Pen v.s. Panic:

Media Narratives during Stock Market Crashes

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Abstract

Narratives can play a pivotal role in shaping beliefs, especially during periods of market panic. This paper investigates the distinctive patterns of media narratives surrounding stock market crashes in China, using a comprehensive dataset of 36 million news articles. We find that following stock market crashes, media significantly increases its emphasis on economic prospects. This shift in narrative following crashes is associated with higher subsequent stock returns and lower stock volatility, both at the aggregate market level and the firm level. Further analysis reveals that narratives focusing on economic prospects are linked to elevated investor expectations, reduced investor disagreement, and increased cumulative net buying activity after crashes. These findings provide new insights into the stabilizing role of media narratives in facilitating market recovery.

Keywords: Media narratives, stock market crashes, economic prospects, belief formation, trading behavior

1. Introduction

Narratives "go viral" and spread far, even worldwide, with economic impact (Shiller, 2017).[1] Media narratives can become especially influential during stock market crashes. First, crashes spur demand for more information in such times of uncertainty and panic, and investors undoubtedly look to the financial press to understand the causes and consequences of market dynamics. (Glasserman, Mamaysky, and Shen, 2024). Second, investors will be particularly sensitive to information during crashes since the capital losses and uncertainty put them in negative mood states (Garcia, 2013).[2] Third, media can have a disproportionate impact relative to their intrinsic informational content during crashes by enabling synchronization (Abreu and Brunnermeier, 2003). These features make it crucial to examine the role of media narratives during crashes for researchers, regulators, and practitioners.

Extant studies on media narratives in the U.S. market highlight their roles in raising investors' concerns about crashes by recalling historic crashes. Goetzmann et al. (2024) suggests that bringing attention to past "rare disasters" positively predicts individual predictions of a catastrophic stock market crash and over-estimation of probability of "rare disasters". For market dynamics, there is higher market volatility, negative market responses, and return reversals, suggesting overreaction (Goetzmann et al., 2024; Mamaysky, 2024). The rationale behind these

[1] Shiller (2017) highlights the important role of narratives in the transmission of economic beliefs. Narratives are a social medium through which an idea can spread rapidly through conversation, potentially affecting aggregate beliefs about asset prices and shaping financial and economic outcomes.

[2] The psychology literature forcefully argues that emotions affect decision making, and in particular information processing (Tiedens and Linton, 2001; Smith and Ellsworth, 1985; Ortony, Clore, and Collins, 1988; Gino, Wood, and Schweitzer, 2009).

narratives is that they provide context and perspective for current events, serve as a cautionary voice and warnings, and attract public attention in the competition for a broader audience. However, these narratives are associated with investor overreaction to price drawdown, spreading panic, and deteriorating market condition, which may contribute to further loop of liquidity evaporation and full-fledged collapse (Abreu and Brunnermeier, 2003; Barlevy and Veronesi, 2003). Given the potential devastating consequences of crash narratives, a crucial yet open question emerges: can media narratives during crisis help restore investor confidence and facilitate market stabilization? Addressing this question is imperative, not only for more comprehensively understanding the role of media narratives, but also for designing effective crisis management to safeguard market stability (Brunnermeier, 2024).

We explore this question in the context of China, where the media environment and institutional setting offer a unique lens for our analysis: first, China's financial system—characterized by speculative dynamics and an inexperienced retail investor base—makes financial stability a particular priority (Brunnermeier et al., 2022). The principle of "seeking progress while maintain stability" has guided economic policymaking since 1988 and remains central to official discourse. For example, the annual Central Economic Work Conference, which outlines China's annual economic priorities and agenda, consistently reinforce the tone of "seeking progress while maintain stability" over the past decade, and 2025 Government Work Report referenced "stability" and its variants ("stable," "stabilize") 66 times, underscoring its institutional salience. Second, for the regulation of media sector, Publicity Department of the Communist Party of China is

responsible for the management of news publication. As mentioned in the National Conference on Propagation and Ideological Work, the propagation should adhere to the principles of unity, stability, and encouragement, with a focus on positive publicity. This regulatory framework provides a distinctive setting to examine whether media narratives can be strategically deployed to reinforce investor confidence and stabilize the market during periods of market stress.

Specifically, this study examines three research questions. First, how do media narratives evolve during episodes of market crashes in China? Second, how do such narratives translate into market dynamics—specifically, do stock returns and volatility respond to this type of crisis-period media narratives? Third, through what mechanisms do these narratives influence investor behavior—do they restore confidence by shaping expectations, reducing disagreement, and altering trading activity in ways that facilitate market stabilization?

To address these questions, we utilize a comprehensive dataset comprising approximately 36 million media news articles from 2007 to 2024. Media is classified into traditional and online media. For traditional media, 16 important nation-wide Chinese economic and financial newspapers and journals are included. Moreover, traditional media includes state-controlled media and market-oriented media which differs in media ownership. Online media news sources consist of financial media, government websites, and WeChat official accounts, covering most of the registered internet news providers in China.

We extract narrative themes of news articles using latent Dirichlet allocation (LDA), which is a widely-used topic-modeling technique in machine learning and natural language processing

(Bybee et al., 2024). Under the unsupervised LDA, the topics are identified as clusters of terms (words or phrases) that tend to co-occur in articles. The model also estimates the proportion of text dedicated to each topic in an article, quantifying the amount of news attention allocated to a given topic. Then we can get a time series of topic attention for each topic by averaging over articles for each day. Firm-level topic attention is calculated by averaging the topic attention for articles related to the firm.

Stock market crashes are identified as days when the value-weighted market return over the preceding week fails below (i) the 5th percentile in the rolling window of past 10 years (520 weeks) and (ii) an absolute threshold of -5%.[3] To focus on crashes in more recent periods, the sample period starts in 2007, beginning with the first major bubble-crash in the Chinese stock market. Based on these criteria, we identify 39 crash weeks, including major downturns examined in the literature such as the 2008~2009 global financial crisis, the 2015~2016 stock market crash, and the 2020 pandemic.

For the first research question, we find that among all topics, *Economic Prospects* receives the highest level of media coverage during stock market crashes. Moreover, media attention to economic prospects, denoted as prospect attention, is much higher in crash periods than in other times. The regression analysis shows that media allocate significantly more attention to economic prospects following stock market crashes. These findings are consistent with the principle of propagation in terms of enhancing people's confidence and encouraging people to move forward.

[3] The main results are robust to alternative definition of crashes. See Section 3.5 for more details.

To answer the second research question, we examine the relation between prospect attention and market dynamics. Market-level prospect attention following crashes is associated with higher market returns and lower market volatility in the subsequent week. For different media types, the effects are concentrated in traditional media, and especially state-controlled media. Firm-level analysis reveals that firm-level prospect attention following market crashes is positively correlated with stock returns and negatively correlated with stock volatility in the next week. Overall, our findings suggest positive market responses and market stabilization effects of media narratives. In the cross section, the relations intensify for large stocks, state-owned enterprises, and stocks with higher institutional ownership.

For the third research question regarding mechanisms, we examine whether investors' expectations, disagreement, and trading activities vary with prospect attention. We find that following crashes, higher prospect attention is related to more optimistic investor expectations and reduced disagreement, aligning with the principle of fostering unity and stability in public communication. We also observe consistent results on investors' trading activities: investors' cumulative net buy is greater corresponding to higher prospect attention in the aftermaths of crashes.

We next conduct an event study to further understand the role of prospect attention during crashes. On December 12, 2023, annual Central Economic Work Conference proposed "Sing the Theory of Light of China's Economy" to further promote the positive publicity. Focusing on a shorter period around the event from 2021 to 2024, we find that positive market responses and

stabilization effects are more pronounced afterwards. Finally, we conduct several robustness checks using alternative definitions of crashes and our main results are robust.

This paper joins the ongoing literature on narrative economics (Shiller, 2017; Bruner, 1991; Herman, 2009; Morag and Loewenstein, 2025; Andre et al., 2025 among many others). Our study builds on Shiller's (2017) notion of narrative economics, which emphasizes the power of stories in shaping economic behavior.[4] Chahrour et al. (2021) show that financial press narratives play an important motivating role in business cycle dynamics. A growing body of research utilizes topic modeling tools to extract thematic narratives from news, and investigate how media topics can help understand business cycles and predict stock returns (Larsen et al., 2021; Bybee et al., 2024; Hirshleifer et al., 2024, 2025).[5] Prior research also have applied other language processing tools in financial news to examine the role of media in real economy (Baker et al., 2016; Fisher et al., 2022; van Binsbergen et al., 2023; Xu and You, 2025), stock market return (Tetlock, 2007; You et al., 2018; Jiang et al., 2021; Mamaysky, 2024; Chen et al., 2025; Lopez-Lira and Tang, 2024; Baker et al., 2025), volatility (Manela and Moreira, 2017; Goetzmann et al., 2024; Baker et al., 2024), and investor beliefs (Bybee, 2024; Goetzmann et al., 2024).[6] This paper differs from these papers by providing novel empirical evidence on how media narratives stabilize fragile markets during

[4] In financial market, media serves as a primary vehicle through which such narratives are disseminated, making it a natural setting to examine how narratives influence investor beliefs and market dynamics.

[5] Jiang et al. (2022a, 2022b) further use economic news narratives in Bybee et al. (2024) to measure real-time economic conditions and propose a narrative-managed portfolio. Bybee et al. (2023) estimate a narrative factor pricing model using LDA.

[6] Other studies examine how media ownership, and coverage affect stock returns, investor trading, and firm behavior. (Houston et al., 2011; Solomon et al., 2014; Baloria and Heese, 2018; Calomiris and Mamaysky, 2019; Guest, 2021; kedia and Kim, 2024; Goldman et al., 2024; Tsang et al., 2025). There are also studies on media bias and newspaper censorship in China (Qin et al., 2018; Hope et al., 2021).

crashes.

Another strand of literature is about stock market crashes. Existing research highlights the potential role of the media in creating asset bubbles and triggering market crashes (Shiller, 2000; Abreu and Brunnermeier, 2003). Some studies focus on return predictability of news tone, investor beliefs and trading, and wealth outcomes during market downturns (Garcia, 2013; Giglio et al., 2021; An et al., 2022). Others examine the effects of government stock purchases and institutional ownership during crashes (Dang et al., 2024; Glossner et al., 2025). For the macroeconomy, Reinhart and Rogoff (2014) examine real economy recovery from financial crises and Brunnermeier (2024) highlight the perspective of resilience. This paper contributes to this literature by offering new insights on how to design effective crisis management to safeguard market stability from the perspective of media narratives.

We also contribute to the literature on understanding Chinese financial markets. Jones et al. (2024) comprehensively study Chinese retail investors' heterogeneity in trading dynamics and performances. Brunnermeier et al. (2022) propose a theoretical framework to rationalize China's approach to managing the financial system, which involves regular and intensive government interventions. Empirically, Huang et al. (2019) and Dang et al. (2024) use the 2015 Chinese stock market crash to examine the value creation and the impact on volatility and price informativeness of government stock purchase. This paper joins this literature by investigating different approaches to stabilizing the stock market during crashes in the Chinese financial market.

The balance of the paper is organized as follows. Section 2 describes the data and variable

construction. Section 3 presents the empirical results. Section 4 concludes.

2. Data, Variable Construction, and Descriptive Statistics

2.1 Data and Sample

The dataset used in this paper is among the most extensive text corpora of Chinese business news studied in the finance literature to date. It consists of approximately 36 million media news articles from comprehensive news sources from 2007 to 2024, covering both traditional and online media.

For traditional media, 16 important nation-wide Chinese economic and financial newspapers and journals are included, which cover the newspapers used in the previous literature (You et al., 2018). Traditional media includes state-controlled media and market-oriented media which differs in media ownership. State-controlled media includes *China Securities Journal, Securities Daily, Securities Times, Shanghai Securities Journal, Economic Daily, China Taxation News, China Banking and Insurance News, Financial Times, Economic Information Daily*. Market-oriented media includes *China Business Journal, First Financial Daily, The Economic Observer, 21st Century Business Herald, National Business Daily, Caijing Magazine, Caixin Weekly*. Following You et al. (2018), this classification is based on ownership structure and control rights obtained from the newspapers' Web sites, company filings, and government disclosures. The state-controlled newspapers are founded by newspaper offices, which are nonprofit organizations directly owned and controlled by the government. The market-oriented newspapers are either

owned or controlled by financial institutions, public companies, or wealthy individuals. None are directly owned or controlled by the government.

Online media news is obtained from ChinaScope SmarTag, a database with extensive coverage of online public news spanning financial media, government websites, and WeChat official accounts. The dataset starts from 2008 and covers 966 out of all 1,358 registered internet news providers in China.

Following Bybee et al. (2024), articles with little supporting text (less than 100 words) are excluded to better apply the textual analysis techniques.[7] The final data set consists of 35,880,933 news articles, including 2,641,693 traditional media articles and 33,239,240 online news.

2.2 Variable Construction

2.2.1 Narrative Attention

The data set is transformed from a collection of raw article text files into numerical term counts for statistical modeling. The model for the structure of economic news text follows the LDA topic modeling approach of Blei et al. (2003). Topic modeling, as a dimension-reduction technique, provides a higher-level abstraction that captures the central themes and concepts within a text. The LDA model is becoming a standard tool in textual analysis for finance and economics. As an unsupervised and data-driven method, LDA estimates topics as clusters of terms that tend to co-occur in articles. The brief description of its structure is in Appendix A.1 and interested readers can refer to Blei et al. (2003) for further details. The number of topics is set to 50 to balance a

[7] This filter only excludes about 6% of the raw news article sample.

trade-off: a model with fewer topics produces mixed topics that contain multiple separate themes; while a larger model delivers similar interpretability as that for the 50-topic model, but with a number of overly specific topics. Specifically, we estimate a variety of models with the number of topics ranging from 20 to 80 topics in increments of 5. We select the model specification from this set as the one with the highest log likelihood. The output of the LDA model includes a probability distribution that defines the term composition of each topic, and a probability vector that describes each article's allocation of attention across topics.[8]

Table 1 presents the list of manually assigned topic labels for each topic based on reading of the key term lists. Appendix Table A1 lists the key terms for each topic, defined as the top 20 vocabulary items based on the estimated probability distribution. These key terms are entirely unsupervised as they are estimated from the data without any guidance from article labels or from the researcher. The label is manually assigned to each topic based on reading of the key term lists. Topic labels serve as a shorthand for referencing topics throughout the paper. The topics collectively form a comprehensive topic structure, which can be classified into five broad groups: Macro, Industry, Company, Capital Market, and Other. Topics within each group encompass its key dimensions, such as "Economic Prospects" and "Institutional Reform" in Macro; "Smart Technology" and "New Energy Vehicles" in Industry; "Corporate Equity" and "Financial Performance" in Company; and "Stock Market" and "Bond Market" in Capital Market.

[8] While we acknowledge that applying the entire sample to LDA would introduce forward-looking bias in predictive regressions, this is not a central concern for our study. Our objective is to document underlying patterns, not to make predictions or construct trading strategies.

[Insert Table 1 here]

With an understanding of the topic structure in place, now turn to the second main output of the model—the estimate of news narrative attention paid to each topic. Attention allocation is a convenient quantitative transformation of news composition that can serve as numerical input to subsequent empirical investigations of economic hypotheses. The estimates describe how allocation of media narrative attention across topics evolves over time. Narrative attention for each topic is estimated at the article level but can be summed to any level of aggregation. Denote the article m's attention allocated to topic l as $q_{m,l}$, where $\sum_l q_{m,l} = 1$. Narrative attention for topic l at the daily frequency is calculated by averaging topic attention for all articles on each day t:

$$Topic\ l_t = \frac{\sum_{m \in t} q_{m,l}}{\sum_{m \in t} \mathbb{1}(m)}, \quad (1)$$

where $\mathbb{1}(m)$ is an indicator variable which equals 1 for the article m and 0 otherwise. Firm-level narrative attention for topic l is calculated by averaging topic attention for articles related to the firm i on each day t:

$$Topic\ l_{i,t} = \frac{\sum_{m \in i,t} q_{m,l}}{\sum_{m \in i,t} \mathbb{1}(m)}, \quad (2)$$

2.2.2 Stock Market Crashes

Stock market crashes are identified as days when weekly value-weighted market return is below the 5th percentile in the rolling window of past 10 years (520 weeks), and below -5%. The weekly (5-day) horizon captures the rapidness of crashes and mitigates the potential effects of confounding events, which is also used in Mishkin and White (2002). The threshold of the 5th percentile aligns with evidence in the previous literature that crises account for approximately 4%

of the sample (Greenwood et al., 2022). The rolling window accounts for varying market conditions, while the -5% cutoff ensures the capture of large-magnitude crashes.[9] To focus on crashes in more recent periods, the sample period starts in 2007, beginning with the first major bubble-crash in the Chinese stock market. Finally, 39 weeks are identified as crashes. Figure 1 plots the cumulative stock market return, with crash periods highlighted by red vertical lines. The figure reveals that the identified market crashes are predominantly concentrated during the 2008-2009 global financial crisis and the 2015-2016 stock market crash.

[Insert Figure 1 here]

2.2.3 Other Variables

For firm-level analysis, we apply several filters following Liu et al. (2019). We eliminate (1) stocks that have become public within the past 6 months, (2) stocks with less than 15 days of trading during the past month and with less than 120 days of trading during the past 12 months, and (3) stocks subject to special treatments (with ST or PT labels).

Stock return and volatility data are obtained from China Stock Market and Accounting Research Database (CSMAR) and Wind. Market returns are calculated using Wind All China A stock index. Market volatility is measured by absolute daily return of Wind All China A stock index following previous literature (Chordia et al., 2002; Rosu et al., 2020; Chan and Fong, 2000). Firm-level volatility is measured using 5-minute intraday returns of each stock:

[9] The main results are robust to alternative definition of crashes. See Section 3.5 for more details. We don't use daily horizon because of the daily price limits in the Chinese A share market.

$$Volatility_{i,t} = \sum_{d=1}^{48} R_{i,t,d}^2, \quad (3)$$

where $R_{i,t,d}$ is 5-minute intraday log returns of each stock.

Investor expectation and disagreement are measured using posts from the social media platform Guba, which was established in 2006 and has become the largest and most active online stock forum in China.[10] Each stock has a dedicated sub-forum on GUBA, where visitors can post their views on specific stocks. The tone scores of the posts are from Chinese Research Data Services (CNRDS). The CNRDS employs a support vector machine (SVM) to analyze the textual content of posts, categorizing each post as positive, neutral, or negative based on tone. Firm-level investor expectation and disagreement are measured by the average and standard deviation of the tone of the posts for each day.

$$Expectation_{i,t} = \frac{\sum_{k=1}^{n_{i,t}} Tone_{i,t,k}}{n_{i,t}}, \quad (4)$$

$$Disagreement_{i,t} = \sqrt{\frac{\sum_{k=1}^{n_{i,t}} (Tone_{i,t,k} - Expectation_{i,t})^2}{n_{i,t}}}, \quad (5)$$

where $Tone_{i,t,k}$ is the tone of post *k* for stock *i* on day *t* (1 for positive, and -1 for negative), $n_{i,t}$ is the number of positive and negative posts for stock *i* on day *t*.

Firm-level net buy is measured by the difference between the buy volume (RMB) and sell volume (RMB), divided by the average daily volume (RMB) over the past trading year, following Titman, Wei, and Zhao (2022). Firm-level net buy is calculated separately for small (<50 thousand RMB), medium (50 thousand RMB~200 thousand RMB), and big trades (200 thousand RMB~1

[10] https://GUBA.eastmoney.com/

million RMB) using data from CSMAR.[11]

$$Net\ buy_{i,t,G} = \frac{RMB\ Buy_{i,t,G} - RMB\ Sell_{i,t,G}}{Average\ Daily\ Volume_{i,t-1,G}}, \quad (6)$$

where $RMB\ Buy_{i,t,G}$ and $RMB\ Sell_{i,t,G}$ are buy volume (RMB) and sell volume (RMB) for stock *i,* day *t,* and order group *G*, respectively. $Average\ Daily\ Volume_{i,t-1,G}$ is the average daily volume (RMB) over the past trading year.

Stock-level characteristics including past day return, past week return, past month return, turnover, the logarithm of the Amihud illiquidity ratio, firm size (logarithm of market value in thousand), asset growth rate, book-to-market ratio, and ROE (return on equity) are obtained from CSMAR. Firm-level measures are winsorized at the 1% and 99% level to eliminate the effect of extreme values.

2.3 Summary Statistics

Table 2 presents the summary statistics. For market-level variables in Panel A, prospect attention, which is media attention to the topic *Economic Prospects* and we will discuss more in the next Section, has an average of 0.061 for all media types in the whole sample. When categorizing media into different types, the average prospect attention is 0.090 for traditional media, higher than that for online media (0.054). Within traditional media, the average prospect attention is similar across state-controlled media (0.090) and market-oriented media (0.092). Panel B reports firm-level variables. To better interpret the effect of prospect attention in the cross section,

[11] We do not report results on trades exceeding 1 million RMB due to the absence of such large trades in about 40% of firm-day observations. Similar results are obtained if we add those trades into big trades.

the measure of firm-level prospect attention is standardized by taking the cross-sectional rank into the interval between 0 and 1. Firm-level prospect attention has an average of 0.501 and a standard deviation of 0.289. Average investor expectation and investor disagreement is 0.181 and 0.796, respectively. Firm-level net buy is -0.010 on average for small trades, -0.032 for medium trades, and -0.031 for big trades. For stock characteristics, the turnover is 0.024, the logarithm of the Amihud illiquidity ratio is -22.465, firm size (logarithm of market value in thousand) is 16.092, asset growth rate is 0.199, book-to-market ratio is 0.656, and ROE is 0.048 for an average firm, which are consistent with previous literature.

[Insert Table 2 here]

3. Empirical Results

3.1 Patterns of Media Narratives During Stock Market Crashes

As mentioned in Section 2.2, we calculate the time series of attention for each topic by averaging topic attention across the articles. Then for each topic, we calculate the average topic attention on the day after a crash, based on which topics are ranked in descending order. The top-ranked topics represent the narratives the media predominantly focuses during crashes.

Figure 2 Panel A shows media average narrative attention for topics with the highest average topic attention on the day after a crash. We also calculate the average topic attention on other days for comparison. Among all topics, media narratives following stock market crashes provide the highest coverage of the topic related to economic prospects, which is consistent with the incentive

to enhance people's confidence and stabilize the market. Moreover, narrative attention to economic prospects significantly increases during crashes, suggesting that media shifts its emphasis toward future economic conditions. In terms of economic magnitude, the share of narrative attention devoted to economic prospects jumps to around 8% during market crashes, compared to approximately 6% in normal times—an increase of one-third. Given the heightened media attention to economic prospects during crashes, this paper focuses on media narrative attention to economic prospects, which is denoted as prospect attention, in the subsequent analysis.

Figure 2 Panel B provides the values for the U.S. using data from Bybee et al. (2024) during the period from 1984 to 2017 for comparison. In stark contrast, the top-ranked topics include financial crisis and recession, indicating they become a primary focus of media narrative during crashes. Therefore, we document distinctive patterns of Chinese media narratives during crashes.

[Insert Figure 2 here]

We further conduct daily time-series regression analysis to formally examine the patterns of media narratives during stock market crashes. The hypothesis is that media allocates greater attention to economic prospects following market crashes, to align with the principle of propagation in terms of spreading confidence and encouraging people to move forward.

$$Prospect_t = b_0 + b_1 \mathbb{1}(Crash)_{t-1} + Day\ of\ Week\ FE_t + \varepsilon_t, \quad (7)$$

where $Prospect_t$ represents prospect attention, calculated by Equation (1) for the topic *Economic Prospects*, $Prospect_t$ for each media type is calculated by Equation (1) within articles of each media type, $\mathbb{1}(Crash)_t$ is an indicator variable which equals one if it is during the stock

market crash periods and is zero otherwise. Day-of-the-week fixed effects are controlled. Standard errors are adjusted using Newey-West's method (Newey and West, 1987). The coefficient b_1 is expected to be positive and significant if media allocates greater attention to economic prospects following market crashes.

The results are presented in Table 3. In Column (1), which includes all media types, the coefficient on the crash indicator is 0.016 (t-stat=5.58). This implies that prospect attention significantly rises by 1.6 percentage points following stock market crashes. In Columns (2)-(5), the results are quantitatively similar across media types, indicating that all media types allocate increased attention to economic prospects following market crashes. For instance, traditional media exhibits a 0.5 percentage-point increase in prospect attention on the day following a stock market crash. Overall, the results suggest that following stock market crashes, media significantly increases its emphasis on economic prospects, consistent with the hypothesis. An intuitive example is provided below to illustrate prospect attention. The news article with high prospect attention on October 12, 2018 by China Securities Journal, shows that "*In the face of global market adjustments, China has ample policy tools to tap into endogenous driving forces, ensuring robust and resilient economic growth*". As shown in the example, narratives of economic prospects are related to economic growth prospects and growth potential, rather than focusing on historical severe crashes. It is consistent with the principle of propagation in terms of enhancing people's confidence and encouraging people to move forward, reflecting the incentive to stabilize the market.

[Insert Table 3 here]

3.2 Market Dynamics

3.2.1 Market-level Evidence

After establishing the patterns of heightened attention to economic prospects following market crashes, next question is how prospect attention is associated with market dynamics. We first examine market-level evidence to investigate whether aggregate market dynamics respond to prospect attention. The second hypothesis posits that prospect attention following market crashes is positively associated with subsequent market returns, and negatively associated with market volatility, thereby helping to foster a recovery and reduce instability.

To test the first part of this hypothesis, we estimate the time series regressions:

$$Return_{t+1\to t+h} = b_0 + b_1\mathbb{1}(Crash)_{t-1} + b_2 Prospect_t + b_3 Prospect_t * \mathbb{1}(Crash)_{t-1} + Day\ of\ Week\ FE_t + Year \times Month\ FE_t + \varepsilon_{t+h}, \quad (8)$$

where $Return_{t+1\to t+h}$ is cumulative market returns over next 1~5 days for h=1,2,…,5. Day-of-the-week and year-month fixed effects are controlled, following Goetzmann et al. (2024). Standard errors are adjusted using Newey-West's method (Newey and West, 1987). The coefficient b_3 is expected to be positive and significant if the hypothesis is true.

The results are reported in Table 4. To save space, only the coefficients on the interaction terms are reported. Each row represents a regression and the results for different media types are also shown. For all media types, the coefficients on the interaction terms are all positive and significant for next 2 days to next 5 days. This indicates that heightened discussions about economic prospects in media following market crashes is associated with significantly higher

cumulative market returns for next 5 days. Specifically, a 1-percentage-point increase in media's prospect attention following market crashes predicts a 0.487-percentage-point higher cumulative market returns for next 5 days. Overall, the results imply positive aggregate market responses of media narratives about economic prospects. Estimates across media types show that the effects are more pronounced for traditional media, perhaps due to its greater perceived authority and in-depth coverage.

[Insert Table 4 here]

To analyze the linkage between prospect attention following market crashes and market volatility, the dependent variable in Equation (8) is replaced with average daily market volatility over next 1~5 days, $Volatility_{t+1\to t+h}$, for h=1,2,…,5. The coefficient on the interaction term, b_3, is expected to be negative and significant if the hypothesis holds. Table 5 presents the results. As expected, higher prospect attention following market crashes is associated with significantly lower market volatility over next 1~5 days. To be specific, a 1-percentage-point increase in media's prospect attention following market crashes predicts a 0.091-percentage-point lower market volatility for next 5 days. Overall, the results imply that heightened discussions about economic prospects in media following crashes have stabilization effects, which is consistent with the preference for stability in the institutional background. Consistent with previous findings on market returns, the effects are concentrated in traditional media. Moreover, within traditional media, the effects are only significant for state-controlled media instead of market-oriented media. Intuitively, this aligns with the perception that state-controlled media are often viewed as conduits

for official policy signals, which the market interprets as having a more direct and significant impact on the economic landscape.

[Insert Table 5 here]

3.2.2 Firm-level Evidence

Previous findings document the market-level evidence about relation between prospect attention following crashes and market dynamics. Do these patterns exist at the firm level? To answer this question, we examine the firm-level evidence and estimate the panel regressions:

$$Return_{i,t+1\to t+h} = c_0 + c_1 Prospect_{i,t} + c_2 Prospect_{i,t} * \mathbb{1}(Crash)_{t-1} + c * Controls_{i,t-1} + Date\ FE_t + Stock\ FE_i + \varepsilon_{i,t+h}, \quad (9)$$

where $Return_{i,t+1\to t+h}$ is cumulative stock returns over next 1~5 days for h=1,2,…,5, $Prospect_t$ represents firm-level prospect attention, calculated by Equation (2) for the topic *Economic Prospects*. We follow previous literature for the choice of control variables. The control variables include the past day return, past week return, past month return, turnover, the logarithm of the Amihud illiquidity ratio, firm size (logarithm of market value), asset growth rate, book-to-market ratio, and ROE (return on equity). Date and stock fixed effects are controlled. Standard errors are double clustered by firm and date. The coefficient on the interaction term, c_2, is expected to be positive and significant if the hypothesis is true.

The results are presented in Table 6. In Column (1), the coefficient on the interaction term is 0.325 (t-stat=2.59), indicating that heightened prospect attention following market crashes significantly correlates with higher next day stock returns. Multiplying the interquartile range, 0.5,

by the regression coefficient of 0.325 generates an interquartile daily return difference of 15 basis points. In Columns (2)-(5) for cumulative returns over next 2 days to next 5 days, the coefficients on the interaction terms are all positive and significant, suggesting that positive effects last for at least one week. In terms of economic magnitude, the interquartile return difference is 32 basis points for next 5 days. Overall, the results imply more positive market reactions for firms with higher prospect attention.

[Insert Table 6 here]

The second part of the hypothesis focuses on stock volatility. To investigate this, the dependent variable in Equation (9) is replaced with average daily stock volatility over next 1~5 days, $Volatility_{i,t+1\to t+h}$, h=1,2,…,5. If the hypothesis holds, the coefficient on the interaction term, c_2, will be negative and significant. The results are reported in Table 7. In Column (1), the coefficient on the interaction is -0.016 (t-stat=-2.48), which is negative and significant. This suggests that higher prospect attention following market crashes is associated with significantly lower next day stock volatility. To be specific, an interquartile increase in media's prospect attention following market crashes predicts a 0.8-percentage-point lower next day stock volatility. For average stock volatility over next 2~5 days, the negative and significant coefficients on the interaction terms in Columns (2)-(5) indicate that the reduction in volatility persists over next one week. For economic magnitude, an interquartile increase of prospect attention is associated with a 0.9 percentage point decrease of average stock volatility over next 5 days. Overall, the results imply that firms receiving more media discussion about economic prospects following crashes

experience greater stabilization effects.

[Insert Table 7 here]

Next, we further examine whether there is heterogeneity in positive market responses and stabilization effects in the cross section. Since large firms have higher weights in market indices, they are considered especially crucial in maintaining investor confidence during crashes. Similarly, state-owned enterprises (SOEs) may serve as another important stabilizing force. Firms with high institutional ownership are likely to exhibit stronger patterns as institutional investors are encouraged to increase counter-cyclical investment to stabilize expectations and confidence during crashes.[12] Therefore, the effects are expected to be more pronounced for large firms, SOEs, and firms with higher institutional ownership. To test this, we estimate the following panel regressions:

$$Return_{i,t+1\to t+h} = c_0 + c_1 Prospect_{i,t} + c_2 Prospect_{i,t} * \mathbb{1}(Crash)_{t-1} + c_3 Prospect_{i,t} * \mathbb{1}(Crash)_{t-1} * Char_{i,t} + c * Controls_{i,t-1} + Date\ FE_t + Stock\ FE_i + \varepsilon_{i,t+h}, \quad (10)$$

where $Char_{i,t}$ is (i) firm size (logarithm of market value in thousand), or (ii) SOE dummy which equals 1 if the firm is SOE and 0 otherwise, or (iii) institutional ownership. Table 8 presents the results. Panel A report the results for stock returns and Panel B for stock volatility. The coefficients c_3 are significantly positive in Panel A and negative in Panel B. As expected, the relations intensify for stocks with larger market value, SOEs, and stocks with higher institutional ownership. Interestingly, our results contradict the findings of Glossner et al. (2025), which shows that during the COVID-19 stock market crash, U.S. stocks with higher institutional ownership (IO) performed

[12] http://www.csrc.gov.cn/csrc/c100028/c7461563/content.shtml

worse than those with lower IO.

[Insert Table 8 here]

3.3 Mechanisms

After documenting the market dynamics associated with prospect attention following market crashes, you may wonder through which mechanisms media's prospect attention can play a role. As in Shiller (2017), media narratives play a key role in the transmission of economic beliefs. Investor beliefs, in turn, shape investor trading behavior, consequently impacting market dynamics. How prospect attention is associated with investor beliefs and trading behavior? The hypothesis is that prospect attention following market crashes is associated with higher investor expectations, lower investor disagreement, and more net buy.

To test the hypothesis, the dependent variable in Equation (9) is replaced with average investor expectation over next 1~5 days, $Expectation_{i,t+1\rightarrow t+h}$, h=1,2,…,5. The coefficient on the interaction term, c_2, is expected to be positive and significant if the hypothesis is true. The results are reported in Table 9 Panel A. Column (1) shows a positive and statistically significant coefficient of 0.019 (t-stat = 2.67) for the interaction term, indicating higher next day investor expectations when there is increased prospect attention following market crashes. An interquartile rise in media's prospect attention following market crashes predicts a 1-percentage-point increase in next day investor expectations. In Columns (2)-(5), the coefficients on the interaction terms are positive and significant for next 2~5 days, suggesting that positive effects on investor expectations last for next one week.

[Insert Table 9 here]

To examine investor disagreement, the dependent variable in Equation (9) is replaced with average investor disagreement over next 1~5 days, $Disagreement_{i,t+h}$, h=1,2,…,5. The coefficient on the interaction term, c_2, is expected to be negative and significant if the hypothesis holds. The results are presented in Table 9 Panel B. In Column (1), the coefficient on the interaction is -0.017 (t-stat=-3.23), which is negative and significant. This suggests lower next day investor disagreement when media increases prospect attention following market crashes. An interquartile increase in media's prospect attention following market crashes is associated with a 0.9-percentage-point decrease in next day investor disagreement. The negative and significant coefficients on the interaction terms in Columns (2)-(5) show that disagreement-reducing effects last for next 5 days.

To summarize, the results support the hypothesis that prospect attention following crashes is related to more optimistic opinions and less divergence, which aligns with the goal of unity, stability, and encouragement for propagation work.

To investigate how prospect attention following market crashes is associated with trading activity, the dependent variable in Equation (9) is replaced with cumulative net buy over next 1~5 days $Net\ buy_{i,t+h,G}$, h=1,2,…,5, defined in Section 2.2. The results are reported in Table 10. Panel A shows the results for small trades. Column (1) shows that the coefficient on the interaction term is 0.661 (t-stat=2.01). An interquartile rise in media's prospect attention following market crashes predicts a 0.3-percentage-point increase in cumulative net buy for small trades in the next day. In

Columns (1)-(5), the coefficients on the interaction term are all positive, and significant for next 1~3 days. It indicates that prospect attention following market crashes is associated with more cumulative net buy for small trades over next 3 days.

Panel B shows the results for medium trades. The coefficients on the interaction terms are all positive and significant for next 5 days, indicating more cumulative net buy in medium trades over next 1 week when there is increased prospect attention following crashes. An interquartile increase in prospect attention following market crashes is associated with a 1.9-percentage-point increase in cumulative net buy over next 5 days for medium trades. Panel C present the results for big trades and similar patterns are observed with larger magnitude. Cumulative net buy over next 5 days for big trades increases by 3.4 percentage point for an interquartile increase in prospect attention following market crashes. Overall, the above results on trading behavior support the hypothesis that prospect attention following crashes correlates with more net buy.

[Insert Table 10 here]

3.4 Event Study

We next conduct an event study to further understand the role of prospect attention during crashes. On December 12, 2023, annual Central Economic Work Conference proposed "Sing the Theory of Light of China's Economy" to further promote the positive publicity. Therefore, it is expected that the impacts will be more pronounced after the event. To examine this, we estimate the following panel regressions, focusing on a short period around the event from 2021 to 2024.

$$Return_{i,t+1\to t+h} = c_0 + c_1 Prospect_{i,t} + c_2 Prospect_{i,t} * \mathbb{1}(Crash)_{t-1} + c_3 Prospect_{i,t} *$$

$$\mathbb{1}(Crash)_{t-1} * Post_t + c * Controls_{i,t-1} + Date\ FE_t + Stock\ FE_i + \varepsilon_{i,t+h}, \quad (11)$$

where $Post_t$ is an indicator variable which equals 1 if the date is after December 12, 2023, and 0 otherwise. Other specifications are similar to those in Equation (9). The coefficient c_3 is expected to be positive and significant if the relations are strengthened afterwards. The results are presented in Table 11 Panel A. As expected, the coefficients c_3 are all positive and significant for next 1 day to next 5 days, suggesting that the positive responses of stock returns are stronger afterwards. Table 11 Panel B shows the results for stock volatility by replacing the dependent variable in Equation (9) with stock volatility. The negative and significant coefficients c_3 in Column (1) to (5) indicate that volatility reducing effects are also strengthened after the event.

[Insert Table 11 here]

3.5 Robustness Check and Further Analysis

3.5.1 Alternative Definitions of Crashes

We conduct a robustness check using two alternative definitions of crashes. First, we change the threshold of 5th percentile: stock market crashes are identified as days when weekly value-weighted market return is below (i) the 1st percentile in the rolling window of past 10 years (520 weeks) and (ii) an absolute threshold of -5%. Second, we change the length of the rolling window: stock market crashes are identified as days when weekly value-weighted market return is below (i) the 5th percentile in the rolling window of past 5 years (260 weeks) and (ii) an absolute threshold of -5%. Table 12 Panel A shows the results for market returns and Panel B shows the results for market volatility. Our main results are robust when using alternative definitions of crashes.

[Insert Table 12 here]

3.5.2 Alternative Measure of Prospect Attention

We also conduct a robustness check using alternative measure of prospect attention, calculated as the proportion of articles that are classified by a large language model as being related to economic prospects. Specifically, we ask the DeepSeek V3 to determine whether the news article talks about economic prospects using the following prompt: "You have a deep understanding of the language of media and financial markets. Please analyze the news article from media. 1) Whether there is discussion of economic prospects: 1 for yes, 0 for no, with a one-sentence explanation for the judgment." Given the time and cost constraints associated with processing the entire corpus of news articles, we first applied a keyword filter (e.g., "stock market", "stock", "A-share", "capital market", "security market", "financial market"). The resulting subset of articles was then classified using a large language model to identify those discussing economic prospects. Finally, we calculated the daily proportion of such articles to construct our measure of economic prospect attention. Table 13 Panel A shows the results for market returns and Panel B shows the results for market volatility. Our main results are robust when using alternative definitions of prospect attention.

[Insert Table 13 here]

3.5.3 Further Analysis

Lastly, we investigate an alternative explanation for our findings. One hypothesis is that the results are driven by investors expecting government intervention, specifically through share

purchases by state-owned financial institutions—the so-called “National Team”—to stabilize the markets (Dang et al., 2024). Therefore, we control for investor attention to the “National Team” using daily Baidu Search Index for the term “National Team saving the market”. Table 14 Panel A shows the results for market returns and Panel B shows the results for market volatility. Our main results are robust when controlling for investor attention to the “National Team”.

[Insert Table 14 here]

4. Conclusion

This paper employs a comprehensive dataset of 36 million news articles to examine how media narratives change around stock market crashes and corresponding market implications in China. We find that following stock market crashes, media significantly increases its emphasis on economic prospects. This shift in narrative following crashes is associated with higher subsequent stock returns and lower stock volatility, both for the overall market and individual firms. Furthermore, narratives focusing on economic prospects are linked to more optimistic investor expectations, less disagreement, and higher cumulative net buying after crashes.

This study provides new evidence on how media narratives can stabilize fragile markets during crashes and offers new insights on how to design effective crisis management to safeguard market stability from the perspective of media narratives.

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Table 1 Topic Structure

This table presents the manually assigned topic labels for each topic based on reading of the key term lists. Those topics are classified into five broad groups: Macro, Industry, Company, Capital Market, and Other. Within each group, the topics are sorted in descending order by average topic attention.

Macro	Industry	Company	Capital Market	Other
Economic Prospects	Mobile Game	Corporate Equity	Stock Market	International Politics
Institutional Reform	Brand Retail	Financial Performance	Corporate IPO	Cultural Heritage
Real Estate Economy	Smart Technology	Corporate Governance	Banking Credit	Administrative Supervision
International Cooperation	Clean Energy	Sales & Operations	Securities Investment	Public Opinion Events
Technological Innovation	Housing Policy	Equity Operations	Commodity Futures	Legal Disputes
Policy Propagation	Real Estate Development	M&A	Bond Market	
Rural Revitalization	New Energy Vehicles	Financial Management	Cross-border Finance	
International Trade	Healthcare	Shareholders' Equity	Securities Compliance	
Financing Management	Tourism & Transportation	Investor Relations		
Regional Development	Education & Training	Financial Audit		
Regional Economy	Agricultural Production			
	Air Transport			
	Semiconductor			
	Technology			
	Environmental			
	Governance			
	Shipbuilding			
	Liquor Industry			

Table 2 Summary Statistics

This table shows the summary statistics for market-level variables in Panel A and firm-level variables in Panel B. In Panel A, *Prospect_All* is market-level media attention to economic prospects, calculated by averaging the topic attention of economic prospects across articles. *Prospect_{MediaType}* is calculated by averaging the topic attention of economic prospects for articles within the media type. Market returns are calculated using Wind All China A stock index. Market volatility is measured by absolute daily return of Wind All China A stock index following Chordia et al. (2002). In Panel B, *Prospect* is firm-level media attention to economic prospects, calculated by averaging the topic attention of economic prospects for articles related to the firm. Firm-level volatility is measured using 5-minute intraday returns of each stock. Firm-level investor expectations are measured by the average of the tone of the posts on the social media platform Guba for each day. Firm-level investor disagreement is measured by the standard deviation of the tone of the posts on the social media platform Guba for each day. Firm-level net buy is measured by the difference between the buy volume (RMB) and sell volume (RMB), divided by the average daily volume (RMB) over the past trading year, following Titman, Wei, and Zhao (2022). Firm-level net buy is calculated separately for small (<50 thousand RMB), medium (50 thousand RMB~200 thousand RMB), and big trades (200 thousand RMB~1 million RMB). The sample period is from 2007 to 2024.The data of investor expectation and disagreement starts from 2009 due to the availability of Guba data. Other stock-level characteristics include past day return, past week return, past month return, turnover, the logarithm of the Amihud illiquidity ratio, firm size (logarithm of market value in thousands), asset growth, book-to-market ratio, and ROE (return on equity).

Panel A. Market-level variables

	Average	Standard Deviation	P25	Median	P75	Number of Observations
Prospect_All	0.061	0.034	0.029	0.062	0.090	4375
Prospect_Traditional	0.090	0.020	0.075	0.088	0.103	4375
Prospect_State	0.090	0.024	0.072	0.088	0.106	4375
Prospect_Market	0.092	0.024	0.074	0.088	0.105	4375
Prospect_Online	0.054	0.030	0.026	0.050	0.078	4124
Return	0.000	0.017	-0.007	0.001	0.009	4375
Volatility	0.012	0.013	0.003	0.008	0.015	4375

Panel B. Firm-level variables

	Average	Standard Deviation	P25	Median	P75	Number of Observations
Prospect	0.501	0.289	0.251	0.501	0.751	3698320
Return (%)	0.034	2.983	-1.478	0.000	1.339	3698320

Volatility	0.090	0.114	0.027	0.050	0.100	3683906
Expectation	0.181	0.473	-0.111	0.167	0.500	3524843
Disagreement	0.796	0.332	0.800	0.943	0.990	3524843
Net buy (Small)	-0.010	0.165	-0.091	-0.010	0.069	3560996
Net buy (Medium)	-0.032	0.202	-0.105	-0.025	0.046	3560989
Net buy (Big)	-0.031	0.449	-0.123	-0.019	0.067	3560762
Past day return	0.002	0.031	-0.014	0.000	0.015	3698320
Past week return	0.004	0.066	-0.033	-0.000	0.035	3698320
Past month return	0.013	0.134	-0.069	-0.002	0.075	3698320
Turnover	0.024	0.027	0.008	0.015	0.031	3698320
Log(Amihud)	-22.465	1.331	-23.331	-22.469	-21.673	3698320
Size	16.092	1.255	15.200	15.934	16.897	3698320
Asset growth	0.199	0.402	0.014	0.099	0.233	3632182
Book to market	0.655	0.268	0.447	0.657	0.869	3577841
ROE	0.048	0.082	0.017	0.046	0.084	3688146

Table 3 Patterns of Prospect Attention during Stock Market Crashes

This table presents the relation between stock market crashes and next day prospect attention of media. *Prospect* represents media attention to economic prospects, calculated by averaging the topic attention of economic prospects. In Column (1), all articles are used in our sample to calculate prospect attention; in Column (2)-(5), those articles of specific media types are used. *𝟙(Crash)* is an indicator variable which equals one if it is during the stock market crash periods and is zero otherwise. Stock market crash periods are defined as days when weekly stock market returns fall below the 5th percentile in the rolling window of past 10 years (520 weeks), and below -5%. Day-of-the-week fixed effects are controlled. The sample period is from 2007 to 2024. T-statistics based on Newey-West's standard errors (Newey and West, 1987) are in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
	All	Traditional			Online
Dep.Var: Prospect		State + Market	State	Market	
𝟙(Crash)	0.016***	0.005***	0.004**	0.006***	0.011***
	[5.58]	[2.63]	[2.35]	[2.73]	[3.56]
Constant	0.058***	0.086***	0.085***	0.093***	0.051***
	[54.11]	[132.20]	[113.16]	[104.64]	[51.89]
Day of Week FE	Yes	Yes	Yes	Yes	Yes
Number of Observations	4373	4373	4373	4373	4123
R-squared	0.013	0.011	0.017	0.014	0.008

Table 4 Prospect Attention and Stock Market Return

This table presents the relation between prospect attention and stock market return. *Prospect* represents media attention to economic prospects, calculated by averaging the topic attention of economic prospects. The dependent variables in Column (1) to (5) are cumulative market returns over next 1~5 days. $\mathbb{1}(Crash)$ is an indicator variable which equals one if it is during the stock market crash periods and is zero otherwise. Stock market crash periods are defined as days when weekly stock market returns fall below the 5th percentile in the rolling window of past 10 years (520 weeks), and below -5%. Day-of-the-week and year-month fixed effects are controlled. T-statistics based on Newey-West's standard errors (Newey and West, 1987) are in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

		Coefficient on Prospect*$\mathbb{1}$(Crash)				
		(1)	(2)	(3)	(4)	(5)
Dep.Var: Market Return		Ret [1]	Ret [1,2]	Ret [1,3]	Ret [1,4]	Ret [1,5]
All		0.083	0.249*	0.326**	0.354**	0.487**
		[1.06]	[1.95]	[2.14]	[2.07]	[2.48]
Traditional	(State + Market)	0.161	0.542***	0.697***	0.732***	0.891***
		[1.25]	[2.64]	[2.88]	[2.82]	[3.26]
	State	0.138	0.430**	0.529***	0.555**	0.742***
		[1.21]	[2.56]	[2.62]	[2.48]	[3.05]
	Market	0.096	0.400**	0.487**	0.525**	0.558**
		[0.94]	[2.24]	[2.30]	[2.37]	[2.31]
Online		-0.033	0.102	0.170	0.189	0.338
		[-0.34]	[0.65]	[1.02]	[1.11]	[1.62]

Table 5 Prospect Attention and Stock Market Volatility

This table presents the relation between prospect attention and realized volatility of China Security Index 300. *Prospect* represents media attention to economic prospects, calculated by averaging the topic attention of economic prospects. The dependent variables in Column (1) to (5) are average daily market volatility over next 1~5 days. $\mathbb{1}(Crash)$ is an indicator variable which equals one if it is during the stock market crash periods and is zero otherwise. Stock market crash periods are defined as days when weekly stock market returns fall below the 5^{th} percentile in the rolling window of past 10 years (520 weeks), and below -5%. Day-of-the-week and year-month fixed effects are controlled. T-statistics based on Newey-West's standard errors (Newey and West, 1987) are in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

		Coefficient on Prospect*$\mathbb{1}$(Crash)				
		(1)	(2)	(3)	(4)	(5)
Dep.Var: Market Volatility		Vol [1]	Vol [1,2]	Vol [1,3]	Vol [1,4]	Vol [1,5]
All		-0.105**	-0.101***	-0.109***	-0.099***	-0.091***
		[-2.17]	[-2.71]	[-3.39]	[-3.36]	[-3.36]
Traditional	(State + Market)	-0.177**	-0.167***	-0.183***	-0.162***	-0.146***
		[-2.26]	[-2.79]	[-3.50]	[-3.25]	[-3.08]
	State	-0.168**	-0.163***	-0.172***	-0.145***	-0.131***
		[-2.38]	[-3.12]	[-3.81]	[-3.41]	[-3.33]
	Market	-0.064	-0.050	-0.071	-0.076	-0.073*
		[-1.09]	[-1.03]	[-1.45]	[-1.63]	[-1.69]
Online		-0.083	-0.069	-0.080**	-0.079**	-0.069**
		[-1.58]	[-1.63]	[-2.11]	[-2.30]	[-2.11]

Table 6 Prospect Attention and Firm-Level Stock Returns

This table presents the relation between prospect attention and firm-level stock returns. *Prospect* is firm-level prospect attention. The dependent variables in Column (1) to (5) are cumulative stock returns over next 1~5 days. *𝟙(Crash)* equals one if it is during the stock market crash periods and is zero otherwise. Firm and date fixed effects are controlled. Standard errors are clustered by firm and date and the associated *t*–statistics are reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Dep.Var: Stock Return (%)	Ret [1]	Ret [1,2]	Ret [1,3]	Ret [1,4]	Ret [1,5]
Prospect	0.016**	0.012	0.003	0.016	-0.006
	[2.23]	[1.20]	[0.21]	[1.11]	[-0.34]
Prospect*𝟙(Crash)	0.325***	0.675***	0.769***	0.719**	0.641*
	[2.59]	[3.10]	[2.95]	[2.41]	[1.94]
Past day return	-0.525	-2.104***	-3.332***	-5.754***	-6.861***
	[-1.53]	[-4.50]	[-5.91]	[-8.56]	[-8.89]
Past week return	-0.942***	-2.122***	-3.160***	-3.897***	-4.419***
	[-5.79]	[-9.37]	[-11.31]	[-11.71]	[-11.67]
Past month return	-0.269***	-0.557***	-0.861***	-1.139***	-1.379***
	[-3.26]	[-4.76]	[-6.06]	[-7.01]	[-7.55]
Turnover	-0.853***	-2.092***	-3.351***	-4.523***	-5.739***
	[-2.70]	[-4.58]	[-5.83]	[-6.62]	[-7.24]
Log(Amihud)	0.032***	0.053***	0.075***	0.102***	0.119***
	[2.78]	[3.20]	[3.59]	[4.07]	[4.09]
Size	-0.165***	-0.299***	-0.442***	-0.581***	-0.724***
	[-8.60]	[-10.71]	[-12.32]	[-13.53]	[-14.56]
Asset growth	0.006	0.016	0.021	0.022	0.024
	[0.70]	[1.22]	[1.22]	[1.08]	[1.03]
Book to market	0.085**	0.163***	0.237***	0.285***	0.366***
	[2.18]	[2.81]	[3.19]	[3.22]	[3.59]
ROE	0.035	0.042	0.058	0.086	0.107
	[0.56]	[0.46]	[0.49]	[0.61]	[0.65]
Firm FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Number of Observations	3521485	3513923	3506512	3499180	3491688
R-squared	0.265	0.276	0.288	0.294	0.298

Table 7 Prospect Attention and Firm-Level Stock Volatility

This table presents the relation between prospect attention and firm-level realized volatility. *Prospect* is firm-level prospect attention. The dependent variables in Column (1) to (5) are average daily stock volatility over next 1~5 days. *𝟙(Crash)* equals one if it is during the stock market crash periods and is zero otherwise. Firm and date fixed effects are controlled. Standard errors are clustered by firm and date and the associated *t*–statistics are reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Dep.Var: Stock Volatility	Vol [1]	Vol [1,2]	Vol [1,3]	Vol [1,4]	Vol [1,5]
Prospect	0.007***	0.006***	0.006***	0.005***	0.005***
	[22.79]	[21.73]	[20.52]	[19.92]	[18.98]
Prospect*𝟙(Crash)	-0.016**	-0.018***	-0.018***	-0.019***	-0.018***
	[-2.48]	[-2.79]	[-2.92]	[-3.07]	[-3.19]
Past day return	0.696***	0.662***	0.628***	0.592***	0.560***
	[47.75]	[48.39]	[48.03]	[47.55]	[47.01]
Past week return	0.429***	0.416***	0.399***	0.382***	0.367***
	[60.34]	[61.63]	[61.66]	[61.72]	[60.85]
Past month return	0.170***	0.167***	0.162***	0.158***	0.154***
	[65.53]	[66.22]	[65.74]	[65.33]	[64.75]
Turnover	0.888***	0.884***	0.869***	0.855***	0.842***
	[66.89]	[68.14]	[67.99]	[67.56]	[67.20]
Log(Amihud)	0.008***	0.009***	0.009***	0.009***	0.008***
	[18.02]	[18.57]	[18.48]	[18.45]	[18.33]
Size	0.008***	0.007***	0.007***	0.007***	0.006***
	[9.21]	[8.70]	[8.28]	[7.98]	[7.65]
Asset growth	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	[-6.52]	[-6.36]	[-6.32]	[-6.36]	[-6.27]
Book to market	-0.019***	-0.019***	-0.019***	-0.018***	-0.018***
	[-10.65]	[-10.72]	[-10.60]	[-10.44]	[-10.26]
ROE	-0.071***	-0.073***	-0.073***	-0.073***	-0.073***
	[-22.52]	[-22.87]	[-22.92]	[-22.83]	[-22.90]
Firm FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Number of Observations	3519700	3518216	3509149	3500270	3491516
R-squared	0.391	0.437	0.458	0.470	0.476

Table 8 Cross-sectional Heterogeneity

This table presents the cross-sectional heterogeneity in relation between prospect attention and firm-level stock returns and stock volatility. *Prospect* is firm-level media attention to economic prospects, calculated by averaging the topic attention of economic prospects for articles related to the firm. In Panel A, the dependent variables in Column (1) to (5) are cumulative stock returns over next 1~5 days. In Panel B, the dependent variables in Column (1) to (5) are average daily stock volatility over next 1~5 days. *𝟙(Crash)* is an indicator variable which equals one if it is during the stock market crash periods and is zero otherwise. Stock market crash periods are defined as days when weekly stock market returns fall below the 5th percentile in the rolling window of past 10 years (520 weeks), and below -5%. *Size* is firm size measured by logarithm of market value in thousands. *SOE* is an indicator which equals 1 if the firm is state-owned enterprise. *INST Hold* is institutional holding percentage. Firm and date fixed effects are controlled. Standard errors are clustered by firm and date and the associated *t*–statistics are reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Stock return

	Coef on Prospect*𝟙(Crash)*Var				
	(1)	(2)	(3)	(4)	(5)
Dep.Var: Stock Return (%)	Ret [1]	Ret [1,2]	Ret [1,3]	Ret [1,4]	Ret [1,5]
Size	0.399**	0.811***	0.986***	1.077***	1.056**
	[2.53]	[2.86]	[2.89]	[2.68]	[2.34]
SOE	0.244*	0.439***	0.448**	0.443*	0.441
	[1.92]	[2.77]	[1.98]	[1.67]	[1.51]
INST Hold	1.625***	3.234***	3.909***	4.313***	4.361***
	[3.24]	[3.64]	[3.60]	[3.33]	[3.02]

Panel B. Stock volatility

	Coef on Prospect*𝟙(Crash)*Var				
	(1)	(2)	(3)	(4)	(5)
Dep.Var: Stock Volatility	Vol [1]	Vol [1,2]	Vol [1,3]	Vol [1,4]	Vol [1,5]
Size	-0.026***	-0.028***	-0.029***	-0.029***	-0.028***
	[-3.63]	[-3.91]	[-3.98]	[-4.03]	[-3.94]
SOE	-0.032***	-0.033***	-0.035***	-0.036***	-0.035***
	[-3.82]	[-4.15]	[-4.18]	[-4.22]	[-4.16]
INST Hold	-0.080***	-0.084***	-0.088***	-0.088***	-0.085***
	[-2.92]	[-3.16]	[-3.34]	[-3.41]	[-3.37]

Table 9 Prospect Attention, Firm-Level Investor Expectation and Disagreement

This table presents the relation between prospect attention and firm-level investor expectation and disagreement measured using posts from social platform Guba. Firm-level investor expectations are measured by the average of the tone of the posts for each day. Firm-level investor disagreement is measured by the standard deviation of the tone of the posts for each day. *Prospect* is firm-level prospect attention. The dependent variables in Column (1) to (5) are average daily investor expectations in Panel A, and average daily investor disagreement in Panel B over next 1~5 days. *𝟙(Crash)* is an indicator variable which equals one if it is during the stock market crash periods and is zero otherwise. Firm and date fixed effects are controlled. Standard errors are clustered by firm and date and the associated *t*–statistics are reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Investor expectation

	(1)	(2)	(3)	(4)	(5)
Dep.Var: Investor expectation	Expect [1]	Expect [1,2]	Expect [1,3]	Expect [1,4]	Expect [1,5]
Prospect	0.001	-0.001	-0.002*	-0.002	-0.002**
	[0.63]	[-0.80]	[-1.67]	[-1.63]	[-2.38]
Prospect*𝟙(Crash)	0.019***	0.022***	0.019***	0.015**	0.010*
	[2.67]	[2.91]	[2.75]	[2.31]	[1.90]
Past day return	0.617***	0.505***	0.423***	0.345***	0.293***
	[32.89]	[31.51]	[28.93]	[24.55]	[21.88]
Past week return	0.242***	0.206***	0.180***	0.164***	0.153***
	[23.15]	[22.23]	[20.72]	[19.85]	[19.25]
Past month return	0.085***	0.081***	0.078***	0.076***	0.073***
	[14.24]	[14.75]	[14.77]	[14.76]	[14.45]
Turnover	-0.925***	-0.906***	-0.890***	-0.879***	-0.869***
	[-22.59]	[-22.59]	[-22.41]	[-22.27]	[-22.04]
Log(Amihud)	0.039***	0.039***	0.038***	0.038***	0.037***
	[19.60]	[19.69]	[19.54]	[19.34]	[19.10]
Size	0.040***	0.038***	0.037***	0.036***	0.035***
	[10.17]	[9.90]	[9.59]	[9.31]	[9.12]
Asset growth	0.000	0.001	0.001	0.001	0.001
	[0.16]	[0.33]	[0.29]	[0.26]	[0.27]
Book to market	0.017*	0.019**	0.019**	0.020**	0.020**
	[1.86]	[2.01]	[2.11]	[2.15]	[2.21]
ROE	0.034**	0.037***	0.037***	0.039***	0.039***
	[2.43]	[2.64]	[2.71]	[2.85]	[2.85]
Firm FE	Yes	Yes	Yes	Yes	Yes

Date FE	Yes	Yes	Yes	Yes	Yes
Number of Observations	3410531	3344497	3287042	3237891	3195489
R-squared	0.180	0.263	0.314	0.350	0.378

Panel B. Investor disagreement

	(1)	(2)	(3)	(4)	(5)
Dep.Var: Investor disagreement	Disagree [1]	Disagree [1,2]	Disagree [1,3]	Disagree [1,4]	Disagree [1,5]
Prospect	0.007***	0.005***	0.005***	0.004***	0.004***
	[8.52]	[8.38]	[7.87]	[7.35]	[7.03]
Prospect*𝟙(Crash)	-0.017***	-0.015***	-0.013***	-0.011***	-0.009***
	[-3.23]	[-3.78]	[-3.54]	[-3.41]	[-2.96]
Past day return	0.171***	0.177***	0.183***	0.187***	0.186***
	[14.44]	[17.97]	[20.26]	[22.15]	[23.56]
Past week return	0.155***	0.153***	0.151***	0.146***	0.141***
	[22.79]	[25.03]	[26.25]	[26.82]	[27.41]
Past month return	0.055***	0.053***	0.051***	0.049***	0.046***
	[14.17]	[14.62]	[14.70]	[14.66]	[14.42]
Turnover	0.890***	0.849***	0.816***	0.785***	0.758***
	[33.17]	[33.80]	[34.05]	[33.85]	[33.66]
Log(Amihud)	-0.070***	-0.066***	-0.064***	-0.062***	-0.060***
	[-47.02]	[-47.48]	[-47.32]	[-46.90]	[-46.46]
Size	-0.035***	-0.034***	-0.032***	-0.031***	-0.031***
	[-13.63]	[-13.73]	[-13.64]	[-13.56]	[-13.45]
Asset growth	0.000	0.000	0.001	0.000	0.000
	[0.24]	[0.29]	[0.36]	[0.29]	[0.29]
Book to market	0.001	0.000	-0.000	-0.001	-0.001
	[0.10]	[0.02]	[-0.05]	[-0.15]	[-0.17]
ROE	-0.027***	-0.028***	-0.028***	-0.028***	-0.027***
	[-3.21]	[-3.61]	[-3.72]	[-3.79]	[-3.80]
Firm FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Number of Observations	3410531	3344497	3287042	3237891	3195489
R-squared	0.226	0.308	0.351	0.378	0.398

Table 10 Prospect Attention and Firm-Level Trading Activity

This table presents the relation between prospect attention and firm-level trading activity. Firm-level net buy is measured by the difference between the buy volume (RMB) and sell volume (RMB), divided by the average daily volume (RMB) over the past trading year, following Titman, Wei, and Zhao (2022). Firm-level net buy is calculated separately for small (<50 thousand RMB), medium (50 thousand RMB~200 thousand RMB), and big trades (200 thousand RMB~1 million RMB). Panel A presents the results for small trades, Panel B for medium trades, and Panel C for big trades. *Prospect is* firm-level media attention to economic prospects, calculated by averaging the topic attention of economic prospects for articles related to the firm. The dependent variables in Column (1) to (5) are cumulative net buy over next 1~5 days. $\mathbb{1}(Crash)$ is an indicator variable which equals one if it is during the stock market crash periods and is zero otherwise. Stock market crash periods are defined as days when weekly stock market returns fall below the 5th percentile in the rolling window of past 10 years (520 weeks), and below -5%. Firm and date fixed effects are controlled. Standard errors are clustered by firm and date and the associated *t*–statistics are reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Small trades

	(1)	(2)	(3)	(4)	(5)
Dep.Var: Cumulative net buy (%)	Small [1]	Small [1,2]	Small [1,3]	Small [1,4]	Small [1,5]
Prospect	0.036	0.042	-0.021	0.022	-0.004
	[0.94]	[0.68]	[-0.24]	[0.21]	[-0.03]
Prospect*𝟙(Crash)	0.661**	1.344**	1.478*	1.169	1.118
	[2.01]	[2.18]	[1.78]	[1.19]	[1.03]
Past day return	-14.535***	-24.531***	-30.009***	-35.473***	-35.422***
	[-15.01]	[-16.06]	[-15.17]	[-13.99]	[-11.36]
Past week return	-2.324***	-3.067***	-2.603**	-1.230	0.186
	[-4.84]	[-3.66]	[-2.16]	[-0.79]	[0.10]
Past month return	1.225***	2.479***	3.583***	4.717***	5.960***
	[5.52]	[6.82]	[7.27]	[7.66]	[8.11]
Turnover	2.950**	5.358**	7.783**	10.071**	11.862**
	[2.26]	[2.42]	[2.53]	[2.56]	[2.50]
Log(Amihud)	-0.112*	-0.232**	-0.395***	-0.546***	-0.725***
	[-1.91]	[-2.25]	[-2.72]	[-2.93]	[-3.20]
Size	1.451***	2.904***	4.336***	5.766***	7.113***
	[17.83]	[19.34]	[19.99]	[20.40]	[20.46]
Asset growth	0.144***	0.317***	0.440***	0.574***	0.732***
	[2.66]	[3.08]	[2.93]	[2.92]	[3.01]

Book to market	0.692***	1.336***	2.026***	2.657***	3.194***
	[3.58]	[3.75]	[3.94]	[3.94]	[3.85]
ROE	-0.607**	-0.994*	-1.044	-1.115	-1.262
	[-2.03]	[-1.78]	[-1.31]	[-1.07]	[-0.99]
Firm FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Number of Observations	3458921	3458921	3458921	3458921	3458921
R-squared	0.068	0.073	0.081	0.087	0.093

Panel B. Medium trades

Dep.Var: Cumulative net buy (%)	(1) Medium [1]	(2) Medium [1,2]	(3) Medium [1,3]	(4) Medium [1,4]	(5) Medium [1,5]
Prospect	0.082*	-0.051	-0.170*	-0.201*	-0.392***
	[1.79]	[-0.69]	[-1.73]	[-1.68]	[-2.78]
Prospect*𝟙(Crash)	0.943**	2.566***	3.325***	3.582***	3.856**
	[2.18]	[3.00]	[2.96]	[2.61]	[2.45]
Past day return	-8.675***	-16.830***	-24.419***	-36.820***	-41.498***
	[-6.40]	[-8.29]	[-9.51]	[-11.63]	[-11.18]
Past week return	-4.805***	-9.123***	-12.700***	-15.090***	-17.089***
	[-7.06]	[-7.98]	[-8.04]	[-7.65]	[-7.36]
Past month return	-0.758**	-1.451***	-2.496***	-3.433***	-4.078***
	[-2.22]	[-2.58]	[-3.28]	[-3.62]	[-3.60]
Turnover	-21.748***	-45.503***	-68.958***	-91.653***	-115.046***
	[-10.43]	[-12.02]	[-12.86]	[-13.29]	[-13.69]
Log(Amihud)	0.520***	1.007***	1.444***	1.898***	2.285***
	[6.97]	[7.70]	[7.92]	[8.07]	[7.98]
Size	1.562***	3.155***	4.688***	6.268***	7.744***
	[15.23]	[17.77]	[18.61]	[19.33]	[19.55]
Asset growth	0.115*	0.265**	0.390**	0.547**	0.714***
	[1.91]	[2.35]	[2.36]	[2.53]	[2.68]
Book to market	-0.146	-0.243	-0.480	-0.656	-0.989
	[-0.62]	[-0.58]	[-0.81]	[-0.86]	[-1.06]
ROE	-2.657***	-5.084***	-7.140***	-9.248***	-11.711***
	[-7.50]	[-8.08]	[-7.98]	[-7.98]	[-8.29]
Firm FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Number of Observations	3458909	3458909	3458909	3458909	3458909

R-squared	0.078	0.085	0.097	0.106	0.114

Panel C. Big trades

	(1)	(2)	(3)	(4)	(5)
Dep.Var: Cumulative net buy (%)	Big [1]	Big [1,2]	Big [1,3]	Big [1,4]	Big [1,5]
Prospect	0.060	-0.310**	-0.683***	-0.689***	-1.018***
	[0.62]	[-2.13]	[-3.61]	[-2.99]	[-3.79]
Prospect*𝟙(Crash)	1.401**	4.277***	5.722***	6.040***	6.784***
	[2.27]	[3.50]	[3.60]	[3.17]	[3.06]
Past day return	-11.794***	-34.788***	-58.278***	-86.919***	-99.323***
	[-3.82]	[-7.62]	[-10.36]	[-12.94]	[-12.56]
Past week return	-14.988***	-28.149***	-40.475***	-52.266***	-63.204***
	[-9.67]	[-11.43]	[-12.16]	[-12.82]	[-13.23]
Past month return	-5.111***	-11.013***	-17.084***	-22.610***	-27.743***
	[-6.47]	[-8.83]	[-10.38]	[-11.23]	[-11.57]
Turnover	-55.492***	-117.005***	-177.358***	-233.704***	-292.038***
	[-11.72]	[-14.64]	[-15.99]	[-16.65]	[-17.29]
Log(Amihud)	0.807***	1.489***	2.142***	2.947***	3.499***
	[5.62]	[6.07]	[6.36]	[6.83]	[6.68]
Size	0.628***	1.373***	2.029***	2.835***	3.285***
	[3.00]	[3.98]	[4.21]	[4.64]	[4.48]
Asset growth	0.020	0.107	0.174	0.231	0.396
	[0.17]	[0.53]	[0.60]	[0.62]	[0.87]
Book to market	-0.688	-1.041	-1.799	-2.658*	-3.640**
	[-1.42]	[-1.30]	[-1.61]	[-1.87]	[-2.13]
ROE	-5.543***	-11.583***	-16.929***	-22.121***	-28.142***
	[-7.68]	[-9.29]	[-9.56]	[-9.72]	[-10.16]
Firm FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Number of Observations	3458941	3458941	3458941	3458941	3458941
R-squared	0.047	0.052	0.059	0.065	0.069

Table 11 Event Study

This table presents the results for event study. *Prospect* is firm-level prospect attention. In Panel A, the dependent variables in Column (1) to (5) are cumulative stock returns over next 1~5 days. In Panel B, the dependent variables in Column (1) to (5) are average daily stock volatility over next 1~5 days. *𝟙(Crash)* equals one if it is during the stock market crash periods and is zero otherwise. *Post* is an indicator variable which equals one if the date is after December 12, 2023. The sample period is from 2021 to 2024. Firm and date fixed effects are controlled. Standard errors are clustered by firm and date and the associated *t*–statistics are reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Stock return

	(1)	(2)	(3)	(4)	(5)
Dep.Var: Stock Return (%)	Ret [1]	Ret [1,2]	Ret [1,3]	Ret [1,4]	Ret [1,5]
Prospect	0.001	-0.007	-0.025	-0.017	-0.056**
	[0.12]	[-0.43]	[-1.30]	[-0.78]	[-2.33]
Prospect*𝟙(Crash)	-0.587*	-0.512*	-0.774***	-1.246***	-1.778***
	[-1.92]	[-1.71]	[-2.78]	[-5.89]	[-7.30]
Prospect*𝟙(Crash)*Post	2.064***	3.378***	4.114***	4.691***	5.212***
	[5.48]	[7.03]	[6.48]	[5.58]	[5.27]
Past day return	-0.866*	-2.676***	-4.062***	-6.251***	-7.512***
	[-1.65]	[-3.71]	[-4.65]	[-5.99]	[-6.26]
Past week return	-1.094***	-2.507***	-3.749***	-4.798***	-5.655***
	[-4.53]	[-7.44]	[-9.00]	[-9.64]	[-9.98]
Past month return	-0.356***	-0.684***	-1.044***	-1.387***	-1.656***
	[-2.78]	[-3.75]	[-4.72]	[-5.51]	[-5.88]
Turnover	-0.239	-0.684	-1.191	-1.486	-1.875
	[-0.48]	[-0.94]	[-1.31]	[-1.36]	[-1.48]
Log(Amihud)	0.042*	0.083**	0.121***	0.164***	0.200***
	[1.86]	[2.52]	[2.97]	[3.42]	[3.63]
Size	-0.459***	-0.854***	-1.283***	-1.709***	-2.109***
	[-9.40]	[-12.25]	[-14.33]	[-16.21]	[-17.42]
Asset growth	0.029	0.064**	0.093***	0.115***	0.132***
	[1.62]	[2.47]	[2.75]	[2.86]	[2.85]
Book to market	0.001	-0.021	-0.052	-0.130	-0.103
	[0.01]	[-0.15]	[-0.29]	[-0.61]	[-0.42]
ROE	-0.101	-0.172	-0.227	-0.282	-0.339
	[-0.89]	[-1.05]	[-1.08]	[-1.14]	[-1.18]
Firm FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes

Number of Observations	2016905	2014001	2011051	2008173	2005090
R-squared	0.235	0.247	0.265	0.273	0.278

Panel B. Stock volatility

	(1)	(2)	(3)	(4)	(5)
Dep.Var: Stock Volatility	Vol [1]	Vol [1,2]	Vol [1,3]	Vol [1,4]	Vol [1,5]
Prospect	0.008***	0.007***	0.006***	0.006***	0.005***
	[17.07]	[15.97]	[14.98]	[14.39]	[13.57]
Prospect*𝟙(Crash)	0.030***	0.027***	0.027***	0.025***	0.022***
	[4.78]	[5.56]	[5.01]	[4.97]	[4.60]
Prospect*𝟙(Crash)*Post	-0.091***	-0.096***	-0.101***	-0.102***	-0.097***
	[-4.02]	[-4.71]	[-6.07]	[-8.89]	[-10.68]
Past day return	0.683***	0.656***	0.626***	0.594***	0.564***
	[30.49]	[31.11]	[30.98]	[30.77]	[30.53]
Past week return	0.438***	0.428***	0.412***	0.395***	0.378***
	[40.59]	[41.72]	[41.88]	[42.02]	[41.46]
Past month return	0.177***	0.174***	0.170***	0.165***	0.160***
	[46.03]	[46.81]	[46.38]	[46.05]	[45.66]
Turnover	0.884***	0.879***	0.863***	0.849***	0.834***
	[42.52]	[42.97]	[42.68]	[42.25]	[41.98]
Log(Amihud)	0.010***	0.010***	0.010***	0.010***	0.010***
	[11.75]	[11.77]	[11.58]	[11.40]	[11.24]
Size	0.019***	0.017***	0.016***	0.015***	0.014***
	[10.28]	[9.59]	[9.04]	[8.58]	[8.11]
Asset growth	-0.004***	-0.003***	-0.003***	-0.003***	-0.003***
	[-4.35]	[-4.06]	[-3.97]	[-4.03]	[-4.00]
Book to market	-0.001	-0.002	-0.001	-0.001	-0.001
	[-0.25]	[-0.43]	[-0.36]	[-0.36]	[-0.35]
ROE	-0.055***	-0.056***	-0.056***	-0.056***	-0.056***
	[-11.97]	[-12.09]	[-12.12]	[-12.05]	[-12.09]
Firm FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Number of Observations	2015123	2013639	2009232	2004818	2000518
R-squared	0.357	0.402	0.422	0.433	0.439

Table 12 Robustness Check: Alternative Definitions of Crashes

This table presents the results for robustness check using alternative definitions of crashes. In Panel A, the dependent variables in Column (1) to (5) are cumulative market returns over next 1~5 days, and the specifications are following Table 4. In Panel B, the dependent variables in Column (1) to (5) are average daily market volatility over next 1~5 days, and the specifications are following Table 5. $\mathbb{1}(Crash)$ is an indicator variable which equals one if it is during the stock market crash periods and is zero otherwise. In the setting (1) of Panel A and B, stock market crash periods are defined as days when weekly stock market returns fall below the 1st percentile in the rolling window of past 10 years (520 weeks), and below -5%. In the setting (2) of Panel A and B, stock market crash periods are defined as days when weekly stock market returns fall below the 5th percentile in the rolling window of past 5 years (260 weeks), and below -5%. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Market return

	Coef on Prospect*1(Crash)				
	(1)	(2)	(3)	(4)	(5)
Dep.Var: Market Return	Ret [1]	Ret [1,2]	Ret [1,3]	Ret [1,4]	Ret [1,5]
(1) threshold: 1st percentile	0.449	1.151***	1.731***	1.852***	1.995***
	[1.62]	[2.86]	[3.59]	[3.10]	[3.11]
(2) rolling window: past 5 years	0.076	0.258*	0.348**	0.377**	0.501**
	[0.87]	[1.80]	[2.04]	[1.96]	[2.23]

Panel B. Market volatility

	Coef on Prospect*1(Crash)				
	(1)	(2)	(3)	(4)	(5)
Dep.Var: Market Volatility	Vol [1]	Vol [1,2]	Vol [1,3]	Vol [1,4]	Vol [1,5]
(1) threshold: 1st percentile	-0.245	-0.227**	-0.313***	-0.294***	-0.273***
	[-1.39]	[-2.00]	[-3.49]	[-3.19]	[-3.11]
(2) rolling window: past 5 years	-0.109**	-0.105**	-0.110***	-0.102***	-0.093***
	[-2.06]	[-2.53]	[-3.11]	[-3.11]	[-3.12]

Table 13 Robustness Check: Alternative Measure of Prospect Attention

This table presents the results for robustness check using alternative measure of prospect attention. In Panel A, the dependent variables in Column (1) to (5) are cumulative market returns over next 1~5 days, and the specifications are following Table 4. In Panel B, the dependent variables in Column (1) to (5) are average daily market volatility over next 1~5 days, and the specifications are following Table 5. *Prospect* represents media attention to economic prospects, calculated as the proportion of articles that are classified by a large language model as being related to economic prospects. *𝟙(Crash)* is an indicator variable which equals one if it is during the stock market crash periods and is zero otherwise. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Market return

	(1)	(2)	(3)	(4)	(5)
Dep.Var: Market Return	Ret [1]	Ret [1,2]	Ret [1,3]	Ret [1,4]	Ret [1,5]
Prospect	0.033	0.082***	0.138***	0.154***	0.141***
	[1.62]	[2.72]	[3.86]	[3.89]	[3.45]
1(Crash)	-0.016***	-0.033***	-0.038***	-0.038***	-0.033**
	[-3.81]	[-4.59]	[-3.85]	[-3.07]	[-2.37]
Prospect*1(Crash)	0.039	0.105*	0.128*	0.161**	0.186**
	[1.15]	[1.90]	[1.82]	[1.97]	[2.13]
Day of Week FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Number of Observations	4374	4374	4374	4374	4374
R-squared	0.082	0.147	0.200	0.241	0.274

Panel B. Market volatility

	(1)	(2)	(3)	(4)	(5)
Dep.Var: Market Volatility	Vol [1]	Vol [1,2]	Vol [1,3]	Vol [1,4]	Vol [1,5]
Prospect	0.026**	0.018**	0.014*	0.003	0.004
	[2.02]	[2.03]	[1.91]	[0.41]	[0.71]
1(Crash)	0.011***	0.010***	0.010***	0.010***	0.010***
	[3.96]	[4.41]	[4.59]	[4.87]	[4.72]
Prospect*1(Crash)	-0.048**	-0.039**	-0.033**	-0.039***	-0.038***
	[-2.27]	[-2.22]	[-2.14]	[-2.72]	[-2.90]
Day of Week FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Number of Observations	4374	4374	4374	4374	4374
R-squared	0.284	0.441	0.541	0.608	0.657

Table 14 Further Analysis

This table presents the results when controlling for investor attention to National Team. The dependent variables are cumulative market returns in Panel A and average daily market volatility in Panel B over next 1~5 days, and the specifications are following Table 4 and Table 5, respectively. National Team BSI is daily Baidu Search Index for the term "National Team saving the market". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Market return

	(1)	(2)	(3)	(4)	(5)
Dep.Var: Market Return	Ret [1]	Ret [1,2]	Ret [1,3]	Ret [1,4]	Ret [1,5]
Prospect	0.017	0.017	-0.02	-0.055	-0.089
	[0.53]	[0.34]	[-0.31]	[-0.75]	[-1.05]
1(Crash)	-0.019***	-0.042***	-0.052***	-0.050***	-0.053***
	[-3.18]	[-4.23]	[-4.01]	[-3.30]	[-3.03]
Prospect*1(Crash)	0.089	0.266**	0.349**	0.379**	0.518***
	[1.15]	[2.12]	[2.32]	[2.23]	[2.66]
National Team BSI	0.016	0.046**	0.061**	0.066**	0.079***
	[1.42]	[2.55]	[2.24]	[2.37]	[3.27]
Day of Week FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Number of Observations	4374	4374	4374	4374	4374
R-squared	0.084	0.153	0.205	0.244	0.282

Panel B. Market volatility

	(1)	(2)	(3)	(4)	(5)
Dep.Var: Market Volatility	Vol [1]	Vol [1,2]	Vol [1,3]	Vol [1,4]	Vol [1,5]
Prospect	0.025	0.015	0.019	0.017	0.017
	[1.36]	[1.08]	[1.51]	[1.47]	[1.48]
1(Crash)	0.012***	0.012***	0.014***	0.013***	0.012***
	[3.32]	[4.46]	[5.42]	[5.23]	[5.08]
Prospect*1(Crash)	-0.098**	-0.095***	-0.104***	-0.095***	-0.088***
	[-2.04]	[-2.60]	[-3.30]	[-3.28]	[-3.29]
National Team BSI	0.018***	0.016***	0.013***	0.009**	0.007**
	[2.91]	[2.93]	[2.69]	[2.44]	[2.16]
Day of Week FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Number of Observations	4374	4374	4374	4374	4374
R-squared	0.289	0.448	0.548	0.612	0.659

Figure 1 Cumulative Stock Market Return and Crash Periods

This figure shows cumulative stock market return with crash periods highlighted in red lines.

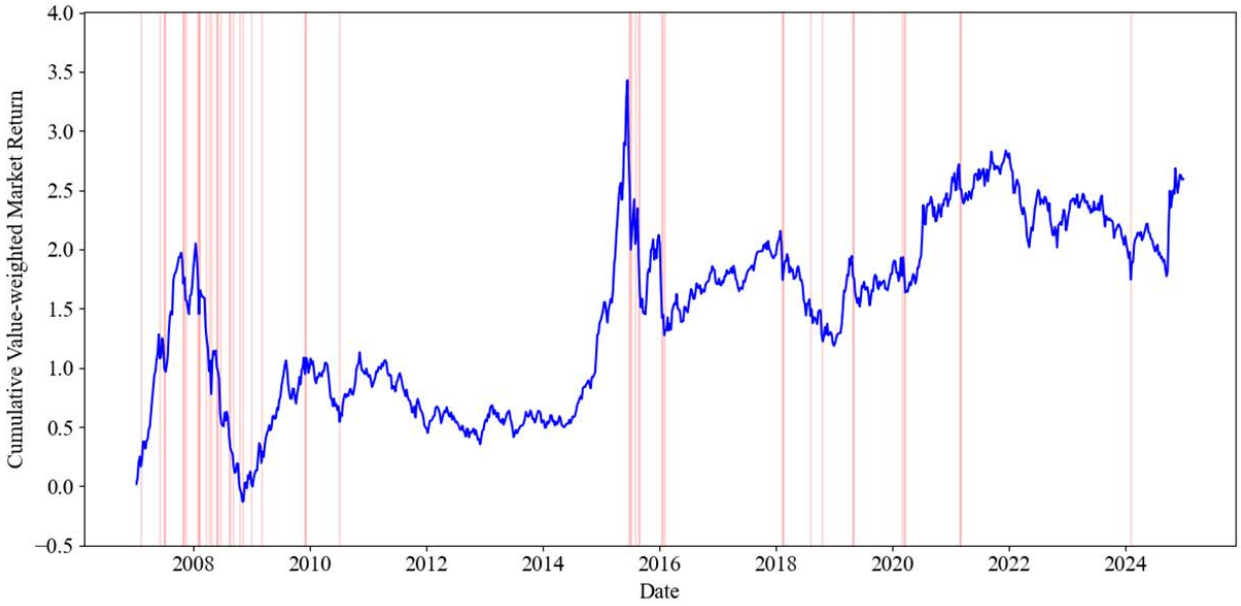
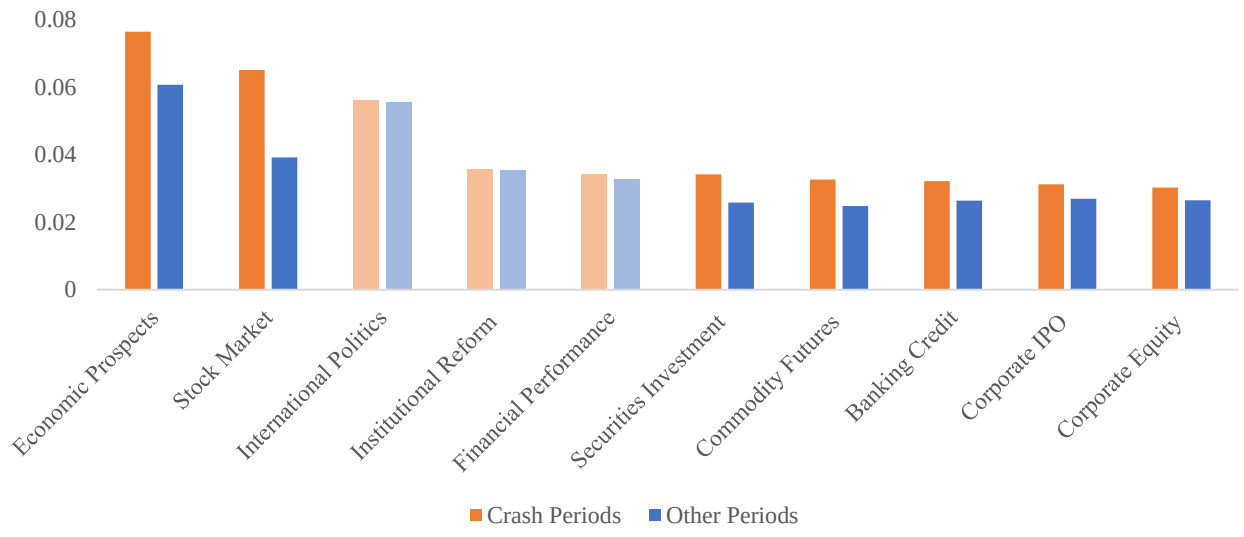


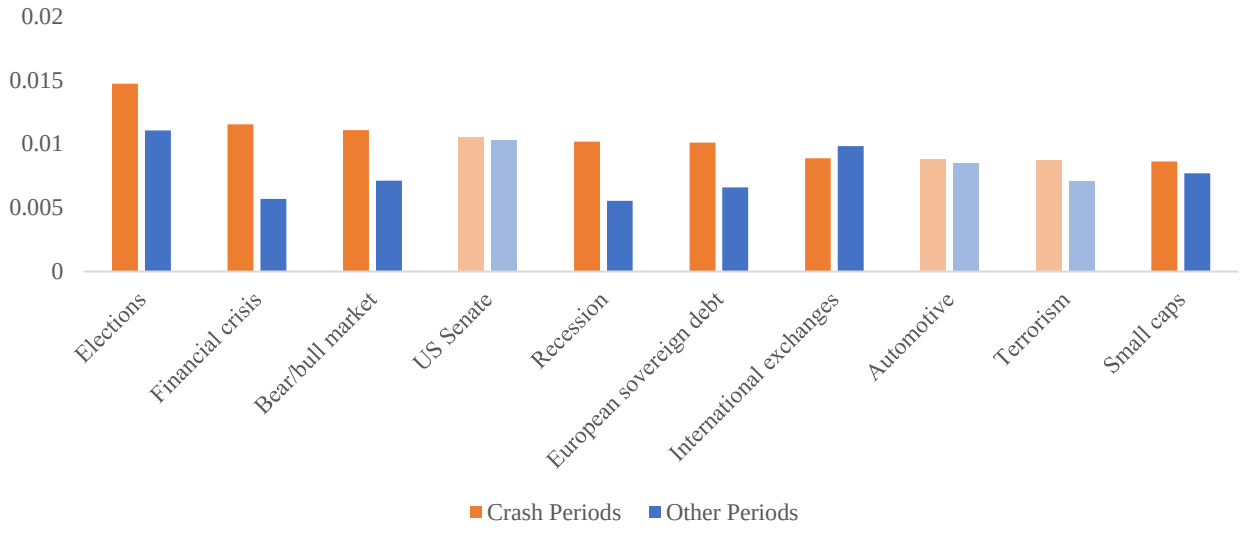
Figure 2 Narrative Attention of Media during Crashes

This figure shows media attention for topics with the highest average topic attention on the day after a crash. The solid bars indicate a statistically significant difference at the 5% level.

Panel A. Topic attention on the day after crash



Panel B. Comparison with the U.S.: Topic attention on the day after crash in the U.S.



Appendix

Table A1 Topic Label and Keywords

This table lists the key terms for each topic, defined as the top 20 vocabulary items based on the estimated probability distribution. I manually assign a label to each topic based on reading of the key term lists. Then I classify those topics into five broad groups: Macro, Industry, Company, Capital Market, and Other.

Macro					
Economic prospects	Institutional Reform	Real Estate Economy	International Cooperation	Technological Innovation	Policy Propagation
Expectations	Promote	Year-on-Year	Cooperation	Industry	Study
Policy	Reform	Nationwide	Build	Innovation	Promote
Growth Rate	Mechanism	Shenzhen	International	Transformation	Spirit
Pressure	System	City	Center	Technology	
Forecast	Optimize	Cumulative	Innovation	High-quality	Implement
Federal Reserve	Improve	Guangzhou	Conference	Industry	Meeting
Interest Rate Cut	High-quality	Decline	Exchange	Industrial Chain	Activity
Factors	Institution	Exceed	Strategy	Technological Innovation	Masses
Consumption	Implement	Transaction	Host	Cultivate	Organize
Interest Rate	Accelerate	Month-on-Month	Theme	Accelerate	Emergency
Inflation	Governance	Month	Activity	Integration	General Secretary
Rebound	Propose	Quantity	Industry	Manufacturing	Ideology
Decline	Establish	Average	Forum	Focus	Responsibility
Recovery	Policy	Scale	Global	Support	Focus
Level	Deepen	Statistics	High-quality	Talent	Deploy
Central Bank	Strengthen	Beijing	Integration	Upgrade	People
Prediction	Target	Consecutive	City	Transformation	Implement
Recovery	Environment	Ranking	Resources	Entrepreneurship	Accomplish
Face	Focus	Newly Added	Advantage	Intellectual Property	Advance
Improvement	Pilot	Sales	Boost	Digitalization	Ensure

Macro				
Rural Revitalization	International Trade	Financing Management	Regional Development	Regional Economy
Community	Logistics	Funds	Chengdu	Guangdong
Rural	Export	Raise	Chongqing	Zhejiang
Masses	Daily News	Wuhan	Yunnan	Jiangsu
Revitalization	Transportation	For	Region	Shandong
Residents	Trade	Hubei	Qingdao	Hainan
Rural	Guangxi	RMB	New Area	Hangzhou
Street	Express Delivery	Self-owned	Yangtze River	Guangdong Province
Employment	Supply Chain	Hubei Province	Xi'an	Anhui
Villagers	Xiamen	Exceed	Hebei	Province-wide
Elderly Care	Port	Issue	Shaanxi	Nanjing
Assistance	Goods	Supplement	High-tech Zone	Henan
Livelihood	International	Idle	Yunnan Province	Ningbo
Society	Customs	Xiangyang	Center	Suzhou
Grassroots	Import & Export	Wuhan City	Kunming	Zhejiang Province
Elderly	Import	Working Capital	Nihao Company	Jiangsu Province
Activity	Wharf	Amount	Qinghai	Hefei
Family	Foreign Trade	Total	Chongqing City	Gas
Elderly	Corridor	Supervision	Secretary	Shandong Province
Agriculture	Cross-border	Fees	Region	Anhui Province
People's Livelihood	Container	Implement	Development Zone	Zhengzhou

Industry					
Mobile Game Industry	Brand Retail	Smart Technology	Clean Energy	Housing Policy	Real Estate Development
Game	Brand	Smart	Energy	Policy	Shanghai
User	Consumption	System	Photovoltaic	Handle	Real Estate

Mobile Phone	Consumer	Model	Electricity	Housing	Hotel
AI	E-commerce	Artificial Intelligence	Energy Storage	Subsidy	Residential Area
Function	Marketing	Device	Production Capacity	Notice	Located
Experience	Live Streaming	Smart	New Energy	Department	Land
Huawei	Store	R&D	Power Generation	Registration	Area
Player	Retail	Scenario	Equipment	Declare	Property
Support	JD.com	Robot	Wind Power	Housing Fund	Land Parcel
Video	Merchant	Solution	Power Grid	Apply	Commercial
Apple	Activity	Design	Green	Standard	Development
News	Channel	Patent	Clean	Approval	Land Use
Adopt	Experience	Digitalization	Material	Process	City
Launch	Product	Capability	Power Supply	Personnel	Housing
Design	Offline	Intelligent	Put into Production	Enjoy	Building
Performance	User	Manufacturing	Base	Support	Shanghai City
Bring	Launch	Technology	Electricity Consumption	Tax	Residential
Equipped	Internet	Digital	Coal	Taxation	Planning
Version	Category	Industry	Module	Employee	Real Estate
Feature	Scenario	Communication	Chemical	Adjustment	Floor Area

Industry				
New Energy Vehicles	Healthcare	Tourism & Transportation	Education & Training	Agricultural Production
Vehicle	Health	Tourism	Education	Agriculture
New Energy	Medical	Project	Activity	Food
Battery	Hospital	Transportation	Student	Cultivation
Driving	Patient	Construction	Training	Food Safety
Model	Treatment	Tourist	School	Weather
Charging	Biology	Travel	Knowledge	Agricultural Product
Electric	Drug	Scenic Spot	Child	Processing

Sales Volume	Test	Railway	Talent	Quality
Vehicle	Disease	Road	Learning	Farming
Power	Medicine	Vehicle	College	Xinjiang
Brand	Medical Insurance	Route	Skill	Base
Factory	Clinical	High-speed Rail	Professional	Grain
Electric Vehicle	Drug	Highway	Vocational	Meteorology
BYD	Research	Operation	University	Warning
New Vehicle	Healthcare	Citizen	Participate	Ocean
Design	Doctor	Win Bid	Site	Temperature
Delivery	Traditional Chinese Medicine	Site	Competition	Vegetable
Bicycle	Medical Device	City	Practice	High Temperature
Automatic	Diagnosis	Expressway	Youth	Sales
Global	Epidemic	Transportation	Cultivate	Typhoon

Industry				
Air Transport	Semiconductor Technology	Environmental Governance	Shipbuilding	Liquor Industry
Aviation	AI	Ecology	Financing	Sichuan
Passenger	Technology	Green	Tianjin	High-end
Russia	Electronics	Environment	Ship	Guizhou
Airport	Semiconductor	Protection	Leasing	Sichuan Province
Oil	Chip	Environmental	Gansu	Government Affairs
Natural Gas	Research	Ecological Environment	Capital	Liquor
Flight	Bulletin	Renovation	Tianjin City	Solid-state
Aircraft	Material	Garbage	Laser	Distributor
Route	News	Utilization	Construction	Moutai
Ukraine	Satellite	Governance	Gansu Province	Guizhou Province
Flight	Institution	Civilization	Lanzhou	Terminal
Petrochemical	Aerospace	Facility	Heavy Industry	Guiyang

Iran	Market Cap	City	Maritime	Brand
International	Background	Restoration	Shipbuilding	China
Pipeline	Closing Price	Emission	Waters	Wine Industry
Attack	Economic News	Rectification	Binhai	Beer
Troops	SZ	Monitoring	Venture Capital	China Resources
LNG	Optoelectronics	Classification	Ocean	Time-honored Brand
Saudi Arabia	Month	Life	Bohai	Red Star
Indonesia	Article	Recycling	Navigation	Wuliangye

Company				
Corporate Equity	Financial Performance	Corporate Governance	Sales & Operations	Equity Operations
Holding	Year-on-Year	Board	Customer	Repurchase
Subsidiary	Net Profit	Meeting	Sales	Plan
Agreement	Revenue	Director	Operation	Shareholder
Equity	Operating	Review	R&D	Reduction
Wholly-owned	Decline	Proposal	Procurement	Company Shares
Abbreviation	Performance	Shareholders Meeting	Capability	Share Capital
Transfer	Report	Company Board	Order	Shareholding
Shareholder	Operating Revenue	Independent	Competitiveness	Incentive
Establish	Shareholder	Committee	Expand	Stock
Guarantee	Gross Margin	Chairman	Supplier	Ratio
Registered Capital	Listed Company	Serve	Core	Disclose
Sign	Forecast	General Manager	Advantage	Company Share Capital
RMB	Decrease	Position	Material	Exceed
Limited Liability	Attributable	Board of Supervisors	Operations	Bidding
Limited Liability Company	Profit	Shareholder	Strategy	Increase Holdings
Hold	Quarter	Vote	Company Product	Pledge
Technology	Company Operating	Vote	Main Business	Hold

Change	Decline	Supervisor	Layout	Share Company
Partnership	Income	Articles of Association	Performance	Transaction Method
Shareholding	Loss	Appointment	Competition	Quantity

Company				
M&A	Financial Management	Shareholders' Equity	Investor Relations	Financial Audit
Transaction	Increase	Annual	Investor	Report
Asset	Amount	Equity	Inquiry	Audit
Acquisition	Net Assets	Dividend	Concern	Value
Restructuring	Decrease	Shareholder	Answer	Unit
Related	Operation	Cash	Hello	Government
Evaluation	Financial	Company Annual	May I Ask	Accountant
M&A	Asset	Plan	Board Secretary	Firm
Sell	Consolidate	Discover	Finance	Change
Equity	Total	Distribution	Company Reply	Measurement
Purchase	Receivable	Share Capital	Information	Accounting
Target	Cash Flow	Record Date	Sina	Confirm
Listed Company	Account	Distribution	Interpretation	Indicator
Trademark	Impairment	Tax-inclusive	Precise	Control
Matter	Liability	Cash Dividend	Massive	Subsidy
Asset Restructuring	Report	Proposal	Research	Annual
Compensation	Activity	Profit Distribution	Thank You	Accounting
Hold	Net Amount	Equity	Daily News	Prepare
Commitment	Total Assets	RMB	Respect	Jewelry
Forecast	Loss	Implement	Center	Furniture
Merger	Listing	Share Conversion	News	Institution

Capital Market

Stock Market	Corporate IPO	Banking Credit	Securities Investment
Stock Price	IPO	Finance	Fund
Rating	Issue	Bank	Index
Turnover	Securities	Loan	Return
Securities	Public	Branch	Securities
Rise	Application	Support	Manager
Market Cap	Stock	Risk	Asset
Buy	Investor	Financial Services	Share
Close	Trust	Financial Institution	Investor
Fall	Listed Company	Sub-branch	Private Fund
Risk	Subscribe	Customer	CSI
Capital	IPO	Financing	Institution
Potential	Exchange	Entity	Scale
Turnover Rate	Abbreviation	Credit	Mixed
Sector	Terminate	Institution	Net Value
Focus	A-share	Prevent	Return Rate
Concept	Registration	Commercial Bank	Wealth
Trend	Target	Real Economy	Establish
Limit Up	SSE	Outlet	Subscribe
Valuation	Stock Issuance	Capital	Allocation
Stock	Placement	Green Finance	Public Fund

Capital Market			
Commodity Futures	Bond Market	Cross-border Finance	Securities Compliance
Price	Bond	Hong Kong	Content
Gold	Interest Rate	International	Securities
Futures	Issue	RMB	Organize
Output	Debt	Financial World	Public

Cost	Credit	Digital	Suggestion
Inventory	Wealth Management	Cross-border	Authorization
Supply	Deposit	Finance	Guarantee
Rise	Government Bond	Macau	Risk
Commodity	Term	HK	Generate
Contract	Fixed	Zhitong	Source
Coffee	Note	Source	Copyright
Volatility	Rating	Mainland	Position
Quote	Bank	US	Accuracy
Increase	Scale	News	Decision
Brazil	Wealth Management Product	Currency	Disclose
Metal	Liquidity	Global	Unrelated
Import	Adjustment	Singapore	Report
Pricing	Interest	Mainland China	Integrity
Price Cut	Repayment	Foreign Capital	Abbreviation
Raw Material	View	Hong Kong-Macau	Author

Other				
International Politics	Cultural Heritage	Administrative Supervision	Public Opinion Events	Legal Disputes
USA	Culture	Supervision	News	Payment
Global	Activity	Illegal	Occur	Contract
Report	Experience	Regulate	Discover	Court
Japan	Tradition	Institution	Complaint	Case
President	History	Public Notice	Personnel	Fee
Europe	Feel	Oversight	Employee	Mediation
World	Art	Law-based	Staff	Account
South Korea	Competition	Disclose	Internet	Litigation
Israel	Story	Law	Rescue	Dispute

Germany	Theme	Violation	Video	Branch
International	Life	People's Republic of China	Fire	People's Court
Plan	Site	Measure	News	Judicial
UK	Display	Administrative	Netizen	Execute
Region	Heritage	Operation	Fraud	Apply
EU	Work	Inspection	Investigate	Amount
India	Audience	Document	Incident	Agree
France	World	Supervision	Site	Law
Chief	Era	Review	Accident	Handle
Support	Bring	Examine	Media	Agent
Cooperation	Show	Fine	Trigger	Responsibility

Appendix

A.1 LDA Model

The LDA model begins from a "bag-of-words" representation of the raw text. LDA searches for a tractable thematic summary of the text with much lower dimensionality than the vocabulary size (denoted as V) to reduce dimensions. To do so, it imposes a factor structure on term counts and nests this in a count distribution. In particular, LDA assumes the V-dimensional vector of term counts for a given article m, denoted as w_m, is distributed according to a multinomial distribution:

$$w_m \sim Mult(PQ_m, N_m), \tag{A1}$$

where N_m is the sum of all term counts for article m (which governs the scale of the multinomial distribution). According to (A1), expected term counts are summarized by a comparatively low dimension set of parameters, Q_m and $P = [p_1, \ldots, p_L]'$. The l^{th} topic is a V-dimensional parameter vector p_l, where $p_{l,v} \geq 0$ for all v and $\sum_v p_{l,v} = 1$. That is, a news topic is a probability distribution that defines the term composition of the topic. Terms with especially high probabilities in p_l convey the topic's thematic content. The model's dimension reduction is achieved by setting the total number of topics L much smaller than the size of the vocabulary. Finally, narrative attention corresponds to article-specific parameter vector $Q_m = (q_{m,1}, \ldots, q_{m,L})'$. It is also a probability vector and describes article m's allocation of attention across topics. I aggregate article attention to a daily attention measure by averaging attention for all articles on day t (denoted as $m \in t$):

$$Q_t = \frac{1}{\sum_{m \in t} \mathbb{1}(m)} \sum_{m \in t} Q_m. \tag{A2}$$

The vector Q_t is main narrative attention time series. $\mathbb{1}(m)$ is an indicator variable which equals 1 for the article m and 0 otherwise.