Dissecting Momentum in China *

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September 2025

Abstract

Stocks outperform on news days on average perform poorly on subsequent non-news days in China. This non-news reversal is stronger among stocks with retail dominance, less recent good news, and strong limits-to-arbitrage. Our results suggest that past returns are contaminated by price pressure from retail investors' temporary attention-driven buying demand, and momentum disappears in China due to a cycle of overpricing from retail investors on news days and mispricing corrections from institutions on non-news days. Using a textual-based fundamental performance proxy, we find a strong underreaction to news in China. Such pattern is not observed in the US stock markets.

Keywords: momentum; reversal; news; investor heterogeneity; underreaction

*We thank Zhi Da, Jian Feng, Xing Hu, Zhen He, Shiyang Huang, Mohammed Kaddouhah, Dong Lou, Wenxi Jiang, Danqing Mei, Vesa Pursiainen, Jianfeng Shen, Jiahong Shi, Hanwen Sun, Jiaxing Tian, Chi-Yang Tsou, Hong Xiang, Huaixin Wang, Jing Zhao, seminar participants at the 18th International Behavioural Finance Conference, the 2025 Dishui Lake International Conference in Finance, the 9th PKU-NUS Annual International Conference on Quantitative Finance and Economics, the 13th China Investment Annual Conference, 2025 CFRN Young Finance Scholars Spring Forum, Shandong University, Wuhan University, Fudan University, Sun Yat-sen University, and University of Macau for helpful comments. Xin Liu: Department of Finance and Business Economics, Faculty of Business Administration, University of Macau, liuxin@um.edu.mo; Songtao Tan: School of Finance, Renmin University of China, Tansongtao@126.com; Yuchen Xu: UNSW Business School, University of New South Wales, yuchen.xu@unsw.edu.au; Peixuan Yuan: School of Business, Hong Kong Baptist University, peixuan@hkbu.edu.hk; Yun Zhu: China Capital Market Institute, zhuyun@ccmi.cn. First draft: February 2025.

1 Introduction

Price momentum, the positive relationship between a stock's return and its recent relative price performance (Jegadeesh and Titman, 1993), is one of the most studied stock market phenomena and has been robustly documented in many countries (Rouwenhorst, 1998; Griffin, Ji, and Martin, 2003; Asness, Moskowitz, and Pedersen, 2013). This phenomenon is often interpreted through the lens of behavioral finance theories (e.g., Barberis, Shleifer, and Vishny, 1998; Daniel, Hirshleifer, and Subrahmanyam, 1998), in which retail investors suffer from various cognitive biases and their underreaction to past information leads to price momentum. However, such a phenomenon is not observed in China (Chui, Titman, and Wei, 2010; Liu, Stambaugh, and Yuan, 2019; Gao, Jiang, Xiong, and Xiong, 2023), the world's second largest stock market, regardless of its strong retail dominance (Song and Xiong, 2018; Hu, Pan, and Wang, 2018; Jones, Shi, Zhang, and Zhang, 2025). This puzzling evidence challenges the classic behavioral explanations and calls for further investigation of the economic insights behind the price momentum.

Recent studies suggest that behavioral explanations do not offer a complete explanation of the momentum profit. Instead, momentum could arise due to persistent institutional trading (e.g., Lou, 2012; Vayanos and Woolley, 2013; Cremers and Pareek, 2014; Dong, Kang, and Peress, 2025). Consistent with this perspective, Chui, Subrahmanyam, and Titman (2022) find that institutions lead to price momentum in China's B-share market (which is dominated by foreign institutions), while retail investors' noise trading leads to return reversals in China's A-share market (which is dominated by retail investors). Such reversals arise because risk-averse liquidity providers need inventory compensation to absorb the demands of noise traders. This inventory compensation could cause excess liquidity demands to temporarily drive up stock prices and lead to subsequent reversals.[1] Du, Huang, Liu, Shi, Subrahmanyam, and Zhang (2024) provide further corroborate this explanation by documenting price momentum for stocks with high nominal prices, which suffer less from noise trading due to retail investors' financial constraints.

Motivated by these recent findings, in this paper, we investigate further into the interactive dynamics between retails and institutions to understand asset returns in China,

[1]See Jegadeesh and Titman (1995); Nagel (2012); Cheng, Hameed, Subrahmanyam, and Titman (2017); Peress and Schmidt (2020) for more details.

and provide a new explanation for the disappearance of momentum in China. First, we document empirical evidence that challenges the liquidity-based explanation, suggesting that noise trading and liquidity premium do not fully explain the disappearance of price momentum in China. Following the logic in Chui et al. (2022), if noise trading indeed masks price momentum through inventory-based reversal, past returns should not only reflect the market perception on fundamental news, but also be contaminated by a liquidity premium. The underreaction to fundamental news could lead to price momentum (Chan, Jegadeesh, and Lakonishok, 1996; Hong and Stein, 1999; Chan, 2003; Jiang, Li, and Wang, 2021), whereas the liquidity premium could lead to price reversal. This interpretation suggests that, if we decompose past returns and isolate the fundamental component, we might find price momentum in China. Considering this, we classify trading days into news days (days with firm-specific news releases) and non-news days (days without firm-specific news releases) and decompose past returns into news-driven and non-news-driven components (termed past news returns and past non-news returns, respectively).[2] It is natural to assume that past news returns could mainly reflect fundamental news, while past non-news returns could mainly reflect the liquidity premium. Thus, we conjecture a positive relation between a stock's return and its recent relative price performance on news days. To our surprise, we continue to find insignificant results. This evidence indicates that the influence of additional factors likely also play a part to drive away momentum in China.

Instead, we find an interesting tug-of-war in stock returns between news days and non-news days. That is, stocks that outperform on news days on average perform relatively poorly on subsequent non-news days. Given this interesting seasonality in stock returns, we provide a new explanation for the disappearance of price momentum in China, based on the interactive dynamics between retails and institutions. Our explanation is rooted on the well-documented phenomenon that retail investors have limited attention and attention-grabbing events (such as news releases) can stimulate excessive buying demands, especially on stocks with past high past news returns (Barber and Odean, 2008; Hirshleifer, Myers, Myers, and Teoh, 2008; Bali, Hirshleifer, Peng, and Tang, 2021).[3]

[2]This method is inspired by Jiang et al. (2021), who decompose daily stock returns into news-driven and non-news-driven components and examine short-term return predictability.

[3]This buying demand does not necessarily depend on the information context in the news release. For

As a result, news returns not only reflect market perceptions on fundamental news, but could also capture retail investors' temporary price pressure due to attention-driven buying demands. Since retail investors dominate market activity on news days, this non-fundamental price pressure persists during news days due to limits to arbitrage, and eventually reverses on non-news days, when institutional investors dominate market activity and correct mispricing.[4] Thus, when aggregating together, the back-and-forth in news returns and non-news returns makes price momentum disappear.

We provide three sets of empirical evidence to support the interactive dynamics between retails and institutions on news days and non-news days from different perspectives. First, we compare return dynamics from subsample analyses. We find that the non-news day reversal is more pronounced for stocks with retail dominance, proxied by low nominal price (Du et al., 2024). Second, we compare retail attentions on news days and non-news days, and across stocks in the quintile portfolios sorted by the past news return. We use the stock-level Baidu search index to proxy for retail attention.[5] We find that retail attention spikes on news days, especially for stocks in the top past news return quintile. Finally, we compare daily order imbalances from retails and institutions on news days and non-news days. We analyze intraday transaction data and use the RMB trading volume of each transaction (trade size) to infer retail / institutional trading. We use small trades to proxy for retail trading and use extra large trades to proxy for institutional trading.[6] We find that, stocks in the top past news return quintile tends to be purchased more by retail investors on news days and tends to be sold more by institutional investors on

example, Barber and Odean (2008) show that individual investors are net buyers of stocks in the news and stocks with extreme (either positive or negative) one-day returns. Hirshleifer et al. (2008) find that individuals are significant net buyers after both negative and positive extreme earnings surprises. Bali et al. (2021) argue that heightened social media activity about a stock positively predicts the probability of an extreme daily price run-up.

[4] We also find that past news returns tend to positively predict subsequent news returns. Two reasons could contribute to this pattern. First, retail investors' behaviors are persistent over time. Therefore, their order flows on recent news days are likely persistent on subsequent news days. Second, firms' fundamentals tend to persist over time, i.e., past good news tends to be associated with good news in the future (Wang, Zhang, and Zhu, 2018). In the presence of fundamental investors, this could also generate the momentum in news returns. The second reason, however, should not lead to reversals on non-news days, as trading activities from fundamental investors on news days should facilitate price discovery and help converge stock prices to fundamentals.

[5] Baidu is the largest search engine in China that accounts for over 85% market shares. The Baidu search index is in analogy to the Google search index introduced by Da, Engelberg, and Gao (2011) to capture retail attention on US stocks.

[6] See Section 2.2 for detailed definitions of these classifications.

non-news days, compared to stocks in the bottom past news return quintile. These order flow patterns are consistent with the interpretation that retail investors push up stock prices on news days due to excessive attention-driven buying demand, while institutions step in on non-news days to correct price overshoot.

Our aforementioned analyses suggest that return signals in China are problematic and are at most noisy proxies for fundamental news, as they also capture the excessive buying demand from retail investors, which could lead to subsequent reversals. This new insight provides a straightforward testable hypothesis. That is, we could develop a proxy for fundamental news that is *independent* from returns, and this proxy might positively predict subsequent stock returns in the cross-section due to the underreaction to news. Considering this, we introduce a variable to directly capture the recent performance of news, instead of the recent performance of price. In our news data, each news article is assigned to a textual-based sentiment index using natural language processing and deep learning techniques, and then is labeled into one of the three categories: good news, neutral news, and bad news.[7] Thus, we screen through recent firm-specific news articles and compute the percentage of good news. Consequently, this recent news performance (termed the good news ratio hereafter) is immune from the the excessive buying demand. Apart from this advantage, the good news ratio is also a reasonable replacement for the past news return for two reasons. First, the good news ratio is highly correlated with the past news return, because good news releases generally have positive market reactions. Second, like the past news return, the good news ratio is also a persistent firm characteristic. This ensures relatively low trading costs when building long-short portfolios.

We document a strong underreaction to news in China: stocks with high good news ratios on average have high subsequent returns. A long-short strategy that buys stocks in the top quintile and sells stocks in the bottom quintile of the good news ratio yields a risk-adjusted return of 1.02% per month (t-statistic = 2.96) under the Liu et al. (2019) CH-4 factor model. This result remains robust under Fama-MacBeth (1973) regressions which controls for other firm characteristics that may affect the cross-section of stock returns in China. For stocks in the top quintile of the good news ratio, their stock

[7] See Section 2.2 for detailed definitions of these classifications.

prices do not revert on subsequent non-news days. This is consistent with the notion that the good news ratio no longer captures excessive buying demand. We provide four empirical findings to examine the economic rationale behind this return predictability and find that: (1) the good news ratio predicts subsequent firm fundamentals; (2) the predictability decays over time and does not revert in the long-run; (3) the predictability is stronger for the subsample of stocks with low retail attention; (4) the good news ratio predicts subsequent institutional ownership. Together, these findings suggest that the good news ratio contains incremental information about future firm fundamentals, and investors underreact to this valuable information embedded in the good news ratio, generating positive return predictability in the cross section.

The contrasting results between portfolios sorted by the past news return and the good news ratio highlight the interactive dynamics between news returns and non-news returns in shaping asset prices in China. Our argument suggests that high past news returns signal overpricing on news days and return reversals on non-news days represent mispricing corrections. With the introduction of the aforementioned good news ratio, we can now evaluate the degree of overpricing from the past news return using the good news ratio as a "benchmark", and provide further evidence on the cycle of overpricing on news days and mispricing correction on non-news days. We conduct two additional analyses to further lend support to this observation. First, we independently double sort stocks by their past news returns and good news ratios, and find that the non-news day reversals mainly come from stocks with high past news returns but low good news ratios. Second, this non-news day reversals is stronger when limits-to-arbitrage conditions are more likely to be binding. Both results are consistent with the interpretation that the observed tug-of-war in stock returns across news days and non-news days is likely a cycle of overpricing and mispricing corrections.

Finally, we extend our analyses to the US stock markets to further support our argument. More specifically, we replicate our main results using data from the US, and find that stocks with high past news returns experience significantly higher returns on *both* subsequent news days and non-news days. The positive return predictability is even higher in magnitude on non-news days than on news days. These results are in sharp contrast to what we have documented for China, but are consistent with our main argument which is build on strong retail influence. It has been well documented that US stock markets are highly institutionalized (e.g., Sias, Starks, and Titman, 2006; Ferreira and Matos, 2008; Lewellen and Lewellen, 2022), while China's stock markets are dominated by retail investors (Hu and Wang, 2022). This huge difference in investor composition could potentially drive the different return dynamics on news days and non-news days for the two countries.

Related Literature. Prior studies have documented that price momentum does not exist in China. Instead, a stock's past return negatively predicts the subsequent return at horizons ranging from one, three, six, twelve months to five years (Liu et al., 2019). Chui et al. (2022) attribute this reversal to retail investors' noise trading, because risk-averse liquidity providers need inventory compensation to absorb the demands of noise traders. Du et al. (2024) corroborate this explanation by documenting price momentum for stocks with high nominal prices, which suffer less from noise trading due to retail investors' financial constraints. In this paper, we contribute to the understanding of price momentum in China in three ways. First, we provide empirical evidence that challenges the liquidity-based explanation, suggesting that noise trading and liquidity premium do not offer a complete explanation for the disappearance of momentum in China. Second, we introduce a new empirical design to tackle this puzzle. Unlike Du et al. (2024), instead of inferring the relevance of retail investors from stock characteristics, we explore whether retail and institutions tend to trade on different days. This idea is enlightened by Lou, Polk, and Skouras (2019), which identify the relevance of different types of investors through the fact that they tend to trade at different times during the day. Finally, based on this empirical approach, we provide a new perspective to understand the disappearance of momentum in China. That is, price momentum does not exist in China because of a back-and-forth cycle of overpricing due to attention-driven buying demands from retail investors on news days and mispricing corrections from institutions on non-news days.

Unlike Chui et al. (2022) and Du et al. (2024), Chui et al. (2010) try to understand the cross-country variations in momentum profits through cultural differences. Drawing from psychological literature, they argue that, compared to people in collectivistic cultures (such as Chinese), people in individualistic cultures (such as Americans) are more prone to behavioral biases that generate underreaction, leading to price momentum. This argument could indicate that, price momentum, or in general, *any* underreaction effect should not be observed in China, given its strong collectivistic cultural orientation. Our paper challenges this cultural explanation by documenting a strong underreaction to news in China. We argue that price momentum does not exist in China not because underreaction does not exist, but because return signals are contaminated by retail investors' excessive attention-driven buying demand, which are subject to subsequent reversals. We contribute to the underreaction literature in China by introducing the good news ratio to directly capture the recent performance of news that is independent from the recent performance of price. Consequently, the good news ratio is immune from the the excessive buying demand and a strong underreaction to news is observed in China. In addition, Gao et al. (2023) document the presence of price momentum in daily returns in China, which also challenges this cultural explanation.

Our paper is different from Engelberg, McLean, and Pontiff (2018). Engelberg et al. (2018) shows that, in US stock markets, anomaly returns are higher on corporate news days and this could be explained by mispricing due to biased expectations. Under this explanation, when new information arrives in the form of a firm-specific news story, investors update their beliefs, resulting in a *correction* to the stock price. However, our paper documents the opposite in China, as retail investors dominate market activities on news days and generate mispricing. Conceptually, this observation is consistent with the finding in Cai, Keasey, Li, and Zhang (2023), which suggests that in low-efficiency markets (such as China's A-share markets), without newswatchers sowing the seeds of price discovery and ensuring the long-run convergence of price to fundamentals, anomalies (such as momentum) could be weak in emerging markets compared to developed markets. Jegadeesh, Luo, Subrahmanyam, and Titman (2025) develop a multiperiod model to understand momentum reversal and predict attenuated reversals after earnings announcements. Yet, our finding differs from their model prediction by showing that reversals are strong after corporate news releases (on non-news days).

Finally, our paper also contributes to an emerging literature on seasonality in stock returns, such as Heston and Sadka (2008); Heston, Korajczyk, and Sadka (2010); Keloharju, Linnainmaa, and Nyberg (2016); Lou et al. (2019); Bogousslavsky (2021); Da and

Zhang (2024); Wang (2024). To our knowledge, we are the first to document the return seasonality between news days and non-news days in China and link this return seasonality to investor heterogeneity.

2 Data and Methodology

2.1 News Dataset

All news-related variables adopted in this paper are from Datayes, a leading data provider in China that offers comprehensive high-quality financial and business data for institutions, with a particular specialization in textual data obtained from various sources. To build its news dataset, Datayes tracks more than 2,600 vetted websites in real time, including mainstream financial media, government websites, and verified official social media accounts, etc.[8] On average, around 60,000 news articles are included in the database on a daily basis, and a further verification is conducted to identify duplicate articles reported from different sources.

For each news article, Datayes adopts an in-depth textual analysis based on natural language processing and deep learning techniques to obtain two key variables: the news relevance index and the news sentiment index. First, the news relevance index, ranging from 0 to 1, describes how accurate a news article is matched to a listed company. For firm-specific news, such as earnings announcements, Datayes retains only the matched firm with the highest relevance index. To facilitate more intuitive interpretation, Datayes classifies the news relevance index into three categories: strongly related, weakly related, and unrelated.[9] To ensure the quality of this news-firm matching procedure, Datayes conducts a rigorous manual screening session and reports a 97% consistency between manually assigned links and automatically assigned ones. Second, the news sentiment index, ranging from -1 to 1, evaluates how good / bad is the news article to the matched firm. Datayes classifies the news sentiment index into three categories: good news, neutral

[8] Examples of these social media accounts include verified official wechat accounts for listed firms and news media.

[9] A news article is strongly related to a listed firm if the news relevance index is higher than 0.75, weakly related to a listed firm if the news relevance index is between 0.25 and 0.75, and unrelated to a listed firm if the news relevance index is smaller than 0.25.

news, and bad news.[10] To ensure the quality of this news sentiment index, Datayes conducts another manual screening session and reports a 80% consistency between manually assigned sentiment and automatically assigned sentiment.

From 2000 through 2021, the news database contains nearly 34 million news articles matched to 4,554 listed firms. However, the news coverage is heavily skewed towards the most recent decade, with sparse firm coverage in earlier years. Therefore, we start our analyses from 2012 onwards. For all analyses in the paper, we retain news articles that are non-duplicate, strongly related to a listed firm, with non-neutral news sentiment indices, and pertain to firm-specific events.

2.2 Order Imbalance

Datayes collects all intraday tick-by-tick transaction details directly from Shanghai and Shenzhen Stock Exchanges. Three variables are important for our analyses at the transaction level: trade direction, share volume, and trade size. Trade direction is an indicator of whether a transaction is buy-initiated or sell-initiated. Share volume is the total number of shares of each transaction. Trade size is the RMB trading volume of each transaction. Datayes classifies all transactions into four categories based on their trade sizes: (1) small trades, with trade sizes no greater than the average RMB trading volume from the past twenty trading days; (2) medium trades, with trade sizes greater than that average but smaller than ten times of that average; (3) large trades, with trade sizes greater than ten times but smaller than a hundred times of that average; (4) extra large trades,with trade sizes greater than a hundred times of that average, or more than one million RMB. For each stock in each day, share volumes and trade sizes from all transactions are aggregated based on trade direction and trade size categories.

Following prior literature (e.g., Barber and Odean, 2008; Barber, Odean, and Zhu, 2008; Boehmer, Jones, Zhang, and Zhang, 2021; Jones et al., 2025), we infer retail and institutional trades based on trade size: small trades are attributed to retail investors, while extra large trades are attributed to institutions.[11] We compute the following variables to

[10] A news articles with a news sentiment index lower than -0.2 are negative news, between -0.2 and 0.2 are neutral news, and above 0.2 are good news.

[11] We are aware that, due to algorithm trading, institutions could split large orders into small ones when they trade. Because of this practice, we could over-identify retail trades and under-identify institutional

capture daily order imbalance:

$$BSI_{i,t}^{S} = (Buy_{i,t}^{S} - Sell_{i,t}^{S})/Total_{i,t}, \tag{1}$$

$$BSI_{i,t}^{XL} = (Buy_{i,t}^{XL} - Sell_{i,t}^{XL})/Total_{i,t}, \tag{2}$$

where $BSI_{i,t}^{S}$ proxies for the buy-sell imbalance for stock i on day t from retail investors, and $BSI_{i,t}^{XL}$ proxy for the buy-sell imbalance for stock i on day t from institutions. $Buy_{i,t}^{S}$ and $Buy_{i,t}^{XL}$ represent the daily trading volume from buy-initiated small trades and buy-initiated extra large trades for stock i on day t, respectively. $Sell_{i,t}^{S}$ and $Sell_{i,t}^{XL}$ represent the daily trading volume from sell-initiated small trades and sell-initiated extra large trades for stock i on day t, respectively. $Total_{t}^{i}$ represents the total daily trading volume from all trades for stock i on day t, respectively. For robustness, we compute buy-sell imbalances using both RMB-based and share-based trading volumes. These variables are available starting from 2014.

2.3 Other Data

We obtain stock returns, accounting details, and institutional ownership from China Stock Market and Accounting Research (CSMAR), one of the prominent data providers focusing on China's security markets. Following Liu et al. (2019), at the end of each month t, we delete stocks with a market capitalization below the bottom 30% and stocks that are listed less than six months. We obtain China's risk factors introduced in Liu et al. (2019) from Professor Robert Stambaugh's website.[12]

We capture the daily retail attention for each stock using its Baidu search index. More specifically, we obtain daily online search index for each stock using both stock name and stock ticker from Baidu, the largest search engine in China that accounts for over 85% market shares. This is in analogy to the Google search index introduced by Da et al. (2011) to capture retail attention on US stocks.

The following control variables are included in regression analyses, following Liu et al.

trades at the same time. However, these issues should bias against our findings. Nevertheless, we find robust order flow patterns that are consistent with the return dynamics we have documented, regardless of these measurement issues.

[12] https://finance.wharton.upenn.edu/~stambaug/

(2019):(1) *Beta*, the market beta estimated from daily returns over the past twelve months; (2) *Size*, the natural logarithm of the market capitalization, in thousands of RMB; (3) EP^+, a variable that equals the earnings-to-price ratio if it is positive, and zero otherwise; (4) *D(EP<0)*, a dummy variable which equals one if the earnings-to-price ratio is negative, and zero otherwise; (5) *Abnormal Turnover Ratio*, the monthly stock turnover rate divided by the average turnover rate from the past twelve months; (6) *Short-Term Reversal*, the stock return from the most recent month; (7) *Illiquidity*, the natural logarithm of the average daily ratio of the absolute stock return to the RMB trading volume from the past one month, following Amihud (2002); (8) *Idiosyncratic Volatility*, the standard deviation of daily return residuals over the past six months from the Liu et al. (2019) CH-4 factor model; (9) *Institutional Ownership*, the percentage of shares held by institutional investors. In addition, to capture the changes in firm fundamentals, we compute the quarterly growth rate in total assets, net income, operating income, and earnings per share, following Ali and Hirshleifer (2020) and Feng, Huo, Liu, Mao, and Xiang (2025). All these variables are winsorized at 1% and 99%.

2.4 Return Decomposition

We classify trading days into news days (days with firm-specific news releases) and non-news days (days without firm-specific news releases). If a news event is announced on non-trading days or after market close, we assign this news to the ensuing trading day. For each firm i, we denote its return on a news day d as r_d^i, and its return on a non-news day s as r_s^i. We decompose the monthly total stock return for firm i in month t ($r_{i,t}$) into a news component ($r_{i,t}^{news}$, termed as news return) and a non-news component ($r_{i,t}^{nonnews}$, termed as non-news return). More specifically,

$$r_{i,t}^{news} = \prod_{d \in t}(1 + r_d^i) - 1, \tag{3}$$

$$r_{i,t}^{nonnews} = \prod_{s \in t}(1 + r_s^i) - 1, \tag{4}$$

$$1 + r_{i,t} = (1 + r_{i,t}^{news})(1 + r_{i,t}^{nonnews}). \tag{5}$$

We mostly focus on portfolio analyses, and the monthly total return, news return, and non-news return for portfolio p in month t is calculated as:

$$r_{p,t}^{news} = \sum_{i \in p} w_{t-1}^{i} r_{i,t}^{news}, \tag{6}$$

$$r_{p,t}^{nonnews} = \sum_{i \in p} w_{t-1}^{i} r_{i,t}^{nonnews}, \tag{7}$$

$$r_{p,t} = \sum_{i \in p} w_{t-1}^{i} r_{i,t}. \tag{8}$$

Note that our portfolio decomposition does not sum exactly to the monthly total return, because $(1 + r_{p,t}) \neq (1 + r_{p,t}^{news})(1 + r_{p,t}^{nonnews})$. That being said, this discrepancy is small in our sample.

In the same vein, we decompose the sorting variable for price momentum (the past total return) into news and non-news components. More specifically, $r_{i,t-5 \to t-1}$, termed as the past total return, denotes the cumulative returns for stock i from month $t-5$ to month $t-1$. $r_{i,t-5 \to t-1}^{news}$, termed as the past news return, denotes the cumulative news returns for stock i from month $t-5$ to month $t-1$. $r_{i,t-5 \to t-1}^{nonnews}$, termed as the past non-news return, denotes the cumulative non-news returns for stock i from month $t-5$ to month $t-1$.[13]

2.5 Summary Statistics

Table 1 presents the descriptive statistics for our sample. On average, a stock experiences 2.46 news days in a month. The average past total return is 7.40%, and the average past new return is 7.12%, indicating that returns from news days mostly contribute to the past total return. The average good news ratio is 69.64%, suggesting that the majority of news releases in our sample are positive. Appendix Table A1 shows that the good news ratio is a persistent firm characteristic: more than 80% of the stocks in the top (bottom) good news ratio quintile in a month stay in the top (bottom) quintile in the subsequent month. This ensures relatively low trading costs when building long-short portfolios.

[13] We can obtain stronger results if we do not skip the most recent month when computing these past returns. However, to make sure our results are not driven by the short-term reversal, we skip the most recent month when constructing these variables from a conservative perspective. See Section 3.1 for more details.

[Table 1 here]

3 Main Result

3.1 News Returns vs. Non-news Returns

To set the stage, we first replicate the classic momentum strategy in our sample. At the end of each month t, we sort all stocks into quintile portfolios using their cumulative returns from month $t-5$ to month $t-1$ ($r_{i,t-5\rightarrow t-1}$), and compute the value-weighted portfolio returns in month $t+1$. We skip the return in month t when computing the cumulative returns due to the well-documented short-term reversal effect (Jegadeesh and Titman, 1993). We use a six-month window to evaluate the relative past performance in the cross-section because we work on a relatively short sample period.[14] Portfolios are rebalanced at the monthly frequency. In column (1) of Table 2, we report the average returns from the quintile portfolios and from a long-short strategy which buys stocks in the winner quintile and shorts stocks in the loser quintile. We compute t-statistics, shown in parentheses, based on standard errors corrected for serial dependence of 6 lags (Newey and West, 1987). Results suggest that momentum does not exist in our sample: the long-short portfolio yields an average monthly return of 0.22% per month (t-statistic $= 0.40$).

[Table 2 here]

Next, we explore the economic rationale behind the disappearance of momentum in China. Prior studies suggest that risk-averse liquidity providers need inventory compensation to absorb retail investors' noise trading in China. This inventory compensation could cause excess liquidity demands to temporarily drive up stock prices and lead to subsequent reversals (Chui et al., 2022; Du et al., 2024). Under this argument, past returns should reflect two components: (1) the market perception on fundamental news; and (2) a liquidity premium. The underreaction to the first component could lead to price momentum (Chan et al., 1996; Hong and Stein, 1999; Chan, 2003; Jiang et al.,

[14] Results remain similar using other window lengths.

2021), while the second component could lead to price reversal, which masks the price momentum. This interpretation points to a straightforward testable hypothesis. That is, if we decompose the past return and only focus on the component that reflects the market perception on fundamental news, we might find price momentum in China. Considering this, we classify trading days into news days (days with firm-specific news releases) and non-news days (days without firm-specific news releases) and decompose the past total return ($r_{i,t-5\to t-1}$) into news-driven and non-news-driven components ($r^{news}_{i,t-5\to t-1}$ and $r^{nonnews}_{i,t-5\to t-1}$, termed the past news return and the past non-news return, respectively). This method is inspired by Jiang et al. (2021), who decompose daily stock returns into news-driven and non-news-driven components and examine short-term return predictability. It is natural to assume that past news returns could mainly reflect fundamental news, while past non-news returns could mainly reflect the liquidity premium. Thus, we conjecture a positive relation between a stock's past news return and its subsequent monthly return.

To test this conjecture, we sort stocks into quintile portfolios using the past news return and compute the value-weighted portfolio returns in month $t + 1$. Portfolios are rebalanced at the monthly frequency. In column (4) of Table 2, we report the average returns from the quintile portfolios and from a long-short strategy which buys stocks in the top news return quintile and shorts stocks in the bottom news return quintile. To our surprise, inconsistent with our conjecture, the past news return cannot predict the subsequent monthly return. The long-short portfolio yields an average monthly return of 0.10% per month (t-statistic = 0.31). This evidence indicates that the influence of additional factors likely also play a part to drive away momentum in China.

To diagnose where our conjecture went wrong, we decompose the stock return in month $t + 1$ into news and non-news components ($r^{news}_{i,t+1}$ and $r^{nonnews}_{i,t+1}$, respectively), and examine the relation between the past news return and each of these two components, separately. Results are reported in columns (5)-(6) of Table 2. We obtain two interesting findings. First, there exists a significant momentum on news returns. That is, stocks that outperform on past news days on average continue to perform relatively well on subsequent news days. Column (5) of Table 2 shows that the long-short portfolio yields an average news return of 0.45% per month (t-statistic = 2.94). However, this sizable news return is largely offset by a reversal on non-news days: stocks that outperform on past news days on average experience a price reversal on subsequent non-news days. Column (6) of Table 2 shows that the same long-short portfolio suffers an average non-news return of -0.33% per moonth (t-statistic $= -1.37$). Even though this reversal is statistically insignificant, the economic magnitude is sizable. Thus, when aggregating news returns and non-news returns together, the past news return does not predict the subsequent total monthly stock return anymore. In other words, there is a tug-of-war between news returns and non-news returns that drives away price momentum in China.

It is natural to wonder if a similar pattern can also be obtained using the past total return ($r_{i,t-5\rightarrow t-1}$) instead of the past news return. Therefore, we conduct a similar exercise and report the results in columns (2)-(3) of Table 2 for comparison. Yet, we do not find a similar pattern. This exercise highlights the importance of focusing on the past news return to understand the momentum and reversal effects in China.

Note that we skip the news returns in the most recent month ($r_{i,t}^{news}$) when computing the past news return for each stock. Therefore, columns (4)-(6) of Table 2 shows the predictability of the market perception on firm-specific information that is from at least one month before portfolio formation. This lagged timing in the empirical design could potentially undermine the actual effect and could bias against us on finding meaningful results. We consider this empirical design throughout the paper mainly from a conservative perspective, because we want to make sure that our results are not driven by the well-documented short-term reversal effect. That being said, in Appendix Table A2, we compute the past news return from the past six months (including news returns from the most recent month), reconduct our analyses in Table 2, and find a stronger tug-of-war between news returns and non-news returns: the long-short portfolio that buys stocks in the top news return quintile and shorts stocks in the bottom news return quintile yields an average news return of 0.73% per month (t-statistic $= 3.09$) but suffers an average non-news return of -0.54% per month (t-statistic $= -1.98$).

Overall, results presented in Table 2 challenge the existing liquidity-based explanation on the disappearance of price momentum in China by presenting an interesting tug-of-war between news returns and non-news returns. To our knowledge, we are the first to document this interesting return seasonality in the literature. In the next section, we connect investor heterogeneity to this phenomenon and support our explanation with empirical evidence from various perspectives.

3.2 The Underlying Mechanism

Given the interesting seasonality in stock returns between news days and non-news days, we offer a new explanation for the disappearance of price momentum in China based on the interactive dynamics between retails and institutions. Our explanation is rooted on the well-documented phenomenon that retail investors have limited attention and attention-grabbing events (such as news releases) can stimulate excessive buying demands, especially on stocks with past high past news returns (Barber and Odean, 2008; Hirshleifer et al., 2008; Bali et al., 2021). As a result, news returns not only reflect market perceptions on fundamental news, but could also capture retail investors' temporary price pressure due to attention-driven buying demands. Since retail investors' behaviors are persistent over time, their order flows on recent news days are likely persistent on subsequent news days, generating a momentum on news returns. Because retail investors dominate market activity on news days, this non-fundamental price pressure persists during news days due to limits to arbitrage, and eventually reverses on non-news days, when institutional investors dominate market activity and correct mispricing. Thus, when aggregating together, the back-and-forth in news returns and non-news returns makes price momentum disappear.

We provide three sets of empirical results from different perspectives to support this underlying mechanism. First, we compare return dynamics from subsample analyses. Our argument implies a stronger tug-of-war between news returns and non-news returns among stocks dominated by retail investors. Therefore, we independently double sort our sample in to 15 portfolios (5 $\times$ 3) by the past news return and a proxy for retail dominance. Following Du et al. (2024), we use low nominal price level to proxy for retail dominance, because retail investors have financial constraints to invest in stocks with a high nominal price level. We report the double sorting results in Table 3.

[Table 3 here]

These results are consistent with our expectation: the tug-of-war between news returns and non-news returns is stronger among the subsample of stocks dominated by retail investors. Panel A of Table 3 shows that, in the subsample of stocks that are in the bottom nominal price tercile, a long-short portfolio that buys stocks in the top news return quintile and shorts stocks in the bottom news return quintile on average experiences a news return of 0.73% per month (t-statistic = 2.85) and a non-news return of −0.67% per month (t-statistic = −2.64). For comparison, Panel B of Table 3 shows that, in the subsample of stocks that are in the top nominal price tercile, the same long-short portfolio on average only experiences a news return of 0.20% per month (t-statistic = 1.03) and a non-news return of −0.15% per month (t-statistic = −0.55).

Second, we compare retail attentions on news days and non-news days, and across stocks in the quintile portfolios sorted by the past news return. We have two predictions: (1) retail attentions should be higher on news days than on non-news days; (2) stocks in the top news return quintile should receive stronger retail attentions on news days, relative to stocks in the bottom news return quintile. We use the daily Baidu search index to proxy for retail attentions at the stock level. In Table 4, we report the summary statistics of the daily Baidu search index on news days and non-news days for quintile portfolios sorted by the past news return.

[Table 4 here]

Table 4 confirm our predictions: retail attentions are significantly higher on news days, especially for stocks in the top news return quintile. Stocks in the top news return quintile experience an average Baidu search index of 1,533 on news days, and 1,021 on non-news days, representing an over 30% drop in retail attentions from news days to non-news days. Moreover, stocks in the bottom news return quintile experience an average Baidu search index of 1,398 on news days, representing a nearly 10% drop in retail attentions from stocks in the top news return quintile on news days. These differences are both statistically significant and economically meaningful.

Finally, we compare daily order imbalances from retails and institutions on news days and non-news days. We have two predictions: relative to stocks in the bottom news return quintile, stocks in the top news return quintile (1) should be purchased more by retail investors on news days; and (2) should be sold more by institutional investors on non-news days. To test these two predictions, following prior literature (e.g., Barber and Odean, 2008; Barber et al., 2008; Boehmer et al., 2021; Jones et al., 2025), we infer retail and institutional trades based on trade size: small trades are attributed to retail investors, while extra large trades are attributed to institutions. For each stock on each day, we aggregate the trading volumes of buy- and sell-initiated trades separately by trade size, and compute daily buy-sell imbalances for small trades and extra large trades. For robustness, we compute buy-sell imbalances using both RMB-based and share-based trading volumes. In Table 5, we report the summary statistics of buy-sell imbalances from small trades and extra large trades on news days and non-news days for quintile portfolios sorted by the past news return.

[Table 5 here]

Table 5 confirm both of our predictions. To start with, column (1) of Panel A shows that, on news days, the RMB-based buy-sell imbalance from small trades on stocks in the bottom news return quintile is 0.0051, and that on stocks in the top news return quintile is 0.0063. The difference, 0.0012, representing a nearly 25% increase in net purchase from retail investors on stocks in the top news return quintile on news days, is significant at all conventional levels (t-statistic = 11.17). This increase in retail net purchase aligns with the increase in retail attentions on news days documented in Table 4, corroborating the argument of attention-driven buying from retail investors on news days. Moreover, column (4) of Panel A shows that, on non-news days, the RMB-based buy-sell imbalance from extra large trades on stocks in the bottom news return quintile is -0.0069, and that on stocks in the top news return quintile is -0.0077. The difference, -0.0008, representing an over 10% increase in net sales from institutions on stocks in the top news return quintile on non-news days, is also significant at all conventional levels. (t-statistic = -6.48). This evidence supports the argument of mispricing correction from institutions on non-news days. Put together, results presented in Table 5 provide direct evidence on the investor heterogeneity and their differential trading behaviors on news days and non-news days, which is aligned with the tug-of-war between news returns and non-news returns. In Appendix Table A3, we replace buy-sell imbalance by daily turnover, and find similar patterns.

We are aware that, due to algorithm trading, institutions could split large orders into small ones when they trade. Because of this practice, we could over-identify retail trades and under-identify institutional trades at the same time based on our empirical design. However, these issues should bias against our findings. Given our argument that institutions tend to trade against retail investors to correct mispricing, the actual net purchase from retail investors on news days and the actual net sales from institutional investors on non-news days could both be stronger than we have documented here. Nevertheless, we still find robust order flow patterns that are consistent with the return dynamics we have document in Table 2, regardless of these measurement issues.

We are aware that an alternative story may also help explain the momentum on news returns. That is, firms' fundamentals tend to persist over time, so past good news tends to be associated with good news in the future (Wang et al., 2018). In the presence of fundamental investors, this could generate momentum on news returns. This alternative interpretation could also explain the strong net purchase from institutions on stocks in the top news return quintile on news days, which is reported in column (2) of Table 5. We do not dispute this channel on news days in this paper. However, the trading activities from fundamental investors on news days should facilitate price discovery and help converge stock prices to fundamentals. Thus, this interpretation cannot explain why prices tend to revert more on non-news days for stocks with high past news returns. Our explanation could explain both the momentum on news returns and the reversal on non-news returns at the same time.

In summary, in this section, we have shown three sets of empirical evidence: (1) the tug-of-war between news returns and non-news returns is more pronounced for stocks dominated by retail investors; (2) retail attentions spike on news days, especially for stocks in the top news return quintile; (3) stocks in the top news return quintile tend to be purchased more by retails on news days and sold more by institutions on non-news days, relative to stocks in the bottom news return quintile. These results lend support to our argument that news returns capture retail investors' temporary price pressure due to attention-driven buying demand, which temporarily push up stock prices on news days, and stock prices eventually reverse on non-news days, when institutional investors dominate market activity and correct mispricing.

3.3 The Underreaction to News

Our aforementioned analyses suggest that, due to the tug-of-war across news days and non-news days, return signals in China are problematic and are at most noisy proxies for fundamental news, as they also capture the excessive buying demand from retail investors. Consequently, conventional return-based signals fail to detect underreactions to fundamental news. This new insight provides a straightforward testable hypothesis. That is, instead of using past returns, we could develop a proxy to directly capture the recent performance of fundamental news that is *independent* from returns, and this proxy might positively predict subsequent stock returns in the cross-section due to market underreactions to news.

To test this hypothesis, we introduce a variable to directly capture the recent performance of news from textual analyses. In our news data, each news article is assigned to a textual-based sentiment index using natural language processing and deep learning techniques, and then labeled into one of the three categories: good news, neutral news, and bad news. We only focus on non-neutral news in our analyses. At the end of each month t, we screen through firm-specific news articles from month $t-5$ to month t and compute the percentage of good news (termed the good news ratio hereafter). Note that we do not need to skip news articles from the most recent month any more, because this textual-based performance of news is not associated with the short-term reversal phenomenon. Consequently, the good news ratio is insulated from the attention-driven excessive buying demand that contaminates past returns. Apart from this advantage, the good news ratio is a plausible substitute for past news returns for two additional reasons: (1) the good news ratio is highly correlated with the past news return, because good news releases generally have positive market reactions; (2) the good news ratio is also a persistent firm characteristic (see Appendix Table A1). This ensures relatively low trading costs when building long-short portfolios.

To examine the relation between the good news ratio and the subusequent stock returns in the cross-section, we design the following trading strategy. More specifically, at the end of each month t, we sort stocks in our sample into quintile portfolios based on the good news ratio obtained from month $t-5$ to month t, and compute equal-weighted and value-weighted portfolio returns in month $t+1$. Our trading strategy buys stocks in the top quintile and shorts stocks in the bottom quintile of the past news ratio. Portfolios are rebalanced at a monthly frequently. We report the average equal-weighted and value-weighted returns from quintile portfolios and the long-short strategy , as well as their alphas with respect to Liu et al. (2019)'s CH-4 factor model in Panel A of Table 6. We compute t-statistics, shown in parentheses, based on standard errors corrected for serial dependence of 6 lags (Newey and West, 1987). We report factor loadings for the long, short and long-short portfolios in Panel B of Table 6.

[Table 6 here]

We document a pronounced market underreaction to news in China: stocks with a high good news ratio on average have a high subsequent return in the subsequent month. The long-short portfolio yields an average monthly value-weighted return of 0.78% (t-statistic = 2.47). After adjusted by Liu et al. (2019)'s CH-4 factors, the strategy becomes even more profitable, earning an average monthly alpha of of 1.02% (t-statistic = 2.96). Panel B of Table 6 shows that this is because the value-weighted long-short portfolio loads negatively on the size factor. Since the size effect is strong and is widely adopted for quantitative investing in China, this new strategy could be beneficial for the investment industry, as it provides a hedge against the size factor and could potentially enhance portfolio Sharpe ratio. As reported in Appendix Table A4, this result is also robust under Fama-MacBeth (1973) regressions which controls for other firm characteristics that may affect the cross-section of stock returns in China.

Comparing Table 6 with Table 2, it is interesting to see that the past news return, though intuitively connected to the good news ratio, cannot predict the subsequent monthly stock returns in the cross-section due to reversals on non-news days. Thus, it is natural to wonder the predictability of the good news ratio on news days and non-news days. To investigate, we decompose stock returns in month $t+1$ into news and non-news components, and examine the predictability of the good news ratio on these two components. Results are reported in Table 7. We obtain two findings: (1) the long-short portfolio profits based on the good news ratio come from both news days (on average 0.38% per month with a t-statistic = 2.44) and non-news days (on average 0.38% per month with a t-statistic = 2.00); (2) for stocks in the top quintile of the good news ratio, their stock prices barely revert on non-news days. This pattern stands in sharp contrast to the results documented in columns (5)-(6) of Table 2, supporting our argument: past news returns are contaminated by excessive buying demand which is subject to reversals, while the good news ratio is textual-based and insulated from this problem, therefore leads to positive return predictability in the cross-section.

[Table 7 here]

What is the economic rationale behind the positive return predictability of the good news ratio? We conduct four analyses from different perspectives to show that investors tend to underreact to value-relevant information embedded in the good news ratio, leading to the positive return predictability in the cross-section. First, we examine the information context in the good news ratio. Following Ali and Hirshleifer (2020) and Feng et al. (2025), we use quarterly accounting details to construct four proxies for firm fundamentals: the seasonal quarterly growth rate of total assets, net profits, operating income, and earnings per share (EPS). In Appendix Table A5, we report results from panel regressions and find that the good news ratio significantly predicts all these fundamental growths, after controlling for the past news return and other firm characteristics. These results suggest that the good news ratio contains value-relevant information about future firm fundamentals in addition to the past news return.

Second, we examine the long-term predictability of the good news ratio. In Figure 1, we plot the cumulative excess returns and the cumulative alphas of the long-short portfolio sorted by the good news ratio. In Appendix Table A6, we report the monthly excess returns and alphas from six months before to twelve months after portfolio formation. We find that the long-short portfolio's monthly excess return declines over time since portfolio formation, becomes insignificant after six months, and does not revert. This long-term time-series pattern is consistent with the underreaction interpretation, as stock prices gradually incorporate information embedded in the past news ratio.

[Figure 1 here]

Third, we conduct subsample analyses based on investor attention and examine the heterogeneity in the predictability of the good news ratio. Prior literature suggests that underreaction anomalies tend to be stronger among firms with low investor attention (e.g., Hirshleifer, Lim, and Teoh, 2009; DellaVigna and Pollet, 2009; Chen, He, Tao, and Yu, 2023). Therefore, at the end of each month t, we independently double sort our sample into 15 portfolios (5×3) by the good news ratio and the average Baidu search index from month $t-5$ to month t. Results are reported in Table 8. We find that the predictability of the good news ratio is mainly concentrated on stocks with low retail attention. For stocks in the bottom Baidu search index tercile, the long-short strategy based on the good news ratio earns an average return of 0.97% per month (t-statistic = 2.74), which is nearly 25% stronger than the full sample result reported in Table 6. Also, for stocks in the bottom Baidu search index tercile and in the top past news ratio quintile, both their subsequent news returns and non-news returns are sizable, consistent with the underreaction interpretation.

[Table 8 here]

Finally, we examine whether institutions also underreact to the value-relevant information embedded in the good news ratio. Since we cannot directly observe institutional trades, we examine whether the good news ratio could predict institutional ownership in the subsequent quarter. Results from Table A7 shows that institutional ownership from the subsequent quarter increases for stocks with a high good news ratio. This evidence could indicate that institutional investors also underreact to the value-relevant information embedded in the good news ratio.

In summary, in this section, we introduce the good news ratio, a textual-based proxy for fundamental news that is insulated from retail investors' excessive buying demand, and find that the good news ratio positively predicts stock returns in the cross-section. We provide four empirical findings from different perspectives to show that this predictability comes from market underreactions to value-relevant information embedded in the good news ratio: (1) the good news ratio predicts subsequent firm fundamentals; (2) the predictability decays over time and does not revert in the long-run; (3) the predictability is stronger for the subsample of stocks with low retail attention; (4) the good news ratio predicts subsequent institutional ownership. These results challenge the argument in Chui et al. (2010) and show that the underreaction effect can exist in China's stock markets regardless of its collectivism cultural heritage.

4 Further Discussions

4.1 Past News Return vs. Good News Ratio

The contrasting results between portfolios sorted by the past news return and the good news ratio highlight the interactive dynamics between retails and institutions in shaping asset prices in China. Our interpretation is that high past news returns partially reflect overpricing on news days from retails, while return reversals on non-news days represent mispricing correction from institutions. With the introduction of the good news ratio from the previous section, we can now gauge the degree of overpricing from the past news return using the good news ratio as a "benchmark", and provide further support to understand the return seasonality.

More specifically, we independently double sort our sample based on the past news return and the good news ratio. The rationale is as follows. For stocks with a high past news return and a high good news ratio, their past news returns should primarily capture the market perception of fundamental news; thus, we should expect a weak reversal on non-news days. In contrast, for stocks with a high past news return but a low good news ratio, their past news returns likely reflects the temporary price pressure resulting from the excessive buying demand on news days; thus, we should expect a strong reversal on non-news days. Since the past news return and the good news ratio are conceptually related and empirically correlated, we independently sort our sample into 4 portfolios (2 $\times$ 2) to make sure all portfolios have sufficient number of stocks, and report the results in Table 9.

[Table 9 here]

The first two columns of Table 9 show that the past news return and the good news ratio enhance each other when predicting news returns. The lower right portfolio (Portfolio D) has the highest average news returns, while the upper left portfolio (Portfolio A) has the lowest average news returns. A long-short portfolio, which buys stocks in the lower right portfolio (Portfolio D) and sells stocks in the upper left (Portfolio A) portfolio yields an average subsequent news return of 0.51% per month (t-statistic = 3.10).

The last two columns of Table 9 show that the non-news return reversal documented in Table 2 is concentrated among stocks with a high past news return but a low good news ratio. The upper right portfolio (Portfolio B) has the lowest average non-news returns, because high past news returns mainly capture strong temporary price pressures which are not justified by the textual-based performance in news for these stocks. By contrast, the stock returns from the lower left portfolio (Portfolio C) barely revert on non-news days. A long-short portfolio, which buys stocks in the upper right portfolio (Portfolio B) and sells stocks in the lower left portfolio (Portfolio C) yields an average subsequent non-news return of -0.61% per month (t-statistic = -4.44).

If non-news day reversals represent mispricing corrections, the degree of such correction should depend on limits-to-arbitrage. When limits-to-arbitrage conditions are less likely to be binding, institutional investors could trade against retails and push down overshooting stock prices on news days. In this case, the reversal on non-news days should be weak. On the contrary, when limits-to-arbitrage conditions are more likely to be binding, institutional investors are difficult to correct mispricing on news days but can do so until they dominate market activities on non-news days. In this case, the reversal on non-news days should be strong. To test these predictions, we independently triple sort our sample into 8 portfolios ($2 \times 2 \times 2$) by the past news return, the good news ratio, and a proxy for limits-to-arbitrage. We use two proxies for limits-to-arbitrage: firm size and idiosyncratic volatility (IVOL). Results reported in Table 10 confirm our predictions: the average return on non-news days from the long-short portfolio which buys stocks in the upper right portfolio (Portfolio B) and sells stocks in the lower left portfolio (Portfolio C) is doubled in magnitude among firms with high limits-to-arbitrage (small firms and high IVOL firms), compared to that among firms with low limits-to-arbitrage (big firms and low IVOL firms).

[Table 10 here]

Overall, results presented in this section lend further support to the underlying economic mechanism of the return seasonality we have documented: a cycle of price overshoots on news days and mispricing corrections on non-news days.

4.2 US Comparison

So far we have focused on China's A-share markets. One might wonder if the tug-of-war in stock returns between news days and non-news days can also be observed in the US stock markets. Unlike China's A-share markets, the US stock markets are highly institutionalized and market activity is heavily influenced by large institutional investors (e.g., Sias et al., 2006; Ferreira and Matos, 2008; Lewellen and Lewellen, 2022). Given this stark difference in investor composition, we do not expect to find a similar pattern in the US stock markets.

To conduct similar empirical analyses in the US stock markets, we obtain firm-specific news release dates from RavenPack Analytics. We select news about U.S. companies from the Dow Jones Package starting in 2000 and from the Press Releases Package starting in 2004. We keep news items with the highest relevance, the highest novelty and news topics most pertinent to business activities. We apply standard sample filters and include only common shares listed in NYSE, AMEX, and NASDAQ, and with a share price higher than 5 USD. At the end of each month t, we follow the same empirical design outlined in Section 2.4 and compute the the sorting variable, the past news return, as the cumulative news returns from month $t-5$ to month $t-1$. We sort our sample into quintile portfolios based on past news returns, and compute the value-weighted portfolio total returns, news returns, and non-news returns in month $t+1$. Portfolios are rebalanced at the monthly frequency. The sample period is from January 2000 through December 2022. In Appendix Table A8, we report the average returns from the quintile portfolios and from a long-short strategy which buys stocks in the top news return quintile and shorts stocks in the bottom news return quintile. We compute t-statistics, shown in parentheses, based on standard errors corrected for serial dependence of 6 lags (Newey and West, 1987).

Results from Appendix Table A8 stand in sharp contrast to what we have documented in Table 2: (1) stocks with high past news returns experience higher returns on *both* subsequent news days and non-news days; (2) the long-short portfolio on average earns higher return on non-news days than news days. These results highlight the uniqueness of our results to the China's A-share markets, and lend further support to our argument on investor heterogeneity from an alternative perspective.

5 Conclusion

Being the world's second largest stock market, China's A-share market, differs markedly from its US counterpart: most well-documented trading strategies that have worked well in the US do not work in China (e.g., Li, Liu, Liu, and John Wei, 2024). One prominent example is the famous price momentum, i.e., the positive relation between a stock's return and its recent relative price performance (Jegadeesh and Titman, 1993), which does not exist in China (Chui et al., 2010; Liu et al., 2019; Gao et al., 2023). This paper addresses this puzzle through a novel perspective: investor heterogeneity and their trading seasonality.

We argue that price momentum does not exist in China because of a cycle of retails' over-reaction on news days and institutions' price corrections on non-news days. This is empirically reflected as a tug-of-war in stock returns across news days and non-news days: stocks that outperform on news days perform relatively poorly on subsequent non-news days. Thus, when aggregating together, the back-and-forth in news returns and non-news returns makes price momentum disappear.

We provide rich empirical evidence to support this view of investor heterogeneity. First, we compare return dynamics form subsample analyses. We find that the non-news day reversal is more pronounced for stocks with retail dominance. Second, we compare retail attentions on news days and non-news days, and across stocks in the quintile portfolios sorted by the past news return. We find that retail attention spikes on news days, especially for stocks in the top news return quintile. Finally, we compare daily order imbalances from retails and institutions on news days and non-news days. We find that stocks in the top news return quintile tends to be purchased more by retail investors on news days and tends to be sold more by institutional investors on non-news days, relative to stocks in the bottom news return quintile. These results suggest that news returns capture retail investors' temporary price pressure due to attention-driven buying demand, which temporarily push up stock prices on news days, and stock prices eventually reverse on non-news days, when institutional investors dominate market activity and correct mispricing.

Our analyses suggest that return signals are problematic and at most a noisy proxy for fundamental news, as they also inevitably capture the excessive buying demand from retail investors, which could lead to subsequent reversals. This new insight inspires us to replace the past news return by the good news ratio, a proxy for the recent performance of firm fundamentals that is textual-based and independent from stock returns. Consequently, this new signal is insulated from the interference of temporary price pressure. With this measure, we document a strong underreaction to news in China: stocks with high good news ratios on average have high subsequent returns. This positive predictability represents market underreaction to value-relevant information embedded in the good news ratio, because (1) the good news ratio predicts subsequent firm fundamentals; (2) the predictability decays over time and does not revert in the long-run; (3) the predictability is stronger for the subsample of stocks with low retail attention; (4) the good news ratio predicts subsequent institutional ownership.

The contrasting results between portfolios sorted by the past news return and the good news ratio highlight the interactive dynamics between retails and institutions in shaping asset prices in China. Our argument suggests that high past news returns signal overpricing on news days and return reversals on non-news days represent mispricing correction. With the introduction of the good news ratio from the previous section, we evaluate the degree of overpricing from the past news return using the good news ratio as a "benchmark". We find that the non-news day reversals concentrate on stocks with high past news returns but low good news ratios, and on stocks with strong limits-to-arbitrage. Both evidences are consistent with the interpretation that our documented return seasonality is likely a cycle of overpricing on news days and mispricing corrections on non-news days.

Finally, we extend our analyses to the US stock markets and find that stocks with high past news returns experience higher returns on both subsequent news days and non-news days. These results stand in sharp contrast to what we have documented for China, but are consistent with our main argument on investor heterogeneity, because, unlike China's stock markets, US stock markets are highly institutionalized.

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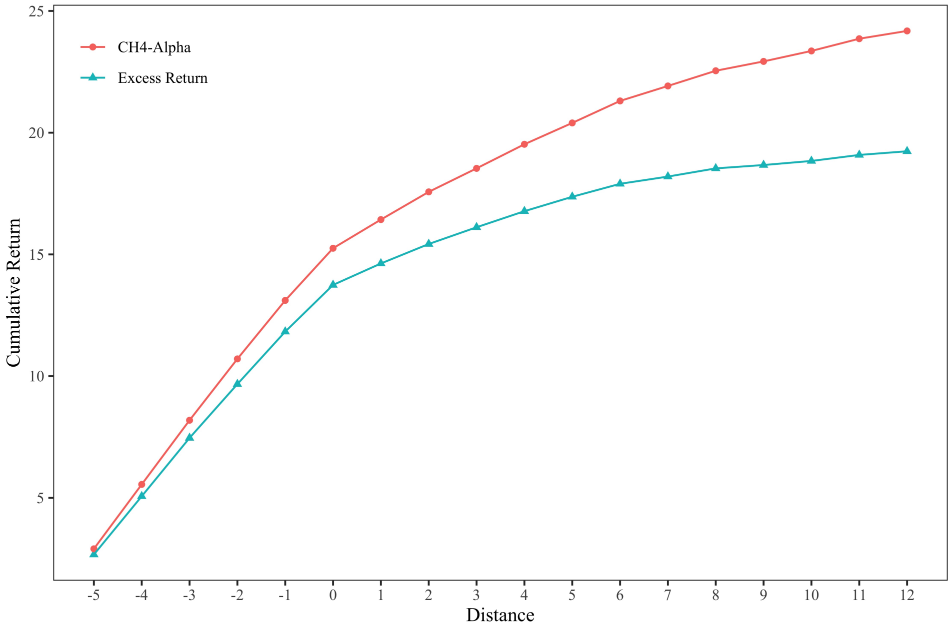
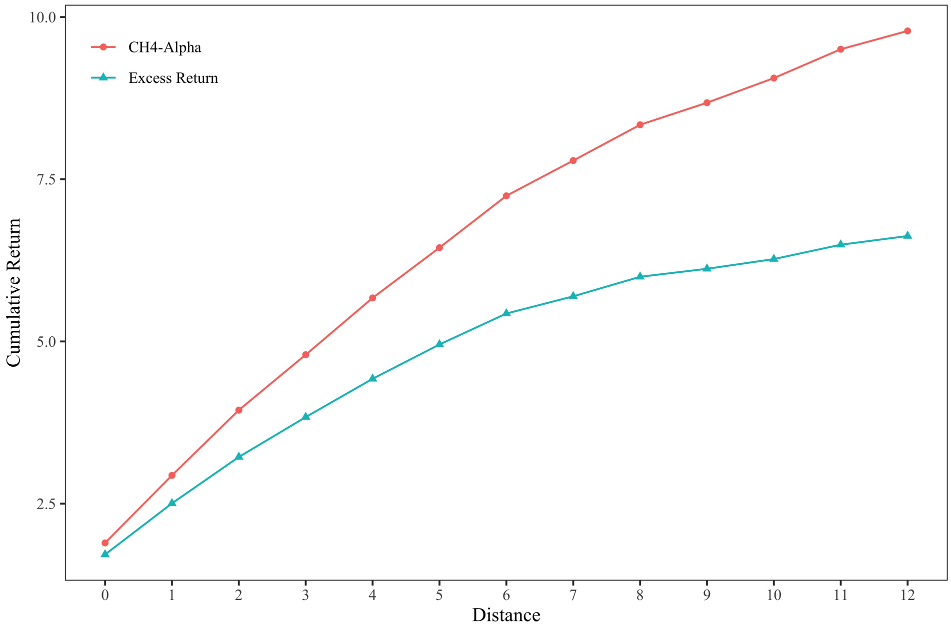


Panel A: Month $t-5$ to Month $t+12$



Panel B: Month t to Month $t+12$

Figure 1. **The Long-term Performance of the Good News Ratio Long-short Portfolio**

This figure plots the cumulative value-weighted excess returns and CH-4 alphas (Liu et al., 2019) of the long-short portfolio based on the good news ratio, from the beginning of portfolio formation (month $t-5$, Panel A) / the end of portfolio formation (month t, Panel B) to twelve months post-formation. Good news ratio is defined as the percentage of good news from month $t-5$ to month t. At the end of each month, we sort stocks into quintile portfolios based on the good news ratio. The long-short strategy buys stocks in the top good news quintile and shorts stocks in the bottom good news quintile.

Table 1. **Summary Statistics**

This table reports the descriptive statistics for our samples. $r_{t-5\to t-1}$ denotes the past total return, which is computed as the cumulative return from month $t-5$ to month $t-1$. $r^{News}_{t-5\to t-1}$ denotes the past news return, which is computed as the cumulative returns on news days from month $t-5$ to month $t-1$. *Good News Ratio* is the percentage of good news from month $t-5$ to month t. *Beta* denotes the market beta, which is coefficient from a twelve-month rolling regression of excess daily returns on excess market returns. *Price* denotes the nominal price level at the end of each month. *Size* denotes firm size, which is computed as the nature logarithm of the market capitalization (in thousands of RMB) at the end of each month. *IVOL* denotes idiosyncratic volatility, which is computed as the standard deviation of daily return residuals from month $t-5$ to month t with respect to the Liu et al. (2019)'s CH-4 factor model. *Baidu Search Index* denotes the daily stock-level Baidu search index. BSI^S *(RMB-based)* denotes the daily RMB-based buy-sell imbalance of small trades, which is computed as the difference in RMB trading volume between buy- and sell-initiated small trades over the total RMB trading volume. BSI^{XL} *(RMB-based)* denotes the daily RMB-based buy-sell imbalance of extra large trades, which is computed as the difference in RMB trading volume between buy- and sell-initiated extra large trades over the total RMB trading volume. BSI^S *(Share-based)* and BSI^{XL} *(Share-based)* are defined similarly using share trading volumes instead of RMB trading volumes. We exclude stocks with a market capitalization below the bottom 30% of all A-share stocks and stocks that are listed less than six months. The sample period is from July 2012 through December 2021, except for variables on order imbalance and the Guba post volume, which start in January 2014.

	N	Mean	SD	P25	Median	P75
$r_{t-5\to t-1}$	236,794	7.401	33.366	-13.401	0.785	20.152
$r^{news}_{t-5\to t-1}$	236,794	7.124	19.543	-2.729	2.046	12.408
Good News Ratio	222,155	69.641	24.877	53.846	75.000	90.000
Price	236,794	17.888	22.647	6.740	11.500	20.400
Size	236,794	16.120	0.923	15.447	15.924	16.605
IVOL	236,794	2.176	0.846	1.565	2.060	2.668
Baidu Search Index	4,005,497	1000.736	917.010	393.000	693.000	1273.000
BSI^S *(RMB-based)*	4,151,626	0.004	0.034	-0.010	0.004	0.019
BSI^{XL} *(RMB-based)*	4,151,626	-0.005	0.079	-0.032	0.000	0.013
BSI^S *(Share-based)*	4,151,626	0.004	0.034	-0.010	0.004	0.019
BSI^{XL} *(Share-based)*	4,151,626	-0.005	0.079	-0.032	0.000	0.013

Table 2. **A Tug-of-war Between News Returns and Non-news Returns**

This table reports the value-weighted average monthly total returns, news returns, and non-news returns in month $t+1$ for quintile portfolios sorted in month t. We consider two sorting variables: the past total return ($r_{t-5\to t-1}$), computed as the cumulative returns from month $t-5$ to month $t-1$ (Panel A), and the past news return ($r^{news}_{t-5\to t-1}$), the cumulative news returns from month $t-5$ to month $t-1$ (Panel B). We construct a long-short portfolio that buys stocks in the top quintile and shorts stocks in the bottom quintile. We exclude stocks with a market capitalization below the bottom 30% of all A-share stocks and stocks that are listed less than six months. We compute t-statistics, shown in parentheses, based on standard errors corrected for serial dependence of six lags (Newey and West, 1987). The sample period is from July 2012 through December 2021.

Sorting Variable	$r_{t-5\to t-1}$			$r^{news}_{t-5\to t-1}$		
	r_{t+1}	r^{news}_{t+1}	$r^{nonnews}_{t+1}$	r_{t+1}	r^{news}_{t+1}	$r^{nonnews}_{t+1}$
1 (Low)	0.58	0.97	-0.53	0.66	0.81	-0.29
2	0.75	0.86	-0.24	0.83	0.69	0.01
3	0.77	0.77	-0.13	0.98	0.82	0.02
4	0.88	0.88	-0.13	0.79	0.92	-0.27
5 (High)	0.81	1.06	-0.38	0.76	1.26	-0.61
High − Low	0.22	0.08	0.15	0.10	0.45	-0.33
	(0.40)	(0.36)	(0.37)	(0.31)	(2.94)	(-1.37)

Table 3. **News Returns and Non-news Returns: Nominal Price Level**

This table reports the value-weighted average monthly total returns, news returns, and non-news returns in month $t+1$ for portfolios independently double sorted by the past total return ($r_{t-5\to t-1}$) quintiles / the past news return ($r^{news}_{t-5,t-1}$) quintiles and nominal price terciles in month t. Panel A reports the results for the subsample of stocks in the bottom nominal price tercile, while Panel B reports the results for the subsample of stocks in the top nominal price tercile. The past total return is the cumulative returns from month $t-5$ to month $t-1$. The past news return is the cumulative news returns from month $t-5$ to month $t-1$. We construct a long-short portfolio that buys stocks in the top quintile and shorts stocks in the bottom quintile. We exclude stocks with a market capitalization below the bottom 30% of all A-share stocks and stocks that are listed less than six months. We compute t-statistics, shown in parentheses, based on standard errors corrected for serial dependence of six lags (Newey and West, 1987). The sample period is from July 2012 through December 2021.

Panel A: Low Nominal Price Level						
Sorting Variable	$r_{t-5\to t-1}$			$r^{news}_{t-5\to t-1}$		
	r_{t+1}	r^{news}_{t+1}	$r^{nonnews}_{t+1}$	r_{t+1}	r^{news}_{t+1}	$r^{nonnews}_{t+1}$
1 (Low)	0.63	0.94	-0.45	0.66	0.70	-0.19
2	0.79	0.75	-0.08	0.94	0.61	0.18
3	0.82	0.80	-0.11	1.00	0.95	-0.09
4	0.95	0.97	-0.15	0.81	0.96	-0.29
5 (High)	0.54	1.27	-0.85	0.67	1.43	-0.86
High − Low	-0.09	0.33	-0.39	0.01	0.73	-0.67
	(-0.18)	(1.03)	(-1.20)	(0.02)	(2.85)	(-2.64)
Panel B: High Nominal Price Level						
Sorting Variable	$r_{t-5\to t-1}$			$r^{news}_{t-5\to t-1}$		
	r_{t+1}	r^{news}_{t+1}	$r^{nonnews}_{t+1}$	r_{t+1}	r^{news}_{t+1}	$r^{nonnews}_{t+1}$
1 (Low)	0.36	1.09	-0.85	0.75	1.01	-0.40
2	0.63	1.01	-0.51	0.65	0.72	-0.18
3	0.71	0.82	-0.24	0.84	0.73	-0.02
4	1.00	0.87	0.00	0.82	0.88	-0.21
5 (High)	0.66	0.97	-0.43	0.78	1.21	-0.54
High − Low	0.30	-0.11	0.42	0.03	0.20	-0.15
	(0.43)	(-0.42)	(0.80)	(0.08)	(1.03)	(-0.55)

Table 4. **Retail Attention on News Days and Non-news Days**

This table reports the summary statistics of the daily Baidu search index on news days and non-news day in month $t+1$ for quintile portfolios sorted by the past news return in month t. The past new return is the cumulative return from news days in month $t-5$ to month $t-1$. We exclude stocks with a market capitalization below the bottom 30% of all A-share stocks and stocks that are listed less than six months. We compute t-statistics, shown in parentheses, based on standard errors corrected for serial dependence of six lags (Newey and West, 1987). The sample period in Panel A is from July 2012 through December 2021, while the sample period in Panel B is from January 2014 to December 2021.

Past News Return	**News Days in month $t+1$**				**Non-news Days in month $t+1$**				**Diff**	
	Mean	Q25	Median	Q75	Mean	Q25	Median	Q75	Mean	t-stat
1 (Low)	1397.90	566	1089	1857	958.14	392	680	1228	439.75	(152.85)
2	1303.74	503	968	1699	927.72	369	630	1181	376.02	(122.75)
3	1286.39	508	959	1670	850.00	334	564	1087	436.39	(153.95)
4	1319.98	537	1013	1710	942.90	390	660	1196	377.08	(133.47)
5 (High)	1533.27	660	1205	2131	1021.35	422	741	1304	511.92	(185.41)
High − Low	135.38				63.21					
	(30.57)				(41.39)					

Table 5. **Buy-sell Imbalance on News Days and Non-news Days**

This table reports the average daily buy-sell imbalances on news days and non-news days in month $t+1$ for quintile portfolios sorted by the past news return in month t. The past new return is the cumulative return from news days in month $t-5$ to month $t-1$. Small trades are trades with RMB trading volumes no higher than the average RMB trading volume from the past 20 trading days. XL trades are trades with RMB trading volumes higher than a hundred times the average RMB trading volume from the past 20 trading days, or over one million RMB. In Panel A, the RMB-based buy-sell imbalance for small trades (XL trades) is defined as the difference in the RMB trading volume between buy- and sell-initiated small trades (XL trades) over the total daily RMB trading volume. In Panel B, the share-based buy-sell imbalance for small trades (XL trades) is defined as the difference in share volume between buy- and sell-initiated small trades (XL trades) over the total daily share volume. We exclude stocks with a market capitalization below the bottom 30% of all A-share stocks and stocks that are listed less than six months. We compute t-statistics, shown in parentheses, based on standard errors corrected for serial dependence of six lags (Newey and West, 1987). The sample period is from January 2014 through December 2021.

Panel A: RMB-based Buy-sell Imbalance				
Past News Return	**News Days in month $t+1$**		**Non-news Days in month $t+1$**	
	Small Trades	XL Trades	Small Trades	XL Trades
1 (Low)	0.0051	0.0043	0.0033	-0.0069
2	0.0047	0.0053	0.0031	-0.0067
3	0.0047	0.0051	0.0030	-0.0070
4	0.0051	0.0065	0.0035	-0.0071
5 (High)	0.0063	0.0086	0.0044	-0.0077
High − Low	0.0012	0.0043	0.0011	-0.0008
	(11.17)	(9.88)	(20.73)	(-6.48)
Panel B: Share-based Buy-sell Imbalance				
Past News Return	**News Days in month $t+1$**		**Non-news Days in month $t+1$**	
	Small Trades	XL Trades	Small Trades	XL Trades
1 (Low)	0.0051	0.0038	0.0033	-0.0072
2	0.0047	0.0047	0.0030	-0.0070
3	0.0047	0.0045	0.0030	-0.0072
4	0.0051	0.0059	0.0035	-0.0074
5 (High)	0.0063	0.0079	0.0044	-0.0080
High − Low	0.0012	0.0041	0.0011	-0.0008
	(11.33)	(9.51)	(21.00)	(-6.88)

Table 6. **The Good News Ratio and the Subsequent Monthly Stock Return**

This table examines the relation between the good news ratio and the subsequent monthly stock return. At the end of each month, we sort stocks into quintile portfolios based on the good news ratio. The long-short strategy buys stocks in the top good news quintile and shorts stocks in the bottom good news quintile. Panel A reports the average equal-weighted and value-weighted monthly excess returns and Liu et al. (2019)'s CH-4 alphas for the quintile portfolios and the long-short strategy in month t. Panel B reports the factor loadings for the long, short, and the long-short portfolios. The good news ratio is the percentage of good news from month $t-5$ to month t. We exclude stocks with a market capitalization below the bottom 30% of all A-share stocks and stocks that are listed less than six months. In Panel A, we compute t-statistics, shown in parentheses, based on standard errors corrected for serial dependence of six lags (Newey and West, 1987). In Panel B, Newey and West (1987) adjusted standard errors are reported in brackets. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. The sample period is from July 2012 through December 2021.

Panel A: Quintile Portfolio Returns

Good News Ratio	**Equal-weighted**		**Value-weighted**	
	Excess Return	CH4-Alpha	Excess Return	CH4 Alpha
1 (Low)	0.38	-0.54	0.40	-0.54
2	0.77	-0.12	0.57	-0.36
3	0.80	-0.06	0.63	-0.26
4	1.05	0.26	0.83	0.10
5 (High)	1.23	0.39	1.17	0.49
High − Low	0.85	0.93	0.78	1.02
	(3.93)	(3.35)	(2.47)	(2.96)

Panel B: Factor Loadings

	Equal-weighted			**Value-weighted**		
	Low	High	High − Low	Low	High	High − Low
Alpha	-0.54 ***	0.39 ***	0.93 ***	-0.54 **	0.49 ***	1.02 ***
	[0.16]	[0.14]	[0.28]	[0.22]	[0.05]	[0.34]
MKTRF	1.05 ***	1.02 ***	-0.02	1.07 ***	1.07 ***	0.00
	[0.02]	[0.02]	[0.03]	[0.04]	[0.03]	[0.06]
SMB	0.69 ***	0.59 ***	-0.10	0.29 ***	-0.00	-0.29 *
	[0.08]	[0.05]	[0.12]	[0.10]	[0.07]	[0.15]
VMG	-0.14	-0.19 ***	-0.05	0.01	-0.14 ***	-0.15
	[0.09]	[0.04]	[0.11]	[0.10]	[0.05]	[0.13]
PMO	0.03	0.07	0.04	0.05	0.04	-0.01
	[0.06]	[0.05]	[0.09]	[0.07]	[0.05]	[0.10]

Table 7. **News Return and Non-news Return for Good News Ratio Quintile Portfolios**

This table reports the average value-weighted monthly returns, news returns, and non-news returns in month $t+1$ for quintile portfolios sorted by the good news ratio in month t. The long-short strategy buys stocks in the top good news quintile and shorts stocks in the bottom good news quintile. The good news ratio is the percentage of good news from month $t-5$ to month t. We exclude stocks with a market capitalization below the bottom 30% of all A-share stocks and stocks that are listed less than six months. We compute t-statistics, shown in parentheses, based on standard errors corrected for serial dependence of six lags (Newey and West, 1987). The sample period is from July 2012 through December 2021.

Good News Ratio	r_{t+1}	r_{t+1}^{news}	$r_{t+1}^{non-news}$
1 (Low)	0.40	0.66	-0.40
2	0.57	0.87	-0.43
3	0.63	0.84	-0.33
4	0.83	1.02	-0.32
5 (High)	1.17	1.04	-0.02
High − Low	0.78	0.38	0.38
	(2.47)	(2.44)	(2.00)

Table 8. **The Good News Ratio and the Subsequent Stock Return: Retail Attentions**

This table reports the value-weighted average total return, news return, and non-news return in month $t+1$ for portfolios independently doubled sorted by the good news ratio quintiles and retail attention terciles (5×3) in month t. We use the average Baidu search index from month $t-5$ to month t to proxy for retail attentions. We consider a long-short strategy that buy stocks in the top quintile and shorts stocks in the bottom quintile of the good news ratio. We exclude stocks with a market capitalization below the bottom 30% of all A-share stocks and stocks that are listed less than six months. We compute t-statistics, shown in parentheses, based on standard errors corrected for serial dependence of six lags (Newey and West, 1987). The sample period is from July 2012 through December 2021.

Good News Ratio	**Low Attention**			**High Attention**		
	r_{t+1}	r_{t+1}^{news}	$r_{t+1}^{nonnews}$	r_{t+1}	r_{t+1}^{news}	$r_{t+1}^{nonnews}$
1 (Low)	0.60	0.75	-0.30	0.49	0.71	-0.35
2	0.74	0.89	-0.28	0.55	0.76	-0.35
3	0.99	0.98	-0.15	0.62	0.79	-0.29
4	1.23	1.26	-0.12	0.80	0.99	-0.34
5 (High)	1.57	0.93	0.48	1.10	1.05	-0.11
High − Low	0.97	0.17	0.78	0.62	0.34	0.24
	(2.74)	(1.17)	(3.12)	(1.73)	(1.80)	(1.12)

Table 9. **Double-sort on Good News Ratio and Past News Return**

This table reports the value-weighted average news returns and non-news returns in month $t+1$ for portfolios independently double sorted by the good news ratio and the past news return ($r^{news}_{t-5\rightarrow t-1}$) in month t (2×2). The good news ratio is the percentage of good news from month $t-5$ to month t. The past news return ($r^{news}_{t-5\rightarrow t-1}$) is the cumulative returns on news days from month $t-5$ to month $t-1$. We exclude stocks with a market capitalization below the bottom 30% of all A-share stocks and stocks that are listed less than six months. We compute t-statistics, shown in parentheses, based on standard errors corrected for serial dependence of six lags (Newey and West, 1987). The sample period is from July 2012 through December 2021.

Predicting Variable: r^{news}_{t+1}				**Predicting Variable: $r^{nonnews}_{t+1}$**			
		Past News Return				**Past News Return**	
		Low	High			Low	High
Good News Ratio	Low	(A) 0.66	(B) 0.88	**Good News Ratio**	Low	(A) -0.22	(B) -0.67
	High	(C) 0.82	(D) 1.16		High	(C) -0.05	(D) -0.25
		(B) − (C)	(D) − (A)			(B) − (C)	(D) − (A)
		0.05	0.51			-0.61	-0.03
		(0.46)	(3.10)			(-4.44)	(-0.19)

Table 10. **Limits-to-Arbitrage**

This table reports the value-weighted average news returns and non-news returns in month $t+1$ for portfolios independently triple sorted by the good news ratio, the past news return ($r^{news}_{t-5\to t-1}$), and a proxy for arbitrage conditions in month t (2 × 2 × 2). We consider two proxies for arbitrage conditions: firm size, the market capitalization in month t (Panel A); and idiosyncratic volatility (IVOL), the standard deviation of daily return residuals from month $t-5$ to month t with respect to the Liu et al. (2019)'s CH-4 factor model (Panel B). The good news ratio is the percentage of good news from month $t-5$ to month t. The past news return ($Ret^{news}_{t-5\to t-1}$) is the cumulative returns on news days from month $t-5$ to month $t-1$. We exclude stocks with a market capitalization below the bottom 30% of all A-share stocks and stocks that are listed less than six months. We compute t-statistics, shown in parentheses, based on standard errors corrected for serial dependence of six lags (Newey and West, 1987). The sample period is from July 2012 through December 2021.

Panel A: Small Size

		Predicting Variable: r^{news}_{t+1}				Predicting Variable: $r^{nonnews}_{t+1}$	
		Past News Return				Past News Return	
		Low	High			Low	High
Good News Ratio	Low	(A) 0.80	(B) 1.22	**Good News Ratio**	Low	(A) -0.26	(B) -0.72
	High	(C) 0.96	(D) 1.49		High	(C) 0.17	(D) -0.33
		(B) − (C)	(D) − (A)			(B) − (C)	(D) − (A)
		0.26	0.68			-0.89	-0.06
		(1.91)	(4.24)			(-5.48)	(-0.41)

Panel B: Big Size

		Predicting Variable: r^{news}_{t+1}				Predicting Variable: $r^{nonnews}_{t+1}$	
		Past News Return				Past News Return	
		Low	High			Low	High
Good News Ratio	Low	(A) 0.63	(B) 0.78	**Good News Ratio**	Low	(A) -0.21	(B) -0.54
	High	(C) 0.81	(D) 1.13		High	(C) -0.11	(D) -0.23
		(B) − (C)	(D) − (A)			(B) − (C)	(D) − (A)
		-0.03	0.49			-0.44	-0.01
		(-0.23)	(2.91)			(-3.08)	(-0.10)

Panel C: Low IVOL

		Predicting Variable: r^{news}_{t+1}				Predicting Variable: $r^{nonnews}_{t+1}$	
		Past News Return				Past News Return	
		Low	High			Low	High
Good News Ratio	Low	(A) 0.57	(B) 0.71	**Good News Ratio**	Low	(A) -0.00	(B) -0.14
	High	(C) 0.74	(D) 1.01		High	(C) 0.11	(D) 0.10
		(B) − (C)	(D) − (A)			(B) − (C)	(D) − (A)
		-0.03	0.44			-0.26	0.10
		(-0.29)	(2.95)			(-1.79)	(0.57)

Panel D: High IVOL

		Predicting Variable: r^{news}_{t+1}				Predicting Variable: $r^{nonnews}_{t+1}$	
		Past News Return				Past News Return	
		Low	High			Low	High
Good News Ratio	Low	(A) 0.92	(B) 1.07	**Good News Ratio**	Low	(A) -0.81	(B) -1.16
	High	(C) 1.03	(D) 1.33		High	(C) -0.57	(D) -0.67
		(B) − (C)	(D) − (A)			(B) − (C)	(D) − (A)
		0.04	0.41			-0.58	0.15
		(0.26)	(2.22)			(-2.75)	(0.76)

A Appendix

Table A1. **The Transition Matrix for Quintile Portfolios Sorted by Good News Ratio**

This table report the transition matrix for quintile portfolios sorted by the good news ratio. The good News Ratio is the percentage of good news from month $t-5$ to month t. We exclude stocks with a market capitalization below the bottom 30% of all A-share stocks and stocks that are listed less than six months. The sample period is from July 2012 through December 2021.

		Month $t+1$					
		Low	2	3	4	High	Total
Month t	Low	82.70	14.47	1.97	0.60	0.91	100
	2	15.82	60.80	18.77	2.87	2.09	100
	3	2.19	18.98	56.61	17.98	4.31	100
	4	0.75	2.92	17.91	62.71	15.95	100
	High	0.69	1.49	3.20	11.83	83.03	100

Table A2. **News Returns and Non-news Returns: Alternative Past News Return**

This table reports the value-weighted average total return, news return, and non-news return in month $t+1$ for quintile portfolios sorted by an alternative measure of the past news return in month t. The past news return $r^{news}_{t-5\to t}$ is computed as the cumulative news day returns from month $t-5$ to month t. We construct a long-short portfolio that buys stocks in the top quintile and shorts stocks in the bottom quintile. We exclude stocks with a market capitalization below the bottom 30% of all A-share stocks and stocks that are listed less than six months. We compute t-statistics, shown in parentheses, based on standard errors corrected for serial dependence of six lags (Newey and West, 1987). The sample period is from July 2012 through December 2021.

Sorting Variable: $r^{rews}_{t-5\to t}$	r_{t+1}	r^{news}_{t+1}	$r^{nonnews}_{t+1}$
1 (Low)	0.61	0.67	-0.21
2	0.75	0.64	-0.03
3	1.08	0.80	0.14
4	0.86	0.97	-0.25
5 (High)	0.77	1.40	-0.75
High − Low	0.16	0.73	-0.54
	(0.47)	(3.09)	(-1.98)

Table A3. **Turnover on News Days and Non-news Days**

This table reports the summary statistics of daily stock turnover (in percentage) on news days and non-news day in month $t+1$ for quintile portfolios sorted by the past news return in month t. The past new return is the cumulative return from news days in month $t-5$ to month $t-1$. Turnover is a stock's daily share trading volume divided by its total shares outstanding. We exclude stocks with a market capitalization below the bottom 30% of all A-share stocks and stocks that are listed less than six months. We compute t-statistics, shown in parentheses, based on standard errors corrected for serial dependence of six lags (Newey and West, 1987). The sample period is from July 2012 through December 2021.

Past News Return	**News Days in month $t+1$**				**Non-news Days in month $t+1$**				**Diff**	
	Mean	Q25	Median	Q75	Mean	Q25	Median	Q75	Mean	t-stat
1 (Low)	2.00	0.55	1.13	2.36	1.47	0.46	0.90	1.77	0.52	(92.03)
2	1.82	0.45	0.95	2.13	1.32	0.38	0.77	1.58	0.50	(84.93)
3	1.89	0.48	1.01	2.23	1.34	0.39	0.78	1.59	0.55	(97.17)
4	2.10	0.57	1.18	2.52	1.48	0.46	0.90	1.79	0.62	(104.83)
5 (High)	2.78	0.83	1.70	3.49	1.94	0.62	1.23	2.42	0.84	(126.63)
High − Low	0.78				0.46					
	(71.99)				(142.41)					

Table A4. **Fama-Macbeth Regressions on the Good News Ratio**

This table reports the average coefficients from monthly firm-level cross-sectional regressions of stock return in month $t+1$ on the good news ratio and other firm characteristics in month t. *Good News Ratio* is the percentage of good news from month $t-5$ to month t. *Good News Ratio Rank* is the quintile rank of *Good News Ratio*. *Beta* denotes market beta, which is calculated as the coefficient from a twelve-month rolling regression of excess daily returns on excess market returns. *Size* denotes firm size, which is computed as the nature logarithm of the market capitalization (in thousands of RMB) at the end of each month t. *EP+* is a variable that equals the positive values of earnings-to-price ratio, and zero otherwise.*D(EP<0)* is a dummy variable which equals one for negative earnings, and zero otherwise. *ATR* denotes abnormal turnover, which is computed as the monthly stock turnover over its average turnover from the past twelve months. *STREV* denotes short-term reversal, which is return from month t. *ILLIQ* denotes the illiquidity measure from Amihud (2002), which is computed as the natural logarithm of the average daily ratio of the absolute stock return to the RMB trading volume from month t. *IVOL* denotes idiosyncratic volatility, which is computed as the standard deviation of daily return residuals from month $t-5$ to month t with respect to Liu et al. (2019)'s CH-4 factor model. All control variables are winsorized at 1% and 99%. We exclude stocks with a market capitalization below the bottom 30% of all A-share stocks and stocks that are listed less than six months. We compute t-statistics, shown in parentheses, based on standard errors corrected for serial dependence of six lags (Newey and West, 1987). The sample period is from July 2012 through December 2021.

	(1)	(2)	(3)	(4)	(5)	(6)
Good News Ratio	0.013 ***	0.013 ***	0.012 ***			
	(3.742)	(4.173)	(4.065)			
Good News Ratio Rank				0.203 ***	0.194 ***	0.183 ***
				(3.906)	(4.142)	(3.957)
Beta		-0.230	-0.042		-0.221	-0.032
		(-0.590)	(-0.126)		(-0.567)	(-0.096)
Size		-0.266	0.045		-0.259	0.050
		(-1.238)	(0.225)		(-1.210)	(0.249)
EP^+		0.450	0.411		0.463	0.426
		(0.583)	(0.580)		(0.600)	(0.600)
D(EP<0)		-0.472 ***	-0.345 **		-0.519 ***	-0.393 **
		(-3.387)	(-2.296)		(-3.499)	(-2.497)
ATR		-0.595 ***	-0.329 **		-0.589 ***	-0.325 **
		(-3.988)	(-2.599)		(-3.951)	(-2.565)
STREV			-0.010			-0.010
			(-1.057)			(-1.056)
ILLIQ			0.427 ***			0.424 ***
			(2.750)			(2.726)
IVOL			-0.269 *			-0.267 *
			(-1.724)			(-1.705)
Number of months	114	114	114	114	114	114
R-squared	0.007	0.062	0.089	0.006	0.062	0.088

Table A5. **The Predictability of the Good News Ratio on Firm Fundamentals**

This table reports coefficient estimates from panel regressions of fundamental growths on lagged *Good News Ratio* and other firm characteristics. We use the quarterly growth rate of total assets, net profits, oerating income, and earnings per share (EPS) to describe firm fundamentals. *Good News Ratio* is the percentage of good news from month $t-5$ to month t. $r^{news}_{t-5\rightarrow t-1}$ denotes the past news return, which is computed as the cumulative returns on news days from month $t-5$ to month $t-1$. *Beta* denotes market beta, which is calculated as the cofficient from a twelve-month rolling regression of excess daily returns on excess market returns. *Size* denotes firm size, which is computed as the nature logarithm of the market capitalization (in thousands of RMB) at the end of each month. *EP+* is a variable that equals the positive values of earnings-to-price ratio, and zero otherwise. *D(EP<0)* is a dummy variable which equals one for negative earnings, and zero otherwise. *ATR* denotes abnormal turnover, which is computed as the monthly stock turnover over its average turnover from the past twelve months. *STREV* denotes short-term reversal, which is return from month t. *ILLIQ* denotes the illiquidity measure from Amihud (2002), which is computed as the natural logarithm of the average daily ratio of the absolute stock return to the RMB trading volume from month t. *IVOL* denotes idiosyncratic volatility, which is computed as the standard deviation of daily return residuals from month $t-5$ to month t with respect to Liu et al. (2019)'s CH-4 factor model. All control variables are winsorized at 1% and 99%. We exclude stocks with market capitalization below the bottom 30% of all A-share stocks. All control variables are winsorized at 1% and 99%. In all regression specifications, we control for firm and year-quarter fixed-effects and double cluster standard errors by firm and year-quarter (reported in brackets). We exclude stocks with a market capitalization below the bottom 30% of all A-share stocks and stocks that are listed less than six months. The sample period is from July 2012 through December 2021. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	Total Asset Growth	***Net Profit Growth***	***Operate Income Growth***	***EPS Growth***
Good News Ratio	0.002 ***	0.022 ***	0.001 ***	0.019 ***
	[0.000]	[0.003]	[0.000]	[0.004]
$r^{news}_{t-5\rightarrow t-1}$	-0.000 **	0.015 ***	0.000 *	0.012 ***
	[0.000]	[0.002]	[0.000]	[0.002]
Beta	-0.048 ***	-0.183	-0.058 ***	-0.191
	[0.018]	[0.199]	[0.022]	[0.205]
Size	0.348 ***	1.417 ***	0.096 ***	0.830 ***
	[0.039]	[0.211]	[0.036]	[0.207]
EP+	0.178 ***	-2.450 ***	0.002	-1.922 ***
	[0.043]	[0.683]	[0.026]	[0.619]
D[EP<0]	-0.027	-0.248	0.023 **	-0.098
	[0.018]	[0.199]	[0.011]	[0.198]
ATR	0.006	0.181 ***	0.005	0.095
	[0.004]	[0.068]	[0.004]	[0.077]
STREV	-0.001 ***	-0.000	-0.000	0.001
	[0.000]	[0.004]	[0.000]	[0.003]
ILLIQ	0.103 ***	0.529 ***	0.029 **	0.220 ***
	[0.017]	[0.098]	[0.012]	[0.065]
IVOL	-0.000	0.032 *	0.000	0.016
	[0.001]	[0.019]	[0.001]	[0.012]
Year-Qtr FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Number of observations	71,314	70,474	69,976	70,474
R^2	0.065	0.021	0.005	0.018

Table A6. **The Long-term Predictability of the Good News Ratio**

This table reports the average value-weighted monthly excess returns and Liu et al. (2019)'s CH-4 alphas to quintile portfolios sorted by the good news ratio in month t. We examine the predictability of the good news ratio from the beginning of the portfolio formation (month $t-5$) to twelve months post-formation (month $t+12$). The good news ratio is the percentage of good news from month $t-5$ to month t. We exclude stocks with a market capitalization below the bottom 30% of all A-share stocks and stocks that are listed less than six months. We compute t-statistics, shown in parentheses, based on standard errors corrected for serial dependence of six lags (Newey and West, 1987). The sample period is from July 2012 through December 2021.

Timing	**Excess Return**		**CH4 Alpha**	
	Mean	t-stat	Mean	t-stat
$t-5$	2.67	(7.52)	2.91	(6.66)
$t-4$	2.33	(6.59)	2.57	(5.83)
$t-3$	2.28	(7.00)	2.5	(5.92)
$t-2$	2.06	(6.64)	2.33	(5.67)
$t-1$	1.97	(6.12)	2.17	(5.41)
t	1.72	(5.49)	1.89	(4.89)
$t+1$	0.78	(2.47)	1.02	(2.96)
$t+2$	0.70	(2.41)	0.98	(2.84)
$t+3$	0.60	(2.11)	0.82	(2.23)
$t+4$	0.57	(1.96)	0.84	(2.36)
$t+5$	0.51	(2.10)	0.73	(2.57)
$t+6$	0.45	(1.76)	0.75	(2.24)
$t+7$	0.25	(1.03)	0.51	(1.71)
$t+8$	0.28	(1.30)	0.51	(1.96)
$t+9$	0.12	(0.58)	0.31	(1.43)
$t+10$	0.14	(0.65)	0.35	(1.55)
$t+11$	0.21	(0.83)	0.41	(1.51)
$t+12$	0.13	(0.45)	0.26	(0.89)

Table A7. **The Good News Ratio and the Subsequent Institutional Ownership**

This table reports coefficient estimates from panel regressions of institutional ownership on lagged *Good News Ratio* and other firm characteristics. *Good News Ratio* is the percentage of good news from month $t-5$ to month t. $r^{news}_{t-5\rightarrow t-1}$ denotes the past news return, which is computed as the cumulative returns on news days from month $t-5$ to month $t-1$. *Beta* denotes market beta, which is calculated as the coefficient from a twelve-month rolling regression of excess daily returns on excess market returns. *Size* denotes firm size, which is computed as the nature logarithm of the market capitalization (in thousands of RMB) at the end of each month. *EP+* is a variable that equals the positive values of earnings-to-price ratio, and zero otherwise.*D(EP<0)* is a dummy variable which equals one for negative earnings, and zero otherwise. *ATR* denotes abnormal turnover, which is computed as the monthly stock turnover over its average turnover from the past twelve months. *STREV* denotes short-term reversal, which is return from month t. *ILLIQ* denotes the illiquidity measure from Amihud (2002), which is computed as the natural logarithm of the average daily ratio of the absolute stock return to the RMB trading volume from month t. *IVOL* denotes idiosyncratic volatility, which is computed as the standard deviation of daily return residuals from month $t-5$ to month t with respect to Liu et al. (2019)'s CH-4 factor model. All control variables are winsorized at 1% and 99%. We exclude stocks with market capitalization below the bottom 30% of all A-share stocks. All control variables are winsorized at 1% and 99%. In all regression specifications, we control for firm and year-quarter fixed-effects and double cluster standard errors by firm and year-quarter (reported in brackets). We exclude stocks with a market capitalization below the bottom 30% of all A-share stocks and stocks that are listed less than six months. The sample period is from July 2012 through December 2021. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
Good News Ratio	0.010 ***		0.011 ***
	[0.003]		[0.003]
$r^{news}_{t-5\rightarrow t-1}$		-0.000	-0.002
		[0.004]	[0.004]
Beta	-2.253 ***	-2.259 ***	-2.243 ***
	[0.372]	[0.380]	[0.380]
Size	9.778 ***	9.888 ***	9.792 ***
	[0.527]	[0.533]	[0.533]
EP+	-1.410 **	-1.277 *	-1.421 *
	[0.718]	[0.680]	[0.726]
D[EP<0]	-0.048	-0.200	-0.040
	[0.243]	[0.240]	[0.244]
ATR	0.288 *	0.293 **	0.298 **
	[0.148]	[0.145]	[0.145]
STREV	-0.037 ***	-0.037 ***	-0.037 ***
	[0.010]	[0.010]	[0.010]
ILLIQ	3.752 ***	3.754 ***	3.748 ***
	[0.380]	[0.379]	[0.380]
IVOL	0.014	0.015	0.017
	[0.024]	[0.023]	[0.024]
Year-Qtr FE	Y	Y	Y
Firm FE	Y	Y	Y
Number of observations	70,697	70,697	70,697
R^2	0.141	0.140	0.141

Table A8. **Predicting News and Non-news Returns in the US**

This table reports the value-weighted average total returns, news returns, and non-news returns in month $t+1$ for quintile portfolios sorted by the past news return ($r^{news}_{t-5\to t-1}$) in month t using the US data. At the end of each month t, we include common shares listed in NYSE, AMEX, and NASDAQ, and with a share price higher than 5 USD. Firm-specific news release dates are obtained from RavenPack Analytics. We select news on U.S. companies from the Dow Jones Package starting in 2000 and from the Press Releases Package starting in 2004. We keep news items with the highest relevance, the highest novelty and news topics most pertinent to business activities. We consider a long-short strategy that buys stocks in the top quintile and shorts stocks in the bottom quintile of the past news return. We compute t-statistics, shown in parentheses, based on standard errors corrected for serial dependence of six lags (Newey and West, 1987). The sample period is from January 2000 through December 2022.

Sorting Variable: $r_{t-5\to t-1}$	r_{t+1}	r^{news}_{t+1}	$r^{nonnews}_{t+1}$
1 (Low)	0.31	-0.12	0.16
2	0.72	0.01	0.57
3	0.80	0.04	0.65
4	0.91	0.07	0.70
5 (High)	0.85	0.10	0.53
High − Low	0.54	0.22	0.37
	(3.43)	(4.87)	(2.80)