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COVID-19 and A-share banks’ stock price volatility: From the perspective of the epidemic evolution in China and the US

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ABSTRACT

With a financial market dominated by indirect financing, China’s banking system played a critical role in the government’s response to COVID-19, which piqued our interest in the short-term impact of COVID-19 on the risk of China’s banks. Examining the stock price of A-share listed banks and the number of confirmed cases in China and the US during the short time window surrounding the COVID-19 pandemic’s outbreak, this study reveals that COVID-19 increased the A-share banking price volatility in both China and the US, reflecting a strong spillover effect of the US economic and financial system. Furthermore, COVID-19 in China has a smaller impact on the stock price volatility of China’s state-owned banks (SOBs) than that of medium- and small-sized (M&S) banks, reflecting the higher risk resistance capability of large SOBs. Further analysis confirms that the impact primarily reflected systematic risk rather than idiosyncratic risk, as small and micro enterprises and M&S banks received more targeted financial support from the government. In contrast, large banks took on more responsibilities in the emergency financial stimulus, narrowing the idiosyncratic risk gap between the two types of banks and allowing the banking industry to better play its core role in the recovery of real economy in China. These findings will assist us in better understanding the effectiveness of financial assistance policies during the epidemic and will provide insights for future policymaking during similar crises.

1. Introduction

The COVID-19 pandemic has been the biggest challenge to the global financial system since the global financial crisis (GFC). Hitherto, the global banking system has generally withstood the difficulties owing to the COVID-19 pandemic because of the two most important factors, namely, firm and strong policy responses and the greater flexibility of the financial system (Financial Stability Board [FSB], 2021; Hjelseth, Solheim, & Vatne, 2021). Unlike for the GFC, the negative impact of the COVID-19 pandemic on the macro-economy neither originated from the banking industry nor from the bursting of asset price bubbles. However, it is attributable to the isolation measures, population lockdown, and the closure of manufacturing and service industries when economic fundamentals were sound, thus imposing simultaneous shocks to demand and supply (Elmahass, Trinh, & Li, 2021; Mazur, Dang, & Vega, 2021). Despite the liquidity pressure on enterprises and banks owing to the interruption of economic activities, banks have not needed to use their capital and liquidity buffers to meet loan demand thus far, owing to the banking system’s strong ability to withstand risks (FSB, 2021). However, if left untreated, interconnectedness would most likely transform the liquidity problem into a solvency problem for firms and concurrently, for banks (Boot et al., 2020). Hence, short-term unconventional support measures may now weaken or postpone the

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https://doi.org/10.1016/j.gfj.2022.100751
Received 31 January 2022; Received in revised form 15 June 2022; Accepted 24 June 2022
Available online 27 June 2022
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impact of potential amplification mechanisms (FSB, 2021).

Although the impact of major public health events on the real economy may take some time to manifest, market expectations could rapidly increase investor panic, thereby resulting in a sharp drop in the stock market and an increase in the stock price volatility. For example, the SARS pandemic increased the stock price volatility through individual investors’ emotions and psychology (Chen, Jang, & Kim, 2007) whereas the Ebola outbreak resulted in negative excess returns and higher implied volatility in the US stock market (Ichev & Marinč, 2018). Baker et al. (2020) found that although the excess death rate during the COVID-19 pandemic was only 1/25 of the death rate in the 1918 influenza pandemic from 1918 to 1920, the US stock market volatility during the pandemic far exceeded that during the 1918 influenza pandemic, mainly owing to the substantial impact of government restrictions on business activities and social distancing in a service-oriented economy. The faster dissemination of information about COVID-19 was also an important reason for the higher volatility (Zaremba, Kizys, Aharon, & Demir, 2020). Jiang, Wu, and Wei (2021) stated that COVID-19 had a significant negative impact on stock markets in China, the US, and Europe, increasing the risk level.

Owing to regulatory and institutional reforms over the past decade, banks have become a part of the solution, rather than part of the problem in the face of the pandemic, serving a critical function in the transmission of multiple support measures of governments and central banks to limit and mitigate the economic fall-out (Beck, 2021; Giese & Haldane, 2020). However, in face of serious downside risk concerns, unconventional short-term support measures for banks were required, as banks may be willing to expand their balance sheets only if they can obtain government public support and risk sharing, reduce capital costs, and increase expected returns on loans (Landier & Ueda, 2009). Owing to governments’ unconventional short-term support measures, higher capital supervision requirements, and stricter stress tests imposed by supervisory authorities after the GFC (Borri & Di Giorgio, 2021), the global banking industry has—at least so far—withstanding the challenge of COVID-19. The banking industry’s liquidity support to the real economy has greatly reduced the risk of nonfinancial companies going bankrupt. The overall bankruptcy rate of enterprises is very low and even decline in 2020 (Banerjee, Cornelli, & Zakrajšek, 2020; International Monetary Fund [IMF], 2021). Furthermore, according to Euler Hermes’s data, the global enterprise bankruptcy rate remained low in 2021.

Following the GFC, the macroprudential regulatory reform has focused on stricter capital requirements for systematically important banks, widening the capital strength gap between large and small banks. After the outbreak of COVID-19, large banks have taken a more prominent role in the global fight against the crisis. In March 2020, the US banking industry experienced the largest increase in liquidity demand in history, which was more concentrated in large banks serving large enterprises (Li, Strahan, & Demir, 2020). Furthermore, Demirgç-Kunt, Pedraza, and Ruiz-Ortega (2021) demonstrated that larger, public banks, and to some extent, important banks, widening the capital strength gap between large and small banks. After the outbreak of COVID-19, large banks have taken a more prominent role in the global fight against the crisis. In March 2020, the US banking industry experienced the largest increase in liquidity demand in history, which was more concentrated in large banks serving large enterprises (Li, Strahan, & Zhang, 2020). Furthermore, Demirgç-Kunt, Pedraza, and Ruiz-Ortega (2021) demonstrated that larger, public banks, and to some extent, better-capitalized banks experienced greater declines in stock returns, reflecting their greater anticipated role in dealing with the crisis. As shown in Fig. 1, the proportion of credit provided by SOBs in China in 2020, particularly credit to small and micro (S&M) enterprises, was higher than in previous years. Because S&M enterprises were generally more affected by COVID-19 owing to smaller buffers and limited credit access (Ebeke, Jovanovic, Valderrama, & Zhou, 2021), the heterogeneity of different banks’ risk caused by COVID-19 may also be affected.

Owing to the financing structure dominated by indirect financing, the Chinese banking system had to play a more critical role in the government’s response to COVID-19. Moreover, the more prudent financial supervision requirements recently in China laid a solid foundation for the banking industry to better serve the real economy during the COVID-19 pandemic. From late January to late February 2020, the China Banking and Insurance Regulatory Commission, the People’s Bank of China, and other ministries and commissions successively introduced a series of financial support policies in terms of corporate loan renewal standards, loan interest rates, and liquidity support, as shown in Table 1, to alleviate the impact of COVID-19 on economic and financial stability. Following the US COVID-19 epidemic outbreak in March 2020, the US government also implemented a series of powerful financial stimulus policies promptly in March and April 2020, as is presented in Table 2. By comparison, we can see that the financial stimulus policies in the US are generally stronger and less targeted than those in China.

![Fig. 1. Proportion of new loans to small and micro enterprises by bank type. Data source: China Banking and Insurance Regulatory Commission (CBIRC). Note: SOBs mean state-owned banks.](image-url)
Table 1
Major financial support policies in China from late January 2020 to February 2020.

| Date          | Relevant financial support policies                                                                 |
|---------------|-----------------------------------------------------------------------------------------------------|
| Jan 26, 2020  | China Banking and Insurance Regulatory Commission (CBIRC). For industries greatly affected by COVID-19, appropriately lower loan interest rates, improve loan renewal policy arrangements, and increase specific loans issuance. |
| Feb 1, 2020   | People’s Bank of China (PBOC) and other five ministries and commissions. Provide differentiated preferential financial services for regions, industries, and enterprises that are more affected by COVID-19. |
| Feb 7, 2020   | The Ministry of Finance and other five ministries and commissions. For key enterprises providing epidemic prevention and control materials, the interest rate of loans with special relending funds does not exceed 3.15% and the central government finance discounts are as high as 50%. |
| Feb 14, 2020  | PBOC. For financing guarantee and reguarantee for institutions in areas severely affected by COVID-19, the National Financing Guarantee Fund will charge half the guarantee fees. |
| Feb 25, 2020  | CBIRC. Provide loan renewal arrangements within one year for small and micro (S&M) loans due before the end of June 2020. Banks will be allowed to further increase their tolerance for loans that require deferred repayment or renewal owing to the impact of COVID-19. Increase the “first loan rate” of S&M enterprises and the proportion of credit loans and further reduce their financing costs. Increase supply of manufacturing loans and strengthen the supply chain financial services. Provide temporary postponement arrangements for loan principals for small, medium, and micro enterprises with temporary liquidity difficulties. Interest payments can be postponed to June 30 without penalty interest. Increase the reloan and rediscount quota of RMB 500 billion mainly for medium- and small-sized banks. |

Data source: Official public information.

Given this background, we emphasized the impact of COVID-19 on the volatility of the stock prices of A-share listed banks and the underlying mechanism.

This study provides three major contributions. First, extant literature on the impact of COVID-19 on the stock market mainly focuses on the overall market. To the best of our knowledge, we are the first to study the impact of COVID-19 on the banking stock volatility in a span of short time around the outbreak of an epidemic. We chose A-share listed banks as the research target because China has the world’s largest indirect-financing-dominated financial market, emphasizing the critical role that banks play in the government’s response to COVID-19. Second, we provide a new perspective on the impact of financial stimulus policies dealing with epidemics on banking system risk by creatively introducing two timelines of newly confirmed cases for the world’s two major economies: China and the US. Finally, by analyzing the impact of COVID-19 on total and idiosyncratic risks of individual banks separately, we demonstrate that the impact of COVID-19 on the banking stock price volatility is primarily due to systematic risk rather than idiosyncratic risk, and the heterogeneity of the impact on idiosyncratic risk of SOBs and non-SOBs is insignificant. This indicates that the implementation of financial support policies following the outbreak of COVID-19 in a forceful and timely manner significantly weakened the gap between big and small banks’ capability of credit supply and potential credit risk, enabling them to better support the recovery of the real economy. These findings will assist us in better understanding the effectiveness of financial support policies during the epidemic and will provide insights for future policymaking during similar crises.

The remainder of the paper is organized as follows. Section 2 introduces the model design, Section 3 provides the empirical results, Section 4 describes the robustness test, and Section 5 summarizes the findings.

Table 2
Major financial support policies in the US from March 2020 to early April 2020.

| Date           | Major relevant financial support policies in the US                                                                 |
|----------------|---------------------------------------------------------------------------------------------------------------|
| Mar 15, 2020   | The Federal Reserve launched a $700 billion program of quantitative easing, buying $500 billion of Treasuries, and $200 billion of mortgage-backed securities. |
| Mar 23, 2020   | The Federal Reserve announced the opening of an unlimited number of QE, expanding its bond purchases to institutional mortgage-backed securities. |
| Mar 17, 2020   | The Federal Reserve established a new liquidity facility, the Commercial Paper Financing Facility, allowing the Fed to lend directly to physical companies for the first time. |
| Mar 18, 2020   | The Federal Reserve launched the Money Market Mutual Fund Liquidity Facility (MMLF), providing liquidity for financial institutions to buy market mutual funds. The US Treasury provided $10 billion of MMLF debt and credit protection for the program. |
| Mar 20, 2020   | The Federal Reserve revived its Great Depression-era program, the Primary Dealer Credit Facility, which aims to provide assistance to market dealers to rescue failing companies in an emergency. |
| Mar 15, 2020   | The Federal Reserve cut its discount rate by 150 bps to 0.25%. |
| Mar 3, 2020    | The Federal Reserve cut interest rates by 50 bps, bringing the interest rate range from 1.50%–1.75% to 1.00%–1.25%. |
| Mar 16, 2020   | The Federal Reserve cut the base rate by 100 bps, bringing the interest rate range from 1.00%–1.25% to 0.00% – 0.25%. |
| April 9, 2020  | The Federal Reserve launched the Paycheck Protection Program Lending Facility (PPPLF) to lend money to banks so that they can, in turn, lend money to small businesses through the Paycheck Protection Program. |
| April 30, 2020 | The PPPLF program expanded the types of lenders that can participate. |

Data source: Official public information.
2. Model and data

2.1. The model

To analyze the impact of the COVID-19 on the stock price volatility of A-share listed banks, we refer to Xiong, Wu, Hou, and Zhang (2020) in designing an ordinary least square model, as shown in Eq. (1).

\[
\text{Vol}_{i,t} = \alpha_0 + \alpha_1 \text{Vol}_{i,t-1} + \alpha_2 \sum_{j=1}^{2} \text{Covid}_{j,t-1} + \alpha_3 \text{lnEPU}_{j,t} + \alpha_4 \text{X}_{i,t-1} + \alpha_5 \text{SOB}_i * \sum_{j=1}^{2} \text{Covid}_{j,t-1} + u_i + \varepsilon_{i,t}
\] (1)

In Eq. (1), \(\text{Vol}_{i,t}\) represents the daily volatility of banking stock price return; \(\text{Covid}_{j,t-1}\) denotes the natural logarithm of 1 plus the number of new cases, where \(j\) represents China and the US; \(\text{lnEPU}_{j,t}\) represents the logarithm of the monthly economic policy uncertainty (EPU) index in each region; \(\text{X}_{i,t-1}\) represents the control variable at the individual bank level; \(\text{Covid}_{j,t-1}\) represents the COVID-19 pandemic evolution in China and the US. In addition, we include the interaction between bank ownership (SOB\(_i\)) and \(\text{Covid}_{j,t-1}\). \(u_i\) denotes the individual fixed effect.

2.2. The variables

2.2.1. Dependent variable

Daily volatility of banking stock price return (Vol). The evolution of COVID-19 is the main factor affecting the dependent variable in a span of short time surrounding the outbreak as the short time window provides a clean environment, eliminating the disturbance of other factors. The 30-day standard deviation of the daily logarithm return of the banking stock price is taken as shown in Eq. (2).

\[
\text{Vol}_{i,t} = \text{Std}_{30}(\ln P_{i,t} - \ln P_{i,t-1}) * 100
\] (2)

2.2.2. Core explanatory variables

We chose the COVID-19 proxy variable with one-period lag in each country, \(\text{Covid}_{j,t-1}\), as the core explanatory variable, calculated as the natural logarithm of 1 plus the number of newly confirmed cases per day.

The National Health Commission of China began disclosing the data for the novel coronavirus from January 11, 2020. On January 19, 2020, it began disclosing the number of newly confirmed cases per day. The epidemic in China was believed to be under control as of early March. For the first time on March 6, 2020, the number of newly confirmed cases per day fell below 100. COVID-19 was effectively contained in China in less than two months, and the initial outbreak coincided with the Spring Festival, allowing the influence of other external factors on the performance of banking stock prices to be avoided. However, although the outbreak in China was effectively contained, the spread of the epidemic in other countries accelerated in March. There were 513 newly confirmed cases in other parts of the world on February 26, 2020, surpassing the domestic epidemic for the first time. The World Health Organization declared the start of the global COVID-19 pandemic on March 11, 2020. There was an exponential increase in new infections worldwide until the end of March. From May 15, 2020, although the disease continued to spread in Latin America, the US and most EU countries decided to relax social distancing restrictions and resume economic activity. The misalignment of the timeline in different regions of the world provides us with the opportunity of a natural experiment to study the impact of the outbreak on stock prices in the short term owing to the exogenous characteristics of the epidemic outbreak. This study introduces two timelines of the COVID-19 outbreak for the world’s two largest economies (i.e., China and the US) to better understand the impact of COVID-19 from different regions. Fig. 2 illustrates the trend of newly confirmed cases per day in the two countries.

Owing to effective control, China’s domestic outbreak had a minor impact on the A-share market in the short term. In February

Fig. 2. Newly confirmed cases per day in China and the US from January 20, 2020, to April 30, 2020.

Data source: WIND.
2020, the largest cumulative decline in the Shanghai Composite Index was <10%. However, as the number of newly confirmed cases in the US increased significantly in late February, the stock market in the US fell sharply from February 20 to March 23, with the S&P 500 index falling by 33%. The impact of COVID-19 deterioration abroad quickly spread to China’s stock market. Moreover, the Shanghai Composite Index fell by 12.2% during the same period, and the China Securities Banking Index fell by 12.6%.

Prior to the outbreak of COVID-19, most publicly traded companies’ balance sheets, profitability, and cash flow were all strong. Stock prices fell in the immediate aftermath of the outbreak primarily owing to the uncertainty of the COVID-19 evolution and short-term liquidity risks, rather than a deterioration of fundamentals or the bursting of asset bubbles. Therefore, the COVID-19 evolution became the most important exogenous factor affecting the stock market performance in the short-window period around the outbreak. Alfaro, Chari, Greenland, and Schott (2020) found that an increase in the number of new infections predicted during the pandemic predicted a decline in the stock market return the following trading day. However, different pandemic timelines may have varying effects on China’s stock market. For example, Albulescu (2020) demonstrated that the COVID-19 death ratio in China has a positive impact on the Volatility Index (VIX), whereas it has a greater impact outside China. Based on the various timelines of the COVID-19 development, this study chooses the number of newly confirmed cases per day in China or the US as proxy variables of the COVID-19 evolution, Covid – ch and Covid – us, calculated as the natural log of 1 plus the daily number of newly confirmed cases in the country. If no new cases are added that day, the value will be 0. For the robustness test, we will use the daily death rate as an alternative proxy for COVID-19.

2.2.3. Control variables

Macrolevel control variables. EPU index was designed by Davis, Bloom, and Baker (2013) and Baker, Bloom and Davis (2016), which has been widely accepted in the literature on the influencing factors of the stock market volatility. Based on Albulescu (2021), we introduce the logarithm of Davis et al. (2013) and Baker et al. (2016) national economic policy uncertainty index (lnEPU-ch, lnEPU-us) as a macrolevel control variable, as extant research shows that higher EPU increases market volatility, and the banking sector in China is especially highly influenced by the macroeconomic policy. Higher policy uncertainty, according to Davis et al. (2013) and Baker et al. (2016), leads to a greater frequency of large equity market moves triggered by policy-related news. Meanwhile, Liu and Zhang (2015) suggested that higher EPU leads to significant increases in market volatility. According to Tsai (2017), EPU in China is the most influential among different continents’ markets, and its contagion risk of investments in the global stock market spreads to different regional markets. Moreover, Li et al. (2020) revealed that fluctuating global EPU can lead to significantly high stock market volatility in China.

To make the EPU data frequency consistent with that of stock price volatility, we use the daily EPU index of the US retrieved from http://www.policyuncertainty.com and the daily EPU index of China retrieved from https://economicpolicyuncertaintyinchina.weebly.com.

Bank-level control variables (X_{it−1}) include the following elements.

Price return volatility with one-period lag. There may be autocorrelation in the stock price volatility, that is, the stock price volatility with one-period lag might also have an impact on the volatility in the current period; therefore, we introduce the stock price volatility

| Variable | Short name | Calculation method | N | Mean | Median | St. dev | Min | Max |
|-----------|------------|--------------------|---|------|--------|---------|----|-----|
| Volatility in daily price returns | vol | 30-day MA standard deviation of daily price return | 3752 | 1.575 | 1.394 | 0.763 | 0.500 | 4.102 |
| Idiosyncratic volatility based on the capital asset pricing model (CAPM) | volcapm | 30-day MA standard deviation of CAPM residual | 3752 | 0.931 | 0.766 | 0.547 | 0.314 | 3.446 |
| Idiosyncratic volatility based on the Fama–French model | volfama | 30-day MA standard deviation of Fama–French residual | 3752 | 0.838 | 0.725 | 0.436 | 0.311 | 2.702 |
| COVID-19 daily cases in China | covid-ch | Natural log of 1 plus daily number of newly confirmed cases in China | 3780 | 2.856 | 3.091 | 2.850 | 0 | 9.555 |
| COVID-19 daily cases in the US | covid-us | Natural log of 1 plus daily number of newly confirmed cases in the US | 3780 | 2.986 | 0 | 4.194 | 0 | 10.461 |
| COVID-19 new deaths in China | death-ch | Natural log of 1 plus the number of new deaths per day in China | 3780 | 1.499 | 0.693 | 1.763 | 0 | 4.970 |
| COVID-19 new deaths in the US | death-us | Natural log of 1 plus the number of new deaths per day in the US | 3780 | 1.745 | 0 | 2.847 | 0 | 7.906 |
| Economic policy uncertainty (EPU) index in China | lnEPU-ch | Natural log of the daily EPU index in China | 3780 | 4.783 | 4.771 | 0.481 | 3.599 | 5.983 |
| EPU index in the US | lnEPU-us | Natural log of the daily EPU index in the US | 3780 | 4.989 | 4.718 | 0.836 | 2.988 | 6.604 |
| Circulation market value | lnMV | Natural log of circulation market value | 3756 | 6.855 | 6.721 | 1.548 | 4.442 | 9.933 |
| PB ratio | PB | Price-to-book ratio | 3756 | 0.925 | 0.862 | 0.294 | 0.541 | 1.870 |
| Turnover rate | turnover | Turnover rate of stock trading | 3756 | 0.014 | 0.005 | 0.024 | 0 | 0.148 |
| Return on equity | ROE | Net profit/Weighted average total equity | 3780 | 0.099 | 0.096 | 0.018 | 0.058 | 0.136 |
| Leverage ratio | EA | Total equity/Total asset | 3780 | 0.078 | 0.079 | 0.010 | 0.051 | 0.096 |
| Bank ownership | SOB | A dummy variable assigned a value of 1 for state-owned banks, and 0 otherwise | 3780 | 0.167 | 0 | 0.373 | 0 | 1 |

Data source: WIND, sorted based on Stata statistical results.
with one-period lag (Vol$_{i,t-1}$) as a control variable.

**Bank-level market data.** Fama and French (1993) demonstrated that the stock market value-to-book market value ratio has a significant impact on the stock price volatility; thus, the logarithm of the circulation market value (lnMV) and the price-to-book ratio (PB) are introduced as control variables. According to Li and Jin (2019), the daily turnover rate is introduced as a control variable because extant research shows that the higher the stock price volatility is, the higher the turnover rate (Turnover) is (Chen, Hong, & Stein, 2001).

**Financial data.** Operating and financial leverage effects can explain asymmetric volatility (increased volatility and negative returns) (Bekaert & Wu, 1997; Kim, Li, & Zhang, 2011; Schwert, 1989). The release date of listed banks’ 2019 annual results is used as the dividing line for return on equity (ROE) and leverage ratio (EA) as financial control variables. Moreover, the financial data for the first three quarters and full year of 2019 are used for the dates before and after, respectively.

We introduce two interaction terms between the dummy variable bank ownership (SOB$_i$) and the COVID-19 variables (Covid$_{i,t-1}$) to investigate the impact of bank ownership on the stock price volatility.

### 2.3. Sample descriptive statistics

We collect market and financial data from the WIND database. The daily stock price data cover the 102 trading days before and after the COVID-19 outbreak, from November 15, 2019, to April 16, 2020. As of the end of 2019, the total assets of A-share listed banks rose to approximately RMB 190 trillion, accounting for two-thirds of the total assets of China’s banking financial institutions, which is highly representative of the entire sector. A total of 3780 daily price return volatility samples are collected from the 38 A-share listed banks. To curb the effects of extreme data, we winsorize the top and bottom 1% of each variable’s distribution. Table 3 reports the main variables involved in the model. Total volatility of daily price return is the highest, followed by the idiosyncratic volatility based on the capital asset pricing model (CAPM), and the idiosyncratic volatility based on the Fama–French three-factor model is the lowest. In China, the average number of newly confirmed cases is much lower than that in the US. However, because the COVID-19 outbreak in China began earlier, the cumulative number of confirmed cases in China from January to early March was higher.

### 2.4. Impact of COVID-19 on banking stock price volatility based on the CAPM residual standard deviation

To further analyze the impact of the COVID-19 on the banking stock price volatility, we refer to the existing measurement methods for the idiosyncratic volatility. We adjust the stock price return volatility to the idiosyncratic volatility of price return, represented by the residual standard deviation of the CAPM model and re-regress Eq. (1). We will use the idiosyncratic volatility represented by the residual standard deviation of the three-factor model of Fama and French (1993) to test robustness.

The CAPM factor model is shown in Eq. (3), and Eq. (4) is the method for residual standard deviation measurement.

\[
R_{it} - R_f = \beta_{i0} + \beta_{if} (R_{m,t} - R_f) + \epsilon_{it}
\]

(3)

\[
\text{volcapm} = \text{std}_{it}(\epsilon_{it})
\]

(4)

$R_{it}$ represents the market rate of return, represented by the Shanghai Stock Exchange Index, and the 10-year Treasury bond yield represents the risk-free interest rate. We first estimate the residual error using Eq. (3), and then, we use Eq. (4) to calculate the idiosyncratic volatility of stock price return. The panel data unit root test in Table 4 shows that the CAPM residual is stationary. The same test will be conducted to check the robustness.

### 3. Results and discussion

#### 3.1. Empirical results of the impact of COVID-19 on the banking stock price volatility

The regression results of Eq. (1) in Table 5 imply that the coefficients of the COVID-19 variables are both significantly positive at the 1% level in China and the US. For both countries, the coefficients of the interactions between COVID-19 and SOB are significantly negative at the 1% level. Accordingly, COVID-19 has a smaller impact on the total stock price volatility of China’s SOBs than it does on M&K banks in both China and the US, reflecting the higher risk resistance capability of large SOBs than small ones in China as well as the strong spillover effect of the US economic and financial system. This conclusion is also consistent with the price volatility trend of

#### Table 4

| Statistic | Ips (m-Pesaran-Shin) | p-value | Fisher-type Statistic | p-value |
|-----------|---------------------|---------|-----------------------|---------|
| t-bar     | −9.1458             |         | Inverse chi-squared(72) P | 1006.7007 | 0.0000 |
| t-tilde-bar| −6.9646             |         | Inverse normal Z        | −27.9297 | 0.0000 |
| Z-t-tilde-bar | −39.6027         | 0.0000  | Inverse logit (184) L*  | −46.3777 | 0.0000 |

Data source: WIND, sorted based on Stata statistical results.
From the perspective of control variables, the coefficient of EPU in China is significantly positive, which is consistent with the conclusions of extant literature. However, the coefficient of the EPU of the US is significantly negative, probably because China mitigates the potential adverse spillover effect of the EPU of the US by creating a low correlation between the EPU of China and the US. The coefficients of individual variables, such as turnover rate, PB ratio, and ROE, are significant and consistent with the economic sense. The higher the PB or ROE is, the lower the volatility is, implying that the market performance of higher quality banks in terms of earnings power and valuation was more stable.

**Table 5**
Impact of COVID-19 on China’s banking stock price volatility.

|            | m1     | m2     | m3     | m4     |
|------------|--------|--------|--------|--------|
| l.vol      | 0.911*** | 0.883*** | 0.881*** | 0.879*** |
|            | (0.014) | (0.010) | (0.010) | (0.010) |
| l.covid-ch | 0.015*** | 0.016*** | 0.017*** | 0.019*** |
|            | (0.002) | (0.002) | (0.002) | (0.002) |
| l.covid-us | –0.001  | 0.003**  | 0.005*** | 0.006*** |
|            | (0.001) | (0.002) | (0.002) | (0.002) |
| l.inepu-ch | 0.030*** | 0.029*** | 0.029*** | 0.029*** |
|            | (0.004) | (0.004) | (0.004) | (0.004) |
| l.inepu-us | –0.023*** | –0.024*** | –0.024*** | –0.024*** |
|            | (0.004) | (0.004) | (0.004) | (0.005) |
| l.lmv      | 0.267   | 0.411**  | 0.458**  |          |
|            | (0.175) | (0.182) | (0.178) |          |
| l.pb       | –0.364*** | –0.473*** | –0.470*** |          |
|            | (0.133) | (0.120) | (0.121) |          |
| l.turnover | 2.384*** | 2.353*** | 2.317*** |          |
|            | (0.264) | (0.260) | (0.257) |          |
| l.roe      | –1.570*   | –1.532*   | –1.532*   |          |
|            | (0.807) | (0.862) | (0.862) |          |
| Lea        | –4.367*   | –4.705*   | –4.705*   |          |
|            | (2.214) | (2.342) | (2.342) |          |
| sob*l.covid-ch | 0.048** |          |          |          |
|            | (0.019) |          |          |          |
| sob*l.covid-us | –0.043*** |          |          |          |
|            | (0.008) |          |          |          |
| Constant   | 0.103*** | –1.421  | –1.815  | –2.113*  |
|            | (0.017) | (1.132) | (1.158) | (1.139)  |
| Observations | 3608   | 3608    | 3608    | 3608     |
| R-squared  | 0.928   | 0.932   | 0.932   | 0.933    |
| Number of banks | 36      | 36      | 36      | 36       |

Data source: WIND, sorted based on Stata statistical results.
Robust standard errors are presented in parentheses.
*** p < 0.01, ** p < 0.05, and * p < 0.1.

SOBs and M&S banks in Fig. 3.

From the perspective of control variables, the coefficient of EPU in China is significantly positive, which is consistent with the conclusions of extant literature. However, the coefficient of the EPU of the US is significantly negative, probably because China mitigates the potential adverse spillover effect of the EPU of the US by creating a low correlation between the EPU of China and the US. The coefficients of individual variables, such as turnover rate, PB ratio, and ROE, are significant and consistent with the economic sense. The higher the PB or ROE is, the lower the volatility is, implying that the market performance of higher quality banks in terms of earnings power and valuation was more stable.

![Fig. 3. Arithmetic average stock price volatility of State-owned banks (SOBs) and medium- and small-sized listed banks.](image-url)
3.2. Empirical results of the impact of COVID-19 on the idiosyncratic volatility of banking stock prices based on the standard deviation of CAPM residual

When the stock price volatility is adjusted to the idiosyncratic volatility of banking price returns using the standard deviation of the CAPM residual, the results show that the impact of COVID-19 on the idiosyncratic volatility is insignificant in both China and the US (Table 6).

Additionally, the coefficient of the interaction between sob and covid-ch is insignificant, signifying little difference between the impacts of COVID-19 in China on the idiosyncratic volatility of the two types of banks. However, the coefficient of the interaction between sob and covid-us remains weakly negative at the 10% significance level, implying that COVID-19 in the US has a slightly lower impact on the idiosyncratic volatility of China’s SOBs compared with non-SOBs, which could be attributed to the high spillover effect of the US economic and financial markets. Barring the turnover variable, the overall impact of the control variables on the idiosyncratic volatility is negligible.

Findings reveal that the impact of COVID-19 on the banking stock volatility is primarily due to systematic risks rather than idiosyncratic risks. Although the non-SOB banks suffered more from the COVID-19 shock in terms of the stock price volatility, the heterogeneity of the impact of COVID-19 in China on the idiosyncratic volatility of the two types of banks is insignificant. There are two reasons for this. First, although M&S banks were more exposed to S&M loans that were more affected by COVID-19, the supervisory authorities have taken a series of preferential support measures for the financing of S&M enterprises and M&S banks timely, alleviating the liquidity and credit risks. Second, big banks played a more important role in dealing with COVID-19, assuming more potential risks, as illustrated in Fig. 1, further narrowing the gap between the two types of banks.

4. Robustness test

To test the robustness of the aforementioned conclusions, we perform robustness tests sequentially by adjusting the proxy for the idiosyncratic volatility, replacing the core independent variable and shortening the sample period. The main conclusions remain essentially consistent.

4.1. Adjust the proxy for the idiosyncratic volatility

Referring to Ang, Hodrick, Xing, and Zhang (2006), we use the standard deviation of residuals of the three-factor model (Fama &

| Table 6 |

| The impact of COVID-19 on the idiosyncratic stock price volatility of A-share banks based on the standard deviation of the CAPM residual. |
|-----------------|-----------------|-----------------|-----------------|-----------------|
|                | m1              | m2              | m3              | m4              |
| l.volcapm       | 0.955***        | 0.934***        | 0.934***        | 0.934***        |
|                 | (0.008)         | (0.008)         | (0.008)         | (0.008)         |
| l.covid-ch      | 0.001*          | 0.001           | 0.001           | 0.001           |
|                 | (0.001)         | (0.001)         | (0.001)         | (0.001)         |
| l.covid-us      | 0.001**         | 0.001           | 0.001           | 0.002           |
|                 | (0.000)         | (0.000)         | (0.000)         | (0.001)         |
| l.lnepu-ch      | −0.000          | −0.001          | −0.001          | −0.000          |
|                 | (0.004)         | (0.004)         | (0.004)         | (0.004)         |
| l.lnepu-us      | 0.005           | 0.004           | 0.004           | 0.004           |
|                 | (0.003)         | (0.003)         | (0.003)         | (0.003)         |
| l.lnmv          | 0.029           | 0.069           | 0.081           | 0.081           |
|                 | (0.107)         | (0.121)         | (0.123)         | (0.123)         |
| l.lpvb          | −0.058          | −0.086          | −0.084          | −0.084          |
|                 | (0.058)         | (0.061)         | (0.061)         | (0.061)         |
| l.turnover      | 1.376***        | 1.361***        | 1.361***        | 1.351***        |
|                 | (0.264)         | (0.260)         | (0.260)         | (0.261)         |
| l.roe           | −0.481          | −0.436          | −0.436          | −0.436          |
|                 | (0.535)         | (0.541)         | (0.541)         | (0.541)         |
| l.ia            | −1.016          | −1.113          | −1.113          | −1.113          |
|                 | (0.942)         | (0.998)         | (0.998)         | (0.998)         |
| sob\*l.covid-ch |                 |                 |                 | −0.007          |
|                 |                 |                 |                 | (0.010)         |
| sob\*l.covid-us |                 |                 |                 | −0.011*         |
|                 |                 |                 |                 | (0.006)         |
| Constant        | 0.034***        | −0.132          | −0.250          | −0.330          |
|                 | (0.008)         | (0.712)         | (0.779)         | (0.797)         |
| Observations    | 3608            | 3608            | 3608            | 3608            |
| R-squared       | 0.936           | 0.939           | 0.939           | 0.940           |
| Number of banks | 36              | 36              | 36              | 36              |

Data source: WIND, sorted based on Stata statistical results.
Robust standard errors are presented in parentheses.
*** p < 0.01, ** p < 0.05, and * p < 0.1.
French, 1993) to measure the idiosyncratic volatility to test the robustness of COVID-19's impact on the idiosyncratic volatility of stock price, as expressed in Eq. (5).

\[ R_{it} - R_{ft} = \beta_{i0} + \beta_{i1} (R_{mt} - R_{ft}) + \beta_{i2} \text{SMB}_t + \beta_{i3} \text{HML}_t + \epsilon_{it} \]  

(5)

\[ \text{SMB}_t = \frac{(SL_t + SM_t + SH_t)}{3} - \frac{(BL_t + BM_t + BH_t)}{3} \]  

(6)

\[ \text{HML}_t = \frac{(SH_t + BH_t)}{2} - \frac{(SL_t + BL_t)}{2} \]  

(7)

\[ \text{volfama}_{it} = \text{Std}_{30} (\epsilon_{it}) \]  

(8)

SMB represents the average return of the small market value group minus the average return of the big market value group. HML denotes the average return of high book-to-market ratio (BM) group minus the average return of the low BM group.

To calculate SMB and HML, first, we divide the samples into big market cap (B) and small market cap (S) groups at a ratio of 1:1, according to the circulation market value. Furthermore, we divide the samples into high (H), medium (M), and low (L) BM groups at a ratio of 3:4:3. Subsequently, we calculate the weighted average rate of return of each group, and finally, we calculate SMB and HML through Eqs. (6) and (7), respectively.

The standard deviation of the residuals in the most recent 30 trading days is used to express the idiosyncratic volatility, Volfama$_{it}$, after the residuals of the Fama–French three-factor model are obtained as shown in Eq. (8). Moreover, the Fama residual passes the panel data unit root test.

The test results in Table 7 indicate that the impact of COVID-19 on the idiosyncratic volatility of stock prices is insignificant in both China and the US. In addition, the interaction term results are consistent with the preceding analysis.

4.2. Replace the core explanatory variable

The core explanatory variable is adjusted to the number of daily new deaths in China and the US, calculated as the natural logarithm of 1 plus the number of daily new deaths (death-us/death-ch). The results in Table 8 reveal that the conclusions are consistent, except that in Column (1), the coefficient of the interaction term between sob and the daily death number in the US is insignificant.

|          | m1      | m2      | m3      | m4      |
|----------|---------|---------|---------|---------|
| l.volfama| 0.947***| 0.929***| 0.929***| 0.929***|
|          | (0.011) | (0.011) | (0.011) | (0.011) |
| l.covid-ch| 0.001*  | 0.001   | 0.001   | 0.001   |
|          | (0.001) | (0.001) | (0.001) | (0.001) |
| l.covid-us| 0.000   | 0.000   | 0.000   | 0.000   |
|          | (0.000) | (0.000) | (0.000) | (0.000) |
| l.lnepu-ch| 0.003   | 0.003   | 0.003   | 0.003   |
|          | (0.004) | (0.004) | (0.004) | (0.004) |
| l.lnepu-us| 0.004   | 0.004   | 0.004   | 0.004   |
|          | (0.004) | (0.004) | (0.004) | (0.004) |
| l.lnmv   | −0.062  | −0.052  | −0.042  | −0.042  |
|          | (0.103) | (0.121) | (0.121) | (0.121) |
| l.pb     | 0.059   | 0.051   | 0.056   | 0.056   |
|          | (0.070) | (0.075) | (0.074) | (0.074) |
| l.turnover| 0.709***| 0.708***| 0.699***| 0.699***|
|          | (0.117) | (0.116) | (0.111) | (0.111) |
| l.roe    | −0.092  | −0.055  | −0.065  | −0.065  |
|          | (0.391) | (0.381) | (0.381) | (0.381) |
| l.ea     | −0.187  | −0.246  | −0.246  | −0.246  |
|          | (0.580) | (0.608) | (0.608) | (0.608) |
| sob*l.covid-ch|      | −0.013  | −0.013  | −0.013  |
|          | (0.012) | (0.012) | (0.012) | (0.012) |
| sob*l.covid-us|       | −0.014* | −0.014* | −0.014* |
|          | (0.007) | (0.007) | (0.007) | (0.007) |
| Constant | 0.036***| 0.377   | 0.340   | 0.269   |
|          | (0.009) | (0.673) | (0.771) | (0.769) |
| Observations | 3716    | 3716    | 3716    | 3716    |
| R-squared| 0.929   | 0.931   | 0.931   | 0.932   |
| Number of banks | 36      | 36      | 36      | 36      |

Data source: WIND, sorted based on Stata statistical results.
Robust standard errors are presented in parentheses.
*** p < 0.01, ** p < 0.05, and * p < 0.1.
4.3. Shorten the time window

To curb the impact of other external factors, we shorten the time window of November 15, 2019–April 21, 2020, to December 9, 2019–April 1, 2020, with the length of time reduced from 102 to 86 trading days. To avoid the randomness of the time window, we also appropriately shorten the time window to 75 trading days from December 16, 2019, to March 25, 2020. Table 9 shows that the conclusions remain essentially consistent.

5. Conclusions

This study demonstrates that COVID-19 significantly increased the stock price return volatility of China’s listed banks in the short term around the pandemic outbreak in both China and the US, reflecting a strong spillover effect of the US economic and financial system. COVID-19 has a smaller impact on the stock price volatility of China’s SOBs than it does on M&S banks, reflecting big SOBs’ higher risk resistance capability. Further analysis confirms that the impact of COVID-19 on A-share bank price return volatility reflects systematic risks rather than idiosyncratic risks, and the heterogeneity of the impact on the idiosyncratic risk of SOBs and non-SOBs is insignificant. After replacing the dependent variable, core explanatory variable, and shortening the sample period, we draw the same robust conclusions. First, the supervisory authorities’ prompt and targeted preferential financial support measures reduced the liquidity and credit risks of S&M enterprises and M&S banks. Second, in response to COVID-19, SOBs played a more crucial role in credit support, taking on more social responsibilities and potential risks. The aforementioned factors narrowed the idiosyncratic risk gap between SOBs and M&S banks, thereby improving the banking industry’s total credit supply capacity during COVID-19 and maintaining financial stability. This means that strong and targeted policy support has been shown to be crucial for an economy’s recovery from a pandemic with a financial system dominated by indirect financing.

Although the banking industry’s fundamentals are currently sound and in good working order, the credit risk of S&M enterprises that received deferred repayment and loan renewal is high. The gradual withdrawal of unconventional forbearance financial policies and the uncertain global economic outlook may expose policy support in the pandemic. The long-term impact of COVID-19 on the global economic and financial stability remains unknown. However, it is important to consider the possibility of the temporary liquidity risk in the early stages of the pandemic evolving into solvency risk for some weaker S&M enterprises and small banks, and the resilience of these banks could be tested if credit losses materialize following the winding down of policy support (Ikeda, Kerry, Lewrick, & Schmieder, 2021). As the pandemic subsides, banks should be encouraged to provide more market-oriented credit support.

| Dependent variables | m1                              | m2                              | m3                              |
|---------------------|---------------------------------|---------------------------------|---------------------------------|
|                     | Total volatility               | CAPM-based idiosyncratic volatility | Fama-based idiosyncratic volatility |
| l.dependent variable | 0.882*** (0.012) | 0.939*** (0.009) | 0.933*** (0.009) |
| l.death-ch          | 0.026*** (0.004) | 0.002 (0.002) | 0.001 (0.002) |
| l.death-us          | 0.008** (0.003) | −0.001 (0.001) | −0.000 (0.001) |
| l.inpeu-ch          | 0.037*** (0.004) | 0.000 (0.005) | 0.004 (0.004) |
| l.inpeu-us          | −0.023*** (0.005) | 0.012** (0.006) | 0.003 (0.004) |
| l.hmv               | 0.262 (0.180) | 0.030 (0.107) | −0.112 (0.090) |
| l.pb                | −0.410*** (0.121) | −0.064 (0.057) | 0.073 (0.053) |
| l.turnover          | 2.307*** (0.249) | 1.271*** (0.257) | 1.046*** (0.192) |
| l.roe               | −1.142 (0.906) | −0.223 (0.462) | 0.104 (0.365) |
| l.ea                | −3.809* (2.035) | −0.335 (0.928) | 0.687 (0.759) |
| sob*l.death-ch      | −0.011* (0.006) | −0.002 (0.003) | −0.002 (0.003) |
| sob*l.death-us      | 0.001 (0.002) | 0.001 (0.001) | 0.001 (0.001) |
| Constant            | −0.965 (1.139) | −0.126 (0.725) | 0.633 (0.601) |
| Observations        | 3608               | 3608               | 3608               |
| R-squared           | 0.932              | 0.940              | 0.931              |
| Number of banks     | 36                 | 36                 | 36                 |

Data source: WIND, sorted based on Stata statistical results. Robust standard errors are presented in parentheses.

*** p < 0.01, ** p < 0.05, and * p < 0.1.
Table 9
Robustness test: shortening time window.

|                  | m1                | m2                | m3                | m1                | m2                | m3                |
|------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
|                  | Total volatility  | CAPM-based idiosyncratic volatility | Fama-based idiosyncratic volatility | Total volatility  | CAPM-based idiosyncratic volatility | Fama-based idiosyncratic volatility |
|                  | Dec. 9, 2019–April. 1, 2020 | Dec. 16, 2019–Mar. 25, 2020 |
| Independent variable | 0.858*** (0.011) | 0.934*** (0.015) | 0.927*** (0.013) | 0.848*** (0.012) | 0.941*** (0.012) | 0.933*** (0.012) |
| l.covid-ch        | 0.018*** (0.003)  | 0.001 (0.002)     | 0.017*** (0.004) | 0.015*** (0.003) | 0.000 (0.002)     | 0.000 (0.002)     |
| l.covid-us        | 0.017*** (0.002)  | 0.000 (0.002)     | 0.015*** (0.003) | 0.015*** (0.002) | 0.000 (0.002)     | 0.000 (0.002)     |
| l.inepu-ch        | 0.042*** (0.005)  | –0.004 (0.004)    | –0.001 (0.005)   | 0.048*** (0.005) | –0.005 (0.006)    | –0.002 (0.005)    |
| l.inepu-us        | –0.078*** (0.008) | 0.003 (0.007)     | 0.007 (0.007)    | –0.089*** (0.007) | –0.000 (0.005)    | 0.007 (0.005)     |
| l.lmrv            | 0.092 (0.266)     | –0.038 (0.187)    | –0.214 (0.191)   | 0.352 (0.253)     | 0.217 (0.295)     | 0.258 (0.255)     |
| 1.pb              | –0.202 (0.242)    | 0.048 (0.130)     | –0.060 (0.261)   | –0.072 (0.143)    | –0.217 (0.143)    | –0.258 (0.139)    |
| l.turn            | 2.453*** (0.259)  | 1.241*** (0.231)  | 1.036*** (0.235) | 2.726*** (0.393)  | 1.376*** (0.329)  | 1.114*** (0.258)  |
| l.roe             | 1.098 (1.467)     | 1.798* (1.016)    | 2.021* (1.062)   | –3.153 (0.947)    | –0.757 (0.856)    | –0.594 (0.757)    |
| l.lean            | 3.252* (1.863)    | 2.340 (1.662)     | 0.899 (1.623)    | 30.057*** (9.799) | 2.163 (3.306)     | 4.402 (2.835)     |
| sob*l.covid-ch    | –0.055** (0.022)  | –0.006 (0.012)    | –0.009 (0.013)   | –0.059** (0.025)  | –0.009 (0.012)    | –0.011 (0.012)    |
| sob*l.covid-us    | –0.077*** (0.012) | –0.024* (0.012)   | –0.019* (0.011)  | –0.071*** (0.013) | –0.027** (0.010)  | –0.019* (0.010)   |
| Constant          | 0.006 (1.651)     | 0.262 (1.269)     | 1.098 (1.235)    | –0.128 (2.352)    | 0.338 (1.275)     | 2.059 (1.800)     |
| Observations      | 2696 2696         | 2696 2696         | 2696 2696         | 2340 2340         | 2340 2340         | 2340 2340         |
| R-squared         | 0.920 0.928       | 0.914 0.914       | 0.907 0.907       | 0.917 0.917       | 0.909 0.909       | 0.909 0.909       |
| Number of banks   | 36 36             | 36 36             | 36 36             | 36 36             | 36 36             | 36 36             |

Data source: WIND, sorted based on Stata statistical results.
Robust standard errors are presented in parentheses.

*** p < 0.01, ** p < 0.05, and * p < 0.1.

to S&M enterprises to avoid excessive risk taking.

Author statement
This is to certify that Shanshan Li has completed all the work of this paper independently.

Declaration of Competing Interest
None.

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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