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Stock market reactions under the shadow of the COVID-19 pandemic: Evidence from China

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ABSTRACT

This paper studies how the Chinese stock market reacts to new COVID-19 infections under the zero-COVID policy. Consistent with the literature, we find that a COVID-19 outbreak within a city adversely affects the performance of local firms, but further unveils the effect's nonlinearity. More importantly, we document an unexpected pattern of spatial spillover of the COVID-19 shock, which is likely to be caused by the policy itself. In addition, firms with significant retail exposure are most vulnerable, while firms with low pandemic exposure, larger size, state-owned enterprise (SOE) status, and robust finances demonstrate greater resilience to the COVID-19 shock. Mechanism analysis indicates that the COVID-19 effects are realized through both cash flow and discount rate channels. Supplementary back-of-the-envelope calculations illustrate the substantial economic consequences of these phenomena, which shed light on the debate on the optimal policy in response to a future pandemic.

1. Introduction

Over the past three years, the COVID-19 pandemic has left indelible impacts on human society, resulting in dramatic consequences for the global economy, geopolitics, and financial markets. One notable development during this pandemic, though not without its challenges, is the diverse range of measures that countries have adopted to combat the virus. Most countries have chosen to coexist with the virus from the outset, while some have pursued "zero-COVID" policies, striving to effectively contain the virus within their borders. These contrasting approaches may yield vastly different outcomes. Despite extensive efforts to understand the pandemic's economic impacts across various dimensions, few existing studies focus on policy scenarios where the virus is under stringent control. In this paper, we offer one of the first investigations into the effects of the COVID-19 pandemic on stock returns within the context of China's distinctive zero-COVID policy.

Our study capitalizes on three distinctive aspects of China's zero-COVID policy. First and foremost, most measures employed in executing the zero-COVID policy, such as mass PCR testing and public transportation lockdowns, are implemented at the city level. For instance, when Shanghai underwent a two-month lockdown from April to May 2022, the transportation system was significantly disrupted, making it challenging for local firms to continue their operations. Conversely, firms outside of Shanghai's jurisdiction were considerably less impacted. Given this characteristic, we can examine the COVID-19 impacts using city-level variations in the severity of the outbreaks.

Second, China established a highly efficient, albeit costly, reporting system to accurately monitor the number of COVID-19 cases at the city level during the pandemic. The central government mandates local governments to publicly release the number of new cases on a daily basis. To ensure the authenticity and accuracy of these figures, the central government consistently penalizes local governors who fail to detect the virus at an early stage. As a result, local governments frequently conduct mass PCR testing to uncover hidden cases. This system allows us to construct measures of COVID-19 severity that are less susceptible to potential measurement errors, as opposed to the case

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numbers reported in many countries, which are often believed to be underestimated.

Third, China is arguably the only country that has persistently endeavored to fully contain the virus from the onset of the pandemic until the emergence of a highly contagious variant rendered the policy unsustainable. As such, the zero-COVID policy remained stable throughout our sample period, offering us a unique opportunity to scrutinize the effects of the COVID-19 pandemic within a policy framework that markedly diverges from those of other countries.

While most existing literature focuses on the weekly effects, we examine the daily effects of the COVID-19 outbreak for two reasons. First, the raw data used in our study, including city-level COVID-19 new cases and stock returns, are available at a daily frequency. Utilizing daily data instead of weekly frequency enables us to maximize the extraction of valuable information. More importantly, conducting the study at a daily frequency allows us to explore the dynamics of investors' responses to outbreak-related information. This examination is particularly interesting as it helps us comprehend how investors process new information.

Our dataset covers 4581 listed firms in the Chinese stock market, headquartered in 246 cities across the country during the period from January 2020 through May 2022. We construct a panel containing more than 2.1 million stock-date observations by matching stock return data to city-level COVID-19 cases, firm characteristics, and other city-level control variables.[1] With this dataset, we employ a panel regression model that includes stock-month fixed effects as well as date fixed effects as our baseline specification. Importantly, these fixed effects account for many potential sources of omitted variables that may lead to endogeneity issues. Specifically, the stock-month fixed effects encompass stock-specific and city-specific characteristics that are time-invariant, such as industry classification, headquarters location, and intrinsic productivity, as well as those that may vary monthly, like CEO's abilities, firms' financial performance, local economic conditions, and more. The date fixed effects further capture country-level shocks affecting all stocks on a given day, such as new virus containment policies adopted by the central government. Additionally, we control for city-level weather conditions and air pollution as they may simultaneously affect stock returns and virus spread.

Overall, we identify a negative relationship between the number of new COVID-19 cases and the stock returns of firms headquartered in the considered city after controlling for the aforementioned stock-month fixed effects, date fixed effects, weather conditions, and air pollution levels. In particular, the daily return would, on average, drop by 0.276% for stocks listed on the main board and 0.474% for stocks listed on the second board if the cumulative number of COVID-19 cases in the city where the firm is headquartered increases by 1%.[2] Remarkably, we find strong evidence suggesting that the scale of the COVID-19 effects on daily stock returns increases monotonically with the severity of the city-level outbreak. For stocks listed on the main board, the daily stock returns would drop by around 0.043% and 0.079% if the number of new cases in the city hosting the firms' headquarters is above 10 but less or equal to 50, and above 50; the effect is not statistically significant if the number of new cases is less than or equal to 10. For stocks listed on the second board, their daily stock returns significantly drop by 0.103% only when the number of new cases exceeds 50. Notably, the monotonicity of the effects aligns with the fact that local governments make specific policy decisions, ranging from mass PCR testing to city-wide shutdowns, depending on the severity of the incoming outbreak, which is inferred from the number of new cases.

We then investigate the dynamics of the main effects. First, we examine whether the impact of increasing new cases on daily stock returns extends to future dates by replacing the contemporaneous COVID-19 measures with various lags. Our findings indicate that the main effect is only significant for daily returns. Second, to uncover the dynamics of the main effect, we include lagged COVID-19 measures up to three trading days alongside the contemporaneous terms in the regression model. For stocks listed on the main board, we discover that only the coefficient estimates on the COVID-19 measures of the same period are statistically significant and negative. For stocks listed on the second board, in addition to the significantly negative coefficients on contemporaneous COVID-19 measures, we also find that the estimated coefficients of the COVID-19 measure one day prior are significantly positive, indicating a pattern of price reversal. These findings not only demonstrate that stock prices on the main board can quickly absorb the shocks from outbreak-related information but also imply that investors of stocks listed on the second board tend to overreact to news on the COVID-19 outbreak.

To elucidate the heterogeneity in the COVID-19 effects on daily stock returns, we conduct four analyses based on firms' industry classification, size, ownership structure, and past financial performance. First, as expected, stock returns of firms in industries more resilient to the negative impacts of the pandemic and virus-containing measures, such as transportation lockdowns, are less affected. Second, our analysis reveals that the effects of the COVID-19 outbreak are more pronounced for smaller firms. Third, only the stock returns of non-state-owned enterprises respond to the city-level COVID-19 outbreaks. Lastly, the stock returns of firms with better past financial performance listed on the main board are less affected by the COVID-19 shocks, which aligns with the findings in Ding et al. (2021). Taken together, these results offer a comprehensive picture of which firms are most and least affected by city-level COVID-19 outbreaks.

Due to the high contagiousness of the SARS-CoV-2 virus, the COVID-19 outbreak has often spread to neighboring cities by the time the infected individuals are discovered. Under the zero-COVID policy, local governments in China frequently implement precautionary measures when confirmed cases arise in nearby cities, leading to negative impacts on the stock returns of local firms. To test the potential spillover, we borrow modeling techniques from spatial econometrics, using two types of spatial matrices – the direct neighbor matrix and the inverse distance matrix – to measure the severity of the COVID-19 outbreak in nearby cities. The results indicate that the returns of stocks listed on both boards are affected by the COVID-19 outbreak in neighboring cities if the weighted sum of new cases exceeds 50, providing strong evidence for the spatial spillover of the COVID-19 effects.

Our findings remain stable under a range of robustness checks. First, we replace the stock-month fixed effects with stock fixed effects, stock-quarter fixed effects, and stock-year fixed effects, respectively. The results continue to be quantitatively similar, indicating that our findings do not rely on a specific model specification. Second, to examine whether our results are driven by a certain group of stocks or cities, we conduct a set of subsample analyses by individually excluding observations related to the Wuhan outbreak period, the Shanghai outbreak period, the four first-tier cities, firms of the bottom 30% in size, and firms in the financial sector. Once again, none of these changes alter our main findings. Lastly, we modify the clustering of standard errors by allowing autocorrelation within each city across quarters and find that the significance levels barely change. These exercises strengthen the validity and robustness of the COVID-19 effects on daily stock returns.

The COVID-19 effects on daily stock returns exhibit high economic significance. Specifically, for stocks listed on the main board, the effects of moderate and severe COVID-19 outbreaks are approximately

[1] Our findings remain quantitatively similar under other specifications of fixed effects; see Section 4.4 for more details.

[2] Similar to most major stock markets, the Chinese stock market consists of a main board and a second board, catering to large/value firms and small/growing firms, respectively. These two boards differ not only in their targeted firms but also in their investor base, as stocks listed on the second board are often more favored by retail investors. To account for this feature, we separately estimate the effects of interest for these two boards.

96% and 176% of the mean daily returns of all stocks, respectively.[3] Furthermore, based on the estimated COVID-19 effects, we calculate the total amount of market capitalization "evaporated" during the sample period due to the unrelenting COVID-19 outbreaks using detailed data on city-level cases and public firms, indicating that the cumulative loss could be as large as 900 billion RMB. Notably, these economic implications are realized contemporaneously, as the COVID-19 effects are demonstrated to be captured by the market on the day when the information is released. Even so, our analysis of the economic implications of city-level COVID-19 shocks highlights a lower bound for the overall impact of the pandemic on the Chinese stock market, as the country-level shocks are absorbed by the date fixed effects.

We find that the COVID-19 effects on daily stock returns can be attributed to two classic drivers of stock price changes: firms' future cash flows and the discount factor. In line with the cash flow channel, the outbreak of city-level COVID-19 epidemics is associated with a significant drop in earnings per share (EPS) forecasts for stocks listed on both the main and second boards. For instance, a severe outbreak, on average, leads to a 0.024 RMB/share drop in EPS forecasts in the following six months for stocks listed on the main board. Although less significant, the results hold for the second board as well. The realized cash flows also support the cash flow channel, as firms' return on assets (ROA), return on equity (ROE), and EPS decrease significantly after the outbreak of a city-level epidemic. To explore the discount factor channel, we estimate the expected rate of return on capital using the price-earnings-growth (PEG) model proposed in Easton (2004) and test whether city-level cumulative COVID-19 cases increase the cost of capital. Our analysis reveals that the expected rate of return on capital increases by roughly 2% for stocks listed on the main board, while the effect on second-board stocks is insignificant, likely due to the small sample size. These results suggest that the COVID-19 effects can be attributed to both firms' deteriorated future cash flows and short-term fluctuations in investors' discount factors.

As highlighted in the existing literature, the Chinese stock market is characterized by a high level of retail investor participation (Jones et al., 2020). In light of this, our final set of analyses investigates whether the prominent role of retail investors intensifies the COVID-19 effects on stock returns. Given that existing literature documents a positive correlation between turnover and the proportion of retail investors, we divide all stocks into two subsamples based on the median of share turnover across the sample period and estimate the COVID-19 effects separately. The results reveal that the COVID-19 effects are more substantial for stocks with high turnover, suggesting a positive correlation between the magnitude of the effects and the proportion of retail investors. This finding aligns with literature indicating that retail investors may overreact to new information due to overconfidence (Peng and Xiong, 2006) or limited attention (Liu et al., 2019). However, pinpointing the specific mechanism is beyond the scope of the current study, and we leave it as a direction for future research.

Our study primarily contributes to three strands of literature. First, we enhance the growing literature that investigates the effects of COVID-19 on asset prices, financial markets, and the real economy (see, for example, Acharya and Steffen, 2020; Levine et al., 2021; Kargar et al., 2021; Duchin and Harford, 2021; Ding et al., 2021, among many others). In this regard, Ding et al. (2021) is the work that closely relates to ours as they examine the common features of firms whose stock prices are more resilient to the COVID-19 shocks, using weekly return data from various countries. Conversely, we concentrate on the Chinese stock market to reveal the COVID-19 effects on stock returns under a policy framework that significantly differs from other countries and provide in-depth insights into heterogeneity, spatial spillover, mechanisms, and more. For the same reason, our study also differs significantly from those examining the impacts of the COVID-19 outbreak on the stock market at the early stage of the pandemic, such as Al-Awadhi et al. (2020), Alfaro et al. (2020), and Baker et al. (2020). In this sense, our study innovatively complements the existing literature.

Second, our study adds to the emerging literature on the Chinese stock market. Compared with other major global stock markets, the Chinese stock market possesses several unique features, including an abundance of retail investors, the prominent role of state-owned enterprises, and a seemingly government-oriented management style (Amstad et al., 2020; Carpenter et al., 2021). Furthermore, it remains one of the fastest-growing capital markets in the world (Carpenter and Whitelaw, 2017). Despite its importance, limited research has examined the pandemic's impact on this market prior to our work.[4] Third, our study also connects with the literature on retail investors. While existing research has demonstrated that retail investors are more prone to irrational trading behaviors (Cornelli et al., 2006; Peng and Xiong, 2006; Jones et al., 2020), we provide suggestive evidence that a high proportion of retail investors corresponds with more pronounced stock return reactions to city-level COVID-19 shocks. This finding underscores the importance of retail investors in shaping market responses to external events, such as the pandemic.

Our study holds considerable practical relevance as well. To the best of our knowledge, we are among the first to evaluate the economic consequences of the COVID-19 pandemic on the Chinese stock market, one of the country's most important financial markets. Our study, although not perfectly comprehensive, still sheds light on the policy debate regarding the effectiveness of the zero-COVID policy in minimizing the aggregate cost of the pandemic. In line with the motivations of the policy, the loss caused by city-level outbreaks remained low before 2022 when it was much easier to control the spread of the virus. However, as the analysis in Section 5.1 implies, the accumulative economic cost on the stock market over the entire pandemic period could be considerable. That being said, our study is rooted in a positive perspective and deliberately avoids normative judgments, as the value of lives should be beyond economic measurement.

The rest of the paper is organized as follows. Section 2 introduces the institutional background of China's zero-COVID policy and the Chinese stock market. Section 3 details the data sources and the process of variable construction. Section 4 discusses the main findings. Section 5 provides additional analyses on the economic implications, underlying mechanisms, and role of retail investors. Section 6 offers concluding remarks.

2. Institutional background

2.1. The zero-COVID policy in China

The coronavirus disease of 2019 (COVID-19) is a highly contagious illness caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The first known case was identified in Wuhan, China, in December 2019, and the virus rapidly spread worldwide, leading to the global COVID-19 pandemic. COVID-19 is exceptionally infectious compared to other common respiratory diseases like influenza, with an estimated R0 of 3 for the original strain (Petersen et al., 2020) and above 10 for the Omicron variant (Burki, 2022).[5] Since its emergence,

[3] To simplify the wording, we define mild, moderate, and severe COVID-19 outbreaks based on the number of daily new COVID-19 cases: mild (above 0 but less than or equal to 10), moderate (above 10 but less than or equal to 50), and severe (above 50).

[4] Recently, Gao et al. (2022, 2023) investigate the effects of the COVID-19 pandemic on China's bond market and bank funding costs, respectively.

[5] R0 is an estimate of the speed at which a specific infectious disease can currently spread through a given population. Generally, it refers to the average number of people one person can infect. For example, influenza has an estimated R0 below 2 (Biggerstaff et al., 2014).

COVID-19 has significantly impacted public health, daily life, and the global economy.

Many countries have allocated substantial resources to fight COVID-19 and save lives, but policies enacted to contain the virus have varied widely. Due to the highly infectious nature of SARS-CoV-2, eradicating it through public health measures alone is challenging, if not impossible. As such, most countries opted to "co-exist" with the virus, adopting protective measures like stay-at-home orders, travel restrictions, mandatory mask-wearing, and closing non-essential businesses to flatten the case curve. However, the effectiveness of these measures largely depends on people's compliance. Conversely, a few countries, including China, Singapore, New Zealand, and Australia, initially implemented the zero-COVID policy during the early stages of the pandemic. Nevertheless, due to the extremely contagious nature of new variants and the availability of effective vaccines, almost all countries, except China, transitioned to the co-exist mode by mid-2021.

China's zero-COVID policy aims to eradicate all COVID-19 cases within its borders to protect its population, particularly those at high risk. Initiated in early 2020, the policy was enforced through stringent border controls, widespread PCR testing, and quarantine measures. During the pandemic, the number of international flights between China and other countries significantly decreased, with all incoming travelers subjected to a mandatory 14-day quarantine. To detect early signs of COVID-19 outbreaks, many Chinese cities, especially large ones, regularly conducted mass PCR testing on their entire populations, particularly after the highly contagious Omicron variant emerged. If an outbreak occurred, local governments would implement additional measures, such as locking down affected areas or even entire cities, to prevent further spread.

Throughout our sample period, this policy successfully contained the virus's spread, as evidenced by the daily number of new cases consistently remaining below 200 before 2022 (Panel C of Fig. 2), and China's COVID-19 case fatality rate (CFR) being significantly lower than in other countries (Chen and Chen, 2022). However, this policy also imposed considerable economic costs. In addition to substantial public health expenditures, strict travel restrictions likely suppressed domestic consumption (Chen et al., 2021; Padhan and Prabheesh, 2021), while lockdown policies may have severely disrupted firms' normal business operations, logistics systems, and distribution patterns (Goldstein et al., 2021; Han et al., 2022; Genc and Arzaghi, 2024). Such disruptions could create investor uncertainty about firms' financial performance, potentially triggering stock sell-offs and corresponding price drops, especially during intense COVID-19 outbreaks. For instance, when Shanghai was under lockdown from April to June 2022, local firms' regular business operations nearly came to a halt.

2.2. The Chinese stock market

Over the past three decades, the fast-growing Chinese economy has led to the emergence of the Chinese stock market as a crucial player in global equity markets. By June 2022, the total value of the Chinese stock market had soared to 95.4 trillion RMB, making it the second-largest in the world. The market comprises two stock exchanges: the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE), both established in the early 1990s to foster economic growth and provide financing for domestic firms. The number of listed stocks has grown dramatically from eight in December 1990 to over 4000 during our sample period. Stocks are listed on either the main board or the second board, depending on the firms' growth stage.[6] Firms listed on the main board must meet strict requirements, including relatively large firm size and stable profitability, such as an accumulative net profit of more than 30 million RMB in the most recent three years. In contrast, the second board caters to small yet promising firms with less stringent requirements regarding recent financial performance.[7]

The Chinese stock market has several distinguishing features compared to other major stock markets globally. First, retail investors highly participate in the market. According to the 2021 yearbook of the Shanghai Stock Exchange, there are 299.456 million stock investors in China, with 99.69% being retail investors. Their typically speculative and short-term trading motives contribute significantly to the high turnover of the Chinese stock market (Jones et al., 2020). The stock market turnover ratio, calculated as the volume of shares traded divided by the total domestic shares, stood at 259% in 2020 in China, compared to around 70% in the United States.[8]

Second, state-owned enterprises (SOEs) have played a critical role in the number of stocks and market value since the Chinese stock market's inception. As of May 2022, which marked the end of our sample period, SOEs accounted for around 29.20% of all public firms in the Chinese stock market and 68.70% of the total value; these numbers were even higher in earlier stages. Although SOEs in China have faced extensive criticism for their lack of information transparency and efficiency, they still have easier access to credit from the banking system and governments compared to private firms (Cull and Xu, 2003).

Additionally, the Chinese stock market enforces several trading limits to maintain stability and avert sudden fluctuations. Stocks on the main board have a daily price fluctuation limit of 10% in absolute value, while those on the second board have a 20% limit. These constraints effectively mitigate price volatility in the market. Furthermore, short-selling is stringently regulated in the Chinese stock market. Before 2010, investors encountered strict short-selling restrictions, which were partially relaxed in March of that year. The Chinese Securities Regulatory Commission (CSRC) now permits certain brokerage firms to conduct short-selling operations, with the number of stocks available for short sale gradually increasing. During our sample period, 1600 stocks, constituting 30% of all firms, were allowed to be shorted.[9]

3. Data and variables

3.1. COVID-19 cases

We obtain daily data on COVID-19 cases for all Chinese cities from Dingxiang Doctor, a leading online medical platform in China, using an open-source web crawler.[10] The sample period spans from January 21, 2020, to May 31, 2022, during which China stringently adheres to the zero-COVID policy. We choose this sample period partly because the city-level number of new cases is considered more accurate before the virus spread spiraled out of control in Fall 2022. Importantly, under the zero-COVID policy, local Centers for Disease Control and Prevention (CDC) are required to disclose detailed daily numbers of city-level COVID-19 cases, ensuring accurate and up-to-date information is available. Although these numbers may be underestimated during severe outbreaks, such as the one in Wuhan, they are generally accurate due to the extensive, high-frequency PCR testing conducted. With this in mind, we collect daily time series data on cumulative COVID-19 cases for each

[6] The main board stocks are traded on both exchanges, while the second board comprises two separate markets: the Growth Enterprises Market (GEM) on the Shenzhen Stock Exchange, established in 2009, and the Sci-Tech Innovation Board (STAR Market) on the Shanghai Stock Exchange, launched in 2019.

[7] For more details on the listing requirements of the main and second boards, please refer to http://www.szse.cn/ipo/guide/requirements/index.html.

[8] See, https://data.worldbank.org/indicator/CM.MKT.TRNR?locations=CN.

[9] Please refer to http://www.sse.com.cn/market/othersdata/margin/detail/index.shtml and https://www.szse.cn/disclosure/margin/margin/index.html for details on the stocks available for short-selling in the Shanghai Stock Exchange and the Shenzhen Stock Exchange, respectively.

[10] See https://github.com/BlankerL/DXY-COVID-19-Crawler for more details on the web crawler used to extract data on COVID-19 from Dingxiang Doctor.

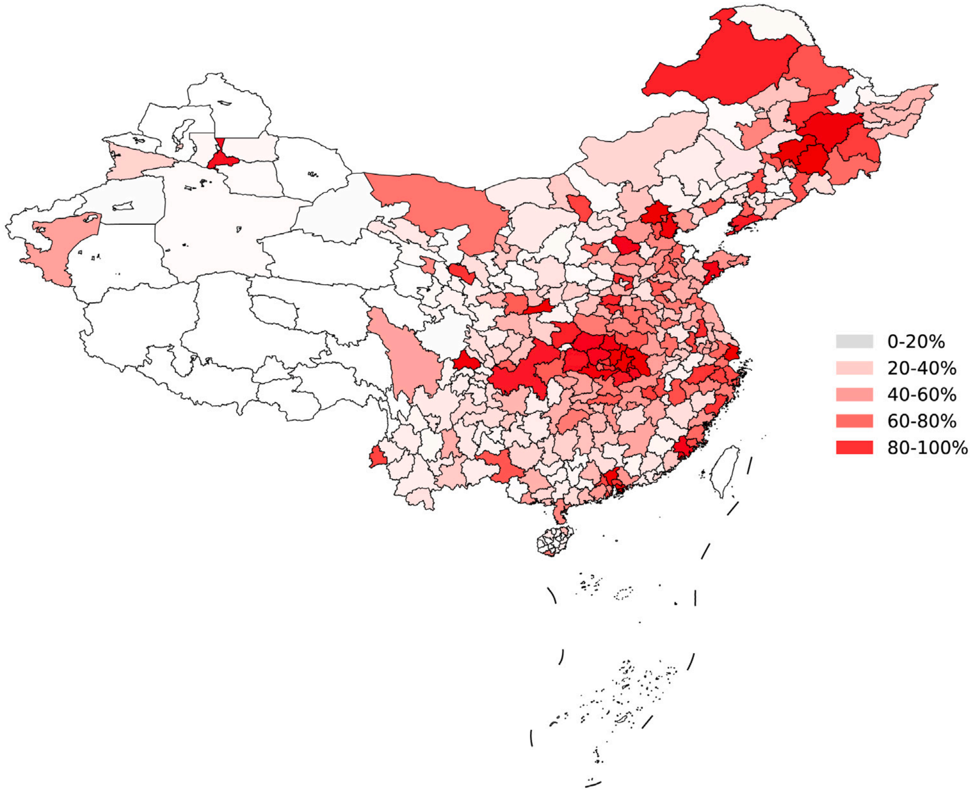

Fig. 1. Geographical distribution of the COVID-19 cases in China.
Note: This figure displays the geographical distribution of cumulative COVID-19 cases in Chinese cities considered in our study. Each city is colored in varying shades of darkness, with darker shades representing a larger number of cumulative confirmed cases. The legends correspond to the colors for the quintiles of the cumulative confirmed cases.

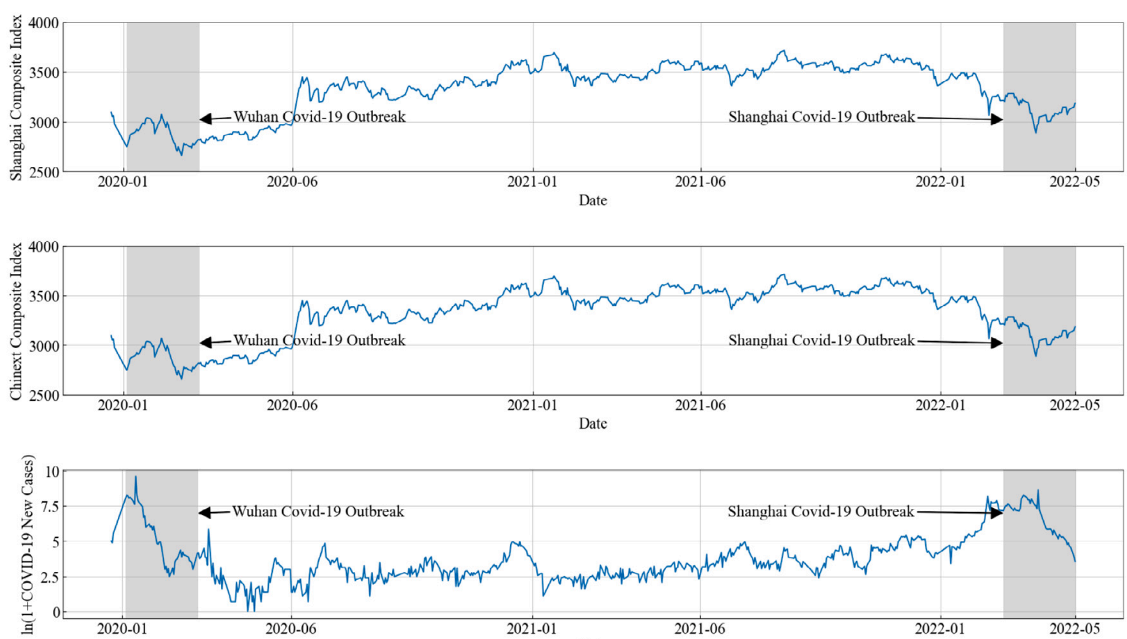

Fig. 2. Stock market indexes and the cumulative confirmed COVID-19 cases in China. *Note*: This figure displays the time series of the Shanghai Composite Index for the main board (Panel A), the ChiNext Composite Index for the second board (Panel B), and the natural logarithm of the cumulative confirmed COVID-19 cases in China. The sample period spans from January 2020 to May 2022. The stock market index data are sourced from the WIND database, and the COVID-19 data are collected from Dingxiang Doctor.

city in China and subsequently construct measures for the severity of the local COVID-19 outbreak. Fig. 1 displays the geographical distribution of the cumulative COVID-19 cases in Chinese cities considered in our study, highlighting significant city-level variations.

We consider two measures to assess a city's exposure to the COVID-19 outbreak. The first measure is the growth rate of the city-specific cumulative number of confirmed COVID-19 cases on a given day, denoted as $\Delta \ln$(COVID-19). For each city c on day t, we compute

Table 1
Summary statistics.

	N	Mean	S.D.	Median	Min	P25	P75	Max
Panel A: Daily city-level COVID-19 measures								
Cumulative confirmed cases	126,688	398.4	3443	33	1	12	83	63,016
$\Delta\ln$(COVID-19)	126,688	0.003	0.032	0.000	0.000	0.000	0.000	3.283
I($0 < \Delta$COVID ≤ 10)	126,688	0.041	0.198	0.000	0.000	0.000	0.000	1.000
I($10 < \Delta$COVID ≤ 50)	126,688	0.006	0.079	0.000	0.000	0.000	0.000	1.000
I(ΔCOVID > 50)	126,688	0.002	0.048	0.000	0.000	0.000	0.000	1.000
Panel B: Daily stock market data								
r^{raw} (main board)	1,555,475	−0.045	2.587	0.000	−10.000	−1.444	1.259	10.000
r^{FF6} (main board)	1,555,475	−0.167	2.256	−0.331	−9.995	−1.381	0.863	9.979
r^{raw} (second board)	675,418	−0.033	3.443	−0.027	−20.000	−1.935	1.661	20.000
r^{FF6} (second board)	675,418	−0.142	3.044	−0.378	−19.920	−1.731	1.150	19.960
Turnover (main board)	1,555,475	2.149	2.953	1.234	0.000	0.643	2.468	79.340
Turnover (second board)	675,418	4.338	5.704	2.555	0.000	1.355	5.055	500.200
Panel C: Firm characteristics								
Size	40,984	15.750	1.096	15.520	13.880	14.950	16.360	19.250
ROA	40,984	0.022	0.042	0.016	−0.152	0.003	0.040	0.160
ROE	46,319	0.042	0.056	0.035	−0.068	0.000	0.076	0.159
SOE	40,984	0.289	0.453	0.000	0.000	0.000	1.000	1.000
EPS	46,319	0.693	2.703	0.208	−24.810	0.035	0.656	195.500
EPS Forecast	46,319	0.687	1.658	0.000	−5.987	0.000	0.913	58.630
IVol	46,319	0.024	0.013	0.022	0.003	0.015	0.031	0.197
B/M	46,319	0.263	0.881	0.320	−1.505	−0.326	0.911	1.729
Leverage	46,319	0.426	0.204	0.417	0.104	0.259	0.576	0.823
BHR	46,319	0.001	0.145	−0.012	−0.715	−0.090	0.065	2.302
Panel D: Daily city-level air pollution and weather conditions								
AQI	126,688	58.92	39.12	50.67	8.04	34.92	70.54	500.00
Temperature (°C)	126,688	15.45	10.50	17.00	−35.00	8.50	24.00	34.50
Precipitation (mm)	126,688	1.13	5.53	0.00	0.00	0.00	0.00	125.00
Wind speed (m/s)	126,688	1.32	1.19	0.90	0.10	0.90	2.45	12.30

This table presents the summary statistics for all variables considered in this study. The sample period spans from January 21, 2020, to May 31, 2022. Panels A, B, C, and D correspond to daily city-level COVID-19 measures extracted from Dingxiang Doctor, stock market data obtained from the WIND database, firm characteristics acquired from the China Stock Market and Accounting Research Database (CSMAR), and city-level air quality index (AQI) and weather conditions collected from the Ministry of Environmental Protection of China and the China Meteorological Administration, respectively. The summary statistics for stock returns and turnover are expressed in percentages. In the column headings, N denotes the sample size, Mean and S.D. represent the sample average and sample standard deviation, Median, Min, and Max indicate the median, minimum, and maximum values of the variable, and P25 and P75 display the 25th and 75th percentile of the variable. Variable definitions can be found in Table A.1 in the Online Appendix.

$\Delta\ln$(COVID-19) as follows:

$$\Delta\ln(\text{COVID-19})_{c,t} = \ln(1 + \text{Cumu. COVID-19}_{c,t}) - \ln(1 + \text{Cumu. COVID-19}_{c,t-1}), \quad (1)$$

where c and t index city and date, and Cumu. COVID-19$_{c,t}$ denotes the cumulative cases. Thus, $\Delta\ln(\text{COVID-19})_{c,t}$ measures the daily growth rate of cumulative cases on day t in city c. Similar measures have also been adopted in previous studies, such as Ding et al. (2021), Tran and Uzmanoglu (2022), and Augustin et al. (2022), to reveal the impacts of COVID-19 on various financial assets. Panel A of Table 1 shows that the average growth rate of confirmed COVID-19 cases in Chinese cities during the sample period is 0.3%.

The stringency of policies implemented by city-level governments in China to contain the virus largely depends on the severity of the local outbreak, which may result in nonlinearity in COVID-19 effects concerning the number of new cases. To capture this feature, we construct three discrete indicators based on the number of daily COVID-19 new cases: I($0 < \Delta\text{COVID}_{c,t} \leq 10$) is an indicator variable equal to one if the number of new COVID-19 cases in city c on day t is above zero but does not exceed 10; I($10 < \Delta\text{COVID}_{c,t} \leq 50$) and I($\Delta\text{COVID}_{c,t} > 50$) are similarly defined.[11] Panel A of Table 1 shows that around 95.1% of the city-date observations do not have any new COVID-19 cases, while 4.1%, 0.6%, and 0.2% of them have a number of new cases between 1 and 10 (mild outbreak), 11 and 50 (moderate outbreak), and above 50 (severe outbreak), respectively.

[11] We have chosen the 10/50 threshold because both central and local governments often use these figures to determine the severity of a COVID-19 outbreak and to inform subsequent virus containment policies. For example, see http://yjgl.sz.gov.cn/zwgk/xxgkml/qt/tzgg/content/post_7775380.html and https://m.mp.oeeee.com/a/BAAFRD000020220413671252.html.

3.2. Stock market data

We collect stock price data, including daily open and close prices, market capitalization, and trading volume, from the WIND database, a leading financial data provider in China. We exclude observations within the first month after the listing date to avoid potential interference from speculative behaviors on newly listed stocks. Additionally, we exclude stock-date observations that are under a trading halt. In total, we gather data on 4581 firms listed on the Chinese stock market, among which 2993 are on the main board, and 1588 are on the second board. We then calculate the daily raw excess returns, $r^{\mathrm{excess}}_{i,t} = r_{i,t} - r_{f,t}$, where $r_{i,t}$ and $r_{f,t}$ represent the daily raw return and the daily risk-free rate calculated using the one-year bond rate, respectively. Additionally, we compute the daily abnormal returns, $r^{\mathrm{model}}_{i,t}$, for stock i on trading day t, where the superscript *model* indicates the asset pricing model employed. Specifically, we compute the abnormal returns as follows:

$$r^{\mathrm{model}}_{i,t} = r^{\mathrm{excess}}_{i,t} - \sum_{k=1}^{K} \hat{\beta}_{k,t} f_{k,t}, \quad (2)$$

where $\hat{\beta}_{k,t}$ are the estimated factor loadings and $f_{k,t}$ are the corresponding factor returns on trading day t. Specifically, to avoid potential look-ahead bias, the factor loadings $\hat{\beta}_{k,t}$ are estimated using the standard rolling-window method with a fixed window size of five years for each trading day t. To ensure our findings do not rely on the specific choice of asset pricing model, we consider the CAPM (Sharpe, 1964), the Fama–French three-factor model (Fama and French, 1993), the four-factor model including the momentum factor (Carhart, 1997), the Fama–French five-factor model (Fama and French, 2015), and the six-factor model (FF-6) adding the momentum factor to the Fama–French five factors (Fama and French, 2018). For completeness, we employ the most comprehensive six-factor model in the main text and relegate the rest to the appendix as robustness checks. Additionally, we calculate all factor returns using the methodology outlined in Fama and French (2015).

Panel B of Table 1 presents the summary statistics of raw and abnormal returns for the main and second boards, respectively. The daily mean returns of both markets are negative during the sample period: The means of daily raw returns and FF-6 adjusted daily returns are −0.045% and −0.167% for the main board, and −0.033% and −0.142% for the second board. Overall, a larger price deviation is exhibited in the second board, consistent with the fact that the second board of the Chinese stock market has a higher proportion of retail investors. Additionally, we note that the absolute values of both maximum and minimum returns of the main and second boards are below 10% and 20%, respectively, due to the daily price limits. Panel B of Table 1 reports also the daily turnover, defined as the daily transaction volume scaled by the total market capitalization. Its values for the main and second boards are 2.15% and 4.34%, respectively, which are more than double the US counterparts and among the highest in the main stock markets globally.[12] This figure aligns with the fact that the Chinese stock market is characterized by the significant role of retail investors, whose trading behaviors can be highly speculative.

3.3. Firm characteristics

We obtain data on firm characteristics from the China Stock Market & Accounting Research Database (CSMAR), a widely used Chinese financial database. We also collect data on daily shares traded from the previously mentioned WIND database. In total, we consider four firm characteristics: (1) the logarithm of stocks' market values; (2) the ratio of net income to total assets (*ROA*); (3) the daily share turnover ratio (*Turnover*); and (4) the status of state-owned enterprises (*SOE*). Specifically, *SOE* equals one if the firm is identified as a state-owned enterprise, with more than half of the shares held by state-owned entities, such as all levels of government and public funds. These characteristics are primarily used for subsample analyses.

Panel C of Table 1 displays the summary statistics of the firm characteristics. The size of the largest firm is 215 ($= e^{19.25-13.88}$) times that of the smallest firm, indicating significant variations in *Size*. A similar pattern is observed for *ROA* and *ROE*. Additionally, we note that a considerable proportion (28.9%) of firms in our sample are SOEs, underscoring the importance of a separate investigation for this group of stocks.

3.4. Air pollution and weather controls

To address the potential omitted variable bias, we also control for the air pollution level and weather conditions in the regressions. Following the literature, we use the Air Quality Index (AQI) as a measure of air quality. We obtain daily observations of AQI for all Chinese cities from the air quality report released by the Ministry of Environmental Protection of China. The AQI index ranges from 8.04 to 500, with a larger value indicating worse air quality. Concurrently, we collect data on city-level weather conditions from the China Meteorological Administration during our sample period. We consider three weather variables that are most likely to correlate with the spread of the coronavirus: the average daily temperature, precipitation, and wind speed.

Panel D of Table 1 displays the summary statistics for the AQI index and weather conditions. The average AQI in our sample is 58.92, with a standard deviation of 39.12. China's Ministry of Environmental Protection divides the AQI index into six categories based on health implications, and an AQI index higher than 50 is considered worrisome for certain groups of individuals. Furthermore, the city-date observations in our sample, on average, have a daily temperature of 15.45 °C, precipitation of 1.13 mm, and a wind speed of 1.32 m/s (2.952 miles/h).

In Table A.2 in the Online Appendix, we report the Pearson correlation coefficients between the main variables considered in our study. As expected, the correlation between the growth rate of cumulative city-level confirmed COVID-19 cases ($\Delta \ln(\text{COVID-19})$) and other variables is quite low, which is consistent with the fact that COVID-19 outbreaks are nearly random. Moreover, risk-adjusted returns are highly correlated with raw returns, exhibiting a correlation coefficient above 0.8, indicating that the six factors can only explain a limited proportion of stock returns.

4. Empirical findings

In this section, we present our empirical findings. In Section 4.1, we establish that an increase in COVID-19 cases leads to negative daily stock returns and examine the short-term dynamics of this effect. We investigate the heterogeneity in these effects and their spatial spillover on geographically neighboring stocks in Sections 4.2 and 4.3, respectively. Finally, we perform a series of robustness checks for our main findings in Section 4.4.

4.1. The COVID-19 effect on daily stock returns

As discussed in Section 2, China established a strict reporting system for new COVID-19 cases at the city level. Local governments were mandated to disclose the precise number of new COVID-19 cases within the past 24 h. Since this information was typically made public in the morning, investors nationwide could utilize it to adjust their portfolios during the trading period on the same day. Building on this observation, we initiate our analysis with the following specification:

$$r^*_{i,c,t} = \beta \cdot \Delta\text{COVID-19}_{c,t} + X^\top_{c,t}\gamma + \phi \cdot r^*_{i,c,t-1} + \theta_{i,m} + \delta_t + \alpha + \epsilon_{i,t}, \tag{3}$$

where the dependent variable $r^*_{i,c,t}$ represents either the raw return or FF-6 adjusted return of stock i located in city c on day t.[13] $\Delta\text{COVID-19}_{c,t}$ corresponds to either the number of new COVID-19 cases in city c or the indicators for the severity of the city-level COVID-19 outbreak, as detailed in Section 3; $X_{c,t}$ is a vector of control variables at the city-date level, including the AQI index and city-level weather conditions; $\theta_{i,m}$ denotes the stock-month fixed effects, and δ_t represents the date fixed effects. Throughout our study, standard errors are clustered by city and date.

The baseline specification (3) allows us to isolate the effect of new COVID-19 cases on daily stock returns from the interference of various confounders. First, the stock-month fixed effects account for all stock-specific characteristics that are time-invariant, such as industry classification, headquarters location, and listing code, as well as those that may change less frequently than every month, like the CEO's background, the net value of fixed assets, and overall financial performance. Additionally, the stock-month fixed effects absorb time-varying and time-invariant characteristics of the city where the firm is located, including factors like economic growth, infrastructure, industry structure, and city-level government policies. Second, the date fixed effects capture common shocks affecting all stocks on a given day.

[12] See https://data.worldbank.org/indicator/CM.MKT.TRNR for detailed data on the country-specific share turnover rate.

[13] We calculate risk-adjusted returns by following the steps detailed in Section 3.2. Specifically, we estimate factor loadings using the standard rolling-window method, which employs a fixed window size of five years, for each trading day t. We then calculate the model-implied expected return as the product of factor exposures and their realizations. Consequently, the risk-adjusted return is determined as the difference between the actual realized return and the model-implied expected return.

Table 2
Effects of city-level new COVID-19 cases on the daily stock returns of local firms.

	Raw returns				Risk-adjusted returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Results for the main board								
$\Delta \ln(\text{COVID-19})_{c,t}$	−0.2681***		−0.2759***		−0.2681***		−0.2759***	
	(0.1032)		(0.1036)		(0.1032)		(0.1036)	
$I(0 < \Delta\text{COVID}_{c,t} \leq 10)$		−0.0074		−0.0071		−0.0074		−0.0071
		(0.0097)		(0.0095)		(0.0097)		(0.0095)
$I(10 < \Delta\text{COVID}_{c,t} \leq 50)$		−0.0439**		−0.0434**		−0.0439**		−0.0434**
		(0.0218)		(0.0219)		(0.0218)		(0.0219)
$I(\Delta\text{COVID}_{c,t} > 50)$		−0.0795***		−0.0791***		−0.0795***		−0.0791***
		(0.0243)		(0.0245)		(0.0243)		(0.0245)
AQI	No	No	Yes	Yes	No	No	Yes	Yes
Weather controls	No	No	Yes	Yes	No	No	Yes	Yes
Lagged return	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1,555,475	1,555,475	1,555,475	1,555,475	1,555,475	1,555,475	1,555,475	1,555,475
Adjusted R^2	0.249	0.248	0.249	0.249	0.013	0.012	0.014	0.013
	Raw returns				Risk-adjusted returns			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel B: Results for the second board								
$\Delta \ln(\text{COVID-19})_{c,t}$	−0.4713***		−0.4740***		−0.4713***		−0.4740***	
	(0.1528)		(0.1546)		(0.1528)		(0.1546)	
$I(0 < \Delta\text{COVID}_{c,t} \leq 10)$		0.0098		0.0091		0.0098		0.0091
		(0.0129)		(0.0129)		(0.0129)		(0.0129)
$I(10 < \Delta\text{COVID}_{c,t} \leq 50)$		−0.0281		−0.0292		−0.0281		−0.0292
		(0.0450)		(0.0450)		(0.0450)		(0.0450)
$I(\Delta\text{COVID}_{c,t} > 50)$		−0.1009**		−0.1030**		−0.1009**		−0.1030**
		(0.0395)		(0.0399)		(0.0395)		(0.0399)
AQI	No	No	Yes	Yes	No	No	Yes	Yes
Weather controls	No	No	Yes	Yes	No	No	Yes	Yes
Lagged return	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	675,418	675,418	675,418	675,418	675,418	675,418	675,418	675,418
Adjusted R^2	0.246	0.246	0.247	0.247	0.035	0.035	0.036	0.036

This table presents the estimation results of the relationship between city-level new COVID-19 cases and the daily stock returns of local firms. Panels A and B correspond to the main board and the second board, respectively. The dependent variables include original daily stock returns (columns (1)–(4) and (9)–(12)) and FF-6 adjusted daily stock returns (columns (5)–(8) and (13)–(16)). The independent variables of interest are either the growth rate of the city-specific cumulative number of confirmed COVID-19 cases in city c on date t, $\Delta \ln(\text{COVID-19})_{c,t}$, or the discrete indicators for the number of city-level new cases in city c on date t, i.e., $I(0 < \Delta\text{COVID}_{c,t} \leq 10)$, $I(10 < \Delta\text{COVID}_{c,t} \leq 50)$, and $I(\Delta\text{COVID}_{c,t} > 50)$. The coefficient estimates are expressed in percentages. We control for lagged returns, stock-month fixed effects, and date-fixed effects in all columns. Numbers in parentheses represent standard errors, which are two-way clustered by stock and date. Variable definitions can be found in Table A.1 in the Online Appendix. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

In the current context, these common shocks may include but are not limited to, the announcement of new epidemic prevention policies and the lockdown of a major city. Lastly, since air quality (Lepori, 2016; Wu et al., 2018) and weather conditions (Hirshleifer and Shumway, 2003; Loughran and Schultz, 2004) may influence both stock returns and the spread of the coronavirus, we also incorporate them in the specification to avoid potential omitted variable bias.

We first focus on the regression results for stocks listed on the main board, as reported in Panel A of Table 2, since this market primarily comprises large firms and represents more than 70% of the total market value of the Chinese stock market. A remarkable observation that emerges is that an increase in daily new COVID-19 cases leads to a significant drop in same-day stock returns, as indicated by the first eight columns. Specifically, when accounting for all fixed effects and control variables, a 1% increase in the cumulative number of COVID-19 cases in a given city is associated with a 0.276% decrease in both unadjusted and adjusted daily stock returns of firms located in the same city.

More importantly, the COVID-19 effects exhibit significant nonlinearity in the severity of the city-level outbreak. For example, column (4) shows that, compared to a zero-COVID city, the stock returns of firms located in a given city experience no change when the number of daily city-level new cases is less than or equal to 10. However, they drop by 0.043% and 0.079% when the number of daily new cases is in the range of 11 to 50 and above 50, respectively. The estimated effects of the three discrete indicators exhibit a clear pattern: the stock returns of firms located in a given city decrease monotonically with the severity of the city-level COVID-19 outbreak. Due to the identified nonlinearity in the COVID-19 effect, we will focus on the discrete case throughout the rest of this paper.

Conceptually, the nonlinearity in the COVID-19 effects is consistent with the implications of China's zero-COVID policy. As introduced in Section 2, the anti-epidemic measures the city-level government takes depend on the severity of the local COVID-19 outbreak. When the number of new cases is small, city-level governments tend to limit mass PCR testing to specific city districts, allowing normal economic activities to remain largely unaffected. However, when the number of new COVID-19 cases becomes large, the government has to implement more radical measures, such as a city-wide lockdown. This aims to impede the spread of the coronavirus while heavily affecting the normal business operations of local firms at the same time. In such cases, investors nationwide may quickly respond by selling off the affected stocks, resulting in a sharp drop in the daily stock returns of these stocks.

Two other observations in Panel A of Table 2 require additional attention. First, the coefficients on ΔCOVID-19 and the discrete ΔCOVID-19 indicators are quantitatively unchanged in regressions with and without air pollution and weather controls, e.g., columns (2) vs. (4), which suggests that the effect of new COVID-19 cases is indeed independent of air pollution and weather conditions. Second, it may appear striking at first glance that the coefficient estimates are the same for regressions based on the raw returns and the Fama–French six-factor adjusted stock returns. However, such a coincidence does not result from an error in data processing but rather reflects that the emergence of the COVID-19 outbreak is simply random due to its nature and, thus, uncorrelated with the factor returns.[14]

Panel B of Table 2 presents the results of the baseline specification for the second board (Science and Technology Innovation Board) of the Chinese stock market. Due to differences in investor structure, price limits, and firm types, the effect of new COVID-19 cases on the second board may potentially differ, warranting a separate investigation. That being said, the overall pattern of the results reported in Panel B is largely consistent with that of the main board, as we also observe a negative effect of new COVID-19 cases on daily stock returns under all specifications. However, for specifications with discrete indicators, the main effect is no longer significant for the medium-level outbreak. Moreover, a one-to-one comparison of the coefficient estimates between the two markets shows that the effect of new COVID-19 cases is stronger in the second board. Given the fact that the second board is characterized by its high share of retail investors, who are known to be less financially sophisticated, the investor structure may be an important element that determines the magnitude of the effect, which is left for further investigation in Section 5.2.

Despite its statistical significance, the effect of new COVID-19 cases on daily stock returns is also economically relevant. To illustrate this point, we first conduct a simple back-of-the-envelope calculation. Assuming an investor holds an "average" stock, the estimates in Panel A of Table 2 suggest that the stock return would drop by 0.043% or 0.079% when this stock is affected by a moderate (11–50 new cases) or severe (>50 new cases) outbreak. Consequently, the resulting incremental underperformance incurred by the COVID-19 outbreak is about 96% (0.043/0.045) or 176% (0.079/0.045) of the expected daily return, which is economically non-trivial.

Our results so far show that an increase in city-level COVID-19 cases leads to a significant drop in the daily stock returns of local firms. A relevant question to ask is whether investors over- or under-react to such a shock so that the negative effect of the city-level COVID outbreak on stock returns may also extend to future trading days. For example, if investors overreact to the COVID-19 outbreak by hastily selling the affected stocks, the prices would drop excessively on the same day when the information becomes public but rebound quickly soon afterward. To test such a possibility, we include the lagged terms of city-specific COVID-19 measures up to 3 trading days. As discussed above, the coefficient estimates based on raw returns and Fama–French six-factor adjusted returns are exactly the same, so for the sake of brevity, we limit our presentation to risk-adjusted returns.

The results reported in Table 3 depict the dynamics of the COVID-19 effects on risk-adjusted daily stock returns. For the main board, the results are barely changed as only the coefficient estimates on the same-day COVID-19 measures are statistically significant; and their directions and magnitudes are consistent with those for the baseline specification. These findings indicate that investors in the main board have reacted appropriately to the local COVID-19 outbreak. On the other hand, the stock prices of firms listed on the second board not only drop (-0.206%) on the day when the number of new COVID-19 cases is released but also rebound ($+0.210\%$) significantly on the next day of a severe outbreak (ΔCOVID > 50), indicating that investors in the second board tend to overreact to the COVID-19 shock.

We conduct a set of t-tests to determine whether the overall dynamic effect under various combinations of outbreak severity is significantly different from zero. Notably, for the main board, the overall effects are always statistically different from zero if a severe outbreak appears on the current trading day in all 27 ($3 \times 3 \times 3$) cases. In contrast, for the second board, the overall dynamic effect is insignificant if the number of new COVID-19 cases in a given city exceeds 50 both on the current trading day and the day before, as the associated p-value equals 0.5995 when all the fixed effects and control variables are included. However, this result is mainly driven by the fact that the negative shock of the same-day new COVID-19 cases is offset by the reversal effect from the last trading day. As the above analyses show that the effects of lagged new COVID-19 cases are only relevant up to one trading day, we thus include one lag of the COVID-19 indicators through the rest of this study.

4.2. Heterogeneity analyses

To explore the potential heterogeneity in the effects of new COVID-19 cases on daily stock returns, we next conduct a variety of subsample analyses based on stock-level characteristics, including industry classification, firm size, ownership structure, and financial performance.

4.2.1. Industry classification

We first investigate the heterogeneity in the COVID-19 effect on daily stock returns across different industries. Intuitively, the COVID-19 pandemic can affect firms of different industries differently. For example, a financial firm tends to allocate its business around the whole country, and a high proportion of its employees can switch to working remotely without losing much productivity. In this case, a city-level, or even regional COVID-19 outbreak, as well as the following lockdown, may not fully suppress the firm's regular business. In contrast, manufacturing firms often concentrate their production facilities in a few cities, generating a high risk of disruption when a city-level COVID-19 outbreak emerges. Based on the above observation, we would expect firms of industries that are more vulnerable to the COVID-19 outbreak and the lockdown policy to exhibit a larger effect than the others.

To test this hypothesis, we adopt the industry classification of listed companies formulated by the China Securities Regulatory Commission in 2012, based on which we classify all stocks in the sample into two disjoint groups according to their vulnerability to the city-level COVID-19 outbreak and the accompanying restrictive measures.[15] We label a given industry as vulnerable to the COVID-19 shock if more than half of the top 10 largest firms within the industry operate their main business only in some key cities or if their business cannot operate normally if a city-level outbreak emerges. Intuitively, firms whose businesses are geographically diversified or less likely to be affected by the virus can better hedge against the negative impacts of the fast-spreading COVID-19 epidemic on firms' performance. By doing so, the 19 primary industries of listed companies are divided into the vulnerable group and the invulnerable group. The vulnerable group consists of 8 industries, such as the manufacturing industry and the entertainment industry; the invulnerable group is composed of 11 industries, including the finance industry, the water and energy industry, and the information technology industry. The details on the industry classification are reported in Table A.4 in the Online Appendix.

Columns (1)–(4) in Table 4 present the results of heterogeneity analysis based on industry classification.[16] In line with our conjecture, the negative effects of the city-level COVID-19 outbreak are

[14] As shown in Table A.2 in the Online Appendix, the correlation coefficients between the number of new COVID-19 cases and the Fama–French factor returns are very close to zero; therefore, by the Frisch–Waugh–Lovell Theorem in econometrics, whether controlling for the factor returns does not affect the coefficient estimates on ΔCOVID-19 and the related discrete indicators.

[15] See http://www.lawinfochina.com/display.aspx?lib=law&id=11930 for more details on the Guidelines for the Industry Classification of Listed Companies (2012 Revision) announced by the China Securities Regulatory Commission.

[16] As mentioned previously, we only include the COVID-19 indicators up to one lag because the results reported in Table 3 show that they are the only relevant lagged measures.

Table 3
Dynamic effects of city-level new COVID-19 cases on the daily stock returns of local firms.

	Risk-adjusted returns							
	Main board				Second board			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$I(0 < \Delta COVID_{c,t} \leq 10)$	−0.0078	−0.0077	−0.0078	−0.0077	0.0060	0.0052	0.0060	0.0052
	(0.0100)	(0.0100)	(0.0100)	(0.0100)	(0.0132)	(0.0130)	(0.0132)	(0.0130)
$I(10 < \Delta COVID_{c,t} \leq 50)$	−0.0469**	−0.0466**	−0.0469**	−0.0466**	−0.0475	−0.0490	−0.0475	−0.0490
	(0.0219)	(0.0220)	(0.0219)	(0.0220)	(0.0462)	(0.0457)	(0.0462)	(0.0457)
$I(\Delta COVID_{c,t} > 50)$	−0.1018***	−0.1008***	−0.1018***	−0.1008***	−0.2045***	−0.2059***	−0.2045***	−0.2059***
	(0.0323)	(0.0327)	(0.0323)	(0.0327)	(0.0468)	(0.0458)	(0.0468)	(0.0458)
$I(0 < \Delta COVID_{c,t-1} \leq 10)$	0.0062	0.0065	0.0062	0.0065	0.0089	0.0095	0.0089	0.0095
	(0.0070)	(0.0068)	(0.0070)	(0.0068)	(0.0170)	(0.0167)	(0.0170)	(0.0167)
$I(10 < \Delta COVID_{c,t-1} \leq 50)$	0.0278	0.0269	0.0278	0.0269	0.0425	0.0425	0.0425	0.0425
	(0.0260)	(0.0254)	(0.0260)	(0.0254)	(0.0328)	(0.0318)	(0.0328)	(0.0318)
$I(\Delta COVID_{c,t-1} > 50)$	0.0140	0.0103	0.0140	0.0103	0.2148***	0.2097***	0.2148***	0.2097***
	(0.0441)	(0.0429)	(0.0441)	(0.0429)	(0.0531)	(0.0521)	(0.0531)	(0.0521)
$I(0 < \Delta COVID_{c,t-2} \leq 10)$	0.0029	0.0033	0.0029	0.0033	−0.0064	−0.0056	−0.0064	−0.0056
	(0.0076)	(0.0074)	(0.0076)	(0.0074)	(0.0179)	(0.0177)	(0.0179)	(0.0177)
$I(10 < \Delta COVID_{c,t-2} \leq 50)$	−0.0053	−0.0040	−0.0053	−0.0040	−0.0414	−0.0395	−0.0414	−0.0395
	(0.0194)	(0.0186)	(0.0194)	(0.0186)	(0.0301)	(0.0298)	(0.0301)	(0.0298)
$I(\Delta COVID_{c,t-2} > 50)$	−0.0045	−0.0016	−0.0045	−0.0016	−0.0630	−0.0542	−0.0630	−0.0542
	(0.0538)	(0.0530)	(0.0538)	(0.0530)	(0.0617)	(0.0615)	(0.0617)	(0.0615)
$I(0 < \Delta COVID_{c,t-3} \leq 10)$	−0.0125	−0.0121	−0.0125	−0.0121	−0.0015	−0.0015	−0.0015	−0.0015
	(0.0119)	(0.0119)	(0.0119)	(0.0119)	(0.0164)	(0.0161)	(0.0164)	(0.0161)
$I(10 < \Delta COVID_{c,t-3} \leq 50)$	−0.0178	−0.0177	−0.0178	−0.0177	0.0293	0.0285	0.0293	0.0285
	(0.0154)	(0.0153)	(0.0154)	(0.0153)	(0.0329)	(0.0325)	(0.0329)	(0.0325)
$I(\Delta COVID_{c,t-3} > 50)$	0.0391	0.0398	0.0391	0.0398	0.0034	0.0016	0.0034	0.0016
	(0.0376)	(0.0370)	(0.0376)	(0.0370)	(0.0468)	(0.0464)	(0.0468)	(0.0464)
AQI	No	Yes	No	Yes	No	Yes	No	Yes
Weather controls	No	Yes	No	Yes	No	Yes	No	Yes
Lagged return	No	Yes	No	Yes	No	Yes	No	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1,555,475	1,555,475	1,555,475	1,555,475	675,418	675,418	675,418	675,418
Adjusted R^2	0.253	0.253	0.014	0.015	0.248	0.249	0.035	0.036

This table presents the estimation results for the dynamics of the effects of city-level new COVID-19 cases on the daily stock returns of local firms. Columns (1)–(4) correspond to the main board; columns (5)–(8) correspond to the second board. The dependent variables include daily stock returns (columns (1)–(2) and (5)–(6)) and FF-6 adjusted daily stock returns (columns (3)–(4) and (7)–(8)). The independent variables of interest are the discrete indicators for the number of new COVID-19 cases in city c on date $t-h$, i.e., $I(0 < \Delta COVID_{c,t-h} \leq 10)$, $I(10 < \Delta COVID_{c,t-h} \leq 50)$, and $I(\Delta COVID_{c,t-h} > 50)$, where $h = 0, 1, 2, 3$. The coefficient estimates are expressed in percentages. We control for lagged returns, stock-month fixed effects, and date-fixed effects in all columns. Numbers in parentheses represent standard errors, which are two-way clustered by stock and date. Variable definitions can be found in Table A.1 in the Online Appendix. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

only relevant and significantly larger for the vulnerable group, as the coefficient estimates for the invulnerable group are much smaller and statistically insignificant. For the vulnerable group, the pattern of the results is qualitatively similar to what we observe in the dynamics of the COVID-19 effects: Stock prices experience a significant decrease when the number of new cases exceeds 50 for firms listed on both the main board and the second board. Additionally, the magnitudes of the COVID-19 shocks on daily stock returns are also comparable to those corresponding to the baseline analysis. Overall, these findings suggest that investors can accurately capture the discrepancy in the negative impacts of the COVID-19 outbreak at the industry level, leading to significant heterogeneity in the shock on stock returns.

4.2.2. Market value

Prior literature has documented that stocks of different market sizes may exhibit significant differences in terms of price dynamics (Cheung and Ng, 1992). Additionally, it is known that retail investors, who play a critical role in the Chinese stock market, contribute a higher proportion to the trading volume of small stocks compared to large ones (Jones et al., 2020). Given the stark contrast between retail and institutional investors regarding information acquisition, processing, and decision-making, it is likely that the effects of the city-level COVID-19 outbreak on the stock price of local firms may also display strong heterogeneity with respect to market size.

To test this, we divide the whole sample based on the median of all stocks' daily market values and re-estimate the baseline specification on each subsample. Columns (5)–(8) in Table 4 report the results, which demonstrate the difference in the COVID-19 effects between small and large stocks. For the main board, both large and small stocks respond to the moderate COVID-19 outbreak in the city where the firms' headquarters are located, while the impact on small stocks are more pronounced. For the second board, however, the magnitudes of the interday COVID-19 effect associated with a severe outbreak remain comparable between small and large stocks.

4.2.3. Firm ownership

A key characteristic of the Chinese stock market is the predominant role of state-owned enterprises (SOEs). As of May 2022, roughly 29.2% of the firms listed on the main and second boards are state-owned, and they account for a significant portion of the total market value. As some researchers argue in their seminal work, SOEs in China not only enjoy preferential statuses in terms of receiving financial and policy support from the governments but they are often criticized for their lack of information transparency. Compared to non-SOEs, SOEs' non-competitive advantages make it easier for them to gain access to external support during the pandemic, which can effectively alleviate the negative shocks of the COVID-19 outbreak. With this in mind, investors may respond very differently to the COVID-19 shock when considering SOEs and non-SOEs, generating substantial heterogeneity with respect to the ownership structure. Given the importance of SOEs in China, such heterogeneity deserves a separate treatment.

Using firm ownership data acquired from the China Stock Market & Accounting Research (CSMAR), we classify all listed firms in our sample into the groups of SOEs and Non-SOEs. Specifically, a stock is classified as an SOE if the proportion of total shares held by government entities

Table 4
Results for heterogeneity analyses.

	Risk-adjusted returns							
	Main board		Second board		Main board		Second board	
	Resilient stocks (1)	Vulnerable stocks (2)	Resilient stocks (3)	Vulnerable stocks (4)	Small stocks (5)	Large stocks (6)	Small stocks (7)	Large stocks (8)
$I(0 < \Delta COVID_{c,t} \leq 10)$	0.0071	−0.0127	0.0284	−0.0023	−0.0140	0.0034	0.0118	0.0124
	(0.0095)	(0.0107)	(0.0201)	(0.0183)	(0.0096)	(0.0134)	(0.0144)	(0.0162)
$I(10 < \Delta COVID_{c,t} \leq 50)$	−0.0692***	−0.0270	−0.0010	−0.0623	−0.0692***	−0.0270	−0.0010	−0.0623
	(0.0194)	(0.0255)	(0.0442)	(0.0441)	(0.0151)	(0.0285)	(0.0360)	(0.0607)
$I(\Delta COVID_{c,t} > 50)$	−0.0275	−0.0910***	−0.0971	−0.0925*	−0.0716**	−0.0681**	−0.0715*	−0.0916*
	(0.0151)	(0.0285)	(0.0360)	(0.0607)	(0.0303)	(0.0317)	(0.0410)	(0.0493)
AQI	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged return	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	361,407	1,191,384	165,547	509,381	776,150	776,846	337,288	337,457
Adjusted R^2	0.032	0.012	0.061	0.037	0.025	0.033	0.055	0.057
	Risk-adjusted returns							
	Main board		Second board		Main board		Second board	
	Non-SOE (9)	SOE (10)	Non-SOE (11)	SOE (12)	Low ROA (13)	High ROA (14)	Low ROA (15)	High ROA (16)
$I(0 < \Delta COVID_{c,t} \leq 10)$	−0.0188	0.0097	0.0090	0.0244	−0.0106	−0.0058	−0.0047	0.0246*
	(0.0117)	(0.0104)	(0.0143)	(0.0341)	(0.0113)	(0.0117)	(0.0174)	(0.0131)
$I(10 < \Delta COVID_{c,t} \leq 50)$	−0.0745***	−0.0093	−0.0232	−0.1120	−0.0516***	−0.0341	−0.0500	0.0001
	(0.0197)	(0.0230)	(0.0525)	(0.0845)	(0.0192)	(0.0339)	(0.0495)	(0.0366)
$I(\Delta COVID_{c,t} > 50)$	−0.0889***	−0.0497	−0.1043**	−0.1257	−0.1070**	−0.0786*	−0.0857*	−0.1558***
	(0.0243)	(0.0309)	(0.0439)	(0.0855)	(0.0468)	(0.0436)	(0.0470)	(0.0531)
AQI	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged return	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	968,121	578,219	604,811	66,059	752,944	751,037	340,644	334,107
Adjusted R^2	0.010	0.035	0.038	0.031	0.019	0.021	0.044	0.045

This table presents the estimation results for the heterogeneity analyses of COVID-19 effects on daily stock returns. Columns (1)–(4), (5)–(8), (9)–(12), and (13)–(16) correspond to industry classification, firms' market value, ownership, and pre-pandemic finances, respectively. The dependent variables are FF-6 adjusted daily stock returns. The independent variables of interest are the discrete indicators for the number of new COVID-19 cases in city c on date $t-h$, i.e., $I(0 < \Delta COVID_{c,t-h} \leq 10)$, $I(10 < \Delta COVID_{c,t-h} \leq 50)$, and $I(\Delta COVID_{c,t-h} > 50)$, where $h = 0, 1$. The coefficient estimates are expressed in percentages. We control for lagged returns, stock-month fixed effects, and date-fixed effects in all columns. Numbers in parentheses represent standard errors, which are two-way clustered by stock and date. Variable definitions can be found in Table A.1 in the Online Appendix. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

exceeds 50%; otherwise, it is classified as a Non-SOE. Columns (9)–(12) in Table 4 report the results of the subsample analysis based on firm ownership. Consistent with our hypothesis, the effects of the city-level COVID-19 outbreak on daily stock returns are more salient for non-SOEs. For example, the daily stock returns of non-SOEs listed on the main board significantly drop by 0.07% and 0.09% if a moderate or severe city-level COVID-19 epidemic breaks out, respectively. In contrast, the daily stock returns of SOEs listed on the same board show no effect in response to a moderate outbreak and only drop by 0.05% under a severe outbreak. This finding also holds for the second board: Only non-SOEs respond to the negative shock of a severe COVID-19 outbreak. In sum, these findings suggest that SOEs' preferential role mitigates the negative impacts of the COVID-19 outbreak on stock prices.

4.2.4. Financial performance

Our final heterogeneity analysis examines if the negative COVID-19 impact on daily stock returns varies according to firms' financial performance. A recent study by Ding et al. (2021) indicates that firms with more robust pre-pandemic finances typically experience a less severe pandemic-induced decline in weekly stock returns, based on international data. However, it remains uncertain whether this finding applies to the zero-COVID policy scenario, as most economies analyzed in Ding et al. (2021) opted for coexistence with the virus due to practical considerations. Moreover, the underlying dynamics of COVID-19's effects on stock returns in relation to firms' financial performance have not been thoroughly investigated. Thus, a deeper analysis of the heterogeneity in COVID-19 effects at the daily level holds considerable empirical significance.

Motivated by these observations, we divide the full sample evenly using the median of firms' return on assets (ROA) for 2019 and reevaluate the COVID-19 effects on each subsample.[17] Columns (13)–(16) in Table 4 reveal a mixed pattern in the COVID-19 effects concerning ROA. For stocks listed on the main board, the COVID-19 effects on daily stock returns only occur among firms with low ROAs, and none of the coefficient estimates on the severity indicators prove significant for the high ROA group. Importantly, this finding aligns with Ding et al. (2021), suggesting that stronger pre-pandemic financial performance can alleviate the COVID-19 shock on stock prices. Conversely, the effects are more pronounced among stocks with high ROAs on the second board. For instance, a severe outbreak corresponds to a decrease of 0.156% and 0.086% in daily stock returns for high- and low-ROA firms listed on the second board, respectively. However, such a difference is statistically insignificant as evidenced by the t-test. These results clearly demonstrate significant heterogeneity in the mitigating effect of strong pre-pandemic finances.

[17] We have performed similar analyses using alternative financial performance metrics, such as return on equity, total debt ratio, and net profitability ratio, and our findings are qualitatively consistent. To maintain brevity, these results are not included in the current draft but can be provided upon request.

4.3. Spatial spillover of the COVID-19 effects

The severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), responsible for causing the coronavirus disease (COVID-19), is among the most contagious viruses known to humans. Its highly infectious nature allows the virus to spread to areas surrounding the epicenter of the pandemic easily, a process further accelerated by the extensive domestic travel flows in China. For instance, when the virus initially emerged in Wuhan in 2020, it rapidly spread throughout the country, with cities in close proximity to Wuhan being most severely affected. The geographic spillover of the COVID-19 outbreak also became a critical policy concern when China adopted the zero-COVID strategy. During this period, prefecture governments closely monitored the number of new cases in neighboring regions and frequently implemented various measures, such as widespread PCR testing and temporary transportation restrictions, in response to sudden COVID outbreak. These preventive measures inevitably impacted local economic growth and firms' regular operations, leading to the spatial spillover of the negative COVID-19 effects on daily stock returns. Moreover, spatial spillovers may also be caused by business relations between local firms and those in neighboring regions, as logistics often come to a halt during an outbreak in neighboring cities.

To investigate this hypothesis, we employ the following specification that refines the baseline specification by incorporating measures of COVID-19 outbreak severity in neighboring cities, i.e.,

$$r^*_{i,c,t} = \beta \cdot \mathrm{I}(\Delta\text{COVID-19}_{c,t}) + \rho \cdot \mathrm{I}\Big(\sum_{k\in\mathcal{N}} w_{c,k} \cdot \Delta\text{COVID-19}_{k,t}\Big) + X_{c,t}^{\top}\gamma + \phi \cdot r^*_{i,c,t-1} + \theta_{i,m} + \delta_t + \alpha + \epsilon_{i,t}, \tag{4}$$

where $\mathrm{I}(\Delta\text{COVID-19}_{c,t})$ denotes the indicators for the number of new COVID-19 cases in city c on day t; $\mathcal{N}$ represents the set of all cities in our sample; $w_{c,k}$ is the (c,k)-th element of the weighting matrix $\mathbf{W}$ in spatial econometrics, which measures the geographic distance between city c and city k; and the remaining variables are defined similarly as in the baseline specification. We let N denote the number of unique cities in our sample, i.e., $N_c = |\mathcal{N}|$, and set $\overline{\Delta\text{COVID}}_{c,t} = \sum_{k\in\mathcal{N}} w_{c,k} \cdot \Delta\text{COVID-19}_{k,t}$ for ease of discussion. Furthermore, we include one lag of the COVID-19 indicators for both local and out-of-town outbreaks to capture the underlying dynamics of the COVID-19 effect.

The spatial weighting matrix $\mathbf{W}$ is a crucial component of the spatial regression model above, as it controls the spillover strength from other cities. Ideally, we would expect $w_{c,k}$ to be small (large) if these two cities are far away from (close to) each other so that the spillover effect of the COVID-19 outbreak is weak (strong). Consequently, we employ two commonly used strategies in spatial econometrics, i.e., direct neighbors and inverse distance, to construct the weighting matrix. For the direct neighbors weighting matrix, $w_{c,k} = 1$ if cities i and k are geographically adjacent and $w_{i,k} = 0$ otherwise; for the inverse distance weighting matrix, $w_{c,k} = 1/d_{c,k}$, where $d_{c,k}$ is the spherical distance between the centers of the two cities c and k. Following convention, we further set $\mathbf{W}$ to be row-normalized, i.e., $\sum_{k=1}^{N_c} w_{c,k} = 1$, and $w_{k,k} = 0$ for $k = 1,\dots,N_c$. Notably, the spatial spillover exists only between geographically connected cities for the direct neighbors weighting matrix and is inversely proportional to the distance between any city pair for the inverse distance weighting matrix.

Table 5 presents the coefficient estimates for the spatial regression model mentioned earlier. The coefficient estimates on the indicators for city-level new COVID-19 cases are quantitatively similar to those for the baseline specification, indicating that the main effects are robust to potential spatial spillover. Additionally, the stock prices of firms listed on the second board experience a significant rebound one day after the outbreak of a severe city-level outbreak, consistent with the findings from the baseline regression. More importantly, the results demonstrate a substantial spillover effect of the COVID-19 outbreak on the stock returns of firms headquartered in nearby cities when the severity of the outbreak is high. For example, when the total number of new cases in neighboring cities exceeds 50, i.e., $\overline{\Delta\text{COVID}}_{c,t} > 50$, the daily stock returns on average decrease by approximately 0.39% and 0.50% for the main and second boards, respectively, as indicated by the coefficient estimates based on the weighting matrix of direct neighbors. In contrast to the city-level COVID-19 outbreak, we do not find a reversal in the stock prices associated with the COVID-19 outbreak in nearby cities for stocks on both boards.

It is worth noting that the estimated price effect of the COVID-19 outbreak in neighboring cities is much larger than that of the city-level outbreak when the number of new cases exceeds 50 in both places. For instance, when the weighting matrix of direct neighbors is used for estimation, the spillover effect (−0.388%) is four times the main effect (−0.097%). Although it is not the primary focus of our paper, a possible explanation for this pronounced difference is that investors' uncertainty about the potential impact of the COVID-19 outbreak in nearby cities can be much higher than that of local ones. In particular, it is relatively easy for investors to judge the severity of the outbreak based on the number of city-level new cases, while inferring the extent of spillover infection from nearby cities can be much more challenging. As indicated by existing literature (Ozoguz, 2009), such differences in investors' uncertainty may lead to significant heterogeneity in the scale of the effects.

4.4. Robustness checks

We conduct a series of robustness checks to confirm the validity of our main results, which are presented in Table 6.

4.4.1. Alternative fixed effects

Recall that we control for the stock-month fixed effects in the baseline specification to capture unobservable characteristics that are time-invariant or vary slower than a monthly frequency. However, if the monthly unobservables not only correlate with the daily number of new COVID-19 cases but also affect daily stock returns, such a setting may underestimate the main effects. To alleviate this concern, we replace the stock-month fixed effects with stock fixed effects, stock-quarter, and stock-year fixed effects, respectively. The corresponding estimates reported in columns (1)–(3) and (9)–(11) in Table 6 show that the effects of the city-level COVID-19 outbreak are quantitatively similar under these alternative choices of fixed effects for both the main and second boards.

4.4.2. Excluding potential outliers

Our baseline estimation utilizes data covering all cities in China over the entire period from January 2020 to May 2022. During this period, there were two large-scale COVID-19 outbreaks that led to prolonged lockdowns. The first major outbreak took place in Wuhan in early 2020 and caused more than 50,000 identified cases according to the report from the city-level CDC, and the city was kept on lockdown for more than two months. The second major outbreak happened in Shanghai in March 2022, and the consequent lockdown also lasted for more than two months.[18] Given the severity of the two major outbreaks, one may wonder whether our main findings are primarily driven by these "outliers". To test for this possibility, we exclude observations subject to the lockdown periods for Shanghai and Wuhan and report the results in columns (4) and (12) of Table 6. The corresponding coefficient estimates are very similar to those for the baseline specification.

[18] According to public information, the lockdown period is January 23rd to April 8th, 2020 for Wuhan (http://www.gov.cn/xinwen/2020-03/24/content_5494927.htm) and March 28th to May 31st, 2022 for Shanghai (https://www.shanghai.gov.cn/nw12344/20220530/ccfdd516456b4c8b855f203d4de9016f.html).

Table 5
Spatial spillover of the COVID-19 effects on the daily stock returns of local firms.

	Risk-adjusted returns			
	Main board		Second board	
	Direct neighbor (1)	Inverse distance (2)	Direct neighbor (3)	Inverse distance (4)
$I(0 < \Delta COVID_{c,t} \leq 10)$	−0.0066	−0.0076	0.0010	−0.0046
	(0.0097)	(0.0103)	(0.0095)	(0.0094)
$I(10 < \Delta COVID_{c,t} \leq 50)$	−0.0438**	−0.0399*	−0.0212	−0.0247
	(0.0219)	(0.0237)	(0.0345)	(0.0346)
$I(\Delta COVID_{c,t} > 50)$	−0.0972***	−0.0850**	−0.1646***	−0.1586***
	(0.0317)	(0.0333)	(0.0478)	(0.0476)
$I(0 < \Delta COVID_{c,t-1} \leq 10)$	0.0067	0.0024	0.0100	0.0115
	(0.0067)	(0.0069)	(0.0119)	(0.0134)
$I(10 < \Delta COVID_{c,t-1} \leq 50)$	0.0254	0.0206	0.0401	0.0322
	(0.0249)	(0.0277)	(0.0255)	(0.0277)
$I(\Delta COVID_{c,t-1} > 50)$	0.0100	−0.0083	0.1822***	0.1589**
	(0.0456)	(0.0458)	(0.0576)	(0.0624)
$I(0 < \overline{\Delta COVID}_{c,t} \leq 10)$	0.0048	0.0372	−0.0134	−0.0063
	(0.0267)	(0.0247)	(0.0380)	(0.0287)
$I(10 < \overline{\Delta COVID}_{c,t} \leq 50)$	−0.0171	−0.0486	−0.0522	0.0451
	(0.0764)	(0.0636)	(0.1183)	(0.1191)
$I(\overline{\Delta COVID}_{c,t} > 50)$	−0.3880**	−0.3486**	−0.4969**	−0.3958*
	(0.1818)	(0.1634)	(0.2293)	(0.2248)
$I(0 < \overline{\Delta COVID}_{c,t-1} \leq 10)$	0.0087	0.0072	−0.0206	0.0029
	(0.0322)	(0.0316)	(0.0408)	(0.0241)
$I(10 < \overline{\Delta COVID}_{c,t-1} \leq 50)$	−0.0569	−0.0229	−0.0638	−0.0097
	(0.0892)	(0.0710)	(0.1103)	(0.0686)
$I(\overline{\Delta COVID}_{c,t-1} > 50)$	−0.0030	−0.0477	0.0714	0.0086
	(0.2025)	(0.1604)	(0.2210)	(0.1631)
AQI	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Lagged return	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes
Stock-month fixed effects	Yes	Yes	Yes	Yes
Number of observations	1,555,475	1,555,475	675,418	675,418
Adjusted R^2	0.016	0.015	0.042	0.043

This table presents the estimation results testing the spatial spillover of COVID-19 effects on the daily stock returns of local firms. The dependent variables are FF-6 adjusted daily stock returns. The independent variables of interest are the discrete indicators for the number of new COVID-19 cases in city c on date $t-h$, i.e., $I(0 < \Delta COVID_{c,t-h} \leq 10)$, $I(10 < \Delta COVID_{c,t-h} \leq 50)$, and $I(\Delta COVID_{c,t-h} > 50)$, as well as the discrete indicators for the weighted sum of COVID-19 cases in the neighboring cities, i.e., $I(0 < \overline{\Delta COVID}_{c,t} \leq 10)$, $I(10 < \overline{\Delta COVID}_{c,t} \leq 50)$, and $I(\overline{\Delta COVID}_{c,t} > 50)$, where $h = 0, 1$. The coefficient estimates are expressed in percentages. We control for lagged returns, stock-month fixed effects, and date-fixed effects in all columns. Numbers in parentheses represent standard errors, which are two-way clustered by stock and date. Variable definitions can be found in Table A.1 in the Online Appendix. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

4.4.3. *Excluding firms in first-tier cities*

One notable characteristic of listed firms in China is that a large proportion of them are headquartered in the four first-tier cities, including Beijing, Shanghai, Guangzhou, and Shenzhen, each with a population of more than 15 million. Many of these firms are either high-tech-oriented or large SOEs, playing a critical role in China's economy and attracting significant attention from investors. Since the coronavirus can spread more easily in densely populated cities, the main effects may also be driven by firms located in these areas. To rule out this possibility, we exclude observations for firms located in first-tier cities. The corresponding results reported in columns (5) and (13) of Table 6 remain quantitatively similar.[19] Furthermore, we exclude firms of the bottom 30% size and those belonging to the financial industry to check if the effects are caused by specific groups of firms, and the results reported in columns (6)–(7) and (14)–(15) in Table 6 are largely unchanged.

4.4.4. *Alternative standard error clustering*

Columns (8) and (16) of Table 6 report the estimation results for alternative clustering of standard errors for the main and second boards, respectively. Specifically, we switch to the two-way clustering at the city and quarter level, which allows for autocorrelation within each city across quarters. The significance levels of all coefficient estimates barely change. Columns (2) and (9) of Table A.5 in the Online Appendix show the standard errors two-way clustered by city and year, and columns (3) and (10) in the same table present the standard errors clustered at the city level. Overall, our main findings remain highly robust to the assumption on the clustering of standard errors.

4.4.5. *Alternative asset pricing models*

Furthermore, we test whether the COVID-19 effects are robust to the choice of asset pricing models used to compute the daily abnormal returns. In columns (4)–(7) and (11)–(14) of Table A.5 in the Appendix, we report the estimates based on the CAPM, FF-3, FF-4, and FF-5 models. It is noteworthy that these estimates are exactly the same as those shown in Table 2 and the only difference is in the R^2. As explained in Section 4.1, such a coincidence simply reflects the fact that the occurrence of the COVID-19 outbreak is independent of the factor returns.

4.4.6. *Alternative thresholds for COVID-19 indicators*

Lastly, we test the sensitivity of our baseline regression findings to the 10/50 threshold by considering alternative threshold choices. Specifically, we examined the thresholds of 10/20 and 25/50 to construct new COVID-19 case indicators. The corresponding estimation

[19] Columns (1) and (8) of Table A.5 in the Online Appendix report the estimates when we exclude observations for firms located in cities with a population of more than 10 million, demonstrating that the main results are qualitatively similar.

Table 6
Robustness checks for the COVID-19 effects on the daily stock returns of local firms.

	Risk-adjusted returns							
	Stock FEs (1)	Stock-quarter FEs (2)	Stock-year FEs (3)	Exclude Wuhan and Shanghai (4)	Exclude first-tier cities (5)	Exclude small firms (6)	Exclude financial firms (7)	Alternative clustering (8)
Panel A: Results for the main board								
$I(0 < \Delta COVID_{c,t} \leq 10)$	−0.0096	−0.0081	−0.0074	−0.0068	−0.0101	−0.0091	−0.0119	−0.0081
	(0.0097)	(0.0098)	(0.0097)	(0.0105)	(0.0125)	(0.0136)	(0.0100)	(0.0106)
$I(10 < \Delta COVID_{c,t} \leq 50)$	−0.0458**	−0.0437**	−0.0459**	−0.0513**	−0.0659**	−0.0452	−0.0561**	−0.0499*
	(0.0203)	(0.0210)	(0.0194)	(0.0257)	(0.0296)	(0.0340)	(0.0232)	(0.0256)
$I(\Delta COVID_{c,t} > 50)$	−0.0936***	−0.0990***	−0.0959***	−0.1272***	−0.1848***	−0.0885**	−0.1074***	−0.0992**
	(0.0335)	(0.0342)	(0.0344)	(0.0371)	(0.0662)	(0.0426)	(0.0325)	(0.0324)
$I(0 < \Delta COVID_{c,t-1} \leq 10)$	0.0012	0.0024	0.0035	0.0020	−0.0082	0.0071	0.0057	0.0029
	(0.0054)	(0.0060)	(0.0055)	(0.0063)	(0.0099)	(0.0093)	(0.0068)	(0.0052)
$I(10 < \Delta COVID_{c,t-1} \leq 50)$	0.0279	0.0286	0.0279	0.0215	0.0391	0.0288	0.0344	0.0251
	(0.0269)	(0.0275)	(0.0276)	(0.0222)	(0.0251)	(0.0324)	(0.0230)	(0.0244)
$I(\Delta COVID_{c,t-1} > 50)$	0.0465	0.0382	0.0441	0.0336	0.1654	0.0190	0.0423	0.0388
	(0.0334)	(0.0322)	(0.0362)	(0.0336)	(0.1031)	(0.0445)	(0.0322)	(0.0459)
AQI	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged return	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	Yes	No	No	No	No	No	No
Stock-month fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes
Stock-quarter fixed effects	No	Yes	No	No	No	No	No	No
Stock-year fixed effects	No	No	Yes	No	No	No	No	No
Number of observations	1,555,475	1,555,475	1,555,475	1,510,133	1,027,329	1,067,051	1,462,575	1,555,475
Adjusted R^2	0.012	0.012	0.013	0.014	0.014	0.023	0.013	0.014

	Risk-adjusted returns							
	Stock FEs (9)	Stock-quarter FEs (10)	Stock-year FEs (11)	Exclude Wuhan and Shanghai (12)	Exclude first-tier cities (13)	Exclude small firms (14)	Exclude financial firms (15)	Alternative clustering (16)
Panel B: Results for the second board								
$I(0 < \Delta COVID_{c,t} \leq 10)$	−0.0063	−0.0010	−0.0050	0.0034	0.0184	0.0056	0.0026	0.0056
	(0.0138)	(0.0151)	(0.0143)	(0.0133)	(0.0192)	(0.0153)	(0.0144)	(0.0146)
$I(10 < \Delta COVID_{c,t} \leq 50)$	−0.0580	−0.0537	−0.0630	−0.0536	−0.0421	−0.0553	−0.0543	−0.0503
	(0.0458)	(0.0479)	(0.0460)	(0.0486)	(0.0582)	(0.0569)	(0.0504)	(0.0445)
$I(\Delta COVID_{c,t} > 50)$	−0.2037***	−0.2083***	−0.2219***	−0.2317***	−0.3842***	−0.2227***	−0.2192***	−0.2128***
	(0.0430)	(0.0429)	(0.0422)	(0.0455)	(0.1417)	(0.0490)	(0.0452)	(0.0563)
$I(0 < \Delta COVID_{c,t-1} \leq 10)$	−0.0043	0.0012	−0.0029	0.0067	−0.0022	−0.0044	0.0096	0.0083
	(0.0169)	(0.0166)	(0.0164)	(0.0175)	(0.0223)	(0.0207)	(0.0168)	(0.0187)
$I(10 < \Delta COVID_{c,t-1} \leq 50)$	0.0265	0.0299	0.0211	0.0279	0.0613	0.0147	0.0351	0.0329
	(0.0282)	(0.0275)	(0.0280)	(0.0287)	(0.0424)	(0.0300)	(0.0287)	(0.0318)
$I(\Delta COVID_{c,t-1} > 50)$	0.1907***	0.1835***	0.1715***	0.1588***	0.3743**	0.1535**	0.1846***	0.1816**
	(0.0500)	(0.0509)	(0.0509)	(0.0545)	(0.1782)	(0.0653)	(0.0534)	(0.0642)
AQI	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged return	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	Yes	No	No	No	No	No	No
Stock-month fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes
Stock-quarter fixed effects	No	Yes	No	No	No	No	No	No
Stock-year fixed effects	No	No	Yes	No	No	No	No	No
Number of observations	675,418	675,418	675,418	661,830	414,022	468,687	667,289	675,418
Adjusted R^2	0.035	0.035	0.034	0.036	0.035	0.046	0.036	0.036

This table presents the estimation results of robustness checks for the impact of COVID-19 on the daily stock returns of local firms. The dependent variables are the FF-6 adjusted daily stock returns. The independent variables of interest are the discrete indicators for the number of new COVID-19 cases in city c on date $t-h$, denoted by $I(0 < \Delta COVID_{c,t-h} \leq 10)$, $I(10 < \Delta COVID_{c,t-h} \leq 50)$, and $I(\Delta COVID_{c,t-h} > 50)$, where $h = 0, 1$. Columns (1)–(3) and (9)–(11) replace stock-month fixed effects in the baseline specification with stock fixed effects, stock-quarter fixed effects, and stock-year fixed effects, respectively. Columns (4)–(7) and (12)–(15) exclude observations pertaining to the lockdown periods for Wuhan and Shanghai, firms headquartered in the four first-tier cities, firms in the bottom 30% size category, and firms belonging to the financial industry. Columns (8) and (16) employ two-way clustering of the standard errors by city and quarter. The coefficient estimates are expressed in percentages, and all columns include controls for lagged returns and date-fixed effects. Numbers in parentheses represent standard errors, which are two-way clustered by stock and date in columns (1)–(7) and (9)–(15). Variable definitions can be found in Table A.1 in the Online Appendix.

results, reported in Table A.7 in the Online Appendix, show that our main findings remain qualitatively similar.

4.4.7. Difference-in-difference regression

To strengthen the main findings of our study, we also consider a difference-in-differences (DID) specification that investigates the impacts of city-level lockdowns on daily stock returns.[20] As introduced in Section 2, many cities in China have experienced lockdowns due to local COVID-19 outbreaks during the pandemic. These lockdowns may

[20] We thank two anonymous referees for suggesting this robustness check.

negatively impact the stock returns of local firms for various reasons, such as impeded transportation. We source information on major Chinese city lockdowns from Chen et al. (2020), which accurately documents lockdown periods for 34 cities in China up to January 2022. Using the data on city-level lockdowns, we consider the following DID specification:

$$r_{i,c,t} = \beta \text{lockdown}_{c,t} + X_{c,t}^{\top}\gamma + \phi r_{i,c,t-1} + \theta_{i,m} + \delta_t + \alpha + \epsilon_{i,t},$$

where $\text{lockdown}_{c,t}$ is a dummy variable that equals one if city c, where firm i is headquartered, is in a full-scale or partial lockdown on date t, and zero otherwise. The remaining regressors and fixed effects are defined similarly to those in the baseline specification (3).

Table A.6 in the Online Appendix reports the estimation results for the above DID specification using risk-adjusted returns as the dependent variable.[21] We find that city-level lockdowns, on average, result in a drop in daily stock returns during the lockdown period by 0.34% for stocks listed on the main board and by 0.16% for stocks listed on the second board. Notably, these results are consistent with our findings from the panel regression models where COVID-19 outbreaks are treated as exogenous shocks. Nevertheless, the interpretation of the COVID-19 effects estimated from the DID specification differs from the baseline panel regression model as the COVID-19 effects span the entire lockdown period in the DID specification.

5. Additional analyses

In this section, we conduct additional analyses on the effects of new COVID-19 cases on daily stock returns. Section 5.1 computes the total market value "evaporated" due to the COVID-19 effects identified in our study. Section 5.2 explores mechanisms for the COVID-19 effects on stock returns. Section 5.3 investigates the role of retail investors.

5.1. Economic implications

What are the economic implications of the local COVID-19 outbreak on the Chinese stock market? To answer this question, we conduct a simple back-of-the-envelope calculation on the accumulative total market value "evaporated" because of the COVID-19 outbreaks based on detailed historical data on city-level new cases and stock market values. In particular, the daily loss of the whole stock market is given by multiplying the total market value of firms affected by the COVID-19 outbreak with the estimated effects. As indicated by the results in Table 2, stock returns of the firms listed on the main board are affected by the moderate and severe outbreaks, with an average drop in the price of 0.04% and 0.08%, respectively. The daily stock returns of firms listed on the second board are only affected by a severe outbreak, with an effect of −0.1%. For each city, we analyze the historical data on new COVID-19 cases to determine whether the local publicly traded firms are affected by the outbreak and compute the city-level loss. The daily nationwide loss is then given by summing over the city-specific loss of all cities on each trading day.

It is worth noting that the market-wide loss considered here should only be interpreted as a measure reflecting the contemporaneous shock of the local COVID-19 outbreak on investors' wealth instead of the aggregate effect. There are two main reasons. First, the COVID-19 effect estimated from the baseline specification is net of the aggregate shock of the outbreak at the country level because we have controlled for the date fixed effects. As shown in Ding et al. (2021), the nationwide COVID-19 shock also significantly affects the stock returns; thus, the market-wide loss we calculated is likely to be a lower bound of the overall economic loss of the COVID-19 outbreak. Second, the results in Section 4.1 have shown that the negative impacts of the city-level COVID-19 outbreak fade quickly. For example, stocks on the second board exhibit a price reversal, making the COVID-19 effect on the two-day accumulative abnormal return insignificant. Nevertheless, the outbreak-induced price drop would inevitably enhance stocks' return volatility, leading to a corresponding loss in investors' utility, as illustrated in Section 4.1.

Fig. 3 depicts the accumulative market cap loss triggered by the local COVID-19 outbreak for the primary and second boards, respectively. As of May 2022, such loss has reached 600 and 300 billion RMB (approximately 85.8 and 42.9 billion USD) for these two markets, which confirms that the main effects identified in our study are of high economic relevance. Notably, there are two periods during which the accumulative market cap loss exhibits a high growth rate. The first period, from January through April 2020, corresponds to the first three months after the coronavirus was first identified in Wuhan, China. During this period, many cities in China, especially those near the epicenter, suffered from the COVID-19 outbreak due to intercity transmission. The second period, which spans from December 2021 through May 2022, is likely to be caused by the fast spread of the Omicron variant in China, which is known to be much more infectious than the original virus. Moreover, there is a flat stage between the two fast-growing periods, indicating the extraordinary success of the zero-COVID policy before the highly infectious Omicron variant appeared. These results thus suggest that the majority of the market cap loss was realized during these two periods of intensive COVID-19 outbreaks.

5.2. Potential mechanisms

Next, we explore the underlying mechanisms driving the COVID-19 impact on stock returns. A basic discounted cash flow model for stock valuation suggests that a negative return – or a decline in stock price – can result from a decrease in a company's anticipated future cash flows or an increase in investors' discount factor. To differentiate between these two channels, we conduct two sets of empirical analyses, presented in Sections 5.2.1 and 5.2.2, respectively.

5.2.1. Cash flow channel

We first examine whether the local COVID-19 outbreak negatively impacts analysts' earnings forecasts, which are commonly used in the literature as a proxy for expected cash flow. As analysts' earning forecasts are largely affected by the information contained in financial reports (Barniv et al., 2005), and the effect of mild or moderate outbreaks could be overwritten by the severe ones, we consider a specification similar to the baseline regression but relying on quarterly observations. Specifically, we aggregate the number of COVID-19 cases at the quarterly level and construct three new case indicators, i.e., $\mathrm{I}(0 < \sum_{t\in Q_k} \Delta\text{COVID}_{c,t} \leq 10)$, $\mathrm{I}(10 < \sum_{t\in Q_k} \Delta\text{COVID}_{c,t} \leq 50)$, and $\mathrm{I}(\sum_{t\in Q_k} \Delta\text{COVID}_{c,t} > 50)$, where Q_k denotes the kth quarter. For each firm i based in city c, we then compute the average of analysts' earnings forecasts within six months before and after a given quarter and calculate the change in analysts' earnings forecasts, denoted as $\Delta\text{Forecast EPS}_{i,t}$. Lastly, we regress $\Delta\text{Forecast EPS}_{i,t}$ on the three quarterly indicators for COVID-19 cases and a set of firm characteristics and control for the quarter-fixed effects to capture other potential confounding factors, such as common macroeconomic shocks.

Table 7 presents the estimated effects of the COVID-19 outbreak on analysts' earnings forecasts. In line with the cash flow channel, the outbreak of the COVID-19 outbreak leads to a decrease in analysts' earnings forecasts, although this effect is only significant for stocks listed on the main board. Specifically, for stocks listed on the main board, a mild, moderate, and severe city-level outbreak results in a decline in EPS forecasts of 0.013, 0.017, and 0.024 RMB, respectively, exhibiting a monotonic pattern. Taking the average EPS forecasts of stocks listed on the main board as the benchmark (0.687 RMB/share), this further implies a decrease of 1.9%, 2.5%, and 3.5%, respectively, indicating

[21] We also conduct a corresponding parallel trends test for the above DID specification, which shows that the model is free from potential pretrend; see Figure A.1 in the Online Appendix.

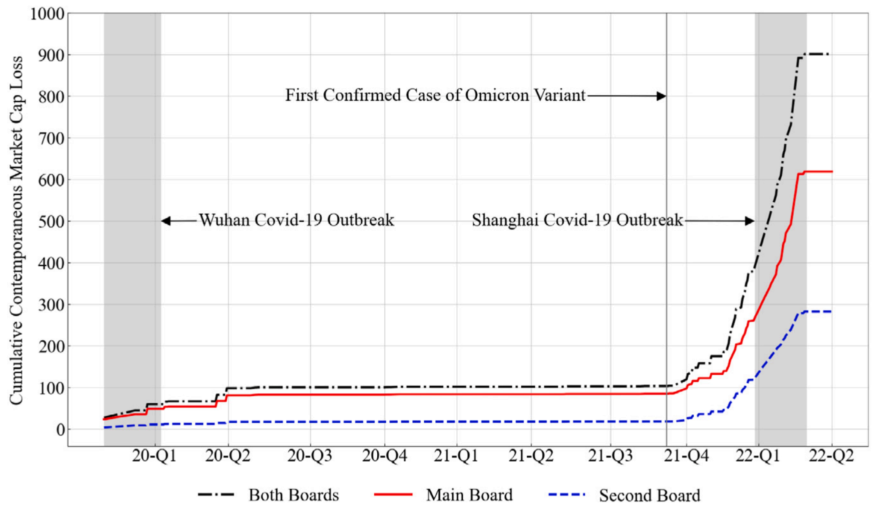

Fig. 3. Estimated cumulative contemporaneous market capitalization loss due to the COVID-19 outbreaks.
Note: This figure shows the estimated cumulative contemporaneous market capitalization loss for the main board (black dotted line), the second board (red solid line), and the pooled sample (blue dashed line) from January 2020 to May 2022. The daily contemporaneous market capitalization loss is calculated based on the effects of city-level COVID-19 outbreaks on daily stock returns of local firms reported in Table 3 and the total market capitalization at the city level. The two shaded areas correspond to the periods of the Wuhan COVID-19 outbreak and the Shanghai COVID-19 outbreak, respectively. The first confirmed case of Omicron variant was reported on December 9th, 2021.

Table 7
Impacts of city-level COVID-19 outbreaks on analysts' EPS forecasts.

	Analysts' earning forecasts	
	Main board (1)	Second board (2)
$I(0 < \sum_{t\in Q_k} \Delta COVID_{c,t} \le 10)$	−0.0127***	−0.0070*
	(0.0038)	(0.0040)
$I(10 < \sum_{t\in Q_k} \Delta COVID_{c,t} \le 50)$	−0.0170***	−0.0076
	(0.0034)	(0.0058)
$I(\sum_{t\in Q_k} \Delta COVID_{c,t} > 50)$	−0.0241***	−0.0107
	(0.0059)	(0.0070)
IVol	0.7863***	0.1591
	(0.1168)	(0.1290)
Size	0.0336***	0.0495***
	(0.0026)	(0.0020)
B/M	0.0279***	0.0389***
	(0.0022)	(0.0043)
Leverage	0.0564***	0.0464***
	(0.0060)	(0.0133)
BHR	−0.0189***	0.0096
	(0.0067)	(0.0076)
Stock fixed effects	Yes	Yes
Quarter fixed effects	Yes	Yes
Number of observations	26,382	10,812
Adjusted R^2	0.125	0.162

This table presents the estimation results examining the impact of city-level COVID-19 outbreaks on analysts' EPS forecasts. The dependent variables are the changes in the averages of analysts' earnings forecasts for each firm i based in city c within six months before and after a given quarter. The independent variables of interest are the discrete indicators for the cumulative number of new COVID-19 cases in city c during the quarter Q_k, i.e., $I(0 < \sum_{t\in Q_k} \Delta COVID_{c,t} \le 10)$, $I(10 < \sum_{t\in Q_k} \Delta COVID_{c,t} \le 50)$, and $I(\sum_{t\in Q_k} \Delta COVID_{c,t} > 50)$. The coefficient estimates are expressed in percentages. We control for a set of firm characteristics, stock fixed effects, and quarter fixed effects in all columns. Numbers in parentheses represent standard errors, which are two-way clustered by stock and date. Variable definitions can be found in Table A.1 in the Online Appendix. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

that the COVID-induced changes in EPS forecasts are economically significant.

Furthermore, we investigate whether local COVID-19 outbreaks indeed impact firms' profits, which contribute to the operating cash flow. To do this, we regress the change in three widely used financial indicators – return on assets (ROA), return on equity (ROE), and earnings per share (EPS) – revealed in any two consecutive financial statements before and after the quarter Q_k on the three discrete indicators for the number of new COVID-19 cases within the quarter, along with a set of firm characteristics. The corresponding results reported in Table 8 clearly demonstrate that firms' realized profitability significantly deteriorates due to the outbreak, particularly when the quarterly cumulative number of new cases exceeds 50. Specifically, we find that the ROA, ROE, and EPS of firms listed on the main board would decrease by 0.38%, 0.69%, and 0.11 RMB/share, respectively, and all these effects are significant at the 1% level. For stocks listed on the second board, we observe a similar pattern. Thus, these findings also support the negative effects of the COVID-19 outbreak on the cash flow channel.

5.2.2. Discount factor channel

In addition to changes in firms' future cash flows, stock price drops may also result from fluctuations in the discount factor. However, the discount factor cannot be directly observed in the data. As such, we adopt the price-earnings-growth (PEG) model proposed in Easton (2004) to infer the expected rate of return on capital, which serves as a proxy for the discount factor.[22] We then adopt a specification similar to the baseline regression and the one used in the analysis of the cash flow channel to explore how COVID-19 outbreaks affect the expected rate of return on capital. However, since EPS forecast data is only available annually for stocks listed in the Chinese stock market, the corresponding specification is revised accordingly.

Turning to Table 9, the estimation results show that the number of city-level confirmed COVID-19 cases is positively associated with the expected rate of return on capital. Specifically, if the annual city-level COVID-19 cases exceed 10, the expected rate of return on capital would increase by around 2% for stocks listed on the main board. However, this effect is not significant for stocks listed on the second board, likely due to the smaller sample size, as there are only limited EPS forecasts for second-board stocks. Overall, these results confirm that COVID-19 outbreaks increase capital costs, which is consistent with the discount rate channel.

[22] For more details on this method, we refer readers to Easton (2004).

Table 8
Impacts of city-level COVID-19 outbreaks on firms' realized financial performance.

	Realized financial performance					
	Main board			Second board		
	Δ ROA (1)	Δ ROE (2)	Δ EPS (3)	Δ ROA (4)	Δ ROE (5)	Δ EPS (6)
$I(0 < \sum_{t\in Q_k} \Delta COVID_{c,t} \leq 10)$	−0.0009*	−0.0017*	−0.0275	−0.0012*	−0.0023**	−0.0748
	(0.0005)	(0.0009)	(0.0183)	(0.0007)	(0.0010)	(0.0923)
$I(10 < \sum_{t\in Q_k} \Delta COVID_{c,t} \leq 50)$	−0.0005	−0.0008	−0.0128	−0.0004	−0.0004	−0.0280
	(0.0006)	(0.0008)	(0.0209)	(0.0009)	(0.0015)	(0.0839)
$I(\sum_{t\in Q_k} \Delta COVID_{c,t} > 50)$	−0.0038***	−0.0069***	−0.1125***	−0.0028**	−0.0050**	−0.0945
	(0.0010)	(0.0016)	(0.0365)	(0.0013)	(0.0025)	(0.1215)
IVol	0.1648***	0.2781***	5.0814***	−0.0695***	−0.1032***	−0.5954
	(0.0193)	(0.0320)	(0.6908)	(0.0236)	(0.0325)	(3.0801)
Size	0.0002	0.0003	−0.0131**	0.0006	0.0009*	−0.1311*
	(0.0001)	(0.0002)	(0.0066)	(0.0003)	(0.0005)	(0.0700)
B/M	0.0005***	0.0006	0.0112	0.0017***	0.0027***	0.1244*
	(0.0002)	(0.0004)	(0.0071)	(0.0004)	(0.0007)	(0.0705)
Leverage	0.0063***	0.0077***	0.2965***	0.0119***	0.0193***	1.0361***
	(0.0008)	(0.0016)	(0.0356)	(0.0017)	(0.0025)	(0.2158)
BHR	0.0024	0.0031	0.2353***	0.0116***	0.0188***	0.4655*
	(0.0016)	(0.0029)	(0.0755)	(0.0020)	(0.0028)	(0.2605)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	28,654	28,654	28,546	12,228	12,228	11,758
Adjusted R^2	0.330	0.339	0.088	0.424	0.379	0.066

This table presents the estimation results examining the impacts of city-level COVID-19 outbreaks on firms' realized financial performance. The dependent variables are the changes in return to equity (ROE), earnings per share (EPS), and return on asset (ROA) revealed in any two consecutive financial statements for each firm i based in city c within six months before and after a given quarter. The independent variables of interest are the discrete indicators for the cumulative number of new COVID-19 cases in city c during the quarter Q_k, i.e., $I(0 < \sum_{t\in Q_k} \Delta COVID_{c,t} \leq 10)$, $I(10 < \sum_{t\in Q_k} \Delta COVID_{c,t} \leq 50)$, and $I(\sum_{t\in Q_k} \Delta COVID_{c,t} > 50)$. The coefficient estimates are expressed in percentages. We control for a set of firm characteristics, stock fixed effects, and quarter fixed effects in all columns. Numbers in parentheses represent standard errors, which are two-way clustered by stock and year-quarter. Variable definitions can be found in Table A.1 in the Online Appendix. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

Table 9
Impacts of city-level COVID-19 outbreaks on the expected rate of return on capital.

	Expected rate of return on capital		
	Both boards (1)	Main board (2)	Second board (3)
$I(0 < \sum_{t\in year_k} \Delta COVID_{c,t} \leq 10)$	0.0166**	0.0209**	−0.0016
	(0.0079)	(0.0090)	(0.0102)
$I(10 < \sum_{t\in year_k} \Delta COVID_{c,t} \leq 50)$	0.0132	0.0204**	−0.0018
	(0.0083)	(0.0093)	(0.0123)
$I(\sum_{t\in year_k} \Delta COVID_{c,t} > 50)$	0.0126	0.0203**	−0.0018
	(0.0084)	(0.0098)	(0.0121)
Stock fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Number of observations	896	694	202
Adjusted R^2	0.570	0.565	0.583

This table presents the estimation results examining the impacts of city-level COVID-19 outbreaks on the expected rate of return on capital. The dependent variable is the expected rate of return on capital calculated using the method of Easton (2004). The independent variables of interest are the discrete indicators for the cumulative number of new COVID-19 cases in city c during the year $year_k$, i.e., $I(0 < \sum_{t\in year_k} \Delta COVID_{c,t} \leq 10)$, $I(10 < \sum_{t\in year_k} \Delta COVID_{c,t} \leq 50)$, and $I(\sum_{t\in year_k} \Delta COVID_{c,t} > 50)$. We control for stock fixed effects and year fixed effects in all columns. Numbers in parentheses represent standard errors, which are two-way clustered by stock and year. Variable definitions can be found in Table A.1 in the Online Appendix. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

5.3. The role of retail investors

As introduced in Section 2, the Chinese stock market is characterized by the prominent role of retail investors, who contribute most of the transaction volumes but are less financially sophisticated. Consequently, we investigate whether the COVID outbreak has a more significant impact on stocks with a higher proportion of retail investors. This question holds both academic and policy relevance. Academically, the heterogeneity in an exogenous shock caused by the investor base has not been extensively explored. From a policy perspective, understanding the reaction of retail investors to the COVID-19 shock may help policymakers enact appropriate policies to protect small investors against extreme market conditions.

Existing literature documents that stocks with high turnover are often associated with a large proportion of retail investors (Jones et al., 2020; Boehmer et al., 2021). Motivated by this relationship, we divide all the stocks in our dataset into two subsamples based on the median of stock turnover, defined as the daily transaction volume scaled by the total market cap, across the sample period and estimate the COVID-19 effects on each of them. Table 10 presents the results. For both stocks listed on the main board and the second board, the magnitudes of the COVID-19 effects are much stronger among stocks with higher turnover. Specifically, for stocks listed on the main board, the coefficient on the severe outbreak indicator is 0.133% in the high turnover group, which is triple that in the low turnover group. Compared with the estimates for the pooled sample, the moderate COVID-19 outbreak also negatively impacts the returns of stocks with high turnover. We also identify a similar pattern for stocks listed on the second board.

Overall, these findings indicate a positive correlation between the magnitudes of the COVID-19 effects and the proportion of retail investors. At the same time, it also suggests that the COVID-19 outbreak may more severely impact retail investors compared to institutional investors. While pinpointing the specific mechanism for the role of retail investors is beyond the scope of this study, our results align with the literature showing that retail investors often overreact to new information due to overconfidence (Peng and Xiong, 2006) or limited attention (Liu et al., 2019). We leave the clarification of the precise mechanism for future research.

6. Concluding remarks

In this paper, we examine the effects of city-level COVID-19 case increases on daily stock returns in the context of the Chinese stock market, considering the unique dynamics of the zero-COVID policy. Our analysis employs a panel dataset containing 4581 listed firms and city-level COVID-19 cases spanning January 2020 to May 2022. We find that city-level COVID-19 outbreaks lead to significant negative daily

Table 10
Relationship between the proportion of retail investors and the magnitude of COVID-19 effects.

	Risk-adjusted returns			
	Main board		Second board	
	Low turnover (1)	High turnover (2)	Low turnover (3)	High turnover (4)
$I(0 < \Delta COVID_{c,t} \leq 10)$	−0.0016	−0.0070	−0.0149	0.0241
	(0.0079)	(0.0155)	(0.0103)	(0.0273)
$I(10 < \Delta COVID_{c,t} \leq 50)$	−0.0085	−0.0674**	0.0040	−0.0886
	(0.0153)	(0.0313)	(0.0273)	(0.0865)
$I(\Delta COVID_{c,t} > 50)$	−0.0401**	−0.1264***	−0.0361	−0.1434**
	(0.0187)	(0.0440)	(0.0370)	(0.0701)
AQI	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Lagged return	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes
Stock-month fixed effects	Yes	Yes	Yes	Yes
Number of observations	775,905	775,565	336,979	337,053
Adjusted R^2	0.091	0.022	0.054	0.063

This table presents the estimation results examining the relationship between the proportion of retail investors and the magnitude of the COVID-19 effects on daily stock returns. Stocks are classified into high turnover and low turnover groups based on the median value of daily turnover, which is defined as the daily transaction volume scaled by the market cap. The dependent variables are FF-6 adjusted daily stock returns. The independent variables of interest are the discrete indicators for the number of new COVID-19 cases in city c on date $t-h$, i.e., $I(0 < \Delta COVID_{c,t-h} \leq 10)$, $I(10 < \Delta COVID_{c,t-h} \leq 50)$, and $I(\Delta COVID_{c,t-h} > 50)$, where $h = 0, 1$. The coefficient estimates are expressed in percentages. We control for lagged returns, stock-month fixed effects, and date-fixed effects in all columns. Numbers in parentheses represent standard errors, which are two-way clustered by stock and date. Variable definitions can be found in Table A.1 in the Online Appendix. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

returns, with the magnitude of this effect rising monotonically with the number of new cases. While stocks listed on the main board respond to both medium and severe outbreaks, only severe outbreaks exhibit significant effects for stocks listed on the second board. We also observe evidence of overreaction by second-board investors to COVID news, as stock prices experience reversals the following day.

The heterogeneity analyses reveal that firms with larger market values, state-owned status, stronger past financial performance, and industries with lower COVID-induced risk exposure are less impacted by COVID-19 shocks. Our findings are consistent across various robustness checks, including different fixed effect specifications, clustering methods, and excluding specific stock groups or potential outliers.

Our study highlights the substantial economic implications of COVID-19 effects on the stock market. Within a simple mean–variance utility framework, the COVID-19 impact may lead to an immediate reduction in investors' utility by over 30%. We estimate the total market value "evaporated" during our sample period to be approximately 900 billion RMB. As for the underlying mechanisms, both cash flow and discount factor channels play a role, with city-level outbreaks negatively affecting expected and realized cash flow while also increasing cost of capital. Finally, our empirical evidence suggests that stocks with a higher proportion of retail investors are more severely impacted by city-level COVID-19 shocks.

Overall, our research not only deepens our understanding of how stock returns respond to COVID-19 shocks within a zero-COVID framework but also provides valuable insights for policy debates on optimal strategies for addressing future pandemics. In particular, it sheds light on the question of whether a public health policy that aims to fully contain the pathogen can be economically sustainable. That being said, further investigation into the responses of different investor types to COVID-19 outbreaks and the ensuing economic outcomes, using account-level data, would offer extra significant academic and practical value. We consider this a promising avenue for future research.

CRediT authorship contribution statement

Wenyu Zhou: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Yujun Zhou:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Adam Zaremba:** Conceptualization, Writing – original draft, Writing – review & editing, Funding acquisition. **Huaigang Long:** Conceptualization, Software, Validation, Formal analysis, Resources, Data curation, Writing – review & editing, Visualization, Funding acquisition.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jbef.2024.100923.

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