stocks (see Table A8) as well as in the small and illiquid stocks (see Table A9). As expected, the long-short return spreads are more significant in magnitude in the small and illiquid stock subsample than in the large and liquid stock subsample.

5.3.6 | Alternative weighting scheme

Our baseline results are based on the market capitalization-based weighting scheme. However, our key empirical pattern—underreaction (overreaction) patterns following the overnight (intraday) jumps—is also robust under alternative weighting schemes such as the equally weighted weighting scheme or the net value of market-cap-based weighting scheme (see Tables A10 in the online appendix).

6 | CONCLUSION

The paper contributes to understanding how limited investor attention impacts the market (mis-)reactions to informational shocks. Prior studies document that limited attention offers a unified explanation of the market underreaction to earnings announcements and the overreaction to accrual information because investors suffer from the capacity constraint (i.e., the total volume of cognitive resources can be allocated). We offer a novel perspective by stressing that limited investor attention has broader meanings: The investor is subject to the capacity constraint and the time constraint (the total amount of time within a day that can be devoted). In particular, small individual investors are subject more to time constraints than large institutional investors because they can only devote limited time within a day (while institutions can deploy more staff to cover a longer timespan within 24 h).

Our paper highlights the interplay between attention allocation and investor sophistication in reshaping the asymmetric market reactions to information: The fact that the strong negative return spread of the long-short portfolio mainly stems from long-leg stocks with the highest intraday jumps is consistent with small individual investors paying close attention during the intraday period, and engage in massive attention-driven buying. Moreover, the pattern that the underreaction strengthens while the overreaction attenuates during the extreme market periods is also consistent with small individual investors who tend to pay little or no attention when the market performance is poor. Our paper also contributes to the evolving literature on cross-sectional return patterns over the overnight and intraday periods. We show that lagged overnight (intraday) informational shocks are a strong positive (negative) return predictor in the cross-section. Moreover, the positive underreaction-related return spread is large in magnitude, which survives transaction cost concerns.

Overall, we present novel empirical evidence to show how attention allocation—investors allocate their attention disproportionately within a day—could offer a parsimonious explanation in reconciling the underreaction to overnight information shocks versus the overreaction to intraday information shocks in financial markets.

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CONFLICT OF STATEMENT

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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