University of Wah Journal of Management Sciences
Volume 9 (Issue 2), December 2025.
DOI: 10.56220/uwjms.v9i2.307

Information Shocks and Investor Behaviour: A Market Model Event Study of Performance Forecasts in China's Telecom Industry

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Article History:

Received:

20th October, 2025

Revised:

14th December, 2025

Accepted:

25th December, 2025

ABSTRACT

Purpose: This paper analyzes the market response to annual performance projections announcements at the initial listing of A-share telecom companies in China between 2023 and mid-2025.

Design and Methodology: A quantitative approach is employed, which is based on an event-study design. Abnormal returns and accumulation abnormal returns are computed in and around announcement dates, and are focused on the. [-1, +1] event windows.

Findings: These findings indicate a high level of asymmetric market response. The abnormal returns caused by bad news are larger and more persistent compared to those caused by good news. The abnormal accumulated bad news returns are approximately -3.4% in the [-1, +1] window. It is increased in the face of macroeconomic uncertainty in early 2024. Evidence indicated that there is anticipatory pessimism in that investors expect to receive bad news at least partially in advance of announcements.

Implications: The results outline the contribution of the behavioural aspects to the equity market of china. These findings can help policymakers and investors to learn more about how investors behave in the new financial markets and how they respond to the market.

Keywords: Event study, Abnormal returns, Performance forecasts, China, telecommunications, Asymmetric information, Investor behaviour, Market efficiency.

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1. Introduction

The capital market of China has become one of the most powerful and liquid financial systems in the world, which makes a greater and greater academic interest in the processing of information at the firm level by investors (Carpenter and Whitelaw, 2017; Allen et al., 2024). The telecommunications industry has a special strategic location in this wider context. It supports the digital infrastructure of China, as well as its fast growing digital economy, and functions on a steady technological upgrades and regulatory changes (Li et al., 2025; Sharma, 2023). These attributes cause the industry to be very sensitive to disclosures in firms, especially performance expectations and earnings directions which are at centre stage in determining investor expectations and ascertaining the prices of assets.

Performance announcements are also one of the most informative indicators in financial markets and their capacity to impact returns has been widely observed (Foster, Olsen and Shevlin, 1984; Brandt et al., 2008; Beaver, McNichols and Wang, 2018). It is important to note that markets tend to respond to such disclosures in a way other than fully information efficient, which gives rise to phenomena like post earnings announcement drift (Ball and Brown, 1968; Thomas, 1989). In order to quantify such responses, the event study model proposed by MacKinlay (1997) is still crucial, as a dependable method of determining abnormal returns at market moving disclosures.

Event studies are specifically relevant in China because of institutional characteristics that influence the incorporation of information on prices. Due to mandatory disclosure of performance forecasts, call auctions overnight, and rigid timing requirements on announcement, a situation is made where price adjustments can be cleanly isolated (Kong, 2008). The price discovery mechanism of the call auction mechanism in particular, is a central location of the post-large announcement price discovery, and its dynamics tend to induce longer-term performance results (Liu et al., 2019; Carpenter, Whitelaw, 2021).The level of investor composition also increases informational effects. The telecommunications industry that is only retail-oriented yet more dominated by institutional investors is characterised by the vivid behavioural patterns of overreaction, loss aversion, and herding, particularly in the cases of firms reporting negative news (Chen et al., 2023; Liang et al., 2022). The exogenous shocks like COVID-19 also complicate the process of price adjustment, and they result in the environment where uncertainty increases investor disclosure sensitivity (Mazur, Dang and Vega, 2021; Sharma, 2023).

Although there are facts that telecom companies often create a greater amount of volatility due to announcements and stronger abnormal-return profiles than other markets (Li et al., 2025; Chen et al., 2023), they have limited sector-specific analysis. Majority of the current research is looking at the market of the country as a whole or earnings announcement generally but not performance forecasts in a strategically important, policy-sensitive and innovation-intensive industry. Moreover, the number of studies that have made unobserved past 2020 is insignificant since it is necessary to comprehend the existing market behaviour considering significant institutional changes and macroeconomic unpredictability.

This study addresses these gaps by an event-study analysis of 150 performance forecasts issued by A-share telecommunications companies during the year 2023 to mid-2025. We test the size, direction, and persistence of abnormal returns, asymmetric response to good and bad news, and variation in cross-period sensitivity of the market. The study can be used to provide new empirical insights into the effects of information shock and investor behaviour on the single-factor market model by providing a critical single-factor market model and a detailed sectoral setting in one of the most strategically important industries in China.

2. Literature Review

2.1. Equity market information processing and adjustment in China.

The scholarly sources give substantial proof that the stock market in China has evolved into a complex system in which information has become a defining factor of asset prices (Carpenter and Whitelaw, 2017; Liu et al., 2019; Allen et al., 2024). However, China has a number of structural and institutional features that differentiate Western market which are more established. The market is especially favourable to an event-study analysis due to the mandatory disclosure policies, the necessity to disclose all events overnight and the requirement to report on the specific sector (Kong, 2008; Cao and Lee, 2002). It has been found that call auctions are important to post-announcement price discovery and are often indicative of informed trading and updated expectations (Liu et al., 2019; Carpenter et al., 2021).

2.2: Earnings Announcements and Performance Predictions.

The announcements of earnings have been a major information event that has an effect on stock returns (Foster et al., 1984; Brandt et al., 2008; Beaver et al., 2018). Classic literature records the return anomalies like the post-earnings-announcement drift (Brown, 1968; Bernard and Thomas, 1989) where investors are shown to under react to announcements and the price adjustments are experienced in later trading days. Despite the fact event-study methodology is highly developed in the international context (MacKinlay, 1997), studies which are based in China focus on the fact that institutional structures have influence on the speed and accuracy of information incorporation (Kong, 2008). Specifically, the compulsory performance of China is more prevalent than in most markets of the west offers more portals through which companies can influence market expectations (Chen et al., 2023).

2.3. Sensitivity of Telecommunications Sector to Information Shocks.

According to sector-specific literature, the announcement effect is more intense and long-lasting in telecommunications firms as compared to other industries because it correlates with the national priorities in technology, is highly attended to by investors, and is vulnerable to regulatory changes influencing these companies (Li et al., 2025; Sharma, 2023). The behavioural effects of a retail investor dominance system include herding and loss aversion, particularly around bad news, and the effects of institutional participation are somewhat buffering volatility (Liang et al., 2022; Chen et al., 2023). Even in the context of such dynamics, comparatively little research examines the specific market responses to performance predictions of telecommunications, which creates a gap in the comprehension of the impact of sectoral characteristics on information processing.

2.4. These effects are Market Shocks, Behavioural Effects and Efficiency.

It is accepted in the literature that market sensitivity to firm disclosures is increased by exogenous events such as the COVID-19 crisis, significant policy responses, and market disruptions (Mazur et al., 2021; Sharma, 2023). Those conditions enhance biased behaviour and tend to lead to asymmetric pattern of returns, where a negative news creates bigger and more enduring effects than a positive news. The behavioural explanations that are most commonly explained include investor pessimism, good news scepticism, pre-announcement drift, but are often not tested with any external data like trading volume or media sentiment (Chen et al., 2023; Liang et al., 2022). Recent theoretical research by Hussain et al. (2025) investigates the connection between information leakage and market efficiency at forecast announcement dates and this study offers a critical perspective on the interpretation of the observed pre-announcement drift in our study. This theoretical context is added to by contemporary factors of behaviour in that Hussain and Komal (2025) indicate how an algorithmic echo chamber within social media may raise the sentiment of investors thus increasing additional anomalies such as the extreme asymmetric response to news. Altogether, this body of work supports the idea that information asymmetry and amplification of sentiment are significant factors in the discovery of prices in the emerging markets such as China.

2.5. Breakthroughs in Event-study techniques and Textual Analysis.

Recent methodological innovations, including reducing the estimation window, the use of multi-factor models, and causal-inference strategies, can further rely on event-study results in volatile markets. Simultaneous development of textual analytics allows the researchers to assess sentiment in analyst and corporate disclosure with the help of BERT and the like (Liang et al., 2022; Sharma, 2023; Chen et al., 2023). Nevertheless, these innovations are not well-explored in sector-specific research of the telecommunications market in China, especially in the context of the situation after 2020.

3. Methodology / Empirical Design

This study would use event-study design to determine the effects of annual performance-forecast announcements on A-share listed telecommunication companies in 2023-2025. After running a systematic screening process, 150 announcement events are retained. Every event is categorized as either a bad news or a good news depending on the improvement or deterioration of the issued forecast compared to the previous performance of the firm as realized in the previous year. This benchmark is selected on purpose: whereas analyst predictions are typically applied on a Western market, they do not cover all the Chinese telecommunications companies effectively and evenly, and the official regulatory-imposed disclosures provide a more stable point of reference when classifying the news. To be able to identify clean events, any corporate activity that will confound indications of the event (e.g., dividend declaration, reorganization announcement, etc.) are eliminated during the event window as long as they occur within it. The RESSET database (daily stock returns and market index returns) is used to obtain them. A standard estimation window of -120, -20 trading days is used to estimate normal returns and -10, +10 to analyse abnormal performance, with robustness checks that are used to check the results with other intervals.

The event-study design permits decomposing returns in an apparent and abnormal component, and thus identifying market responses that can be directly linked to the forecast announcement. Besides the basic analysis based on price changes, the research explains some market trends like pre-announcement drift or purportedly anticipatory responses in a behavioural context. Although these interpretations are still exploratory, they demonstrate some productive areas to be explored in future studies using high-frequency news analytics, investigator- attention proxies or trading-volume-related metrics.

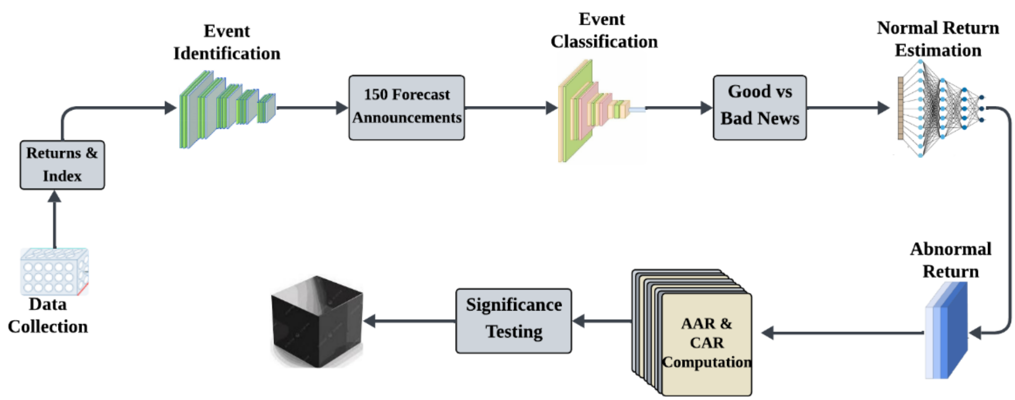


Figure 1: Methodology System Diagram

4. Model Specification

4.1. Normal Return Model

Expected returns are estimated using the single-factor market model:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{1}$$

Rit is the stock i returns on day t, Rmt is the market returns (CSI 300 Index), and ε_{it} firm-specific interceptive and market sensitivity. The estimation of parameters is done through OLS using estimation window that precedes the event.

This method of selecting the one-factor specification is a decision based on a number of methodological and data-driven factors. The first, the sample only includes telecommunication companies in one national market, which implies a comparatively homogeneous macroeconomic and sectoral exposure. The value of added factors like size, value or momentum in these environments is likely to be low, especially in short horizon event windows where systematic risk premia are changing gradually compared to firm-specific news.

Second, parsimony of the single factor model minimizes the error in estimation that is a considerable strength since the estimation horizon is short and may be subject to multicollinearity between multifactor regressors or multifactor samples. The existing empirical studies in the Chinese and emerging markets have also indicated that the single-factor model is effective in explaining the anticipated returns in the cases of information-driven corporate events.

Overall, there are no limitations of this choice. Omitting size, value, profitability, or momentum might cause a small bias in the case where the risk exposures of such firms vary around the event window or the cross-sectional characteristics of firms vary more than expected. Even though these effects are generally dampened within narrow event windows and sector-based samples, they are a theoretical caveat and point to an organic evolution of the future by using a multifactor or high-frequency risk adjustment.

The OLS estimators are:

$$\hat{\beta}_i = \frac{\sum_{t=T_0}^{T_1}(R_{mt}-\bar{R}_m)(R_{it}-\bar{R}_i)}{\sum_{t=T_0}^{T_1}(R_{mt}-\bar{R}_m)^2} \qquad \hat{\alpha}_i = \bar{R}_i - \hat{\beta}_i\bar{R}_m \tag{2}$$

With $\bar{R}_i$ and $\bar{R}_m$ representing mean stock and market returns during the estimation period.

4.2. Abnormal Return Calculation

Abnormal returns (AR) are calculated as:

$$AR_{it} = R_{it} - \left(\hat{\alpha}_i + \hat{\beta}_i R_{mt}\right) \tag{3}$$

This isolates price changes specific to a firm that can be linked to the announcement's information content. In a number of instances, anomalous returns show patterns that are similar to anticipatory pessimism, which is characterised by a slight negative drift in negative news events even prior to disclosure, which corresponds with unpredictability or selective information leakage. These phenomena show the potential value of expanding future analyses to sentiment indicators, news spreading metrics, or disaggregated trading-volume responses, even though the study focusses on price reactions.

Aggregate Measures

Average Abnormal Return (AAR):

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} A\,R_{it} \tag{4}$$

With variance:

$$\widehat{Var}(AAR_t) = \frac{1}{N^2}\sum_{i=1}^{N} \hat{\sigma}_{AR,i}^2 \quad (5)$$

Cumulative Abnormal Return (CAR):

$$CAR_{(\tau_1,\tau_2)} = \sum_{t=\tau_1}^{\tau_2} AAR_t \quad (6)$$

With variance:

$$\widehat{Var}\left(CAR_{(\tau_1,\tau_2)}\right) = \sum_{t=\tau_1}^{\tau_2} \widehat{Var}\,(AAR_t) \quad (7)$$

CARs quantify the integrated market reaction over windows such as [–1, +1], [0, +5], or [–5, +5].

5. Statistical Testing

As is standard in event-study research, parametric t-tests are used to evaluate the statistical significance of both AAR and CAR:

$$t(AAR_t) = \frac{AAR_t}{\sqrt{\widehat{Var}(AAR_t)}}, \qquad t\left(CAR_{(\tau_1,\tau_2)}\right) = \frac{CAR_{(\tau_1,\tau_2)}}{\sqrt{\widehat{Var}\left(CAR_{(\tau_1,\tau_2)}\right)}} \quad (8)$$

At the 1%, 5%, and 10% levels, significance is assessed. The analysis also breaks down events by reporting period (year and quarter) and news type (good vs. bad) in order to capture temporal heterogeneity. AAR/CAR line charts are used to visualise the empirical results, which are backed up by comprehensive tables that show daily abnormal returns and cumulative estimates for every event class.

Python is used for all analytical processes, including data extraction, event filtering, model estimation, and statistical testing. To comply with open-science standards, transparent, repeatable code and anonymised event identifiers are made available upon request.

6. Results

In the context of the event studies that follow, good news events are those in which businesses report higher earnings or provide guidance that has been revised upward from the prior year. Conversely, negative news events are characterised by lower earnings or downward revisions based only on the official adjustments.

6.1. Overview, Data, and Example An explanation:

150 performance forecast events from A-share telecom listings between 2023 and 2025 are the subject of this study, which classifies them as either good or bad news. Although there is a discernible decrease in the numbers as time goes on, positive news events typically outnumber negative ones. An optimism bias and the evolution of disclosure patterns are evident in the quarterly and year-end trends, which are important for the event study analysis.

Table 1: Event Frequency and Temporal Patterns in Performance Forecasts

Year	Quarter	Bad News	Good News
2023	1	44	27
2023	2	13	5
2023	3	41	28
2024	1	50	30
2024	2	5	5
2024	3	39	20
2024	4	2	4
2025	1	36	17
2025	2	2	5

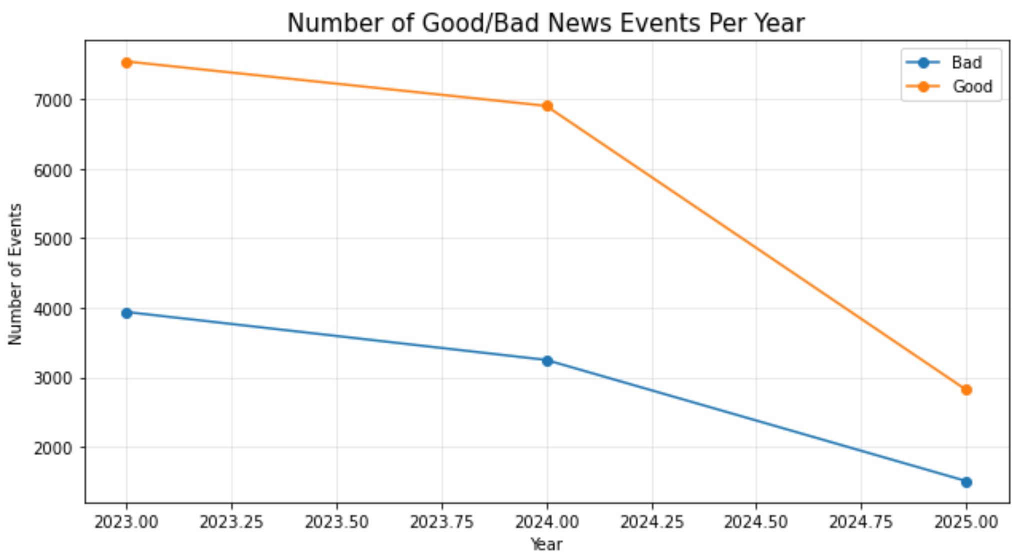


Table 1 details quarterly good and bad news forecasts by China's telecom firms (2023–2025), with ***Graph*** showing annual trends of Number of Good/Bad News events per year.

6.1.1. Comparative Insights

The idea of optimism bias or cautious reporting is supported by the descriptive statistics, which demonstrate that good news forecasts are typically higher than bad news. Between 2023 and 2025, there was a notable decline in both kinds of news, but the decline in positive news was greater. Strong fluctuations are evident in the disclosure patterns, especially in the first few quarters. These fluctuations can be explained by seasonal or regulatory influences. The Appendix Figures also show a significant concentration of data in the first and third quarters, highlighting the significance of timing when examining abnormal returns and promoting dataset transparency and the reliability of the results.

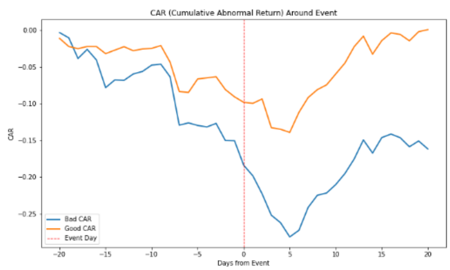
6.2. Average Abnormal Returns (AAR) and Cumulative Abnormal Returns (CAR)

For every day in the event window of the set [-10, +10], we summarise the mean abnormal returns (AAR), their standard errors, t-statistics, p-values, and cumulative abnormal returns (CAR) for both good and bad news events.

Table.2: Comparative AAR and CAR for Good News and Bad News Events [-10, +10]

t	AAR Good News	Std-Err	t-stat	p-value	CAR Good News	AAR Bad News	Std-Err	t-stat	p-value	CAR Bad News
-10	0.0008	0.00404	0.2	0.84315	-0.0247	0.00859	0.00633	1.36	0.17408	-0.0475
-9	0.00377	0.00477	0.79	0.43081	-0.02093	0.00131	0.00494	0.27	0.78535	-0.0462
-8	-0.02249	0.00613	-3.67	0.00039	-0.04342	-0.01711	0.01247	-1.37	0.17009	-0.0633
-7	-0.04008	0.00567	-7.07	0	-0.0835	-0.06594	0.01138	-5.8	0	-0.1293
-6	-0.00122	0.00283	-0.43	0.66809	-0.08471	0.00314	0.00378	0.83	0.40689	-0.1261
-5	0.0184	0.00681	2.7	0.00816	-0.06632	0.00023	0.00655	0.04	0.96829	-0.1259
-4	0.00143	0.00372	0.38	0.70168	-0.06489	0.01081	0.00477	2.27	0.02637	-0.1151
-3	0.00156	0.00242	0.65	0.5201	-0.06333	-0.00644	0.00493	-1.31	0.19173	-0.1215
-2	-0.01737	0.00311	-5.59	0	-0.0807	-0.0084	0.00697	-1.21	0.2257	-0.1299
-1	-0.00996	0.00331	-3.01	0.00335	-0.09065	-0.0162	0.00718	-2.26	0.02519	-0.1461
0	-0.00753	0.00537	-1.4	0.16424	-0.09818	-0.01988	0.00751	-2.65	0.00823	-0.166
1	-0.00133	0.00382	-0.35	0.72859	-0.09951	0.00203	0.00589	0.34	0.73077	-0.164
2	0.00594	0.01017	0.58	0.56094	-0.09357	0.01297	0.00706	1.84	0.0664	-0.151
3	-0.03911	0.00493	-7.93	0	-0.13269	-0.02239	0.00813	-2.75	0.00667	-0.1734
4	-0.00213	0.00417	-0.51	0.6103	-0.13482	0.00658	0.00641	1.03	0.30713	-0.1668
5	-0.00428	0.00363	-1.18	0.24058	-0.1391	0.01422	0.00809	1.76	0.08142	-0.1526
6	0.02726	0.00535	5.09	0	-0.11184	0.0171	0.00823	2.08	0.04104	-0.1355
7	0.02019	0.00418	4.83	0	-0.09165	0.01117	0.00593	1.88	0.06214	-0.1244
8	0.01075	0.0032	3.36	0.0011	-0.0809	0.00274	0.00705	0.39	0.69784	-0.1216
9	0.00651	0.00416	1.57	0.12065	-0.07439	0.00662	0.00617	1.07	0.28832	-0.115
10	0.0149	0.00335	4.45	0.00002	-0.05949	0.00154	0.00588	0.26	0.794	-0.1135

Primary Results and Discussion: It is intriguing to observe how the stocks usually tend to fall immediately before the announcement of good news. This may be because of doubt or even leakages of the news but they tend to rebound after the announcement. Bad news on the other hand, results in steep drops both prior to and after the news gets out and then a somewhat recovery but further losses in the long run. Our abnormal returns (ARs), are not merely statistically significant; they also have economic substance that is particularly given the peculiarities of the Chinese A-share market MacKinlay, A. C. (1997). This market is characterized by excessive speculation and transaction cost by investors and the round-trip costs of trade reached approximately 1 in some periods in history. The short-window cumulative abnormal returns (CARs) reported such as the Bad News CAR [-1, +1] of -3.4 evidently exceeds this cost level. It implies that performance forecasts generate an economically significant information shock that brings about a wealth transfer. Among the most interesting results that can be discussed further is a negative drift that is surprising in advance (before Good News) is announced (CAR [-10, -1] of Good News = -9.065 in Table 2). This is a common anomaly in the new markets. This negative pattern suggests that investors are sceptical too strongly on management (another frequent problem in these markets) or that it is the results of anticipatory pessimism and noises trade. In this respect, the day when the official announcement (t=0) occurred serves as a reset button of the expectations, and the actual price response to good news could take its due.



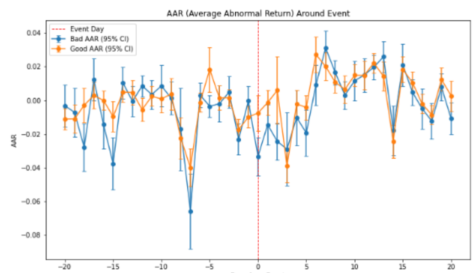


Figure 2: **CAR (Cumulative Abnormal Return) Around Event (Good vs. Bad) Good vs. Bad News Events of CAR/AAR comparison around days**

According to the CAR, news of good results in moderate and short-term stock price gains whereas news of bad news results in severe and enduring decreases in stock prices which show that there is a difference in the reaction of investors. The AAR indicates that the volatility is elevated around announcement dates, the bad news causes bigger and longer downward abnormal returns before and after news is announced.

Interval Market Response: We compare the average abnormal return (AAR) on the day of event (t=0) of different kinds of news to further comprehend how the market differently responds to the news made up of good or bad news.

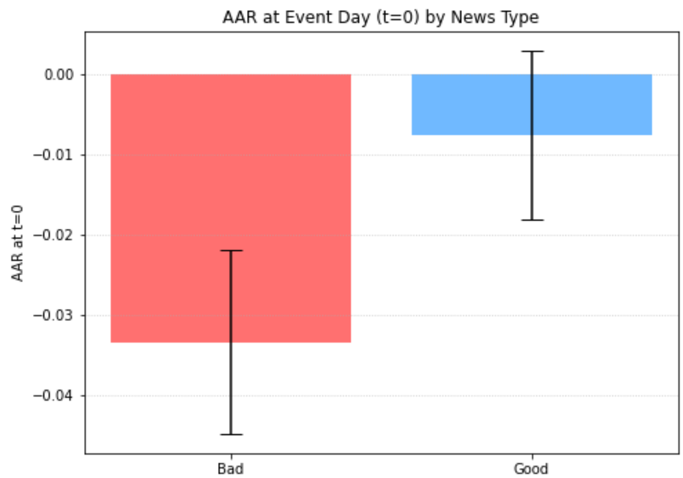


Figure.3.Market Response

A negative bias among investors is demonstrated by Figure 3, which shows that bad news produces noticeably larger negative abnormal returns than good news. AAR, t-statistics, and cumulative returns in the announcement neighbourhood in Table 2 provide additional evidence for this conclusion. Chen et al., 2023

Table 4. Summary Statistics for Key Event Intervals

Event Type	**Interval**	**Mean AAR**	**Mean t-stat**	**Total CAR**
Good News	[-1,1]	-0.00178	-0.93	-0.00189
Good News	[0,2]	-0.00098	-0.74	0.00594
Bad News	[-1,1]	-0.01135	-1.89	-0.03405
Bad News	[0,2]	-0.00196	-0.18	-0.00488

Table 4 highlights a glaring asymmetry in investors' reaction to expectations by confirming that bad news produces larger, longer-lasting negative returns than good news, which has a weak, short-lived effect.

6.5. Visualization of Market Reaction

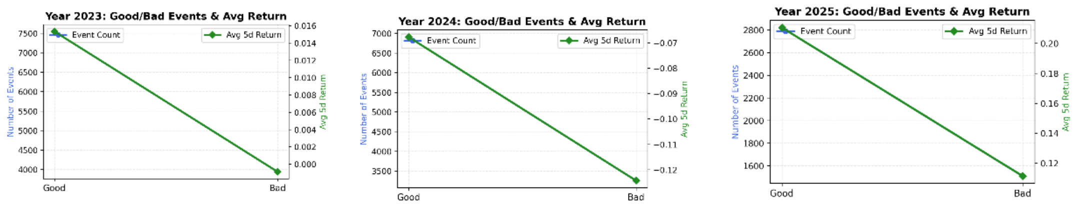


Figure.4: Annual Events 2023-2025

The annual good and bad news forecast figures for 2023–2025, along with their immediate reactions, are displayed in Fig. 4. The bad news causes steeper, longer-lasting price drops, particularly in 2024, and confirms the identified asymmetry in the market response, while the good news is more frequent, Sharma, 2023.

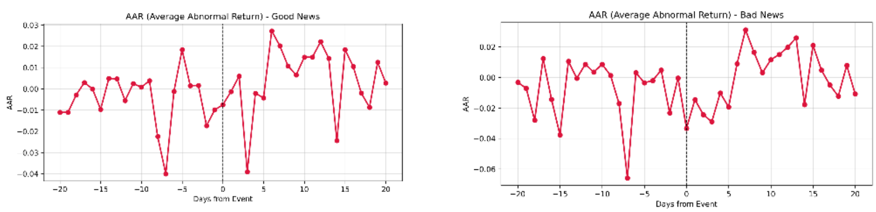


Figure 4.1: Average Good/Bad News AAR/CAR

The previously mentioned visualisations show 40-day average abnormal returns for both good and bad news, emphasising different responses from the market to forecasts that are positive and negative.

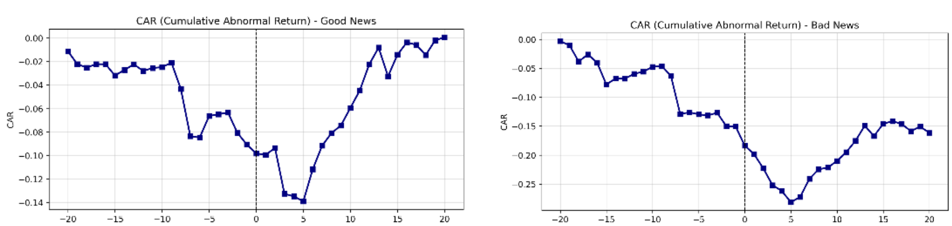


Figure 4.1(a): Good/Bad News CAR

The period of Q1 2024 was a big one particularly in cases of bad news. This sensitivity early in the year is also agreeable with the general macro-economic uncertainty, which we were experiencing at the time.

Although GDP had certain positive signals, the consumer sentiment was beaten a blow, and we experienced continuous deflationary pressures especially where PPI was low. Behavioural biases such as loss aversion among investors may have been exacerbated in this high-uncertainty atmosphere resulting in a more intense and long-lasting negative response to bad news, Allen et al., 2024. This confirms past results and demonstrates that the market was more responsive in periods of economic volatility that the long-run cumulative losses almost doubled because of regulatory and macroeconomic EPS setbacks. It also stands out the downside risks which have developed over the first two years of the new regulatory environment in 2024.

7. Robustness and Additional Analyses

The robust tests conducted for both the year and the quarter reveal a clear asymmetry: negative news tends to trigger more intense and prolonged negative reactions compared to positive news, especially noticeable in the first quarter of 2024. By using a single-factor market model that fits well with the similarities in the telecom sector and the short duration of the events, we can replicate these findings without encountering any anomalies. A -1% abnormal return corresponds to a market loss of 200 million RMB, highlighting the significant impact of disclosure and the value of transparency. For a detailed look at the year-by-year results, check out Figure 4, and you can find additional quarterly event response plots and supporting statistics in *Appendix A for reference?*

8. Conclusion and Implication

The study has discussed the Chinese telecommunications industry in response to annual announcements of foreseeable performance through the establishment of an event-study framework built upon the foundative empirical literature of asset-pricing frameworks, and informed by the current literature of market-microstructure. The data indicates that there is a sharp and systematic asymmetry in market responses in that negative performance forecasts lead to much sharper, deeper and longer-lasting abnormal returns than the weak and transient ones attributable to positive forecasts. This asymmetry is year-spanning, quarter-to-quarter, and event-window specific, and it is particularly acute during the times of increased macroeconomic uncertainty, which is exactly the case in early 2024.The findings help to better understand information transmission and investor behaviour in the emerging markets, where the presence of institutional investors, retail participation, and policy-sensitive industries can be observed. The reactions observed can be well explained by the behavioural finance theories of loss aversion, asymmetric information processing and negative-bias sensitivity that can be used to explain why adverse disclosure has a significantly greater price effect than favourable disclosure, Liang et al., 2022. To corporate managers, the disclosure of forecasts is an important issue not only in a qualitative sense but also in a quantitative sense: the nature of the disclosure, the wording, and the time period of the release can have a significant impact on how the market reacts. To investors, the results give significance to the disproportional causality of negative guidance shocks and the necessity to take care of the disclosure cycles, especially in volatile macro economies. The high degree of asymmetry, on the part of regulators, highlights the significance of ensuring high quality and transparency of the disclosure in order to alleviate overreactions and overcome information-based volatility in strategically sensitive areas like telecommunications. Although the study has strengths, it has limitations. The event-study designs are mainly sensitive of price-based market adjustments and are unable to be fully isolating against the effect of concurrent market events, sector-wide effects, or firm-specific events taking place around disclosure dates. In addition, the analysis is solely based on price information and does not incorporate complementary behavioural measures like trading volume, media sentiment or investor-attention measures. It would be possible to incorporate these variables and enable future studies to better test behavioural hypotheses like anticipatory pessimism, information leakage, and sentiment-driven drift and generate a more detailed mapping of the relationship between news properties and market response strength.

Future research can extend this piece of inquiry with the aid of an event-study approach and text-analytic technology, machine-learning-managed sentiment models, and high-frequency trading data to further break down the linguistic, temporal, and structural elements of forecast announcements. The opportunity to apply the analysis to cross-industry or cross-country context is also available to assess the external validity of the observed asymmetry patterns seen in the telecom industry in China based on other information-sensitive markets. Since the telecommunication industry in China is rapidly growing in both magnitude and strategic significance, the question of how investors decode and compensate corporate guidance will continue to play a key role in the assessment of market efficiency, regulatory design and the overall dynamics of information flow within the rapidly developing financial systems.

Data and Code Availability: Anonymized event lists, complete Python analysis scripts, and replication instructions are available from the author upon request.

APPENDIX A: Supplementary Data, Robustness Checks, and Additional Visualizations

Table A.0: Sample Characteristics of the Study Sample

Statistic	No of Firms	Mean daily log return	Median closing price (last date, RMB)	Mean closing price (last date, RMB)
Value	31	0.000311	10.71	13.18

A.1. Detailed Event Distribution

Table A.1 details quarterly performance forecast events by type and year, complementing *Table 2* and supporting replication and subgroup analyses.

Year	Quarter	Good News	Bad News
2023	Q1	27	44
2023	Q2	5	13
2023	Q3	28	41
2024	Q1	30	50
2024	Q2	5	5
2024	Q3	20	39
2024	Q4	4	2
2025	Q1	17	36
2025	Q2	5	2

A.2: Robustness: Alternative Event Windows

Robustness checks using alternative event windows (e.g., [-5, +5], [-3, +3]) confirm consistent direction, timing, and significance of abnormal returns, as summarized in *Table A.2*.

Table A.2 Robustness checks using alternative event windows

Event Type	Window	Mean AAR	Mean t-stat	Total CAR
Good News	-3,3	-0.00969	-2.44	-0.06780
Good News	-5,5	-0.00494	-1.42	-0.05439
Bad News	-3,3	-0.01716	-2.73	-0.12014
Bad News	-5,5	-0.01412	-2.23	-0.15529

A3. Additional Visualizations

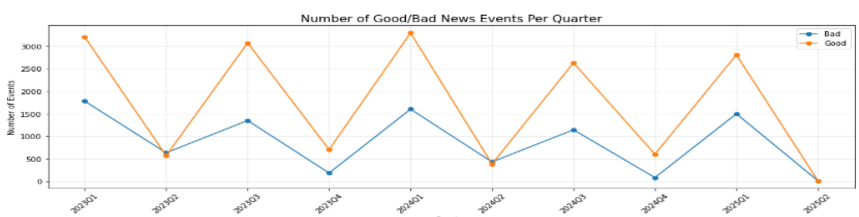
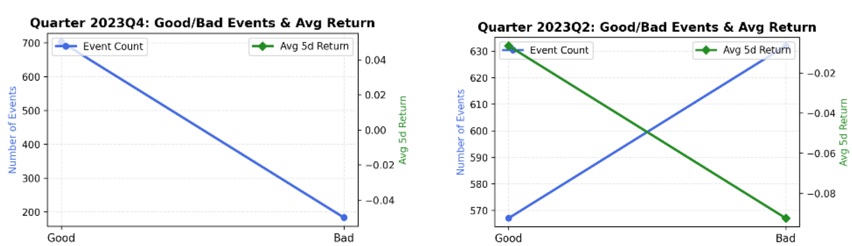


Figure A.1. Quarterly Distribution of Good/Bad News Events (2023Q1–2025Q2).

Chinese telecom firm quarterly counts of positive and negative news forecasts are displayed in this figure; Q1 spikes correspond with high reporting and more robust market responses. Asymmetry in event timing and unusual earnings are highlighted by the fact that good news frequently exceeds bad news.

Figure: Quarterly AAR and CAR Plots for Good/Bad News Events and Average return (2023Q1 to 2025Q2)



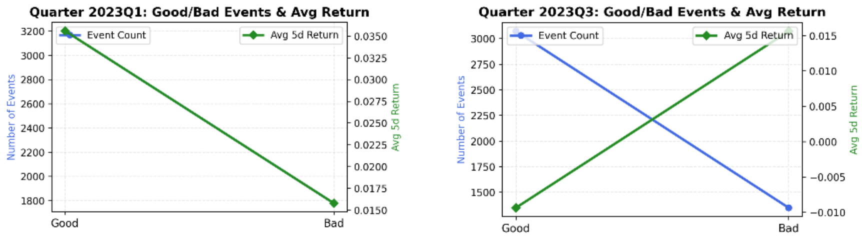


Figure A.1 (a): 2023 Quarters Good/Bad News and Average return

Figure A.1 (a) displays 2023 quarterly counts of good and bad news forecasts alongside their average short-term returns for China's telecom firms.

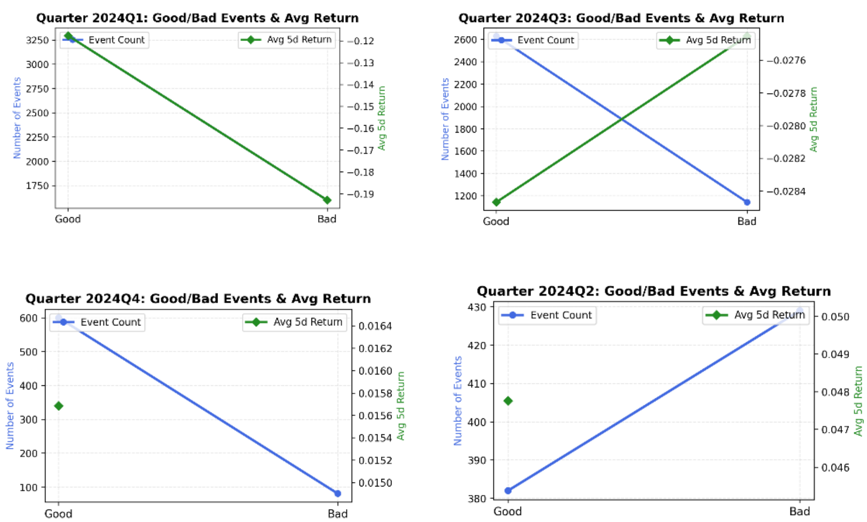


Figure A.1 (b): 2024 Quarters Good/Bad News and Average return

Figure A.1 (b) shows quarterly counts of good and bad news forecasts and corresponding average short-term returns for China's telecom firms in 2024.

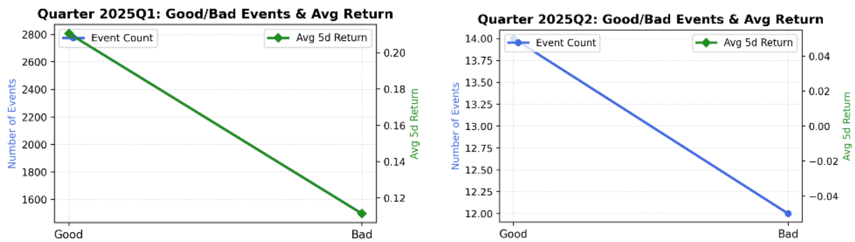


Figure A.1(c): 2025 Quarters Good/Bad News and Average return

Figure A.1(c) displays quarterly counts of good and bad news forecasts and their average short-term returns for China's telecom firms in 2025.

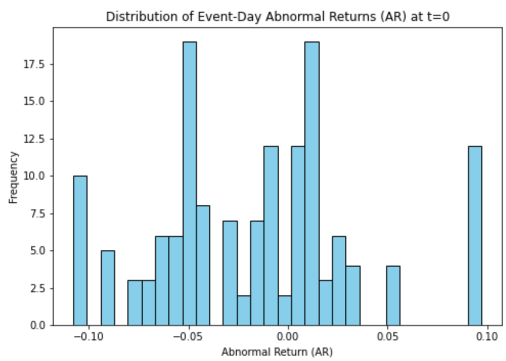


Figure A.2 (a): Distribution and Descriptive Statistics of Event-Day Abnormal Returns

This histogram illustrates the distribution of abnormal returns on announcement day (t = 0) across all events, highlighting market reaction variability and confirming event study reliability.

Table A.3: Descriptive Statistics for Abnormal Returns at the Event Day (t=0)

Statistic	Mean	Median	Std.Dev	Min	Max	Skewness	Kurtosis	N(Event)
Values	-0.01614	-0.01376	0.051249	-0.10782	0.097208	0.393248	2.920951	150

This table summarizes distributional statistics of abnormal returns on event day (t = 0) for 150 forecast events, assessing market react ion variability and event study assumptions.

Abbreviations:

Abbreviation	Full Term	Description
AAR	Average Abnormal Return	Aggregate measure of abnormal returns.
AR	Abnormal Returns	Price changes specific to a firm linked to the information content of the announcement.
BERT	Bidirectional Encoder Representations from Transformers	A deep learning model commonly used in textual analytics.
CAR	Cumulative Abnormal Return	Quantifies the integrated market reaction over the event window.
N(Event)	Number of Events	Total number of announcement events analyzed.
OLS	Ordinary Least Squares	Method used to estimate parameters ($\alpha i, \beta i$) in the normal return model.
Std-Err	Standard Error	Standard deviation of the Average Abnormal Return (AAR).
Std.Dev	Standard Deviation	A statistical measure of data dispersion.
t-stat	t-statistic	Used to evaluate the statistical significance of AAR and CAR.

Acknowledgment

The authors acknowledge the use of a large language model, like Chat-GPT, for assistance with language polishing and grammatical editing of the final manuscript. All research, analysis, and conclusions presented in this study are the sole responsibility of the authors.

Conflict of Interest: The authors declares no known conflict of interest.

Authors Contribution: All authors contributed to the manuscript equally.

Funding: The research contain no external funding's.

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