Dissecting Momentum in China *

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October 2025

Abstract

Why is classic momentum absent in China? We document a tug-of-war where stocks that outperform on news days underperform on subsequent non-news days. The back-and-forth in news returns and non-news returns, when aggregated, makes momentum disappear. Our results suggest that news returns are contaminated by excessive price pressures from the temporary attention-driven buying demand of retail investors, while non-news-day-reversals represent mispricing corrections from institutional investors. Such a pattern is not observed in the U.S. stock markets, which are highly institutionalized. Using a textual-based proxy that is insulated from the attention-driven excessive buying demand, we find a strong underreaction to news in China.

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

*We thank Zhi Da, Jian Feng, Xing Hu, Zhen He, Shiyang Huang, Mohammed Kaddouhah, Xiaoquan Liu, Dong Lou, Alexandre Jeanneret, Wenxi Jiang, Danqing Mei, Soyun Nam, Vesa Pursiainen, Jianfeng Shen, Jiahong Shi, Hanwen Sun, Jiaxing Tian, Chi-Yang Tsou, Hong Xiang, Huaixin Wang, and Jing Zhao, seminar participants at the 18th International Behavioral 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.[1] However, such a phenomenon is not observed in China, the world's second largest stock market (Song and Xiong, 2018; Hu, Pan, and Wang, 2018). Recent studies suggest that the absence of momentum in China could be a result of strong noise trading from retail investors and liquidity-premium required by institutional investors (Chui, Subrahmanyam, and Titman, 2022; Du, Huang, Liu, Shi, Subrahmanyam, and Zhang, 2024).[2]

Inspired by these recent studies, we examine whether momentum exists on news days (days with firm-specific fundamental news releases), which have been shown to be less affected by noise trading (Jegadeesh, Luo, Subrahmanyam, and Titman, 2023).[3] However, we continue to find no evidence of momentum. This finding suggests that the liquidity-premium explanation alone does not fully account for the absence of momentum in China. Instead, we uncover a tug-of-war pattern in stock returns between news and non-news days. That is, stocks that outperform on news days on average perform relatively poorly on subsequent non-news days.

We argue that this pattern can be explained by retail investors' attention-driven trading and their interactions with institutional investors, which together shed light on the absence of momentum in China. Our explanation is rooted in the well-documented behavioral bias that attention-grabbing events (such as news releases) can stimulate excessive buying demands from retail investors, especially on stocks with high past news returns (Barber and Odean, 2008; Hirshleifer, Myers, Myers, and Teoh, 2008; Bali, Hirshleifer,

[1] For international evidence, see, e.g. Rouwenhorst (1998); Griffin, Ji, and Martin (2003); Asness, Moskowitz, and Pedersen (2013)

[2] In the presence of noise traders, risk-averse institutional investors demand a liquidity premium in the short run (an inventory compensation for absorbing the demands of noise traders) and only step in to correct prices once noise trading subsides, leading to subsequent price reversals. Consequently, short-term reversals should be weaker (stronger) in settings where retail investors are less (more) active. Consistent with this view, Chui et al. (2022) and Du et al. (2024) disentangle China's A- and B-share markets, as well as high- versus low-nominal-price stocks, to provide empirical evidence supporting this mechanism.

[3] Jegadeesh et al. (2023) theoretically and empirically show that short-term reversals caused by noise trading attenuate after news release. Because the market receives more information during news days than in other periods, a stronger price underreaction weakens the reversals.

Peng, and Tang, 2021).[4] As a result, returns on news days not only reflect market perceptions on fundamental news, but may 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; it eventually reverses on non-news days, when institutional investors dominate market activity and correct mispricing.[5] Thus, the back-and-forth in news returns and non-news returns, when aggregated, makes price momentum disappear.

We provide three sets of empirical evidence to support the interactive dynamics between retail and institutional trading 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, as proxied by low nominal price (Du et al., 2024). Second, we compare retail attention 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.[6] 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.[7] We find that stocks in the top past news return quin-

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

[5]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.

[6]Baidu is the largest search engine in China and accounts for more than 85% of market shares. The Baidu search index is analogous to the Google search index introduced by Da, Engelberg, and Gao (2011) to capture retail attention on U.S. stocks.

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

tile —compared to those in the bottom past news return quintile—tend to be purchased more by retail investors on news days and tend to be sold more by institutional investors on non-news days. These order flow patterns are consistent with the interpretation that excessive attention-driven buying demand from retail investors pushes up stock prices on news days, 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 because 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 that directly captures 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. It is labeled according to one of three categories: good news, neutral news, and bad news.[8] Thus, we screen recent firm-specific news articles and compute the percentage of good news. Consequently, this recent news performance (hereafter termed the "good news ratio") is immune from 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 persistency 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 CH-4 factor model of Liu, Stambaugh, and Yuan (2019). This result remains robust under Fama-MacBeth (1973) regressions which control 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,

[8] See Section 2.1 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. They further suggest that investors underreact to this valuable information embedded in the good news ratio, thereby generating positive return predictability in the cross-section.

The contrasting results between portfolios sorted by past news return and by good news ratio highlight the interactive dynamics between news returns and non-news returns in shaping asset prices in China. Our argument suggests that: (1) high past news returns signal overpricing on news days; and (2) 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 returns using the good news ratio as a "benchmark". We can also provide further evidence of the cycle of overpricing on news days and of the mispricing correction on non-news days. We conduct two additional analyses to lend further 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 come mainly from stocks with high past news returns but low good news ratios. Second, this non-news-day reversal 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 U.S. stock markets to further support our argument. More specifically, we replicate our main results using data from U.S., and find that stocks with high past news returns have 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 built on strong retail influence. It has been well documented that U.S. 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 between the two countries could potentially drive the difference in their return dynamics on news days and non-news days.

Related Literature. Prior studies have documented the absence of price momentum in China. Instead, a stock's past return negatively predicts the subsequent return at horizons ranging from one, three, six, or 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 the price momentum of stocks with high nominal prices; these stocks suffer less from noise trading due to the financial constraints of retail investors. 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; we suggest that noise trading and liquidity premiums do not offer a complete explanation for the absence 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 institutional investors tend to trade on different days. This idea is enlightened by Lou, Polk, and Skouras (2019), who identify the relevance of different types of investors through their tendency 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 price momentum does not exist in China because of a back-and-forth cycle: 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, Titman, and Wei (2010) tried 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, which leads 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 there is no underreaction, but because return signals are contaminated by the excessive attention-driven buying demand of retail investors, which is 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 excessive buying demand and a strong underreaction to news is observed in China. In addition, Gao, Jiang, Xiong, and Xiong (2023) document the presence of price momentum in daily returns in China, which also challenges this cultural explanation.[9]

Our findings are different from those of Engelberg, McLean, and Pontiff (2018) who shows that, in U.S. stock markets, anomaly returns are higher on corporate news days and suggest that this can 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 where retail investors dominate market activities on news days and generate mispricing. Conceptually, this observation is consistent with the finding of Cai, Keasey, Li, and Zhang (2023), who suggest that in low-efficiency markets (such as China's A-share markets), without news watchers sowing the seeds of price discovery and ensuring the long-run convergence of price to fundamentals, anomalies (such as momentum) could be weaker in emerging markets than in developed markets. Jegadeesh, Luo, Subrahmanyam, and Titman (2025) have developed a multiperiod model to understand momentum reversal and predict attenuated reversals after earnings

[9]Our paper is different from Gao et al. (2023) in two ways. First, we investigate the classic price momentum in monthly returns first documented by Jegadeesh and Titman (1993), while Gao et al. (2023) focus on a different momentum phenomenon at the daily frequency. Second, Gao et al. (2023) focus on the trading behavior of new investors (with account ages of less than three months), while our paper studies the trading behavior of retail and institutional investors more generally.

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 to 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. To build its news dataset, Datayes tracks more than 2,600 vetted websites in real time; these include mainstream financial media, government websites, and verified official social media accounts.[10] On average, around 60,000 news articles are included in the database daily, and 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 the accuracy of a news article 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.[11] To ensure the quality of this news-firm matching procedure, Datayes

[10] These social media accounts include verified official WeChat accounts for listed firms and news media.

[11] A news article is strongly related to a listed firm if the news relevance index is greater 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 less than 0.25.

conducts a rigorous manual screening session and reports 97% consistency between manually and automatically assigned links. Second, the news sentiment index, ranging from -1 to 1, evaluates the news article as "good" or "bad" relative to the matched firm. Datayes classifies the news sentiment index into three categories: good news, neutral news, and bad news.[12] To ensure the quality of the news sentiment index, Datayes conducts another manual screening session and reports 80% consistency between manually assigned sentiment and automatically assigned sentiment.

For the years 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 toward the most recent decade, with sparse firm coverage in earlier years. Therefore, we start our analyses with 2012. For all analyses in our paper, we retain news articles that are non-duplicate, strongly related to a listed firm, with non-neutral news sentiment indices, and pertinent to firm-specific events.

2.2 Order Imbalance

Datayes collects all intraday tick-by-tick transaction details directly from the 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 indicates whether a transaction is buy-initiated or sell-initiated. Share volume is the total number of shares in each transaction. Trade size is the trading volume of each transaction in RMB. 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 that average; (3) large trades, with trade sizes greater than ten times but smaller than a hundred times that average; (4) extra large trades,with trade sizes greater than a hundred times 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 the categories of trade direction and trade size.

Following prior studies (e.g., Barber and Odean, 2008; Barber, Odean, and Zhu,

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

2008; Boehmer, Jones, Zhang, and Zhang, 2021; Jones, Shi, Zhang, and Zhang, 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.[13] We compute the following variables to 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 $BSI_{i,t}^{XL}$ proxies 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. 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 have been listed less than six months. We obtain China's risk factors introduced in Liu et al. (2019) from Professor Robert Stambaugh's website.[14]

We capture the daily retail attention for each stock using its Baidu search index. Specifically, we obtain the daily online search index for each stock using both the stock

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

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

name and stock ticker. This is analogous to the Google search index introduced by Da et al. (2011) to capture retail attention on U.S. stocks.

The following control variables are included in regression analyses, following Liu et al. (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 month, following Amihud (2002); (8) *Idiosyncratic Volatility*, the standard deviation of daily return residuals over the past six months from Liu et al. (2019) CH-4 factor model; (9) *Institutional Ownership*, the percentage of shares held by institutional investors. In addition, to capturing 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 as 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 a non-trading day or after market close, we assign this news to the following 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 focus mostly on portfolio analyses; the monthly total return, news return, and non-news return for portfolio p in month t are 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, , the past total return ($r_{i,t-5 \to t-1}$) is the cumulative returns for stock i from month $t-5$ to month $t-1$; the past news return ($r_{i,t-5 \to t-1}^{news}$) is the cumulative news returns for stock i from month $t-5$ to month $t-1$; the past non-news return ($r_{i,t-5 \to t-1}^{nonnews}$) is the cumulative non-news returns for stock i from month $t-5$ to month $t-1$.[15]

2.5 Summary Statistics

Table 1 presents the descriptive statistics for our sample. On average, a stock has 2.46 news days in a month. The average past total return is 7.40%, and the average past news return is 7.12%, indicating that returns from news days contribute mostly 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

[15] 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.

ratio is a persistent firm characteristic: More than 80% of the stocks in the top (bottom) good news ratio quintile remian in the top (bottom) quintile in the subsequent month. This ensures relatively low trading costs when building long-short portfolios.

[Table 1 here]

3 Main Result

3.1 News Returns versus 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 $t-1$ ($r_{i,t-5\to t-1}$), 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.[16] Portfolios are rebalanced at the monthly frequency. In Table 2 column (1), we report the average returns from the quintile portfolios and from a long-short strategy that 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 six 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 absence of momentum in China. Prior studies suggest that, in China, risk-averse liquidity providers need inventory compensation to absorb the noise trading of retail investors. 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

[16] Results remain similar using other window lengths.

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, Jegadeesh, and Lakonishok, 1996; Hong and Stein, 1999; Chan, 2003; Jiang, Li, and Wang, 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 focus only on the component that reflects the market perception of 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 ($r_{i,t-5\rightarrow t-1}$) into news-driven and non-news-driven components ($r^{news}_{i,t-5\rightarrow t-1}$ and $r^{nonnews}_{i,t-5\rightarrow t-1}$, termed "past news return" and "past non-news return", respectively). This method is inspired by Jiang et al. (2021), who decomposed daily stock returns into news-driven and non-news-driven components and examined short-term return predictability. It is natural to assume that past news returns could reflect mainly fundamental news, while past non-news returns could reflect mainly 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 Table 2, column (4) we report the average returns from the quintile portfolios and from a long-short strategy that buys stocks in the top quintile and shorts stocks in the bottom 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 contribute to driving 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 Table 2, columns (5)-(6). 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. Table 2, column (5) 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 have, on average, a price reversal on subsequent non-news days. Table 2, column (6) shows that the same long-short portfolio suffers an average non-news return of -0.33% per month (t-statistic = -1.37). Even though this reversal is statistically insignificant, the economic magnitude is sizable. Thus, when news returns and non-news returns are aggregated, the past news return no longer predicts the subsequent total monthly stock return. 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 whether a similar pattern can also be obtained using the past total return ($r_{i,t-5\to t-1}$) instead of the past news return. Therefore, we conduct a similar exercise and report the results in Table 2, columns (2)-(3) 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, Table 2, columns (4)-(6) show 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 our 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 quintile and shorts stocks in the bottom 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 of the absence 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 Section 3.2, 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 absence of price momentum in China, one based on the interactive dynamics between retail and institutional trading. Our explanation is rooted in the well-documented phenomena that retail investors have limited attention and that attention-grabbing events (such as news releases) can stimulate excessive buying demands, especially for stocks with high past news returns (Barber and Odean, 2008; Hirshleifer et al., 2008; Bali et al., 2021). As a result, news returns might not only reflect market perceptions on fundamental news, but could also capture retail investors' temporary price pressure. 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; it eventually reverses on non-news days, when institutional investors dominate market activity and correct mispricing. Thus, when aggregated, 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 (5×3) 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. Table 3, Panel A 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, Table 3, Panel B shows that, in the subsample of stocks that are in the top nominal price tercile, the same long-short portfolio on average experiences a news return of only 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 confirms our predictions: Retail attention is significantly higher on news days, especially for stocks in the top news return quintile. Stocks in the top news return quintile have an average Baidu search index of 1,533 on news days, and 1,021 on non-news days; this represents a drop in retail attention of more than 30% drop between news days and non-news days. Moreover, stocks in the bottom news return quintile have an average Baidu search index of 1,398 on news days; this represents a drop of nearly 10% in news-day retail attention from stocks in the top news return quintile. 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 confirms both of our predictions. To start with, Panel A, column (1) 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 attention on news days documented in Table 4; this corroborates the argument for attention-driven buying by retail investors on news days. Moreover, Panel A, column (4) 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 increase of more than 10% 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 that the mispricing correction is the result of institutional sales on non-news days. Put together, results presented in Table 5 provide direct evidence of investor heterogeneity and of investors' differential trading behaviors on news days and non-news days, which aligns with the tug-of-war between news returns and non-news returns. In Appendix Table A3, we replace buy-sell imbalance with daily turnover, and find similar patterns.

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

We are also 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 institutions' strong net purchase of stocks in the top news return quintile on news days, reported in Table 5, column (2). 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 simultaneously explain both the momentum on news returns and the reversal on non-news returns.

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 attention spikes 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 retail investors 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 the temporary price pressure for retail investors; this pressure is due to attention-driven buying demand, which temporarily pushes up stock prices on news days. 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; it is then labeled into one of three categories: good news, neutral news, and bad news. We focus only on non-neutral news in our analyses. At the end of each month t, we screen firm-specific news articles from month $t-5$ to month t and compute the percentage of good news (termed "good news ratio" hereafter). Note that we no longer need to skip news articles from the most recent month, 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 subsequent 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 frequency. 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 Table 6, Panel A. We compute t-statistics, shown in parentheses, based on standard errors corrected for serial dependence of six lags (Newey and West, 1987). We report factor loadings for the long, short and long-short portfolios in Table 6, Panel B.

[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). The strategy becomes even more profitable after it is adjusted according to the CH-4 factors of Liu et al. (2019), earning an average monthly alpha of of 1.02% (t-statistic = 2.96). Table 6, Panel B 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 the portfolio's Sharpe ratio. As reported in Appendix Table A4, this result is also robust under Fama-MacBeth (1973) regressions, which control for other firm characteristics that may affect the cross-section of stock returns in China.

In comparing Table 6 with Table 2, it is interesting 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 about 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 each. 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) the prices of stocks in the top quintile of the good news ratio barely revert on non-news days. This pattern stands in sharp contrast to the results documented in Table 2, columns (5)-(6) and supports our argument: Past news returns are contaminated by excessive buying demand, which is subject to reversals, while the good news ratio, which 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 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 areas of growth, 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 information embedded in 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 monthly excess return of the long-short portfolio declines over time after 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) according to 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 concentrated mainly on stocks with low retail attention. For stocks in the bottom tercile of the Baidu search index, 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 tercile of the Baidu search index and in the top quintile of the past news ratio, both 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 reported in Table A7 show that institutional ownership in 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 have introduced the good news ratio, a textual-based proxy for fundamental news that is insulated from the excessive buying demand of retail investors, 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 Discussion

4.1 Past News Return versus. Good News Ratio

The contrasting results between portfolios sorted by past news returns and those sorted by good news ratios highlight the interactive dynamics between retail and institutional trading in shaping asset prices in China. Our interpretation is that high past news returns partially reflect the overpricing by retail investors on news days, while return reversals on non-news days represent the mispricing correction of institutional investors. With the introduction of the good news ratio from Section 3.3, we can now gauge the degree of overpricing from the past news return using the good news ratio as a benchmark and can provide further support to explain 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, 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, past news returns likely reflect the temporary price pressure resulting from 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 four portfolios (2×2) to ensure all portfolios have a sufficient number of stocks; we report the results in Table 9.

[Table 9 here]

The first two columns of Table 9 show that past news returns and good news ratios enhance each other when predicting news returns. Portfolio D (lower right) has the highest news returns on average, while Portfolio A (upper left) has the lowest news returns on average. A long-short portfolio, which buys stocks in Portfolio D (lower right) and sells stocks in Portfolio A (upper left) 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. Portfolio B (upper right) has the lowest non-news returns on average, because high past news returns mainly capture strong temporary price pressures which are not justified by the information embedded in the textual context of the news. By contrast, the stock returns from Portfolio C (lower left) barely revert on non-news days. A long-short portfolio, which buys stocks in Portfolio B (upper right) and sells stocks in Portfolio C (lower left) 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 have difficulty correcting 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 eight portfolios ($2 \times 2 \times 2$) by past news returns, good news ratios, 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 Portfolio B (upper right) and sells stocks in Portfolio C (lower left), is doubled in magnitude among firms with high limits to arbitrage (small firms and high IVOL firms) compared to the average return 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 U.S. Comparison

So far we have focused on China's A-share markets. One might wonder whether the tug-of-war in stock returns between news days and non-news days can also be observed in U.S. stock markets. Unlike China's A-share markets, U.S. 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 U.S. stock markets.

To conduct similar empirical analyses in U.S. 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 and the highest novelty and with 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 greater than 5 USD. At the end of each month t, we follow the same empirical design outlined in Section 2.4 and compute 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 that 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 six 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 have higher returns on *both* subsequent news days and non-news days; (2) the long-short portfolio on average earns higher returns on non-news days than on news days. These results highlight the uniqueness of our findings regarding China's A-share markets, and lend further support to our argument on investor-heterogeneity from an alternative perspective.

5 Conclusion

As the world's second largest stock market, China's A-share market differs markedly from its U.S. counterpart: Most well-documented trading strategies that have worked well in U.S. do not work in China (e.g., Li, Liu, Liu, and John Wei, 2024). One prominent example is the famous price momentum, that is, the positive relation between a stock's return and its recent relative price performance (Jegadeesh and Titman, 1993); this 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: the heterogeneity and trading seasonality of investors.

We argue that price momentum does not exist in China because of a cycle involving the over-reaction of retail investors on news days and of price corrections by institutional investors on non-news days. This is reflected empirically 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 aggregated, 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 from subsample analyses. We find that the non-news-day reversal is more pronounced for stocks with retail dominance. Second, we compare retail attention 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 retail and institutional investors on news days and non-news days. We find that stocks in the top news return quintile tend to be purchased more by retail investors on news days and tend 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 the temporary price pressure of retail investors that is due to attention-driven buying demand. This demand temporarily pushes 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 are 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 with 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; and (4) the good news ratio predicts subsequent institutional ownership.

The contrasting results between portfolios sorted by past news returns and by good news ratios highlight the interactive dynamics between retail and institutional investors in shaping asset prices in China. Our argument suggests that high past news returns signal overpricing on news days and that return reversals on non-news days represent mispricing corrections. With the introduction of the good news ratio, we evaluate the degree of overpricing from the past news return using the good news ratio as a benchmark. We find that non-news-day reversals are concentrated among stocks with high past news returns but low good news ratios, and among stocks with strong limits to arbitrage. Both observations 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 U.S. stock markets and find that stocks with high past news returns have 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, U.S. stock markets are highly institutionalized.

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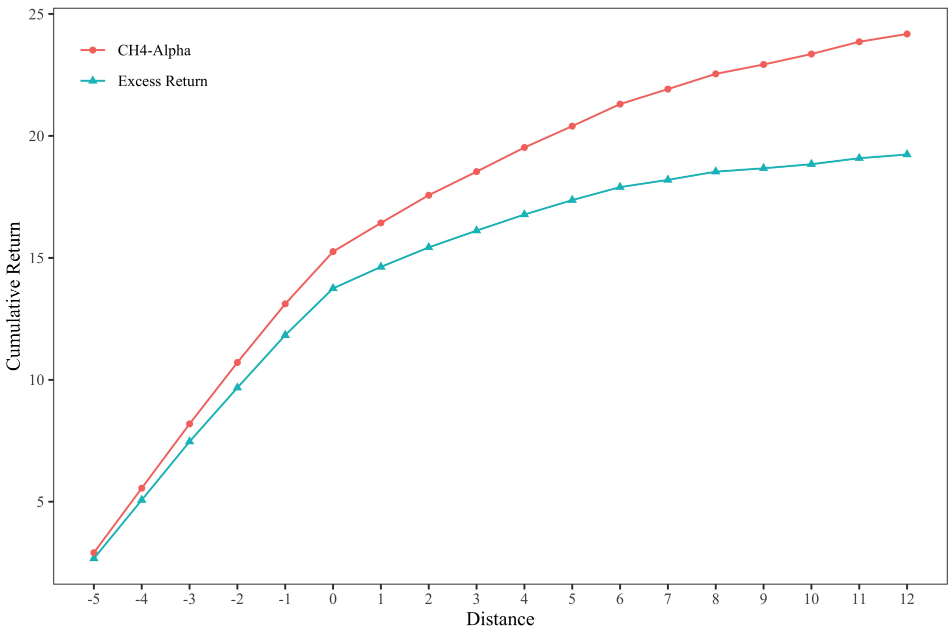
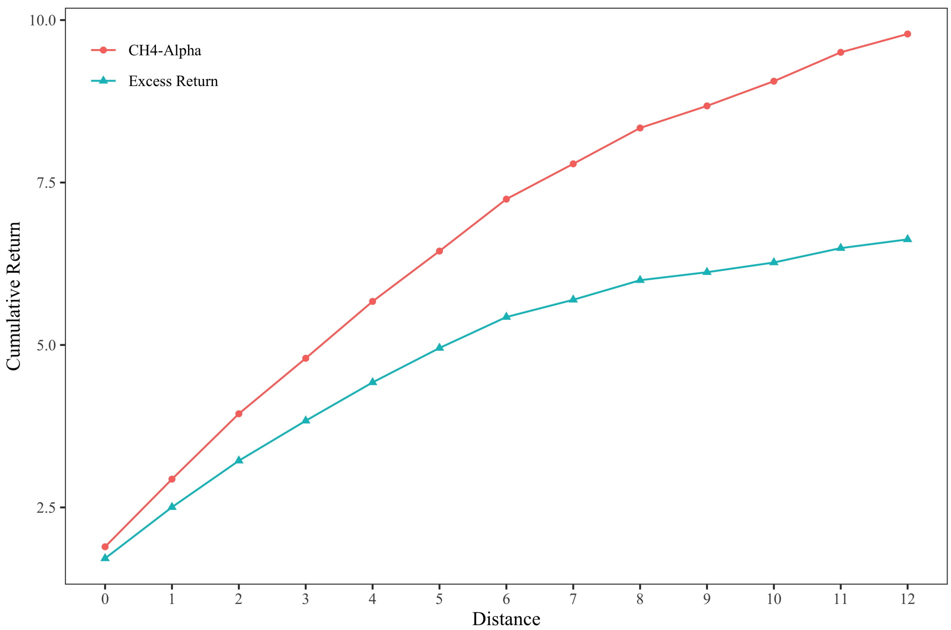


Panel A: Month $t-5$ to Month $t+12$



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. $r_{t-5\rightarrow t-1}$ denotes the past total return, which is computed as the cumulative return from month $t-5$ to month $t-1$. $r^{News}_{t-5\rightarrow t-1}$ denotes the past news return, which is computed as the cumulative returns on news days from month $t-5$ to month $t-1$. *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
$r_{t-5\rightarrow t-1}$	236,794	7.401	33.366	-13.401	0.785	20.152
$r^{news}_{t-5\rightarrow t-1}$	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 Attention**

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 attention. 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 ($r^{news}_{t-5\to t-1}$) 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 ($r^{news}_{t-5\to t-1}$) 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.

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 ($r^{news}_{t-5\rightarrow t-1}$), and a proxy for arbitrage conditions in month t (2 $\times$ 2 $\times$ 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 ($Ret^{news}_{t-5\rightarrow t-1}$) 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.

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. $r^{news}_{t-5\to t-1}$ denotes the past news return, which is computed as the cumulative returns on news days from month $t-5$ to month $t-1$. *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]
$r^{news}_{t-5\to t-1}$	-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. $r^{news}_{t-5\to t-1}$ denotes the past news return, which is computed as the cumulative returns on news days from month $t-5$ to month $t-1$. *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]
$r^{news}_{t-5\to t-1}$		-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 U.S.**

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 U.S. 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)