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Epidemic experience, analyst sentiment, and earnings forecasts: Evidence from SARS exposure☆

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ABSTRACT

This study examines whether exposure to dangerous infectious diseases affects how analysts assess risks. We use the outbreaks of the severe acute respiratory syndrome (SARS) at analysts' previous office locations across China as a plausibly exogenous shock in the analysts' life experience. We show that compared to their less-affected counterparts, analysts in provinces with more SARS cases issue more optimistic forecasts for firms. This effect is stronger for affected analysts in provinces perceived as more salient during the SARS epidemic period. Mechanism tests show a high level of unexpected economic growth and positive media reports can motivate optimistic forecast bias induced by SARS exposure. Further heterogeneity tests indicate that our findings are particularly pronounced among busier analysts, those with less industry specialization, and female analysts. Overall, these findings suggest that exposure to the SARS epidemic influences the information intermediaries' judgment.

1. Introduction

Risk preferences are crucial not only in individual decision-making related to economic activities, such as investment, saving, and consumption, but also in how financial professionals make forecasts. Recent studies increasingly indicate that individuals' risk preferences, and consequently their risk-taking behaviors, can be modified by various adverse events, including natural hazards (e.g., flooding, hurricanes, tsunamis, and earthquakes) and epidemics, the Great Chinese Famine, and financial crises (Alok et al., 2020; Cheng et al., 2021; Dessaint & Matray, 2017). However, the specific influence of these adverse events on risk preferences remains unclear, as existing research reveals varied outcomes, sometimes contradictory, even within identical contexts. Specifically, in assessing the effects of disruptive incidents, some studies observe a rise in risk aversion (Alok et al., 2020; Dessaint & Matray, 2017), whereas others report a decline (Bui et al., 2019; Eckel et al., 2009). Moreover, more recent studies indicate that the effects of disruptive events on risk preferences depend on the severity of the event (Gao et al., 2020).

As for sell-side analysts, a recent growing literature finds that disruptive life events which cause extreme destruction (e.g.,

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earthquakes, hurricanes, and terrorist attacks) can lead analysts to make more pessimistic risk estimates and thus issue less optimistic forecasts (Cuculiza et al., 2021; Dong et al., 2021; Kong et al., 2018; Li et al., 2020; Wang et al., 2019). However, we observe that there has not yet been any research exploring the impact of disruptive events that do not have the expected extreme economic consequences on analysts' optimism bias.

We have utilized the SARS event to investigate how events with less severe impacts than initially anticipated affect analysts' forecasts mainly for the following reasons[1]: Firstly, the SARS epidemic was the first novel infectious disease that occurred in the 21st century and spread across more than 24 countries, including those in Asia, North America, South America, and Europe. The disease was treated as a global danger in March 2003.[2] A cumulative total of 8422 SARS cases and 916 deaths were reported from November 2002 to August 5, 2003.[3] China was the the most severely affected country by SARS. SARS was first discovered in November 2002 in Guangdong Province in China and ended in July 2003 with a total of 5327 clinically diagnosed cases in mainland China and 349 deaths. The SARS outbreak, with its high morbidity, mortality, and no specific treatment, caused global anxiety and an estimated economic cost of $3–10 million per case (Fang & Feng, 2021; Lee & McKibbin, 2004). Accordingly, the consequences of the SARS outbreak have attracted widespread attention from scholars (Chen et al., 2020; He et al., 2022; Ru et al., 2021; Wen et al., 2021).

Secondly, the SARS epidemic provides us with a disruptive event that does not cause severe long-term destructive effects that were expected. During the SARS outbreak in 2003, the economy was anticipated to be in a poor condition, but it turned out to be much better than expected, with a strong rebound in the third and fourth quarters of 2003. After the epidemic subsided, China's economy stabilized and rebounded, driven by investment, with GDP growth rising by around 10% in 2003 compared to 2002. [4]

We could observe that the SARS epidemic has both similarities and differences to the COVID-19 pandemic. The similarities include both being caused by a new unknown coronavirus, being highly contagious, and having caused market panic. The differences are that SARS was prevalent for 8 months, whereas the COVID-19 epidemic has lasted for over three years. Since January 8, 2023, China lifted the preventive and control measures for novel coronavirus infection as a Class A infectious disease under the Prevention and Control of Infectious Diseases Law of the People's Republic of China. Additionally, the number of COVID-19 cases is much higher.[5] More importantly, economic growth in China is projected to slow to 4.3 percent in 2022 before rebounding to 5.2 percent in 2023, reflecting the economic damage caused by the persistence of COVID-19. Thus, unlike COVID-19 or other disruptive events (e.g., the earthquake, hurricanes, and terrorist attacks), the 2003 epidemic's impact on China's economy was a temporary, one-off effect. This makes the SARS experience an ideal situation to study how analysts' forecasts are influenced by disruptive events without severely negative consequences that were expected.[6]

Thus this study investigates whether and how exposure to SARS, which is an exogenous event and irrelevant to the financial market, affects analysts' sentiment and their earnings forecast bias. The SARS experience might affect analysts' forecast performance in two ways. First, the SARS experience may lead analysts to adopt a more cautious or conservative approach in their forecasts than their peers without SARS experience. Existing studies have indicated that exogenous and extremely negative events affect analysts' sentiments and forecasts. Specifically, analysts with a disruptive life experience, such as natural disasters (e.g., earthquakes and hurricanes) and terrorist attacks, make more pessimistic risk assessments (Bourveau & Law, 2021; Cuculiza et al., 2021; Kong et al., 2021). Furthermore, previous literature has indicated that SARS exposure increased psychological panic and stress (Fang & Feng, 2021; Sim & Chua, 2004). In this case, we predict that analysts who are located in provinces with more SARS cases during the SARS epidemic period would have their sentiments negatively affected, which could induce them to issue more pessimistic risk assessments.

Second, the SARS experience might cause analysts to become more optimistic than their peers without SARS experience, considering a sharp economic recovery after the epidemic. Existing studies have suggested that the SARS crisis had a limited effect on the economy. For example, Keogh-Brown and Smith (2008) find that the magnitude of the effect of SARS on the economy was far smaller than indicated by model estimates and media reports. Thus, we predict that analysts with more severe SARS exposure will be more optimistic than their counterparts in earnings forecasts.

[1] The main reason we focus on analysts is as follows: sell-side analysts play an important role in information collection, analysis and dissemination for capital markets and their earnings forecasts are a useful information source for investors (Cornaggia et al., 2020; Kong et al., 2021; Zhang, 2022). Thus, improving analysts' forecast performance has received a lot of attention from scholars. Specifically, existing studies show that both macro-level and micro-level factors—language commonality, cultural proximity, and gender—affect the accuracy of analysts' forecasts (Bochkay & Joos, 2021; Du et al., 2017; Fang & Huang, 2017).

[2] Source: https://www.hopkinsmedicine.org/health/conditions-and-diseases/severe-acute-respiratory-syndrome-sars.

[3] Source: https://www.phsciencedata.cn/Share/en/index.jsp.

[4] We acknowledge that exposure to the pandemic differs from other disruptive life events like earthquakes, hurricanes, and terrorist attacks. Unlike such catastrophic events, epidemics typically do not inflict extensive physical damage to possessions, real estate, and community facilities, nor do they provoke widespread, irreversible relocation of people (Watson et al., 2007; Wen et al., 2021). Furthermore, unlike these catastrophic events, which typically lead to prolonged economic downturns, the economic recovery following the SARS epidemic was notably swift.

[5] According to WHO data, there are 761,402,282 confirmed COVID-19 cases and 6,887,000 confirmed deaths around the world as of 29 March 2023.

[6] Our decision not to focus on COVID-19 is driven by two main reasons: First, the significant impact of COVID-19 has already been extensively explored in the literature, particularly its influence on analyst behavior (Bilinski, 2023; Gao et al., 2021; Zhang et al., 2022). Current research on the changes in analysts' behavior under the COVID-19 environment focuses on the role of information channels. However, because COVID-19 is a recent occurrence, we are still unable to explore the pandemic's impact on analysts' psychology and its subsequent long-term effects on their behavior. Second, COVID-19 caused severe and lasting economic damage, whereas the impact of the SARS epidemic was transient, leading to a rapid economic recovery and serving as an example of an event with less severe destruction than expected.

Based on detailed data of analysts' brokerage firms during the SARS epidemic period in 2003, we construct key variables to measure analysts' exposure to the SARS crisis. We then estimate panel regressions using firm–analyst–year level data to examine the long-term effect of the SARS experience on analysts' earnings forecast performance from 2002 to 2017. We control for all the possible firm- and analyst-specific factors in our model. We also include year, analyst, and broker fixed effects.

The main results show that analysts more affected by the SARS epidemic have issued more optimistic forecasts. The t-values range between 1.87 and 2.91, with coefficients between 0.45 and 0.679. This finding, consistent with our second prediction, indicates that analysts became more optimistic due to the brief duration of the SARS epidemic and the rapid economic recovery that followed. Our results are robust across a variety of tests, including the parallel trend test, alternative measures of earnings forecast optimism and SARS exposure, and the exclusion of confounding factors such as city of work and the nature of listed firms.

Furthermore, we investigate whether the greater the extent of analysts' exposure to the SARS pandemic, the greater the degree of its impact on their sentiment. We use two proxies to measure SARS epidemic salience: the number of deaths from SARS and the overall duration of SARS. Consistent with our intuition, results suggest that analysts in provinces that were more significantly impacted by SARS epidemic tend to generate more optimistic biased earnings forecasts.

Next, we examine whether the SARS experience affects the analyst earnings forecast accuracy of impacted analysts. We measure forecast accuracy (i.e., forecast error) by subtracting the actual earnings per share (EPS) from the forecasted EPS (FEPS), and then scaling this difference by the stock price from the previous year. We find that analysts with SARS exposure tend to have less accurate forecasts than other analysts without SARS experience.

Our next tests provide evidence on the mechanisms and heterogeneity effects. Existing research shows macroeconomic conditions and micro-level media reports about firms significantly influence analyst forecasts, leading us to explore how pre- and post-pandemic economic growth and changes in media sentiment about firms during the SARS epidemic impact analyst forecasts. We split the sample firms into two subsamples according to the unexpected economic growth patterns of provinces where analysts were located during the SARS outbreak and the unexpected positive media reports of the listed firms that analysts were following in 2003. We find that a high level of unexpected economic growth and a high level of unexpected positive media sentiment about firms analyst were following can motivate the SARS exposure-induced optimistic forecast bias.

In the heterogeneity section, to align with our mechanism findings, we grouped the samples based on analysts' susceptibility to emotional or psychological biases. Cross-sectional test results show that our findings are more significant for analysts with high levels of busyness, analysts with less industry specialization, and female analysts, who have been found in some studies to be more susceptible to psychological or emotional factors.

These results contribute to several strands of analysts' forecast performance and infectious diseases-related literature in accounting and finance. First, we contribute to studies that explore the determinants of analysts' earnings forecast performance. Previous studies have investigated the impact of significant "life events" on analysts' earnings forecast performance. For example, Cuculiza et al. (2021) find that analysts located near the sites of terrorist attacks and mass shootings issue more pessimistic forecasts. Bourveau and Law (2021) suggest that analysts affected by hurricanes provide less optimistic earnings forecasts for non-affected firms after hurricanes. Kong et al. (2021) document that natural disasters negatively affect the optimism bias in analysts' earnings forecasts for affected firms in China. We extend this literature by showing that the SARS exposure experience has a long-term influence on analysts' forecasts and positively affects their optimistic forecast bias, which is different from the existing studies that suggest that disruptive life events make analysts issue less optimistic forecasts. We provide new evidence for the effect of availability heuristics on forecast optimism and financial analysts' behavioral biases.

Second, we extend the literature that on the economic consequences of infectious diseases. Previous studies have investigated the macro- and micro-economic implications of infectious diseases (Choi, 2020; De Backer et al., 2021; Jin et al., 2022; Krieger et al., 2021). For example, Sun et al. (2021) suggest that COVID-19-related news and economic-related announcements can affect investors' sentiment, which may then be reflected in the pricing of medical portfolios. Fang and Feng (2021) find that epidemic exposure can affect old-age mortality significantly. The potential mechanisms might be the increased psychological stress and limitations in physical activities, induced by the SARS crisis. We extend these studies and show that SARS exposure can affect analysts' sentiment and, consequently, forecast performance in the long term.

In three related papers, Gao et al. (2021) demonstrate that the mobility restriction induced by the COVID-19 pandemic will increase forecast dispersion for firms located in the COVID-19-affected zones, and this effect is due to information lockdown. Hao et al. (2022) suggest that the uncertainty incurred by COVID-19 decreases analysts' forecast accuracy. Ru et al. (2021) document that individuals in countries with SARS infections in 2003 searched more intensively for COVID-19-related information on Google in late January 2020.

Our study differs from these studies in several ways. On the one hand, the SARS outbreaks examined in our study and the COVID-19 outbreaks examined by Gao et al. (2021) and Hao et al. (2022) produce highly different economic consequences. The actual impact of the SARS epidemic was far smaller than that indicated by model estimates. Thus, we provide further evidence that negative events with lower negative consequences than expected will make people more optimistic. On the other hand, we focus on analysts' sentiment and provide evidence of SARS exposure's long-term effects during normal periods without other negative shocks. We use the SARS outbreak as a quasi-natural experiment to investigate analysts' forecast bias through the Difference-in-Differences (DID) model, which helps mitigate potential concerns of whether the forecast bias is due to the economic/information uncertainty or analysts' sentiment.

The remainder of this study is organized as follows. In Section 2, we present the related literature and develop our hypothesis. Section 3 describes our data sources and defines the key variables. Section 4 presents the main empirical findings, the results from various robustness tests, and excludes potential alternative explanations for our findings. Section 5 shows the results of the mechanism and heterogeneity. Section 6 concludes the study with a brief summary.

2. Literature review and hypothesis development

2.1. Economic consequences of extremely negative events

In recent years, numerous sociological and psychological studies have linked stress and disruptive life events experience to changes in risk preferences, but there is no consensus on how these shocks (e.g., disruptive events) influence decision-making patterns and risk assessment (Barberis et al., 2001; Eckel et al., 2009). Based on the psychology literature, extremely negative events often result in more conservative and risk-averse behavior (Loewenstein et al., 2001). As for management, Dessaint and Matray (2017) find that hurricane events induce liquidity risks, leading managers to increase cash holding and express concern about risks in their financial reports. For investors, fund managers who have experienced a major disaster tend to underweight disaster zone stocks due to salience bias (Alok et al., 2020), and their risk-taking significantly decreases after the disaster (Bernile et al., 2021; Guiso et al., 2018; Liu et al., 2023). What's more, Huynh and Xia (2023) suggest that bond investors tend to reduce the current price for firms affected by disasters, resulting in lower contemporaneous bond returns for these firms.

Nonetheless, other studies have found that when people focus on the positive aspects in the aftermath of natural disasters, they will feel less threatened by the extremely negative events. For example, Hanaoka et al. (2018) suggest that men who experienced a more intense earthquake became more risk-tolerant. They further point out that the impact on men's risk preferences remains consistent even five years following the earthquake, maintaining a similar level to that observed shortly after the event. Bui et al. (2019) indicate that individual investors who experienced major natural disasters tend to engage in more aggressive trading. Eckel et al. (2009) point out that women exhibited significantly higher risk tolerance in the initial Katrina sample. Cheng et al. (2021) find that people who endured greater hardship during the famine are more likely to become entrepreneurs.

Furthermore, other studies indicate that the effects of disruptive events on risk preferences depend on the severity of the event. For example, Gao et al. (2020) indicate that disaster-affected households will perceive less risk if the negative event has lower fatalities than expected. Furthermore, Bernile et al. (2017) report that managers make more aggressive decisions when the negative consequences of a disaster are less severe than anticipated.

Collectively, the findings of the literature on the economic consequences of extremely negative events are mixed. The relationship might depend on the extent to which natural disasters affect the economy and people's risk perception.

2.2. Negative event experience and analysts' forecast performance

An increasing number of studies have investigated the effect of analysts' negative event experience on their forecast performance. The existing literature provides evidence for the effects of different types of negative event. Specifically, some scholars have indicated that local weather can affect the frequency of issuing revision reports (Dehaan et al., 2017), and forecast bias (Lo & Wu, 2018). Moreover, air pollution can negatively affect analysts' earnings forecast accuracy (Dong et al., 2021; Kong et al., 2018; Li et al., 2020). Cuculiza et al. (2021) indicate that terrorist attacks will negatively influence analysts' sentiment and prompt them to issue more pessimistic forecasts. Bourveau and Law (2021) find that analysts in districts affected by hurricanes make less optimistic earnings forecasts than those in unaffected areas. Furthermore, Kong et al. (2021) document that analysts are less optimistic about firms located in areas affected by earthquakes.

Overall, studies on the influence of negative event experiences on analysts' forecast performance have consistently suggested that disruptive life events lead to analysts being more pessimistic and issuing less optimistic forecasts than their counterparts. Yet, there has been no research exploring the impact of fatal disasters without severely negative consequences on analyst forecast performance, which is why we chose to discuss the SARS experience, primarily due to the rapid economic recovery following the SARS event.

2.3. The consequences of SARS

The existing literature on the consequences of SARS primarily focuses on discussing its impacts on the economy, people's psychology and health, and future behavioral decision-making.

In terms of economic consequences, some literature emphasizes the economic damage caused by SARS. For example, Hai et al. (2004) find the SARS outbreak potentially caused a total economic loss of about $25.3 billion and reduced the 2003 GDP growth rate by 1–2 percentage points compared to a scenario without the outbreak. Wong (2008) finds that prices in residential areas of the real estate market directly affected by the epidemic fell by an average of 1–3%, while the overall market experienced a 1.6% decline. However, other studies indicate that the impact of the SARS event on the economy was less severe than expected (Chen et al., 2009; Hanna & Huang, 2004; Noy & Shields, 2019). Specifically, Siu and Wong (2004) point out that despite initial alarmist predictions regarding SARS, the outbreak did not lead to a supply shock, and the economy quickly recovered after the initial panic subsided and the outbreak was controlled.

As for people's psychology and health, some literature finds that the experience of SARS has led people to become more depressed and pessimistic (Bennett et al., 2015; Lau et al., 2005). For instance, Fang and Feng (2021) find that intense exposure to the SARS epidemic significantly increased old-age mortality and suggests that exposure to SARS heightened psychological stress and physical limitations among the elderly. However, other studies show the SARS experience could create a positive effect on mental and physical health. Specifically, Ji et al. (2004) find both Chinese students in Beijing and European Canadians in Toronto exhibited what is known as "unrealistic optimism" and this optimistic bias was more pronounced among the Chinese participants than their Canadian counterparts. Wen et al. (2021) suggest that exposure to an epidemic like SARS, which serves as a significant health shock, may lead to enduring positive alterations in health behaviors among those who survive.

In terms of the impact on future behavioral decision-making, Chen et al. (2020) find that cities with past experiences of SARS in 2003 and strong migration links to Wuhan exhibited earlier, more pronounced, and sustained awareness. This allowed them to be better prepared due to the memory of the previous disaster. Similarly, Ru et al. (2021) show that countries that did not experience SARS in 2003 were slower in their attention and response to COVID-19, while those with prior SARS experience engaged in more intensive searches for COVID-19 information in January 2020 and implemented social distancing policies more rapidly, demonstrating that the profound imprint of similar virus experiences is a key mechanism for timely response to the COVID-19 pandemic. He et al. (2022) suggest that the experience of the SARS epidemic in early life among Chinese influences their willingness to donate for the prevention and control of the COVID-19 pandemic, finding that these experiences have a lasting and profound impact on their willingness to donate.

2.4. Hypothesis development

Tversky and Kahneman (1973) indicate that personal experience plays a crucial role in decision-making, and people often overestimate future risks of salient events based on the availability of heuristics. Numerous subsequent studies have shown that people who experience extremely negative disasters are likely to become more risk-averse or may exhibit more aggressive behavior.

On the one hand, the existing literature suggests that extremely negative events will not only have negative effects on people's sentiments but also experience increased risk perception in unrelated domains (Slovic et al., 2007; Wachinger et al., 2013). The people affected by such events are more likely to predict that such disruptive life events will occur again in the future (Siegrist & Gutscher, 2006) and make more pessimistic risk assessments (Lerner and Keltner, 2001). Among the negative events, infectious diseases stand out as extremely disruptive life events that usually lead to severe fatalities and damage. Consistent with these predictions, the recent literature shows that dangerous infectious diseases can negatively affect individuals' sentiments and general risk perceptions (Benzion et al., 2009; Sun et al., 2021). Motivated by the evidence presented, we predict that analysts with SARS experience will issue less optimistic forecasts.

On the other hand, other studies find that disruptive events can lead people to increase risk tolerance and engage in more aggressive behaviors, with long-lasting effects (Bui et al., 2019; Eckel et al., 2009; Hanaoka et al., 2018). Furthermore, some other studies indicate that people might be more optimistic after experiencing negative events when these events do not cause severe harmful consequences (Bernile et al., 2017; Gao et al., 2020) and focus on the upside of the risk (Erev & Barron, 2005). Regarding the consequences of the SARS epidemic, some studies indicate that the impact of the SARS event on the economy was not as severe as anticipated (Keogh--Brown & Smith, 2008; Noy & Shields, 2019). The rapid recovery of the economy after the SARS epidemic can positively affect analyst sentiment and forecasts, especially considering that the macroeconomic situation (e.g., GDP growth) is crucial information for analysts when making forecasts (Lin et al., 2022; Yang & Chen, 2021). Besides, analysts usually overreact to positive news and underreact to negative news (Easterwood & Nutt, 1999), thus the positive media reports following the epidemic would also promote analysts' optimistic bias. Therefore, we predict that analysts with SARS experience will exhibit more optimism in earnings forecasts than their counterparts.

Based on the above analysis, we propose the following opposing hypotheses:

Hypothesis 1a. Analysts in provinces with more SARS cases issue less optimistic earnings forecasts than their counterparts.

Hypothesis 1b. Analysts in provinces with more SARS cases issue more optimistic earnings forecasts than their counterparts.

3. Data and empirical strategy

3.1. Data sources and descriptive statistics

This subsection describes the data sources and variables used in the estimations. We directly use the analyst forecast information from the China Stock Market and Accounting Research Database (CSMAR) with a sample period starting in 2001. Since several observations from 2001 are excluded from the calculation of the key indicators, our sample actually starts from 2002. Given that the CSMAR doesn't provide analyst characteristic data, we cannot determine whether analysts with the same name are the same person. Thus, we manually supplemented analysts' previous experience information through Chinese Research Data Services (CNRDS) and websites of the Securities Association of China (https://www.sac.net.cn/) and Sohu Security (https://stock.sohu.com/s2011/jlp/) to determine whether analysts with the same name are the same person.

We hand-collect the geographic location of the analysts according to their office locations. Specifically, we collect the broker of the analyst in a specific year from CSMAR and then search the broker's name in the Tianyancha website to identify the analysts' location.[7] We finally define the variable of analysts' exposure to the SARS epidemic according to their location. We collect the SARS cases data

[7] The Tianyancha website: https://www.tianyancha.com/.

from the National Population and Health Science Data Sharing Platform.[8]

We define a variable, ***SARS_Case***, as the natural logarithm of one plus number of SARS infection cases (per 1, 000 people) of analysts' location in 2003.[9] We define a variable, ***Post***, as a dummy variable that equals 1 if the time is after the year 2003 and 0 otherwise. Detailed information on the distribution of SARS-infected patients in Mainland China is presented in Appendix 2.[10]

To obtain the forecast bias information, we retrieve analysts' earnings forecast data from the CSMAR. Forecast bias is calculated using firms' actual annual ***EPS*** and analysts' ***FEPS*** for each year *t*, and the sample is restricted to the analyst *j*'s latest report for firm ***i*** in year *t*. Referring to previous literature (Hong & Kacperczyk, 2010), we measure forecast bias ($\boldsymbol{Bias_{i,j,t}}$) as the difference between the ***FEPS*** for the year *t* made by analyst *j* and the actual ***EPS*** of firm *i* for the year *t*. Specifically, we express ***Bias*** as a percentage of the firm's stock price at the end of the previous year.

$$Bias_{i,j,t} = \frac{FEPS_{i,j,t} - EPS_{i,t}}{Price_{i,t-1}}, \tag{1}$$

where *t* denotes year, *j* denotes analyst, and *i* denotes firm.

Following existing literature (Demers, 2002; Dhaliwal et al., 2012; Jennings et al., 2017; Liu et al., 2022; Platikanova & Mattei, 2016), we control for standard deviation of stock returns over the past 36 months (***RETVOL***), firms' analyst coverage measured by the natural logarithm of one plus the number of analysts constructing earnings forecasts for the firm in a given year (***Coverage***), firm size measured by the natural logarithm of the total assets (***Size***), financial leverage measured by the debt-to-assets ratio of a company (***LEV***), natural logarithm of the number of years since the firm's initial listing (***AGE***), the standard deviation of returns on asset over the past three years (***ROAVOL***), firms' loss status (***LOSS***), cash flow from operations scaled to the total assets (***Cash_Flow***), natural logarithm of the number of days between the fiscal period end date and the forecast issuance date (***LN_Horizon***), the natural logarithm of one plus the number of firms an analyst follows in a specific year (***Ana_Coverage***), the natural logarithm of per capita GDP of the province where the analyst is located (***PCGDP***), and the value of birth rate minus population mortality rate of the province where the analyst is located (***Population_Growth***). Definitions of the variables (including the analysts' forecast bias and SARS exposure) in our empirical tests are summarized in Appendix 1.

Our initial sample is all the analyst-firms observations on the Shenzhen and Shanghai stock exchanges over the 2002–2017 period.[11] In order to conduct DID based on the experimental setting of SARS outbreak, we only keep the analyst earnings forecast observations who released forecast reports in 2003, which is important for determining geographic location information during the SARS epidemic period.[12] We exclude analyst-firms observations when an analyst shares the same name with analyst in 2003 but is different individuals. We further exclude observations of financial firms, firms with negative or zero net assets, and observations with missing data. We also construct data at the analyst-firm-year level for our regression. All of the continuous variables are winsorized at the 1% level at both tails of their distribution to control for extreme outliers. Our matched sample covers 1333 firms, 4121 firm-year observations, and 6020 analyst-firm-year observations between 2002 and 2017. Appendix 3 presents our sample processing process.

Table 1 reports the summary statistics of our main variables. The first row reports the statistics of our considered variables: the value of analysts' forecast bias of firms made in year *t* for the earnings of the same year. The mean of ***Bias*** is 1.096, and the median is 0.6. In our sample, 38.5% of the analysts have SARS experience. On average, for firms, the financial leverage is 46.6%, and the loss is 2.2%. Overall, the sample is comparable to the data in related studies (Liu et al., 2022).

3.2. Empirical strategy

To estimate how SARS exposure affects analyst forecast performance among listed firms, we use a DID approach in the following form as the baseline estimation strategy:

$$Bias_{i,j,t} = \alpha_0 + \alpha_1 SARS\_Case \times Post + \alpha_n Controls_{i,j,t}$$

$$+ Year/Analyst/Broker\ FE + \varepsilon_{ijt}, \tag{2}$$

[8] Website of National Population and Health Science Data Sharing Platform: https://www.phsciencedata.cn/Share/en/index.jsp.

[9] We defined whether an analyst was in an area more severely affected by the epidemic based on work location for two main reasons: (1) work locations are often where analysts spend the most time and have a greater perception of the epidemic; (2) this is a common treatment according to existing literature. For example, Bourveau and Law (2021) examine the impact of hurricanes on analysts' forecasts, and they determine whether analysts are affected by hurricanes through their office locations. Liu et al. (2022) explore analysts' overseas experiences on forecasts and they also judge analysts based on their work and study locations. Fang and Feng (2021) also used the location of the elderly to determine the extent to which they were affected by the epidemic when exploring the effect of epidemic experience on mortality among the elderly.

[10] Source: National Population and Health Science Data Sharing Platform (https://www.phsciencedata.cn/Share/en/index.jsp).

[11] We believe that analyzing the impact of analysts' SARS experience on their behavior is important for two reasons: firstly, analysts at this stage had unique characteristics due to their SARS experience, and their behavior, not yet marketized, was more susceptible to psychological factors, thereby affecting their forecast performance. This provides a richer perspective for our study. Secondly, our focus is on the impact of this experience on analysts' behavior in subsequent years. After the epidemic, the Chinese capital market has become increasingly mature, necessitating this analysis.

[12] We thank two anonymous reviewers and editor for the helpful suggestions.

Table 1
Summary statistics.

Variable	Obs	Mean	Standard deviation	P25	Median	P75
Bias	6020	1.096	2.096	0.080	0.600	1.680
SARS_Case×Post	6020	0.385	0.459	0.007	0.008	0.921
RETVOL	6020	0.138	0.046	0.103	0.132	0.166
Coverage	6020	2.742	0.770	2.197	2.833	3.367
SIZE	6020	22.613	1.661	21.486	22.270	23.296
LEV	6020	0.466	0.215	0.306	0.467	0.622
AGE	6020	1.989	0.678	1.386	2.079	2.565
ROAVOL	6020	0.021	0.021	0.007	0.014	0.026
LOSS	6020	0.022	0.146	0.000	0.000	0.000
Cash_Flow	6020	0.074	0.078	0.025	0.069	0.123
LN_Horizon	6020	4.703	0.933	4.174	4.883	5.513
Ana_Coverage	6020	2.881	0.874	2.303	2.890	3.497
Population_Growth	6020	4.836	2.627	2.700	4.740	7.020
PCGDP	6020	10.761	0.592	10.419	10.836	11.239

where $\boldsymbol{Bias}_{i,j,t}$ is the forecast bias of analyst j for firm i at year t. ***SARS_Case*** is the natural logarithm of one plus the number of SARS cases (per 1, 000 people) of the analyst's location in 2003. ***Post*** is a dummy variable that equals 1 if the time is after the year 2003, and 0 otherwise. Our primary interest is the coefficient α_1, which determines the marginal effect of analysts' SARS exposure on their forecast bias. As described as control variables in the previous section, the vector $\boldsymbol{Controls}_{i,j,t}$ captures other relevant firm-level and analyst-level characteristics. We also include the year fixed effect to eliminate common time trends, and analyst fixed effect to control for time-invariant analyst-specific factors. Furthermore, Cowen et al. (2006) indicate that the types of analysts' firms affect research optimism among securities analysts. In this case, the optimistic bias may result from the firms that analysts work for rather than their SARS exposure experience. Therefore, we further control the working firms (i.e., brokerage firms) fixed effect to alleviate this concern. ε_{ijt} is the error term.

4. Main results

4.1. Baseline results

The baseline estimation, Equation (2), is used to explore the relationship between analysts' SARS exposure and forecast bias. Table 2 presents the estimation results. The dependent variable is ***Bias***. Column (1) reports the estimation results with year and analyst fixed effects. Column (2) shows the estimation results when we further control all year- and analyst-level control variables. Column (3) shows the estimation results when we further include the broker fixed effects. The coefficient of ***SARS_Case×Post*** is 0.679 in Column (3), which is significant at the 5% level. The results suggest that the SARS exposure experience is associated with an increase in forecast bias and makes analysts issue more optimistic earnings forecasts.

As for the control variables, the coefficient of ***Coverage*** in Column (3) is −0.44 and significant at the 1% level, indicating that firms with a higher level of analyst coverage can construct less biased earnings forecasts than their peers, which is consistent with the existing literature (Hong & Kacperczyk, 2010). For other control variables, forecast bias increases with firms' leverage (***LEV***), age (***AGE***), volatility of profitability (***ROAVOL***), loss status (***LOSS***), and forecast horizon (***LN_Horizon***). On the contrary, forecast bias is lower for firms with a higher level of operating cash flow (***Cash_Flow***).

4.2. Robustness tests

4.2.1. Parallel trend tests

In this subsection, we test whether firms experienced different trends in forecast bias before analysts' SARS exposure. Specifically, we run regression (2) as follows to examine the parallel trends through event studies:

$$Bias_{i,j,t} = \alpha_0 + \sum_{t=2002}^{2017} \alpha_1 Y_t \times SARS\_Case + \alpha_n Controls_{i,j,t}$$
$$+ Year/Aanalyst/Broker\ FE + \varepsilon_{ijt}, \tag{3}$$

We construct the interaction term ($\boldsymbol{Y_t} \times \boldsymbol{SARS\_Case}$) between the year dummy variable and the indicator of SARS exposure, where the year 2003 is used as the baseline. The year dummy variable, $\boldsymbol{Y_{2002}}$, is equal to 1 for observations for the year 2002 and 0 otherwise. Other year dummy variables $\boldsymbol{Y_{2004}}$, $\boldsymbol{Y_{2005}}$, $\boldsymbol{Y_{2006}}$, $\boldsymbol{Y_{2007}}$, $\boldsymbol{Y_{2008}}$, $\boldsymbol{Y_{2009}}$, $\boldsymbol{Y_{2010}}$, $\boldsymbol{Y_{2011}}$, $\boldsymbol{Y_{2012}}$, $\boldsymbol{Y_{2013}}$, $\boldsymbol{Y_{2014}}$, $\boldsymbol{Y_{2015}}$, $\boldsymbol{Y_{2016}}$, *and* $\boldsymbol{Y_{2017}}$ are defined similarly.

The regression results are shown in Table 3. The results show that the coefficient of $\boldsymbol{Y_{2002}} \times \boldsymbol{SARS\_Case}$ is statistically insignificant, indicating that the forecast bias for analysts with different SARS exposure is similar before SARS outbreaks. Conversely, after the SARS outbreaks, we find that the coefficients on the interaction terms are significantly positive. Overall, the result in Table 3 is consistent with the parallel trend assumption and thus validates the analysis of the DID model. Besides, this finding indicates that the effect of

Table 2
Baseline results.

	Dependent Variable: *Bias*		
	(1)	(2)	(3)
SARS_Case × *Post*	0.450*	0.664***	0.679**
	(1.87)	(2.91)	(2.40)
RETVOL		−0.869	−0.775
		(-0.91)	(-0.81)
Coverage		−0.447***	−0.440***
		(-7.71)	(-7.57)
SIZE		0.042	0.045
		(1.42)	(1.53)
LEV		0.808***	0.774***
		(3.79)	(3.68)
AGE		0.267***	0.267***
		(5.89)	(5.97)
ROAVOL		7.262***	7.288***
		(3.71)	(3.74)
LOSS		3.737***	3.755***
		(11.03)	(10.98)
Cash_Flow		−4.341***	−4.323***
		(-9.02)	(-9.03)
LN_Horizon		0.356***	0.358***
		(13.37)	(13.23)
Ana_Coverage		−0.076	−0.051
		(-1.28)	(-0.78)
Population_Growth		0.011	−0.063
		(0.35)	(-1.31)
PCGDP		0.165	−0.286
		(0.80)	(-0.69)
Constant	0.922***	−2.872	2.160
	(9.52)	(-1.18)	(0.46)
Analyst FE	YES	YES	YES
Year FE	YES	YES	YES
Broker FE	NO	NO	YES
N	6020	6020	6020
Adjusted R^2	0.087	0.279	0.284

Notes: This table represents the coefficients of regressions examining the effect of analysts' SARS epidemic experience on the forecast bias for the listed firms in China. The dependent variable is the forecast bias (***Bias***). ***SARS_Case***×***Post*** is the interaction term of ***SARS_Case*** and ***Post***. All variables are defined in section 3 and Appendix 1. Fixed effects of analyst, year, and broker are controlled. *t*-statistics (reported in parentheses) are based on standard errors clustered by firm level. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

SARS exposure on forecast bias becomes apparent from the second year following SARS outbreaks ($\boldsymbol{Y_{2005}}$ × ***SARS_Case)***, with the coefficient and statistical significance increasing in the third year ($\boldsymbol{Y_{2006}}$ × ***SARS_Case***) but decreasing in the fourth year ($\boldsymbol{Y_{2007}}$ × ***SARS_Case***) as shown in Column (2). This effect persists until 2015, suggesting that the SARS experience of analysts has a long-term effect on their forecast performance. However, the results were not significant in 2008 and between 2012 and 2013. We predict that the insignificance in 2008 was primarily due to the market being impacted by the financial crisis, which suppressed analysts' optimism. As for the non-significant results in 2012 and 2013, the downturn in China's economy was the main influence.

4.2.2. Alternative measurement of variable

In this subsection, we conduct two additional tests to confirm the robustness of our findings. First, we re-measure our dependent variable in two alternative ways. Following the existing literature (Kong et al., 2021), we measure forecast bias (***Bias1***) as the difference between the FEPS and the actual EPS, scaled by the actual EPS, multiplied by 100. Following Dehaan et al. (2017), we further measure forecast optimism relative to consensus forecasts (***Bias2***) to proxy for analysts' risk perception. Specifically, it is defined as an analyst's FEPS minus the consensus FEPS (the median of a firm's FEPS among all analysts), scaled by price in year t-1. Columns (1) and (2) of Panel A in Table 4 show that the coefficients of ***SARS_Case*** × ***Post*** are 0.689 and 0.293, respectively, and are statistically significant at the 5% and 10% levels, respectively. These results are consistent with the findings in Table 2, indicating that the main results are robust to alternative forecast bias measurement.

Second, we re-measure our independent variable in two alternative ways. On the one hand, we re-measure our SARS exposure by the SARS cases divided by the permanent resident population at the beginning of the year 2003 in a specific province (***SARS_PP***). On the other hand, we use a dummy variable to measure the SARS exposure. Specifically, we define ***Exp_SARS*** as a dummy variable that equals one if the analyst worked in the province with SARS cases during the period of the SARS epidemic, and zero otherwise. Columns (1) and (2) of Panel B in Table 4 show that the coefficient of ***SARS_PP*** × ***Post*** is 1.059 and significant at the 10% level and the coefficient of ***Exp_SARS*** × ***Post*** is 1.099 and significant at the 5% level. These results suggest that our main findings are robust to alternative SARS exposure measurement.

Table 3
Parallel trends assumption.

	Dependent Variable: *Bias*	Dependent Variable: *Bias*
	(1)	(2)
Y_{2002}×*SARS_Case*	−0.744	−0.790
	(-0.84)	(-1.34)
Y_{2004}×*SARS_Case*	0.447	0.425
	(0.94)	(0.89)
Y_{2005}×*SARS_Case*	0.642	0.637**
	(1.57)	(1.98)
Y_{2006}×*SARS_Case*	1.514***	1.383***
	(3.14)	(3.03)
Y_{2007}×*SARS_Case*	0.781**	0.693*
	(2.00)	(1.72)
Y_{2008}×*SARS_Case*	0.314	0.534
	(0.85)	(1.40)
Y_{2009}×*SARS_Case*	0.637	0.701*
	(1.64)	(1.80)
Y_{2010}×*SARS_Case*	0.646*	0.748**
	(1.79)	(1.99)
Y_{2011}×*SARS_Case*	0.768**	0.722*
	(2.11)	(1.89)
Y_{2012}×*SARS_Case*	0.713*	0.492
	(1.82)	(1.17)
Y_{2013}×*SARS_Case*	0.456	0.430
	(1.07)	(0.97)
Y_{2014}×*SARS_Case*	0.909*	0.863*
	(1.88)	(1.82)
Y_{2015}×*SARS_Case*	1.373**	1.114*
	(2.22)	(1.83)
Y_{2016}×*SARS_Case*	0.557	0.196
	(0.62)	(0.22)
Y_{2017}×*SARS_Case*	−0.747	−0.778
	(-1.34)	(-1.53)
RETVOL		−0.855
		(-0.89)
Coverage		−0.443***
		(-7.62)
SIZE		0.050*
		(1.68)
LEV		0.774***
		(3.66)
AGE		0.263***
		(5.86)
ROAVOL		7.502***
		(3.84)
LOSS		3.741***
		(10.99)
Cash_Flow		−4.317***
		(-9.03)
LN_Horizon		0.359***
		(13.15)
Ana_Coverage		−0.032
		(-0.47)
Population_Growth		−0.035
		(-0.60)
PCGDP		−0.135
		(-0.32)
Constant	0.844***	0.267
	(6.64)	(0.06)
Analyst FE	YES	YES
Year FE	YES	YES
Broker FE	YES	YES
N	6020	6020
Adjusted R^2	0.094	0.286

Notes: This table represents the results of parallel trends estimation. The year dummy variable, $\boldsymbol{Y_{2002}}$, is equal to 1 for observations for the year 2002 and 0 otherwise. Other year dummy variables $\boldsymbol{Y_{2004}}$, $\boldsymbol{Y_{2005}}$, $\boldsymbol{Y_{2006}}$, $\boldsymbol{Y_{2007}}$, $\boldsymbol{Y_{2008}}$, $\boldsymbol{Y_{2009}}$, $\boldsymbol{Y_{2010}}$, $\boldsymbol{Y_{2011}}$, $\boldsymbol{Y_{2012}}$, $\boldsymbol{Y_{2013}}$, $\boldsymbol{Y_{2014}}$, $\boldsymbol{Y_{2015}}$, $\boldsymbol{Y_{2016}}$, ***and*** $\boldsymbol{Y_{2017}}$ are defined similarly. All variables are defined in section 3 and Appendix 1. Fixed effects of analyst, year, and broker are controlled. *t*-statistics (reported in parentheses) are based on standard errors clustered by firm level. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

Table 4
Robustness tests: Alternative measurement.

Panel A: Alternative Dependent Measurement

	Dependent Variable: *Bias1*	Dependent Variable: *Bias2*
	(1)	(2)
SARS_Case × *Post*	0.689**	0.293*
	(2.43)	(1.89)
RETVOL	−0.780	0.415
	(-0.85)	(0.86)
Coverage	−0.436***	0.057**
	(-7.54)	(2.23)
SIZE	0.045	0.008
	(1.53)	(0.59)
LEV	0.756***	0.011
	(3.61)	(0.11)
AGE	0.264***	−0.003
	(5.94)	(-0.13)
ROAVOL	7.315***	0.968
	(3.80)	(1.13)
LOSS	3.706***	−0.291**
	(11.16)	(-2.46)
Cash_Flow	−4.290***	−0.015
	(-9.06)	(-0.07)
LN_Horizon	0.357***	0.215***
	(13.26)	(12.85)
Ana_Coverage	−0.048	−0.014
	(-0.75)	(-0.38)
Population_Growth	−0.057	−0.028
	(-1.16)	(-1.03)
PCGDP	−0.267	0.018
	(-0.65)	(0.07)
Constant	1.923	−1.396
	(0.41)	(-0.50)
Analyst FE	YES	YES
Year FE	YES	YES
Broker FE	YES	YES
N	6020	6020
Adjusted R^2	0.284	0.076

Panel B: Alternative Independent Measurement

	Dependent Variable: *Bias*	
	(1)	(2)
SARS_PP × *Post*	1.059*	
	(1.85)	
Exp_SARS × *Post*		1.099**
		(2.01)
RETVOL	−0.765	−0.789
	(-0.80)	(-0.83)
Coverage	−0.442***	−0.443***
	(-7.59)	(-7.62)
SIZE	0.046	0.047
	(1.54)	(1.58)
LEV	0.774***	0.772***
	(3.67)	(3.66)
AGE	0.268***	0.267***
	(5.97)	(5.96)
ROAVOL	7.268***	7.263***
	(3.74)	(3.75)
LOSS	3.757***	3.760***
	(10.99)	(11.00)
Cash_Flow	−4.327***	−4.308***
	(-9.04)	(-8.98)
LN_Horizon	0.355***	0.356***
	(13.18)	(13.22)
Ana_Coverage	−0.055	−0.046
	(-0.84)	(-0.71)
Population_Growth	−0.099**	−0.110**
	(-2.24)	(-2.49)
PCGDP	−0.362	−0.384

(*continued on next page*)

Table 4 (*continued*)

Panel B: Alternative Independent Measurement

	Dependent Variable: *Bias*	
	(1)	(2)
	(-0.88)	(-0.93)
Constant	3.302	2.698
	(0.71)	(0.58)
Analyst FE	YES	YES
Year FE	YES	YES
Broker FE	YES	YES
N	6020	6020
Adjusted R^2	0.284	0.284

Notes: This table represents the robust results when re-measure the key variables. In Panel A, the dependent variables are the ***Bia1*** and ***Bia2***. ***SARS_Case*×*Post*** is the interaction term of ***SARS_Case*** and ***Post***. In Panel B, the dependent variable is the forecast bias (***Bias***). ***SARS_PP*** is the SARS cases divided by the permanent resident population at the begin of year 2003 in a specific province. ***Exp_SARS*** is a dummy variable that equals one if analysts worked in provinces with SARS cases during the period of SARS epidemic, and zero otherwise. All variables are defined in section 3 and Appendix 1. Fixed effects of analyst, year, and broker are controlled. *t*-statistics (reported in parentheses) are based on standard errors clustered by firm level. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

Table 5
Robustness tests: Excluding Analyst Working City Factors.

	Dependent Variable: *Bias*	
	(1)	(2)
SARS_Case×Post	0.753**	0.674**
	(2.52)	(2.38)
RETVOL		−0.775
		(-0.81)
Coverage		−0.440***
		(-7.56)
SIZE		0.046
		(1.53)
LEV		0.775***
		(3.67)
AGE		0.266***
		(5.94)
ROAVOL		7.277***
		(3.74)
LOSS		3.752***
		(10.96)
Cash_Flow		−4.320***
		(-9.03)
LN_Horizon		0.358***
		(13.14)
Ana_Coverage		−0.048
		(-0.73)
Population_Growth		−0.057
		(-1.13)
PCGDP		0.021
		(0.03)
Constant	0.806***	−1.182
	(7.04)	(-0.17)
Analyst FE	YES	YES
Year FE	YES	YES
Broker_City FE	YES	YES
N	6020	6020
Adjusted R^2	0.093	0.284

Notes: This table represents the robust results when we exclude analyst working city factors. The dependent variable is the forecast bias (***Bias***). ***SARS_Case*×*Post*** is the interaction term of ***SARS_Case*** and ***Post***. All variables are defined in section 3 and Appendix 1. Fixed effects of year, analyst, and working city are controlled. *t*-statistics (reported in parentheses) are based on standard errors clustered by firm level. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

4.2.3. Excluding the factor of analysts' working cities

Our findings might also be driven by the analysts' working locations. Kong et al. (2018) suggest that analysts' workplace-level factors affect analysts' forecast accuracy, and workplace's air pollution significantly reduces analysts' earnings forecast accuracy in response to earnings announcements. Thus, we collect the analysts' address information according to their brokerage firms and then

Table 6
Robustness tests: Excluding listed firms factors.

	Dependent Variable: *Bias*	
	(1)	(2)
SARS_Case×Post	0.738***	0.675**
	(2.62)	(2.41)
RETVOL		−0.327
		(-0.31)
Coverage		−0.447***
		(-7.74)
SIZE		0.043
		(1.37)
LEV		0.793***
		(3.74)
AGE		0.265***
		(5.57)
ROAVOL		6.948***
		(3.54)
LOSS		3.663***
		(11.14)
Cash_Flow		−4.248***
		(-8.45)
LN_Horizon		0.367***
		(12.77)
Ana_Coverage		−0.021
		(-0.32)
Population_Growth		−0.071
		(-1.45)
PCGDP		−0.085
		(-0.20)
Constant	0.808***	−0.081
	(7.52)	(-0.02)
Analyst FE	YES	YES
Broker FE	YES	YES
Province×Year FE	YES	YES
N	5975	5975
Adjusted R^2	0.142	0.323

Note: This table represents the robust results when we exclude the listed firms factor. The dependent variable is the forecast bias (***Bias***). ***SARS_Case×Post*** is the interaction term of ***SARS_Case*** and ***Post***. All variables are defined in section 3 and Appendix 1. Fixed effects of analyst, broker, and interaction of year and province are controlled. *t*-statistics (reported in parentheses) are based on standard errors clustered by firm level. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

manually collect the specific city information of the analysts via Tianyancha website. In our regression, we further control for the working city fixed effect to control for the workplace environment factors.

Table 5 reports the estimated results. The coefficients of ***SARS_Case*** × ***Post*** are 0.753 and 0.674, respectively, and both are significant at the 5% level when we control for the analysts' working city fixed effects. The results are qualitatively similar when we further control the working firm fixed effect, as reported in Table 2. Therefore, differences in working cities among the analysts are less likely to be the mechanism through which they issue a more biased forecast.

4.2.4. Excluding the factor of listed firms

Furthermore, our results might be driven by the listed firms' location information. The optimistic forecast might also be driven by the earnings status of SARS-affected listed firms, which is affected by the economic status after the epidemic of the province where the listed firm is located. Thus, we further control the interaction of province and year fixed effects to control for possible contemporaneous effects at the province level.

Table 6 reports the estimated results. The coefficients of ***SARS_Case*** × ***Post*** are 0.738 and 0.675, respectively, and significant at the 1% and 5% levels, respectively. The results are consistent with our main findings. Therefore, differences in province factors of listed firms, which are affected by the epidemic, are less likely to be the mechanism through which more optimistic forecasts are issued.

4.3. Event salience and analysts' forecast bias

Our main results indicate that the SARS epidemic experience can make analysts issue more optimistic forecasts. Thus, we predict that a more salient impact of the SARS epidemic will generate more optimistic biased earnings forecasts. To verify this prediction, we use two measures of salience. First, we use the number of deaths from SARS, measured by the natural logarithm of the number of deaths (in 1000 people) plus one (***Number of Deaths***). Second, following Fang and Feng (2021), the long duration of exposure to SARS could be one of the causes of psychological problems. Specifically, the duration of SARS (***SARS_Duration***) in each province is measured

Table 7
Event salience and analyst forecast Bias.

	Dependent Variable: *Bias*	
	(1)	(2)
Number of Deaths ×Post	9.660**	
	(2.49)	
SARS_Duration×Post		0.004**
		(2.48)
RETVOL	−0.768	−0.780
	(-0.80)	(-0.82)
Coverage	−0.441***	−0.441***
	(-7.57)	(-7.58)
SIZE	0.045	0.046
	(1.52)	(1.54)
LEV	0.774***	0.774***
	(3.68)	(3.68)
AGE	0.268***	0.267***
	(5.98)	(5.97)
ROAVOL	7.276***	7.294***
	(3.74)	(3.75)
LOSS	3.755***	3.756***
	(10.99)	(10.98)
Cash_Flow	−4.326***	−4.317***
	(-9.04)	(-9.02)
LN_Horizon	0.358***	0.359***
	(13.23)	(13.26)
Ana_Coverage	−0.052	−0.047
	(-0.80)	(-0.73)
Population_Growth	−0.072	−0.067
	(-1.55)	(-1.40)
PCGDP	−0.301	−0.286
	(-0.73)	(-0.69)
Constant	2.376	1.916
	(0.51)	(0.41)
Analyst FE	YES	YES
Year FE	YES	YES
Broker FE	YES	YES
N	6020	6020
Adjusted R^2	0.284	0.284

Note: This table represents further results. The dependent variable is the forecast bias (***Bias***). ***Number of Deaths*** is measured by natural logarithm of the number of deaths (per 1, 000 people) plus one. The duration of SARS (***SARS_Duration***) in each province is measured by the period between the first SARS case report date in a province until June 25, 2003. All variables are defined in section 3 and Appendix 1. Fixed effects of analyst, year, and broker are controlled. *t*-statistics (reported in parentheses) are based on standard errors clustered by firm level. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

by the period between the first SARS case report date in a province until June 25, 2003, when mainland China was removed from the list of SARS epidemic areas. We match these province-level data with our earnings forecast data based on the analysts' location.

Table 7 reports the estimated results. The coefficient of ***Number of Deaths*** × ***Post*** is 9.66 and significant at the 5% level in Column (1). The coefficient of ***SARS_Duration*** × ***Post*** is 0.004 and significant at the 5% level in Column (2). Collectively, the results in this section indicate that the analysts in provinces perceived as more salient during the SARS epidemic period generate more optimistically biased earnings forecasts than their counterparts.

4.4. SARS exposure and forecast accuracy

We find that the analysts affected by SARS issue more optimistic earnings forecasts. However, it remains unclear whether these optimistic biases stemming from SARS exposure lead to less accurate forecast accuracy or actually improve accuracy. In this subsection, we investigate whether SARS exposure-induced optimism affects analysts' accuracy. Thus, following the previous literature (Hong & Kubik, 2003; Liu et al., 2022), we measure forecast error (***FERROR1***) as the absolute difference between the analysts' FEPS for the year-ended *t* made by analyst *j* minus the actual ***EPS*** of firm *i* for the year-ended *t*, scaled by the ending stock price of firm *i* for the year-ended t-1.

The estimated results for the forecast accuracy in Table 8 suggest that the analysts with SARS exposure experience are less accurate than their counterparts. This finding is consistent with the existing literature that sentiment-induced optimistic bias negatively affects forecast performance. Our results are robust regardless of whether we include the control variables.

Table 8
SARS exposure and forecast accuracy.

	Dependent Variable: *FERROR1*	
	(1)	(2)
SARS_Case×Post	0.527**	0.592**
	(1.99)	(2.42)
RETVOL		1.673*
		(1.85)
Coverage		−0.436***
		(-8.02)
SIZE		0.124***
		(4.23)
LEV		1.127***
		(6.14)
AGE		0.188***
		(4.72)
ROAVOL		16.555***
		(9.29)
LOSS		3.243***
		(9.26)
Cash_Flow		−1.856***
		(-4.78)
LN_Horizon		0.428***
		(16.62)
Ana_Coverage		−0.047
		(-0.94)
Population_Growth		−0.027
		(-0.61)
PCGDP		0.110
		(0.31)
Constant	1.308***	−4.670
	(12.32)	(-1.14)
Analyst FE	YES	YES
Year FE	YES	YES
Broker FE	YES	YES
N	6020	6020
Adjusted R^2	0.112	0.344

Note: This table represents the results of SARS exposure and forecast accuracy. The dependent variable is the forecast error(***FERROR***). ***SARS_Case×Post*** is the interaction term of ***SARS_Case*** and ***Post***. All variables are defined in section 3 and Appendix 1. Fixed effects of analyst, year, and broker are controlled. *t*-statistics (reported in parentheses) are based on standard errors clustered by firm level. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

5. Mechanism and heterogeneity

5.1. Possible mechanism

Thus far, we have obtained evidence that the analyst's SARS exposure could promote optimistic bias. Our findings are consistent with our second prediction (Hypothesis 1b). In this subsection, we further verify the mechanism. Specifically, we construct a new variable that reflects the deviation between the actual consequence and the predicted impact of the SARS outbreak over different areas to capture the effect of availability heuristics.[13] Existing research indicates that both the macroeconomic situation (Bochkay & Joos, 2021; Lin et al., 2022; Pavlopoulou-Lelaki, 2023; Yang & Chen, 2021) and micro-level media reports about listed firms (Cao et al., 2022; Frijns & Huynh, 2018; Jiang & Hong, 2021; Kyung & Tsang, 2022) are significant sources of information for analyst forecasts. Therefore, we aim to investigate the specific impact mechanisms by examining the macroeconomic growth before and after the pandemic, as well as changes in the sentiment of media reports for firms followed by analysts during the SARS epidemic.

First, as for the macroeconomic growth, Pavlopoulou-Lelaki (2023) reveals that analysts positively link expected GDP growth to corporate earnings growth. Thus, we predict that the unexpected economic growth patterns where analysts are located during the SARS outbreak (i.e., year 2003) can affect analysts' sentiment. If the economy recovers quickly after the SARS outbreak, analysts will become more optimistic and feel that the impact of the epidemic is not significant.

Thus, we manually collected the target GDP growth data for each province in the government work report and the actual GDP growth data from the National Bureau of Statistics of China.[14] We define an analyst as more affected by a high level of unexpected economic growth if they are located in a province where the difference between actual GDP growth minus target GDP growth is above

[13] We thank reviewers for this helpful suggestion.
[14] The website is http://www.stats.gov.cn/.

Table 9
Mechanism: The unexpected economic growth in 2003.

	Dependent Variable: *Bias*	
	High Level of Unexpected Economic Growth	Low Level of Unexpected Economic Growth
	(1)	(2)
SARS_Case×Post	1.497**	0.196
	(2.47)	(0.69)
RETVOL	1.268	−1.182
	(0.85)	(-0.78)
Coverage	−0.334***	−0.565***
	(-3.88)	(-5.38)
SIZE	0.038	0.125**
	(0.80)	(2.26)
LEV	0.581*	0.556*
	(1.92)	(1.67)
AGE	0.157**	0.366***
	(2.35)	(4.80)
ROAVOL	4.727*	9.794***
	(1.77)	(2.90)
LOSS	3.725***	3.946***
	(6.24)	(8.14)
Cash_Flow	−3.676***	−5.566***
	(-5.69)	(-7.68)
LN_Horizon	0.364***	0.397***
	(8.86)	(7.44)
Ana_Coverage	0.045	−0.123
	(0.40)	(-1.30)
Population_Growth	−0.249**	0.066
	(-2.44)	(0.61)
PCGDP	−1.163**	0.111
	(-2.01)	(0.11)
Constant	11.407*	−3.783
	(1.70)	(-0.34)
Analyst FE	YES	YES
Year FE	YES	YES
Broker FE	YES	YES
Diff in Coef: High vs. Low	*p*-value = 0.0421**	
N	2271	2161
Adjusted R^2	0.245	0.299

Note: This table represents the results of mechanism. The dependent variable is the forecast bias (***Bias***). ***SARS_Case×Post*** is the interaction term of ***SARS_Case*** and ***Post***. All variables are defined in section 3 and Appendix 1. Fixed effects of analyst, year, and broker are controlled. *t*-statistics (reported in parentheses) are based on standard errors clustered by firm level. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

the sample median in 2003. Otherwise, we define analysts as more affected by a low level of unexpected economic growth.

Table 9 reports the estimation results of how analysts' SARS exposure experience affects forecast bias for analysts located in provinces with high and low levels of unexpected economic growth differently. The coefficient of ***SARS_Case*** × ***Post*** is 1.497 and significant at the 5% level in Column (1), but 0.196 and insignificant in Column (2). Overall, the results indicate that the high level of unexpected economic growth can motivate the SARS exposure-induced optimistic forecast bias.

Second, existing studies show that media reports are a crucial channel for analysts to acquire information on publicly listed companies, and the sentiment of media reports can affect the forecast bias among analysts (Cao et al., 2022; Frijns & Huynh, 2018; Jiang & Hong, 2021; Kyung & Tsang, 2022). Thus, we believe that changes in the sentiment of media reports about publicly listed companies before and after the SARS pandemic will impact analysts' sentiment and thus affect forecast bias.[15] Specifically, if there are more positive reports about publicly listed companies after the pandemic, it may lead to analysts developing a greater tendency towards optimistic bias.

We collected data on listed firms' online media news reports during the pandemic from the CNRDS database, and manually compiled sentiment indicators of online news media reports of listed companies during and in the year following the pandemic. Specifically, we define unexpected positive reports of listed companies as the net positive news reports (i.e., the number of positive reports minus the number of negative reports) in the year following the pandemic minus the net positive news reports during the SARS pandemic. We classify analysts as more affected by a high level of unexpected positive reports if the unexpected positive reports of the listed firms they followed in 2003 are above the sample median in 2003. Otherwise, they are classified as more affected by a low level

[15] We thank reviewers for considering exploring the emotional content of media coverage as part of the mechanism analysis.

Table 10
Mechanism: The unexpected positive report in 2003.

	Dependent Variable: *Bias*	
	High Level of Unexpected Positive Report	Low Level of Unexpected Positive Report
	(1)	(2)
SARS_Case×Post	1.063**	−0.183
	(2.45)	(-0.35)
RETVOL	−1.085	1.743
	(-0.80)	(0.92)
Coverage	−0.510***	−0.337***
	(-5.46)	(-2.86)
SIZE	0.100**	0.033
	(2.32)	(0.54)
LEV	0.284	0.950**
	(0.93)	(2.50)
AGE	0.270***	0.245***
	(3.82)	(2.94)
ROAVOL	12.112***	1.222
	(3.98)	(0.37)
LOSS	3.858***	3.743***
	(7.83)	(5.71)
Cash_Flow	−4.878***	−4.580***
	(-7.21)	(-6.04)
LN_Horizon	0.401***	0.355***
	(9.10)	(6.74)
Ana_Coverage	−0.147	−0.153
	(-1.59)	(-1.06)
Population_Growth	−0.055	−0.003
	(-0.67)	(-0.03)
PCGDP	−0.389	0.367
	(-0.68)	(0.33)
Constant	2.361	−4.693
	(0.36)	(-0.37)
Analyst FE	YES	YES
Year FE	YES	YES
Broker FE	YES	YES
Diff in Coef: High vs. Low	*p*-value = 0.0493**	
N	2596	1452
Adjusted R^2	0.281	0.276

Note: This table represents the results of mechanism. The dependent variable is the forecast bias (***Bias***). ***SARS_Case×Post*** is the interaction term of ***SARS_Case*** and ***Post***. All variables are defined in section 3 and Appendix 1. Fixed effects of analyst, year, and broker are controlled. *t*-statistics (reported in parentheses) are based on standard errors clustered by firm level. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

of unexpected positive report.

Table 10 reports the estimation results of how analysts' SARS exposure experience affects forecast bias for analysts following firms with high and low levels of unexpected positive report differently. The coefficient of ***SARS_Case*** × ***Post*** is 1.063 and significant at the 5% level in Column (1), but −0.183 and insignificant in Column (2). Overall, the results indicate that the high level of unexpected positive sentiment of firms that analysts were following during the SARS epidemic can motivate the SARS exposure-induced optimistic forecast bias.

5.2. Cross-sectional analysis

Our mechanism test reveals that unexpected economic growth observed by analysts during the pandemic, coupled with unexpectedly positive media coverage of companies they track, impacts their emotions, leading to a more optimistic outlook and consequently, reports with higher levels of optimistic forecast bias. In the heterogeneity section, to align with our mechanism findings, we grouped the samples based on analysts' susceptibility to emotional or psychological influences. Specifically, we examined three variables: the analysts' busyness, gender, and industry specialization. We hypothesize that analysts who are busier, are female, and have a lower level of industry specialization are more susceptible to psychological or emotional influences, thus exhibiting more pronounced optimistic bias in their forecasts.

5.2.1. Analyst busyness

Existing studies document that busy analysts face effort and time constraints and the busyness of analysts can significantly impair the quality of forecast performance (Clement, 1999; Kini et al., 2020). Specifically, Clement (1999) notes that analysts who follow a

Table 11
Heterogeneity: Analyst's busyness.

	Dependent Variable: *Bias*	
	High Level of Busyness	Low Level of Busyness
	(1)	(2)
SARS_Case×Post	1.635**	0.279
	(2.33)	(0.70)
RETVOL	−0.963	−0.471
	(-0.83)	(-0.36)
Coverage	−0.391***	−0.494***
	(-5.40)	(-6.14)
SIZE	0.056	0.044
	(1.52)	(1.15)
LEV	0.262	1.091***
	(1.05)	(3.74)
AGE	0.291***	0.264***
	(5.35)	(4.39)
ROAVOL	3.890	10.762***
	(1.64)	(3.91)
LOSS	4.205***	3.328***
	(8.82)	(8.04)
Cash_Flow	−4.404***	−4.422***
	(-8.14)	(-6.46)
LN_Horizon	0.327***	0.385***
	(8.86)	(9.58)
Ana_Coverage	−0.180	−0.002
	(-0.95)	(-0.01)
Population_Growth	0.179*	−0.102
	(1.69)	(-1.22)
PCGDP	0.289	−1.105*
	(0.46)	(-1.74)
Constant	−4.972	11.018
	(-0.69)	(1.54)
Analyst FE	YES	YES
Year FE	YES	YES
Broker FE	YES	YES
Diff in Coef: High vs. Low	*p*-value = 0.0755*	
N	2815	3189
Adjusted R^2	0.297	0.292

Note:This table represents the results of heterogeneity among analyst's busyness.The dependent variable is the forecast bias (***Bias***). ***SARS_Case×Post*** is the interaction term of variable ***SARS_Case*** and ***Post***. All variables are defined in section 3 and Appendix 1. Fixed effects of analyst, year, and broker are controlled. *t*-statistics (reported in parentheses) are based on standard errors clustered by firm level. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

large number of companies and industries typically face greater task complexity and have less time to devote to each company they follow. In this case, we predict that the busy analysts would be more affected by their sentiment due to the SARS exposure experience when they issue forecast reports.

Following prior research (Clement, 1999; Kini et al., 2020), we measure analyst busyness as the number of firms followed by an analyst. We classify analysts whose number of firms followed is above the sample median in a specific year as analysts with a high level of busyness and as analysts with a low level of busyness otherwise.

Table 11 reports the estimation results of how analysts' SARS exposure experience affects analysts with low and high levels of busyness differently. The coefficient of ***SARS_Case*** × ***Post*** is 1.635 and significant at the 5% level in Column (1), but 0.279 and insignificant in Column (2). Overall, the results indicate that the high level of busyness of analysts can further motivate the SARS exposure-induced optimistic forecast bias.

5.2.2. Analyst industry specialization

Previous studies have highlighted the significance of analysts' industry expertise, noting that analysts often specialize in covering firms within the same industry, and this specialization can have a notable influence on the performance of their forecasts (Boni & Womack, 2006; Clement, 1999; Gilson et al., 2001; Jacob et al., 1999; Mehtra et al., 2018). In particular, Boni and Womack (2006) discover that analysts demonstrate exceptional skill in ordering individual stocks within specific industries. In this case, we predict that the analysts with a higher degree of industry specialization would be less affected by their sentiment incurred by the SARS exposure experience when they issue forecast reports.

Following prior research (Mehtra et al., 2018), we measure analyst industry specialization as the number of years between the analyst's first forecast for a specific industry in the database and the year t report. We classify analysts whose following years of specific

Table 12
Heterogeneity: Analyst's industry specialization.

	Dependent Variable: *Bias*	
	Low Level of Industry Specialization	High Level of Industry Specialization
	(1)	(2)
SARS_Case×Post	0.904***	−0.334
	(2.62)	(-0.50)
RETVOL	−0.407	−1.888
	(-0.38)	(-1.12)
Coverage	−0.536***	−0.229**
	(-8.02)	(-2.42)
SIZE	0.051	0.075
	(1.57)	(1.29)
LEV	1.059***	0.238
	(4.32)	(0.75)
AGE	0.295***	0.106
	(5.96)	(1.46)
ROAVOL	7.488***	5.055*
	(3.53)	(1.69)
LOSS	3.643***	3.811***
	(9.64)	(6.20)
Cash_Flow	−4.607***	−3.007***
	(-8.23)	(-4.93)
LN_Horizon	0.398***	0.245***
	(12.15)	(4.99)
Ana_Coverage	0.004	−0.149
	(0.04)	(-1.39)
Population_Growth	−0.046	−0.223**
	(-0.72)	(-2.50)
PCGDP	−0.259	−1.137
	(-0.56)	(-1.06)
Constant	1.302	12.819
	(0.25)	(1.06)
Analyst FE	YES	YES
Year FE	YES	YES
Broker FE	YES	YES
Diff in Coef: High vs. Low	*p*-value = 0.0953*	
N	4456	1545
Adjusted R^2	0.298	0.256

Note:This table represents the results of heterogeneity among analyst's industry specialization.The dependent variable is the forecast bias (***Bias***). ***SARS_Case×Post*** is the interaction term of ***SARS_Case*** and ***Post***. All variables are defined in section 3 and Appendix 1. Fixed effects of analyst, year, and broker are controlled. *t*-statistics (reported in parentheses) are based on standard errors clustered by firm level. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

industry are above the sample median in a specific year as analysts with a high level of industry specialization and as analysts with a low level of industry specialization otherwise.

Table 12 reports the estimation results of how analysts' SARS exposure experience affects analysts with a low and a high levels of industry specialization differently. The coefficient of ***SARS_Case*** × ***Post*** is 0.904 and significant at the 1% level in Column (1), but −0.334 and insignificant in Column (2). Overall, the results indicate that the low level of industry specialization of analysts can further motivate the SARS exposure-induced optimistic forecast bias.

5.2.3. Analyst gender

Prior research indicates that females have higher emotional sensitivity in interpersonal interactions than males and are more likely to be influenced by emotions compared to their male counterparts (Hall et al., 2008). Specifically, Fehr-Duda et al. (2011) point out that women's mood positively correlates with their likelihood of being optimistic, while many men are less influenced by mood due to their reliance on logical decision-making criteria like expected value maximization. As for professional analysts, existing literature indicates that the gender of analysts has a significant impact on forecast performance (Bosquet et al., 2014; Fang & Huang, 2017; Li et al., 2020). Therefore, we can predict that females might be more affected by their sentiment incurred by the SARS exposure experience when they issue forecast reports.

Table 13 reports the estimation results of how analysts' SARS exposure experience differently affects female and male analysts. The coefficient of ***SARS_Case*** × ***Post*** is 1.076 and significant at the 10% level in Column (2), but −0.230 and insignificant in Column (1). Overall, the results indicate that female analysts can further motivate the SARS exposure-induced optimistic forecast bias.

Table 13
Heterogeneity: Analyst's gender.

	Dependent Variable: *Bias*	
	Male	Female
	(1)	(2)
SARS_Case×Post	−0.230	1.076*
	(-0.57)	(1.70)
RETVOL	−1.709	−0.022
	(-1.29)	(-0.01)
Coverage	−0.479***	−0.421***
	(-5.71)	(-5.17)
SIZE	0.030	0.047
	(0.77)	(0.98)
LEV	1.163***	0.572**
	(3.73)	(1.99)
AGE	0.328***	0.183***
	(5.02)	(3.00)
ROAVOL	6.685**	5.897**
	(2.33)	(2.52)
LOSS	3.471***	4.304***
	(8.87)	(7.48)
Cash_Flow	−4.545***	−3.987***
	(-6.48)	(-6.53)
LN_Horizon	0.353***	0.373***
	(8.59)	(9.39)
Ana_Coverage	−0.055	−0.036
	(-0.63)	(-0.33)
Population_Growth	−0.119	0.073
	(-1.41)	(1.07)
PCGDP	−0.933	0.490
	(-1.16)	(1.21)
Constant	10.043	−7.187
	(1.13)	(-1.47)
Analyst FE	YES	YES
Year FE	YES	YES
Broker FE	YES	YES
Diff in Coef:Female vs. Male	*p*-value = 0.0560*	
N	3207	2099
Adjusted R^2	0.255	0.326

Note:This table represents the results of heterogeneity among analyst's gender.The dependent variable is the forecast bias (***Bias***). ***SARS_Case×Post*** is the interaction term of ***SARS_Case*** and ***Post***. All variables are defined in section 3 and Appendix 1. Fixed effects of analyst, year, and broker are controlled. *t*-statistics (reported in parentheses) are based on standard errors clustered by firm level. Significance levels at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

6. Conclusions

This study provides evidence linking analysts' SARS epidemic experiences to earnings forecast bias. Using analysts' location information during the period of the SARS epidemic, we analyze the influence of analysts' SARS exposure on forecast bias. We find that analysts with SARS experience are more likely to issue optimistic earnings forecasts compared to their peers. Our findings are robust when we use alternative dependent and independent variables and exclude the analyst working city factors, and listed firms' factors. We confirm the presence of behavioral biases by providing evidence of event salience. We further find that the availability of heuristics, motivated by the unexpected economic growth and positive sentiment in media reports, is the mechanism. The heterogeneity analysis shows that our results are more significant for analysts more affected by sentiment, such as those with higher levels of busyness, analysts with lower levels of industry specialization, and female analysts.

Data availability

Data will be made available on request.

Appendix 1. Variable Definitions

Variables	Definition
Bias	The difference between the ***FEPS*** and the actual ***EPS*** scaled by the firms' stock price at the end of previous year, multiplied by 100
SARS_Case	The natural logarithm of one plus number of infection cases of SARS (per 1, 000 people) of analyst's location in 2003
Post	A dummy variable that equals 1 if the time is after year 2003, and 0 otherwise
RETVOL	Rolling variance of monthly equity return calculation considering reinvestment of cash dividends
Coverage	The natural logarithm of one plus the number of analysts making earnings forecasts for the company in a given year
SIZE	The natural logarithm of a company's total assets
LEV	Debt-to-assets ratio of a company
AGE	Natural logarithm of the number of years since the firm's initial listing
ROAVOL	The standard deviation of returns on asset over the past three years
LOSS	A dummy variable, which equals one if the company's net profit is negative, and zero otherwise
Cash_Flow	Cash flow from operations scaled to total assets
LN_Horizon	Natural logarithm of the number of days between the fiscal period end date and the forecast issuance date
Ana_Coverage	The natural logarithm of one plus the number of firms an analyst follows in a specific year
PCGDP	Natural logarithm of per capita GDP of the province where the analyst is located
Population_Growth	The value of birth rate minus population mortality rate of the province where the analyst is located
Year FE	Year fixed effect
Analyst FE	Analyst fixed effect
Broker FE	Broker fixed effect

Appendix 2. Distribution of SARS Infected Patients in Mainland China

Province	Numbers of Cases	Province	Numbers of Cases
Beijing	2521	Hubei	7
Guangdong	1512	Hunan	6
Shanxi	448	Ningxia	5
Inner Mongolia	282	Zhejiang	4
Hebei	215	Fujian	3
Tianjin	175	Chongqing	3
Jilin	35	Jiangxi	1
Guangxi	22	Shandong	1
Sichuan	20	Heilongjiang	0
Henan	15	Hainan	0
Shaanxi	12	Guizhou	0
Anhui	10	Yunnan	0
Shanghai	8	Tibet	0
Gansu	8	Qinghai	0
Liaoning	7	Xinjiang	0
Jiangsu	7		

Appendix 3. The Sample Formation

The evolvement from the original sample to the final sample	N
Initial sample: all the analyst-firms observations on the Shenzhen and Shanghai stock exchanges over the 2002–2017 period	217,812
excluding the analyst-firms observations without forecast records in 2003	209,330
excluding the analyst-firms observations who shares same name with analyst in 2003 but are different individuals	1295
excluding the analyst-firms observations when the listed firms belongs to financial industry	335
excluding the analyst-firms observations when the listed firms' leverage is greater than one	197
excluding the analyst-firms observations with missing data	635
Final sample	6020

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